Inter-individual Music Preferences:

Traits Influencing Appreciation of Melodic Complexity

Karl A. Neumann
260617609

Course: PSYC 494D1/D2
Supervisor: Dr. Robert J. Zatorre
Due Date: April 16th, 2018

McGill
UNIVERSITY

Abstract:

Variance in individual differences in music preferences are nearly infinite; no two individuals are bound to have the same taste in music. Until recently, scientific investigation into the factors that influence these variations has been scarce. Underlying each individual's unique preferences for artists, genres, or songs is their more general appreciation of complexity in music. This behavioral experiment of 44 participants aimed to further understand inter-individual preferences for musical complexity via questionnaires and ratings of subjective pleasure while participants listened to a variety of musical excerpts. A formalized measure of complexity along with state-of-the-art synthesis of realistic musical stimuli made this among the most ecologically valid tests of individual preferences for musical complexity yet.

Results utilizing stepwise regression, linear and quadratic regression, and F tests indicated a significant negative correlation between trait 'Neuroticism' and mean liking of the 10 least complex stimuli ($R^2 = 0.105$, $F(1, 40) = 4.71$, $p = 0.0359$). Additionally, when analyzing results from a previously studied subset of the stimuli, there was a significant positive correlation between 'Agreeableness' and average preference for the 10 most complex stimuli ($R^2 = .098$, $F(1, 41) = 4.46$, $p = .0409$) in addition to replication of a significant inverse quadratic relationship between information content and liking ($R^2 = 0.323$, $F(2, 47) = 11.2$, $p < .001$).

Based on prior experiments utilizing many of the same stimuli used in this project, we expected an 'inverted-U' relationship between musical complexity and preference, disputing the prospect of a negative linear relationship**.** Correlations were expected between Agreeableness, Neuroticism, and Openness to Experience and average preferences for information content based on previous research. Hypotheses concerning Agreeableness and Neuroticism were confirmed

and lay the groundwork for further investigation of personality characteristics and musical preferences. Moreover, the inverted-U hypothesis was supported by some of the data, although the true relationship between these variables might actually be better described as an asymmetrical inverted-U, in which low information content music is preferred to similarly high information content music with highest preference for middling complexity.

Introduction:

My work the past three years with the Zatorre Lab has centered around a simple question: how and why does instrumental music invoke pleasure, and why do some arrangements of pitches conjure more pleasure than others? How is it that a flute solo or orchestral arrangement can perk our ears, bring us to tears, or bore us? We theorize that complexity, as formally measured by information content, is central to understanding these musical preferences. While no note is complex by itself, the relation a note has to notes that come before it in addition to a listener's baseline expectations give rise to each note's information content. Furthermore, each listener's personality and background may also influence these preferences. Therefore, the primary question for this project is also simple yet confounding: what inter-individual differences significantly impact preferences for complexity of melodies regardless of genre or timbre?

It seems as though individual melodic complexity preferences rely heavily on musical expectations **[Huron, 2006; Pearce et al., 2010]**. No two people hold the exact same musical expectations, and yet shared culture and tradition form similar expectations that give rise to a type of cultural musical grammar **[Baroni et al., 1983]**. Every piece of music listened to throughout one's lifetime adds to these expectations and therefore the same person's musical preferences also change with time **[Pearce & Wiggins, 2006]**. Popular composers and artists, both modern and classical, can have major influences on this collective set of musical expectations. The Beatles' music, for example, likely heavily informs contemporary Western music; similarly, Bach's body of work likely shapes the base expectations that most modern listeners have but don't even recognize.

With these baseline expectations each listener brings to the table, more expectations are generated as one listens to a song **[Brattico & Pearce, 2013, Huron 2006].** These two intertwined sets of expectations can then either be fulfilled or broken, both of which have been shown to create pleasure **[Huron, 2006; Steinbeis et al., 2006].** Listeners seem to be engaged in a game of prediction, involving rewards for success when assuming predictable or low information content events coupled with pleasure from gaining new knowledge when encountering high information-content notes that keep them guessing with little to no consequences for failure **[Vuust & Kringelbach, 2010]**. If this "music game" is too predictable or too chaotic for a listener, they will likely lose interest and enjoy the music less.

