<u>Project Notes:</u>

<u>Project Title: Exploring Emotional Sentience in AI-Created Music</u>
<u>Name: Neil Kale</u>

<u>Note Well:</u> There are NO SHORT-cuts to reading journal articles and taking notes from them. Comprehension is paramount. You will most likely need to read it several times so set aside enough time in your schedule.

<u>Contents:</u>

Knowledge Gaps:

This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved
Can the survey be online?	DKC	In MSSEF documentation	10/28/2019
Should I test AI-written music, or robot-produced music	Prof. Scott Barton	In Notes from Barton meeting in this doc.	10/08/2019
How should a project title be selected?	Victoria Bowen	In lab notebook on V. Bowen Meeting Notes page	11/04/19

Literature Search Parameters:

These searches were performed between (Start Date of reading) and XX/XX/2019.
List of keywords and databases used during this project.

Database/search engine	Keywords	Summary of search
google	Ai produced music	Many e-magazine articles on sites such as “Wired”, “Gizmodo”, etc. A good basis in the topic.
google	Emotions in music	Lots of work by Juslin (see article 7). Not much here though.
google	Ai music production techniques	There is a lot of literature from early 2000s, and even 1990s - I.e. David Cope. I’m still looking for more recent stuff.
google	Algorithmic composition	A technical term for ai-produced music, this search resulted in more scholarly sources.
youtube	Ai music	Lots of amateurs dabbling in machine learning, however, there are also some official songs by artists such as Aiva.
google	Guido d’arezzo	Created the first known algorithm for music, I looked for a better source on him than the glancing reference in article 6. Found article 13 but it was behind a paywall so I conducted the search below:
Wpi library search	Making Music with Algorithms: A Case-Study System	Had found this article through google, but it was behind a paywall. WPI library gave me online access to it through JSTOR.

Article #1 Notes: Climate Change and Human Health

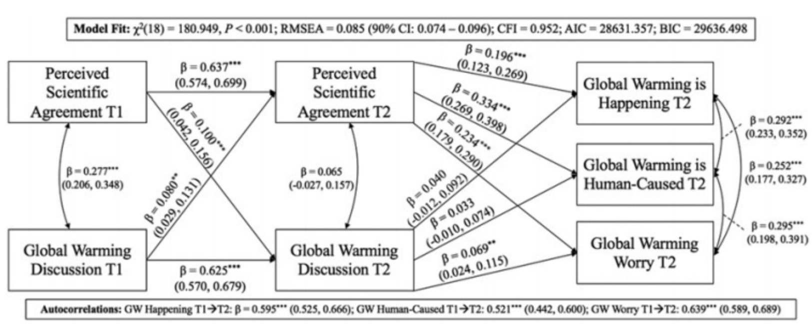
Article notes should be on separate sheets

Source Title	Climate Change and Human Health
Source Author	G. Luber and N. Prudent
Source citation	Luber, George, and Natasha Prudent. "Climate Change and Human Health." *Transactions of the American Clinical and Climatological Association*, vol. 120, 2009.
Original URL	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2744549/
Source type	pdf
Keywords	Climate change, Health, Urban Heat Island,
Summary of key points	Climate change will cause: - Increased heat waves, especially in cities - Heavy precipitation which may lead to dangerous disease outbreaks - More tropical cyclones - More drought-affected areas - Higher sea levels Coral reefs will be injured Changing social environment will play a part in expediating or slowing the process
Important Figures	Most warming in last 50 yrs ios due to greenhouse gases By 2030, 60% of mankind will live in cities Increased heat waves and more heavy rainfall have >90% probability as per IPCC 2007 Report
Reason for interest	A general overview of the proven effects of climate change.
Notes	
Follow up Questions	How can we educate the future generations to combat these problems? Are most youth even aware of these problems?

Article #2 Notes: Discussing Global Warming Leads to Greater Acceptance of Climate Science

Article notes should be on separate sheets

<table>
<tr><td>Source Title</td><td>Discussing global warming leads to greater acceptance of climate science</td></tr>
<tr><td>Source Author</td><td>Matthew H. Goldberg, Sander van der Linden , Edward Maibach , and Anthony Leiserowitz</td></tr>
<tr><td>Source citation</td><td>Goldberg, Matthew H., et al. “Discussing Global Warming Leads to Greater Acceptance of Climate Science.” *Proceedings of the National Academy of Sciences*, vol. 116, no. 30, Aug. 2019, pp. 14804–14805., doi:10.1073/pnas.1906589116.</td></tr>
<tr><td>Original URL</td><td>https://www.pnas.org/content/116/30/14804</td></tr>
<tr><td>Source type</td><td>pdf</td></tr>
<tr><td>Keywords</td><td>Climate Change, Global Warming, Reciprocal Causation, Discussion, Friends & Family, Politicization</td></tr>
<tr><td>Summary of key points</td><td>Discussing global warming with friends and family increases belief in climate change and knowledge of scientific consensus.

Increased knowledge of scientific consensus increases likelihood of discussion. Therefore, a positive social feedback loop is formed.</td></tr>
<tr><td>Important Figures</td><td>

(above) reciprocal causation between scientific agreement and global warming</td></tr>
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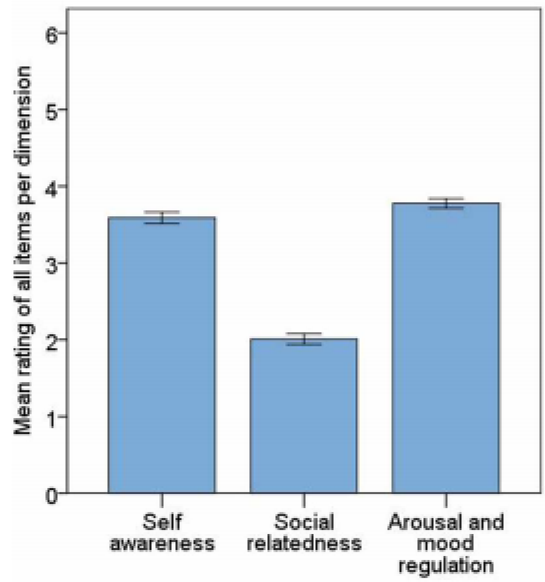
	discussion at T1 and T2 depicted through a net. 1,263 adults surveyed, 7 mo apart. Completion rate: 72% (above)
Reason for interest	Relates social behaviors and policies to climate change, albeit friend/family discussion not education.
Notes	
Follow up Questions	What do the B and CI values mean for any given statement in the results? How did this study deal with potential political bias? Has it been repeated? How might education level in the respondents have affected their responses?

Article #3 Notes: The Psychological Functions of Music Listening

Article notes should be on separate sheets

Source Title	The Psychological Functions of Music Listening
Source Author	Thomas Schäfer , Peter Sedlmeier , Christine Städtler and David Huron
Source citation	Schäfer, Thomas, et al. "The Psychological Functions of Music Listening." Frontiers in Psychology, vol. 4, 13 Aug. 2013, doi:10.3389/fpsyg.2013.00511.
Original URL	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3741536/pdf/fpsyg-04 -00511.pdf
Source type	pdf
Keywords	Music, Behavior, Arousal and Mood, Self-awareness, social-relatedness
Summary of key points	Many dimensions and functions of music have been identified; this goes to show that music likely has multiple functions. Some of these studies have had an evolutionary approach, others have been experimental. Music has three main dimensions of function in modernity: - Self-awareness - Social Relatedness - Arousal and Mood Regulation Social relatedness is less valued than the other two.

Important Figures	 **FIGURE 1 | The three distinct dimensions emerging from 129 reasons for listening to music.** Error bars are 95% confidence intervals. Self-awareness: $M = 3.59$ ($SE = 0.037$); social relatedness: $M = 2.01$ ($SE = 0.035$); arousal and mood regulation: $M = 3.78$ ($SE = 0.032$). (above) Data was collected via survey with 129 questions in the form “I listen to music because…” on a scale from 1-6. Each question was placed in a dimension - Self-Awareness, Social-Relatedness, Arousal and Mood Regulation. The vertical axis shows the mean rating of all items per dimension.
Reason for interest	Interested in determining the impact of AI-created music on psychology, and whether it differs from the impact of manmade music. This article covers some of the ways that music’s psychological impact has been studied so far, and what results have been found to which I could then compare findings for robomusic.
Notes	See text.
Follow up Questions	How were the questions sorted into a dimension - was there any overlap? How do the experimentally determined musical functions hint at an evolutionary origin? Could the original functions of music differ from its functions in the modern day? What is the difference between mood and emotion?

Article #4 Notes: A Few Remarks on Algorithmic Composition

Article notes should be on separate sheets

Source Title	A Few Remarks on Algorithmic Composition

Source Author	Martin Supper
Source citation	Supper, Martin. "A Few Remarks on Algorithmic Composition." *Computer Music Journal*, vol. 25, no. 1, 2001, pp. 48–53., doi:10.1162/014892601300126106.
Original URL	https://muse.jhu.edu/article/7797
Source type	pdf
Keywords	Computer Music, Algorithm, Composition, Instruments, Synthetic sound
Summary of key points	Computer music falls into 3 categories - modelling traditional music (I.e. mozart imitations), developing totally new musical styles, and using algorithms from other fields and applying them to music generation L-Systems from computational biology, which work by setting some base rules then generating a sequence from those rules, can be used to develop music. Rules are set for tempo, tone, pitch, etc Computers have to ability to model nature far better than humans because they can take in more information and do faster calculations, and some music is meant to have natural form.

Important Figures

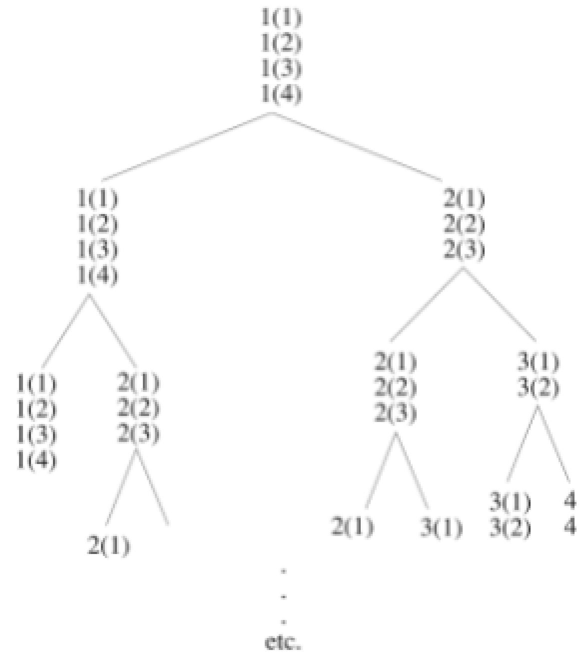


Table 1. Rules used in producing the musical excerpt shown in Figure 1

Axiom	*Rule*
1(a)	if (a < 4), then apply Axiom 1(a + 1)
1(a)	if (a = 4), then apply Axioms 1(1) 2(1)
2(a)	if (a < 3), then apply Axiom 2(a + 1)
2(a)	if (a = 3), then apply Axioms 2(1) 3(1)
3(a)	if (a < 2), then apply Axiom 3(a + 1)
3(a)	if (a = 2), then apply Axiom 3(1)
4	4 → 4

	Figure 1. Cells, for saxophone and ensemble (1993–1994) by Hanspeter Kyburz. Third movement, fourth section, alto saxophone part.  An example of an L-System being used to generate music. The rules lead to a decision tree which can then be applied to make choices on what note to play and what duration to play it for.
Reason for interest	Though I'm not interested in writing my own music algorithms, I think it's good to have a basic understanding of the tool that I'll be using. This article helps me reach that goal.
Notes	See OneNote.
Follow up Questions	This article was written in 2001. How have music algorithms developed since then? If L-System developed music can spool on indefinitely, is it being used anywhere to produce constant ambient noise or muzak, such as in hotel lobbies or hospitals? The article refers to "sound synthesis" composition, which is music that no human instruments nor players could play in 2001. Have robots in 2019, like Shimon the 10-armed xylophonist, overcome that barrier to some degree?

Article #5 Notes: Automatic Composition from Non-musical Inspiration Sources

Article notes should be on separate sheets

Source Title	Automatic Composition from Non-musical Inspiration Sources
Source Author	Robert Smith, Aaron Dennis and Dan Ventura
Source citation	Smith, Robert, et al. "Automatic Composition from Non-Musical Inspiration Sources." International Conference on Computational Creativity, 2012, http://computationalcreativity.net/iccc2012/wp-content/uploads/2012/06/160-Smith.pdf.
Original URL	http://computationalcreativity.net/iccc2012/wp-content/uploads/2012/06/160-Smith.pdf
Source type	pdf
Keywords	Musical composition, inspiration, audio input, melody/harmony generation, voice models, snap-to-grid
Summary of key points	The researchers attempted to write an algorithm to create music from non-musical sources such as the sounds of nature or famous speeches. Their method analyzed the most prominent note throughout the audio file. The algorithm assumed that the highest pitched note was the melody, then developed a harmony line to go along with the pseudosong. Via post-processing, they improved the rhythm and melody via another algorithm - snap-to-grid. In the future, the team aims to write algorithms that can derive metaphors from non-musical audio files, and extract aural qualities from those metaphors to add further meaning to the piece.

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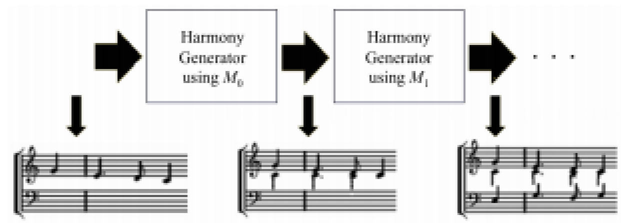
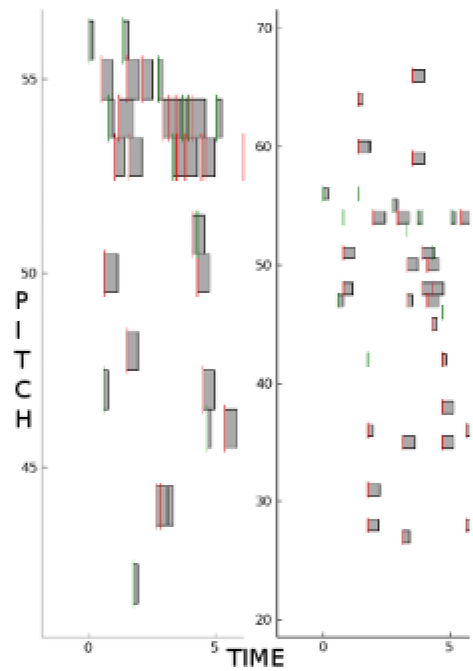


A representation of the algorithmic harmony generator. The team found that M1, which outputs 2 harmony lines was empirically (qualitatively) the most appealing.



An example of how snap-to-grid cleans up the pitches and rhythms of the unprocessed piece. On the left is the unprocessed piece with no easily identifiable pitch intervals or rhythms. On the right is processed, with gaps between notes both in pitch and timing.
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<tr>
<td>Reason for interest</td>
<td>My fundamental interest is in making people feel a certain way with algorithmic music. Speeches by famous individuals, and the sounds of nature can also elicit emotion from humans. As such, I am interested in how this team converted such noises to music. However, after reading their article, I believe the team lost the basic elements that make nature and speeches appealing - in speeches, it’s the message the contain that really matters, tambre is just an add-on. In nature, it’s the familiarity, and the metaphors which we see - such as birds reminding us of freedom, or the roar of a lion being scary to us. Can music solely based on pitch and tone not on meaning of the noise retain these emotional qualities?</td>
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<tr>
<td>Notes</td>
<td>See text.</td>
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<tr>
<td>Follow up Questions</td>
<td>Could a machine-learning algorithm find meaning from noises? I.e. if it is fed an audio file of a party, can it recognize the energy and mood in that noise, not just the</td>
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	prominent notes it can pull out? What is the Markov process?

Article #6 Notes: Algorithmic composition: computational thinking in music

Article notes should be on separate sheets

Source Title	Algorithmic composition: computational thinking in music
Source Author	Michael Edwards
Source citation	Edwards, Michael. "Algorithmic Composition." *Communications of the ACM*, vol. 54, no. 7, Jan. 2011, p. 58., doi:10.1145/1965724.1965742.
Original URL	https://cacm.acm.org/magazines/2011/7/109891-algorithmic-composit on/fulltext
Source type	pdf
Keywords	Algorithmic composition, computer music, familiarity, formalized, programming, software implementation
Summary of key points	Algorithmic composition existed as far back as 1026 AD. It doesn't need to be on a computer. Other examples include the structure of the Classical rondo, Baroque fugue, and Classical sonata. The algorithms are based in mathematics - Lindenmayer (L) Systems which determine the next state based on the current and possibly past states. (Examples include fibonacci numbers, which lead to golden ratio $\lim_{n\to\infty} \frac{F(n+1)}{F(n)}$ Algorithmic music can be defined as stochastic (random, will generate different results in each run), deterministic (Like David Cope's "EMI" produces the same results every time the program is run), or a mixture There is academic and cultural opposition to algorithmic computer-aided composition, based on the concern that the computer is replacing the composer. This is unfounded, because someone still needs to write the program, and write it so that it captures the musical ideas. The composer turns programmer, and he is still the creator!

Important Figures

Figure 9. Foreground rhythmic pattern (quaver/eighth-note durations) of *Désordre*.[26]

right hand:	left hand:
cycle 1: a: 3 5 3 5 5 3 7	3 5 3 5 5 3 8
a': 3 5 3 5 5 3 7	3 5 3 5 5 3 8
b: 3 5 3 5 5 3 3 4 5 3 3 5	3 5 3 5 5 3 3 5 5 3 3 5 3 5 3 5 5 3 8
cycle 2: 3 5 3 4 5 3 8	3 5 3 5 5 3 8
3 5 3 4 5 3 8	3 5 3 5 5 3 8
3 5 3 4 5 3 3 5 5 3 3 4	3 5 3 5 5 3 3 5 5 3 3 5 3 5 3 5 5 3 8
cycle 3: 3 5 3 5 5 3 7	3 5 3 5 5 3 8
3 5 3 5 5 3 7	3 5 3 5 5 2 7
3 5 3 5 5 3 3 4 5 3 3 5	3 4 3 4 4 2 2 4 4 2 2 3 2 3 1 3 3 1 4
cycle 4: 3 5 3 4 5 2 7	1 3 1 2 2 1 3
2 4 2 4 4 2 5	1 2 1 2 2 1 3
2 3 2 3 3 1 1 3 3 1 1 3	1 2 1 2 2 1 1 2 2 1 1 2 1 2 1 2 2 1 3
cycle 5: 1 2 1 2 2 1 3	1 3 1 2 2 1 3
1 2 1 2 2 1 3	1 2 1 2 2 1 3
1 2 1 2 2 1 1 2 2 1 1 2	1 2 1 2 2 1 1 2 2 1 1 2 1 2 1 2 2 1 2
...	...

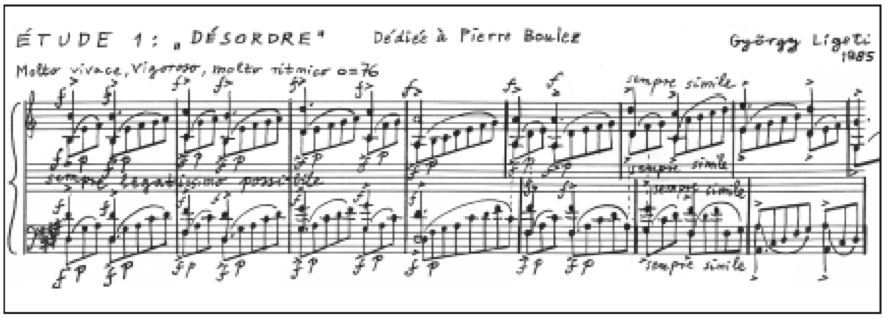

Figure 10. *Désordre*. First system of score © 1986 Schott Music GmbH & Co. KG, Mainz, Germany. Reproduced by permission. All rights reserved.

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Figure 6. Fibonacci-based transition from material 0 to material 1. Note the first appearance of 1 is at position 13, with the next eight positions after that, the next again five positions after that, and so on; all these numbers are so-called Fibonacci numbers.

0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0
0 1 0 0 1 0 1 0 1 0 1 1 0 1 0 1 0 1 0 1 1 0 1 1 0 1 1 1 1 0 1 1
1 1 1 1 1 1

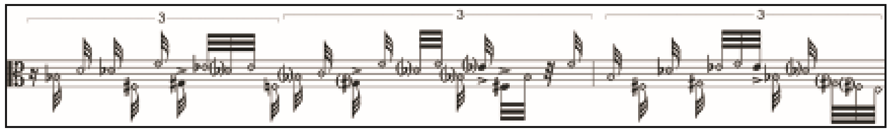
Figure 7. Extract beginning bar 293 of the author's Tramontana for viola and computer.

Figure 8. Foreground melodic pattern (scale steps) of Désordre.[26]

Right hand (white notes), 26 notes, 14 bars
Phrase a: 0 0 1 0 2 1 -1
Phrase a': -1 -1 2 1 3 2 -2
Phrase b: 2 2 4 3 5 4 -1 0 3 2 6 5

Left hand (black notes), 33 notes, 18 bars
Phrase a: 0 0 1 0 2 2 0
Phrase a': 1 1 2 1 -2 -2 -1
Phrase b: 1 1 2 2 0 -1 -4 -3 0 -1 3 2 1 -1 0 -3 -2 -3 -5

Some more excerpts from pieces created via L Systems - Desordre and Tramontana.
</td></tr>
<tr><td>Reason for interest</td><td>This further solidified my understanding of algorithmic composition which helps me further specify my study and look at various aspects of the field - deterministic vs. stochastic music, process composition vs algorithmic composition. Do I want to generate music that replicates existing styles as a researcher, or create totally new compositions as a composer? This article allows me to ask these baseline questions.</td></tr>
<tr><td>Notes</td><td>See OneNote.</td></tr>
<tr><td>Follow up Questions</td><td>Is it important that these pieces sound good, or is that not a criteria to qualifying as music?

How have computers changed algorithmic music other than allowing for more complex trends? Has the refinity of algorithmic composition - its ability to capture the imagination more eloquently - also improved?

Can we start from a piece, and reverse-engineer an L-System that created it? In that way, could we analyze human compositions more quantitatively?</td></tr>
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Article #7 Notes: What does music express? Basic emotions and beyond

Article notes should be on separate sheets

Source Title	What does music express? Basic emotions and beyond
Source Author	Patrick N. Juslin
Source citation	Juslin, Patrik N. “What Does Music Express? Basic Emotions and Beyond.” *Frontiers in Psychology*, vol. 4, 6 Sept. 2013, doi:10.3389/fpsyg.2013.00596.
Original URL	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3764399/pdf/fpsyg-04-00596.pdf
Source type	pdf
Keywords	Music, emotions, categories, dimensions,Icon Coding, Symbol Coding, Index Coding, basic emotions, musical expectations, intrinsic coding, associative coding,emotional arousal,
Summary of key points	Emotion theories fall into two categories: categorical and dimensional. Categorical theories state that there is a clear delineation between different emotional states. Dimensional theories suggest that there are infinite possible emotional states which exist as points on a 2D/3D graph whose axes are components of any emotion (I.e. Gaiety-Gloom, Tension-Relaxation, Solemnity-Triviality) The author believes that the categorical model is a better representation. Music expresses emotion via icon, symbol, and index coding. Icon coding is achieved by musical cues that remind listeners of vocal expression and human movements that suggest certain emotions. These are mainly for basic emotions. Which emotions are basic is a contested topic, but happiness, sadness, disgust, surprise, anger, fear is one list. Iconic coding tends to be universal in expressing emotion. Symbol coding is a syntactic relationship within the music I.e. a minor chord, ascending arpeggio, etc that causes the listener to feel a certain way. Index/associative coding is by connecting the music to the real world. I.e. organ music is mainly heard in church, so a churchgoer might feel religious when he/she

hears that music. This is very dependent on the individual's life experience, so not universal.

Expression marks in music can elicit different emotions. I.e. spiritoso is related to surprise, dolce to tenderness, espressivo to desire, furioso to anger, and temeroso to anxiety

Music can also elicit different emotions based on intensity of the emotion (I.e. serenity→ joy → ecstatic) Music usually operates at the lower end of this intensity spectrum, therefore slight variations in emotion are harder to measure.

Iconic coding in music universally elicits the same emotion from people, hence music is sometimes called the universal language of emotions.

Important Figures

Table 1 | Ratings of the extent to which specific emotions can be expressed in music.

	Kreutz (2000)	Lindström et al. (2003)	Juslin and Laukka (2004)
Subjects	**50 students**	**135 expert musicians**	**141 volunteers**
No. of emotions Subjects	**32**	**38**	**38**
RANK ORDERING			
1.	**Happiness**	**Joy**	**Joy**
2.	**Sadness**	**Sadness**	**Sadness**
3.	Desire	**Anxiety**	**Love**
4.	Pain	**Love**	Calm
5.	Unrest	Calm	**Anger**
6.	**Anger**	Tension	**Tenderness**
7.	**Love**	Humour	Longing
8.	Loneliness	Pain	Solemnity
9.	**Fear**	**Tenderness**	**Anxiety**
10.	Despair	**Anger**	Hate

Only the ten most highly rated emotions in each study have been included in the Table. Those emotion categories that correspond to the basic emotions are set in bold text. (Anxiety belongs to the "fear family," and tenderness to the "love" family, see, e.g., Shaver et al., 1987.) The original lists of emotion terms contained both "basic" and "complex" emotions, as well as some terms commonly emphasized in musical contexts (e.g., solemnity).

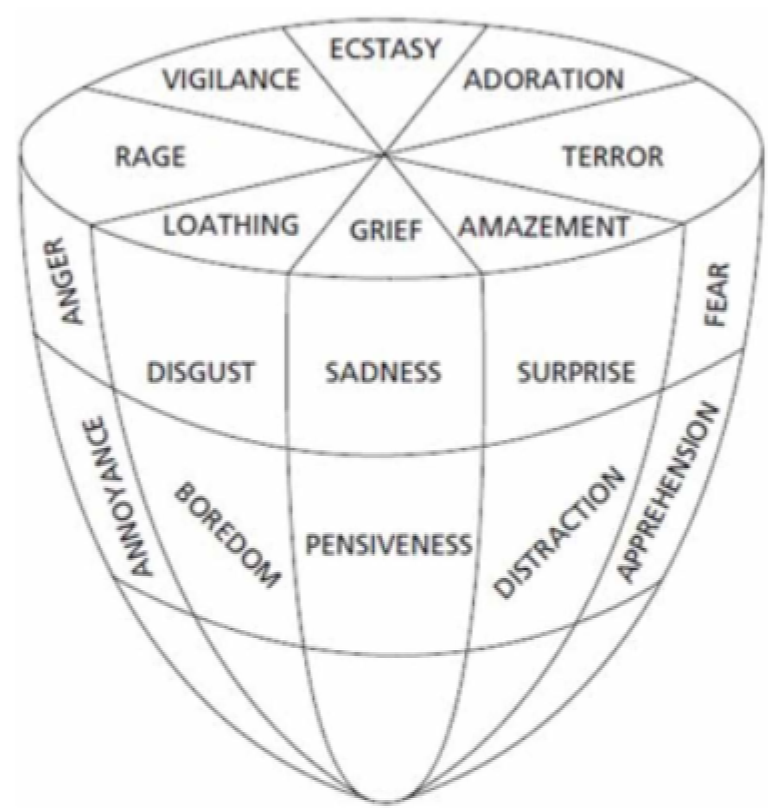
Responses to the question: What emotions are evoked by music?

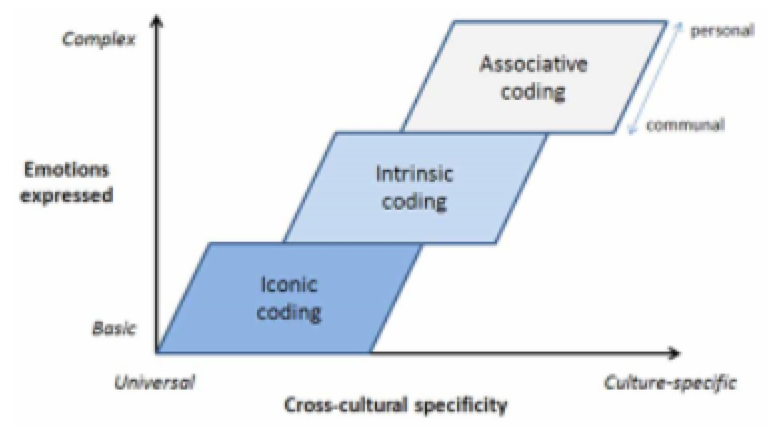
Table 2 | Examples of correlations between commonly used expression marks in music scores and basic-emotion labels used by psychologists.

Expression mark	Emotion label	Correlation (*r*)
Dolce	Tenderness	0.98*
Espressivo	Desire	0.85*
Furioso	Anger	0.92*
	Disgust	0.79*
Grave	Sadness	0.88*
Scherzando	Happiness	0.76*
Spiritoso	Surprise	0.94*
Temoroso	Anxiety	0.97*
	Fear	0.82*

*$p < 0.01$.
(based on Juslin and Wiik, submitted).

More data from the expression mark - emotion correlation study.

	 **FIGURE 1 | Plutchik's "cone model" of emotion (adapted from Plutchik, 1994).** Plutchik's 8 basic emotions (Anger-fear, disgust-trust, sadness-joy, surprise-anticipation) and how they change depending on intensity.

	 **FIGURE 2 | Multiple-layer conceptualization of musical expression of emotions.** The various layers of emotional coding in music.
Reason for interest	I've learned that algorithms can create music, however, what I'm really interested in is whether they can use music as a medium to incite emotion. To start down this path, I found this article which explains how human music elicits emotion and overviews other literature on this topic.
Notes	See OneNote.
Follow up Questions	What are some examples of iconic coding? Does associative coding change over time? If so, is it possible that classical music from the 1800s may no longer hold the same meaning today as it did when it was written? Is it possible that some emotions are intrinsically coded by sounds that are impossible to generate with real instruments? Could computer-produced music access these emotional states which otherwise can't be incited by music? Are certain forms of emotional expression, such as music, more idiosyncratic - deeply personal? Which ones are more communal - meaning that the emotions they generate are fairly consistent throughout many people? Emotional communication via music is closely related to emotional communication via vocal expression. Is there a connection like this between music and art, or literature, or facial expression as well? What about musicians' faces while they play? Do great musicians (emotional communicators) emote that way as well? If an algorithm can't emote by facial expression (because it has no face) will that inhibit its ability to emotionally communicate? Which matters more to intrinsic coding: The composition (melodies, harmonies, expression marks, dynamics, etc) , or how it is played (human variations in tambre, ?

Article #8 Notes: Designing Emotionally Sentient Agents
Article notes should be on separate sheets

Source Title	Designing Emotionally Sentient Agents
Source Author	Daniel McDuff Mary Czerwinski
Source citation	Mcduff, D., & Czerwinski, M. (2018). Designing emotionally sentient agents. *Communications of the ACM*, *61*(12), 74–83. doi: 10.1145/3186591
Original URL	https://cacm.acm.org/magazines/2018/12/232878-designing-emotionally-sentient-agents/fulltext
Source type	Journal article
Keywords	Emotionally sentient, affective computing, conversational agents, Nonverbal/Verbal Emotion Sensing, Emotion Labels, Emotional Agents, Embodied agents, Interpersonal variability
Summary of key points	Affective computing is the field of designing computer systems to "sense, interpret, adapt, and potentially respond appropriately to human emotions" Affective computing could enhance personal assistants like Siri, Cortana, etc Affective computing can make computer systems more trustworthy, allowing robots to complete complex tasks in a public setting without opposition It could also have a use in doctor's offices, as people may feel more comfortable talking with a robot than a human about private matters, and they may feel less pressure to conform to social expectations (I.e. I've never smoked in my life, doc!). Companies commercially track their audience's emotional response to ads, and then determine which ad elicits the response they want. Some jobs shouldn't be automated: I.e. air traffic controller The main ways of tracking human emotional response is verbal (what they say), and nonverbal. Nonverbal includes prosody (how we say things), facial expression,

	body language, and more. Each person expresses emotion in a unique way, so exact models would have to be personalized and also dependent on the unique characteristics of the situation Emotional agents also come in some different types. Dialogue systems, or chatbots, are one. These mainly use verbal emotion, but some (Xiaoiced) can do text-to-speech and thus use prosody. Virtual agents like Siri and Cortana are another type Embodied agents may be better at communicating emotion because they can use nonverbal cues like deixis, eye contact, speech patterns, head nods, body language, etc. A study using conversational agents in a clinical setting got more honest answers than with actual doctors. Conversely, robots that show human-like emotions and politeness can get more assistance from humans. The next frontier for personal assistants like Siri and Cortana will be how well they can emotionally connect to the user People may change how they talk because they subconsciously are mimicking affective agents. This is supported by research which shows that people have changed how they think as a result of using internet search engines.
Important Figures	No figures
Reason for interest	Article #7 taught me about emotion expression in music, and how humans are affected by music. I want to know more about how an algorithm could express emotion itself, and also how an algorithm might measure human response both to algorithm creations and human creations. This article introduced me to the term affective computing, and showed me several new applications of my research. Furthermore, it showed me how I could go about testing my second hypothesis, which is that algorithm-generated emotional expression (music, literature, art, speech, facial expression) can incite an emotional response from humans. I learned several ways that I could measure the presence/non-presence of that emotional response.
Notes	See OneNote
Follow up Questions	How have companies tracked audience's emotional response to a stimulus en masse? Do animals express emotions through verbal/non-verbal cues? Are there any algorithms that measure this emotion?

Article #9 Notes: AI Methods for Algorithmic Composition

Article notes should be on separate sheets

Source Title	AI Methods for Algorithmic Composition
Source Author	George Papadopoulos and Geraint Wiggins
Source citation	AI Methods for Algorithmic Composition: A Survey, a Critical View and Future Prospects. (1999). In *Computer Music Journal* (4th ed., Vol. 23, pp. 79–82). Edinburgh. Retrieved from https://www.mitpressjournals.org/doi/10.1162/comj.1999.23.4.79
Original URL	http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.3.8064
Source type	Conference Proceedings
Keywords	Algorithmic Composition, Mathematical models, knowledge based systems, grammars, genetic algorithms, machine learning, artificial neural networks (ANN), computational creativity, musical cognition
Summary of key points	Music creation algorithms can be divided into 6 categories: ● Mathematical models ● Knowledge based systems ● Grammars ● Evolutionary methods ● Systems which learn ● Hybrid systems All systems have their own pros and cons, but at the time when this was written in 1999, hybrid systems looked promising. They were just very computationally complex and difficult to create at the time. The major problems at the time with computer-generated music were: the computers have no emotion, and thus they can't tell any story with the emotion. I.e.

	if a statistical analysis finds that 10% of the notes in a given piece are loud, an algorithm which makes 10% of its notes loud won't have the same effect. It doesn't account for why those 10% were loud, what story they were telling. The hardest aspect of music to incorporate is creativity. Some possible ways to incorporate creativity are through ambiguity - leaving some notes and rhythms to chance, and or to include trial-and-error processes that require human input. At the time, some believed that certain aspects of music couldn't be represented by a computing process. Also, the performance of a piece can't be discounted. Computer performed pieces (at the time) were quite jarring, and didn't have the same rhythm and "gesture" as human played pieces. This is similar to prosody in human speech.
Important Figures	None
Reason for interest	After having read some recent papers on AI-created music and how music elicits emotions, I wanted to see how these views had changed since the advent of computer music in the 1990s. Additionally, I'm curious as to what challenges seemed impossible at that time, but might be overcome with modern technology and resources.
Notes	
Follow up Questions	Do limiting-computing processes (aspects of music that can't be represented by a computer) still exist? What are they? Are algorithm produced pieces from that era produced "for MIDI", meaning they'll sound better on MIDI than a standard piece, written by humans for humans, would sound on MIDI? Is the music produced by computational models still considered meaningless? Has the emergence of affective computing changed that? Could algorithms convergently evolve into human-like music, or must they follow the same steps as a human composer in composing a song?

Article #10 Notes: Magenta.js: A JavaScript API for Augmenting Creativity with Deep Learning

Article notes should be on separate sheets

Source Title	Magenta.js: A JavaScript API for Augmenting Creativity with Deep Learning
Source Author	Adam Roberts , Curtis Hawthorne , Ian Simon
Source citation	Roberts, A., Hawthorne, C., & Simon, I. (2018). Magenta. js: A javascript api for augmenting creativity with deep learning.
Original URL	https://ai.google/research/pubs/pub47115
Source type	Conference Proceeding from *Joint Workshop on Machine Learning for Music*
Keywords	Javascript, Deep Learning, TensorFlow, Music generation
Summary of key points	Google Magenta is a machine learning system designed to apply machine learning to creative problems like music and art generation among others. Magenta.js is a Javascript API that makes Magenta more accessible to those without a background in ML. It is designed to aid humans with music generation rather than create compositions fully unaided. The two tools available right now are MusicRNN and MusicVAE. MusicRNN can “auto-complete” a phrase of music that is passed into it. MusicVAE allows users to convert note sequences into vectors, then interpolate, sample, etc with those vectors, and then convert vectors back into note sequences. In the future, Magenta.js may allow websites to tailor music and art to your tastes in browser.

<table>
<tr>
<td>Important Figures</td>
<td>

```
<html>
  <head>
    <script src="https://cdn.jsdelivr.net/npm/@magenta/
        music@1.0.0"></script>
    <script>
      // Instantiate model by loading desired config.
      const model = new mm.MusicVAE(
        'https://storage.googleapis.com/magentadata/js/
            checkpoints/music_vae/trio_4bar');
      const player = new mm.Player();

      function play() {
        mm.Player.tone.context.resume();  // enable audio
        model.sample(1)
          .then((samples) => player.start(samples[0]));
      }
    </script>
  </head>
  <body><button onclick="play()">Play Trio</button></body>
</html>
```

An example block of code using MusicVAE. This one samples and plays back a 4-bar trio.
</td>
</tr>
<tr>
<td>Reason for interest</td>
<td>Professor Barton told me about Google Magenta. At this time, my primary focus is on studying how people react to algorithm/human produced music, not producing my own algorithm-written music. That said, I wanted to explore what functionalities I have if I were to create my own music for this study, and ascertain whether that is/isn’t worthwhile.</td>
</tr>
<tr>
<td>Notes</td>
<td>See OneNote</td>
</tr>
<tr>
<td>Follow up Questions</td>
<td>What samples have already been created using Magenta? Are there any that distinguish the input note sequences based on the emotions that they arouse?

Has any research been done into personalized music with Magenta? What were the results?</td>
</tr>
</table>

Article #11 Notes: Tonal Pitch Space

Article notes should be on separate sheets

Source Title	Tonal Pitch Space
Source Author	Fred Lerdahl
Source citation	Lerdahl, Fred. “Tonal Pitch Space.” *Music Perception: An Interdisciplinary Journal*, vol. 5, no. 3, 1988, pp. 315–349., doi:10.2307/40285402.
Original URL	None, paper source
Source type	Journal Article
Keywords	Topological models, pitch space, tonal theories, tonal hierarchy, event hierarchy, time span reduction, prolongation reduction, stability conditions
Summary of key points	The author suggests a relationship between topological models of music such as chart of regions (Schoenberg), which determine which chord progressions sound good, with 20th century tonal theories which explain why people prefer certain sounds. The two main reasons that certain chord progressions sound good is tonal hierarchy, how we understand pitc placement, harmonics, scales, and so on. Event hierarchies are inferred from temporal musical sequences, and are how listeners perceive rhythm and recursive patterns such as tension and relaxation, verse and refrain, within the music.
Important Figures	
Reason for interest	This paper appeared in my mailbox. It illustrates the complexity of the music theory that underlies my project, and starts diving into “why” people prefer certain tonal and event hierarchies - what differentiates music from random noise.In the end, an AI that produces music is doing nothing but producing familiar or pleasant tonal and event hierarchies.
Notes	
Follow up Questions	

Article #12 Notes: How Music and Instruments Began

Article notes should be on separate sheets

Source Title	How Music and Instruments Began: A Brief Overview of the Origin and Entire Development of Music, from Its Earliest Stages
Source Author	Jeremy Montagu*
Source citation	Montagu, J. (2017). How music and instruments began: A brief overview of the origin and entire development of music, from its earliest stages. Frontiers in Sociology, 2, 8. doi:10.3389/fsoc.2017.00008
Original URL	https://www.frontiersin.org/articles/10.3389/fsoc.2017.00008/full
Source type	Journal Article
Keywords	
Summary of key points	
Important Figures	
Reason for interest	
Notes	
Follow up Questions	

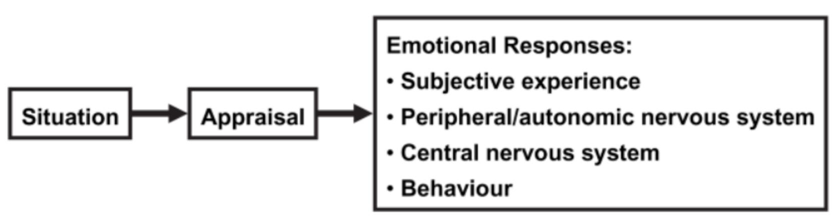
Article #13 Notes: Making Music with Algorithms: A Case-Study System

Article notes should be on separate sheets

Source Title	How Music and Instruments Began: A Brief Overview of the Origin and Entire Development of Music, from Its Earliest Stages
Source Author	Jeremy Montagu*
Source citation	Montagu, J. (2017). How music and instruments began: A brief overview of the origin and entire development of music, from its earliest stages. Frontiers in Sociology, 2, 8. doi:10.3389/fsoc.2017.00008
Original URL	https://www.frontiersin.org/articles/10.3389/fsoc.2017.00008/full
Source type	Journal Article
Keywords	
Summary of key points	
Important Figures	
Reason for interest	
Notes	
Follow up Questions	

Article #14 Notes: Measures of Emotion - A Review

Article notes should be on separate sheets

Source Title	Measures of Emotion - A Review
Source Author	Iris B. Mauss Michael D. Robinson
Source citation	See Refworks
Original URL	None, recieved as PDF in email from Dr. C
Source type	Journal Article
Keywords	Experiential, physiological, behavioral measures, emotion-evocative stimuli, affective science, (valence, arousal, approach-avoidance), (dimensional, discrete), self-report measures, alexithymia, autonomic measures, (electrodermal, cardiovascular, SCL, SCR, BP, TPR, CO, PEP, HRV), startle response magnitude, (EMG, startle probe), brain states, (EEG, neuroimaging, fMRI, PET), behavior, (vocal characteristics, facial behavior, observer ratings, electromyography, whole-body behavior, summary),
Summary of key points	Essentially, no form of emotion measurement is perfect. That said, self-report methods (I.e. survey) can perform well in a dimensional framework to show currently experienced emotion.
Important Figures	 **Figure 1.** A consensual component model of emotional responding. Fig. 1. The pathway through which an emotion-evocative stimulus lead to response
Reason for interest	
Notes	

Follow up Questions

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TABLE 1

Overview of response systems, measures, and emotional states to which they are sensitive

Response system	Measure	Sensitivity
Subjective experience	Self-report	Valence and arousal
Peripheral physiology (ANS)	Autonomic nervous system (ANS) measures	Valence and arousal
Affect-modulated startle	Startle response magnitude	Valence, particularly at high levels of arousal
Central physiology (CNS)	EEG	Approach and avoidance
	fMRI, PET	Approach and avoidance
Behaviour	Vocal characteristics: Amplitude, pitch	Arousal
	Facial behaviour: Observer ratings	Valence; some emotion specificity
	Facial behaviour: EMG	Valence
	Whole body behaviour: Observer ratings	Some emotion specificity

Table 1: What aspects of emotion are measured by the various means available (and what response systems do they rely upon)

Potential Music

Song/Album	Artist	Genre	Notes
Hello World	SKYGGE	Pop	Not purely AI-generated. Flow Machine (algorithm) created the parts of the song. Humans then rearranged the pieces and added lyrics. (Youtube -> MP3 -> MIDI)
Classical Music Composed by Computer: Experiments in Musical Intelligence	David Cope	Classical	David Cope's pieces are purely algorithmic. The algorithm is fed on human pieces, and outputs unique computer-generated pieces. This album is 20+ years old, but still a first class example of algorithm produced music. Algorithmic Bach Chorales: http://artsites.ucsc.edu/faculty/cope/5000.html
Chorales	Bach (human comparison)	Classical	For comparison w/ DeepBach and Cope - http://www.bachcentral.com/midiindexcomplete.html
Genesis	Aiva	Movie Soundtrack	Purely algorithm written, AIVA is designed to produce music for movies and video games - i.e. music that incites emotion. On its website, it is labelled as "The Artificial Intelligence composing emotional soundtrack music"
On the Edge	Aiva	Rock	This is remarkably good. Indie rock might be an interesting genre to explore - lyric-free of course. https://www.youtube.com/watch?v=gA03iyI3yEA&feature=youtu.be
	Aiva	All	Can generate my own algorithmic MIDIs at: beta.aiva.ai
Break Free	Taryn Southern (human) and AMPER	Pop	AI wrote the instrumentation and played it. Taryn Southern added and sung vocal lines. https://www.youtube.com/watch?v=XUs6CznN8pw
	DeepBach	Classical	Algorithm trained on JS. Bach's pieces. There is an easy to use Musescore extension that allows users to indefinitely extend phrases of music that they have written with algorithm-produced Bach-esque music that flows from that seed. Studies in the Netherlands show that DeepBach can successfully imitate the real thing. The code: https://github.com/Ghadjeres/DeepBach
	Balmorhea	Post-rock minimalist	Human band that produces instrumental pieces with very simple tones.

On matching AI music with human music: A service such as "Shazam", which offers similar music to the song being played, may be able to match AI music with similar human pieces.

Results Critique

Source Title	Music and Emotions in the Brain: Familiarity Matters
Source Author	Carlos Silva Pereira, João Teixeira, Patrı´cia Figueiredo, Joao Xavier, Sa˜o Luı´s Castro, Elvira Brattico
Source citation	Pereira, Carlos Silva, et al. "Music and Emotions in the Brain: Familiarity Matters." *PLoS ONE*, vol. 6, no. 11, 16 Nov. 2011, doi:10.1371/journal.pone.0027241.
Original URL	https://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0027241&type=printable
Source type	pdf
Summary	The researchers attempted to determine how the familiarity of a musical piece affects the emotional response it elucidates from a listener. They measured emotional response in two ways. Initially, through a Yes/No survey which asked listeners whether they liked a piece, and later on, by measuring brain activity in the limbic system and reward circuitry via an fMRI. The researchers found that familiar music incited more brain activation and tended to be more liked than unfamiliar music. The claim that a null result for (Unfamiliar Music > Familiar Music) is physiologically impossible should be moved from results to discussion. Additionally, the result (Familiar Music > Unfamiliar Music) should be moved higher in the results section as it is the primary focus of the study. The data for each of the 4 tested comparisons (see pg. 6) could be split into 4 separate tables rather than one long table. Similarly, the figures for the 4 comparisons (see pg. 7) could also be split into 4 separate tables. Significant digits for the measured values were to the hundredths place for Z values (not Z scores) and to the units place for (x,y,z) location of brain areas in the MNI space.

Expert #1: Dr. Cuthbert

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Expert #2: Dr. Rockmore

Full Name	Daniel N. Rockmore
Bio	professor of computer science and mathematics at Dartmouth College and the author of Stalking the Riemann Hypothesis: The Quest to Find the Hidden Law of Prime Numbers
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LinkedIn	
Correspondence	In OneDrive

Expert #3: Dr. Barton

Full Name	Scott D Barton
Bio	Humanities and Arts **ASSOCIATE PROFESSOR OF MUSIC**
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Website	https://www.wpi.edu/people/faculty/sdbarton
LinkedIn	
Correspondence	In OneDrive
Meeting (October 8) Notes	**Start simple - just deterministic can people tell the difference between robot produced and human produced music** **Maybe two MIDI files so human playing variations are controlled for** **robots composing music vs robots playing music** **Ask whether his improv algorithms are stochastic or deterministic, does this matter for my research?** **Algorithmic music can't be too perfect, we need variation** **What we like in robots- precision, accuracy, predictability - epitomize human ideals** **Composers → Programmers** **Survey could time stamp when people respond while listening to the piece** **Ontology, how our mind organizes music. Pop verses are ~15 second, the length of short term memory**

Expert #4: Jason the Ref. Librarian

Full Name	Jason ?
Bio	Reference librarian at the Westborough Public Library
Email	
Website	
LinkedIn	
Correspondence	In person
Meeting (Nov 3) Notes	**How to find information?** ● **Boston E-Card will let me access the BPL archives for information** ● **I should contact the ref librarian at WPI for information and resources** ● **Shoot emails to ref librarians at other schools (music schools and even MIT for AI aspect) to ask if they can help me. If not, they may be able to point me to someone who can.** ● **If BPL doesn't have what I need, shoot an email to NYPL. Worst come to worst they say no** ● **There is no cost associated with sending emails** ● **Contact department heads for field-specific research.** ● **If there's a certain college I want to communicate with, he can help me find a good contact within that community** **He's there every Sunday (May be busy on 11/10 because the library is short staffed)**

Non-Expert #4: Alex Romine

Full Name	Alex Romine
Bio	Previous MAMS student w/ similar project
Email	alromine@hotmail.com
Website	x
LinkedIn	x
Correspondence	Phone Call: Hello Shadow song Modern physics with Isabella Strow Music Psych with Scott Barton Rationale behind methods is important to prove Survey based projects don't perform very well? What is the non-risky decibel range? Collect data by December fair (1 set of trials) WILL need a human experimentation form Set up when I will do testing and get it ready I do have to submit consent forms before experimentation

Non-Expert #5: Neil Tamhankar

Full Name	Neil Tamhankar
Bio	**My best friend, who studies psychology**
Email	
Website	x
LinkedIn	x
Correspondence	Survey vs Case Study for measuring emotion Could an EEG be used to measure brain activity? Population is Juniors at Mass Academy

Non-Expert #6: Victoria Bowen

Full Name	Victoria Bowen
Bio	Previous MAMS student w/ similar project
Email	bowen.v@husky.neu.edu
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LinkedIn	x
Correspondence from Meeting (11/4)	In lab notebook