Other researchers have proposed comprehensive models that integrate aspects of the multi-modal perceptual experience of listening to music to describe the resulting positive affect **[Juslin et al., 2008; Juslin & Västfjäll 2010]**. Juslin and colleagues' BRECVEMA model breaks down the experience of listening to music into eight categories: brainstem reflexes, rhythmic entrainment, evaluative conditioning, (emotional) contagion, visual imagery, episodic memory, musical expectancy, and aesthetic judgment. The experimental methodology detailed below will attempt to isolate musical expectation and control for the seven other factors.

Although the focus of this project is limited to melodic expectations, similar experiments have tested the presence of inverted-U complexity and preference relationships in other facets of music such as rhythm, harmony, and genre, indicating the possibility for similar complexity preferences extending beyond melody. **[Fung, C. V., 1996; Gordon, J., & Gridley, M. C., 2013; Steinbeis, N., Koelsch, S., & Sloboda, J. A., 2006; Witek et al., 2016].**

In terms of individual differences that affect these expectations, an intuitive factor in preference for melodic complexity is musical experience. Based on recent research, someone with extensive musical experience will likely prefer higher complexity music, on average, than a non-musician **[Burke & Gridley, 1999; Gordon & Gridley, 2013].** This correlational understanding of the relationship between expertise and complexity preference lacks identification of an exact mechanism. Does the experienced musician's increased musical exposure cause them to interpret the music to be less complex, increase their threshold for complexity, or do individuals who put more time into music have increased complexity preferences in the first place? Furthermore, the concept of musical experience can be broken down into subcategories such as music theory exposure, history of formal training, and regularity of practice. Alternatively, many individuals have an intimate relationship with music, despite not playing an instrument or singing, that cannot be assessed when only using measures of musicianship. Lastly, it remains possible that non-musical factors such as personality differences could account for differences in preference. Each of these factors were measured via well-validated questionnaires in the experiment detailed below.

Prior studies have shown promising results regarding the factors mentioned directly above. For example, Rentfrow and colleagues utilized the Big Five Inventory of personality traits to show differences in 'Openness to Experience' between individuals positively correlated with changes in music preferences **[Rentfrow & Gosling, 2003]**. Furthermore, BFI 'Neuroticism' has been shown to positively correlate with preferences for more complex genres such as classical music and jazz **[Dunn et al., 2012].**

The question that remains to be answered is: if Big 5 personality characteristics correlate with changes in complexity preference, what is it about these traits that cause this change? The literature examining musical preferences and personality characteristics tends to focus on Openness to Experience, Agreeableness, and Neuroticism, which will each be elaborated upon below. Extraversion and Conscientiousness have seen comparatively less results, although Extraversion has been shown to be significantly related to musical preferences at least once in the literature **[Nave et al., 2018].**

Openness to Experience has been described as the complexity of an individual's experiences and mental life and willingness to try new things **[John & Srivastava, 1999]**. This seems to be directly related to a listener's willingness to appreciate music that has higher information content as these are, by definition, deviations from what is expected when presented with musical stimuli.

Agreeableness can also be understood as "social adaptability" and therefore the ability to quickly alter expectations and preferences given a changing situation **[John & Srivastava, 1999]**. In regards to music listening, a listener high on trait Agreeableness will likely be comfortable with and appreciate a variety of music and therefore rate music that deviates from the "ideal" amount of complexity as more pleasurable —whether it be lower or higher in information content— than those low on Agreeableness. Moreover, those higher in trait

Agreeableness tend to have larger emotional responses to all types of music and this may be the mechanism that causes them to rate all music as more pleasurable [**Ladinig & Schellenberg, 2012].**

Lastly is Neuroticism, which has a different connotation in this context than it does in everyday discourse. Neuroticism on the BFI indicates one's emotional stability and general temperament towards their own thoughts **[John & Srivastava, 1999]**. Despite previous results indicating a relationship between Neuroticism and musical complexity preference, the mechanism of this relationship is currently unknown **[Langmeyer et al., 2012; Dunn et al., 2012]**. Previous studies have demonstrated that those higher in Neuroticism tend to use music to regulate their negative emotions more often **[Chamorro-Premuzic et al., 2009; Chamorro-Premuzic et al., 2010].** It's possible that individuals higher on Neuroticism may seek distraction from their own thoughts and thus prefer more complex music in order to maintain more intense distraction or to be distracted for a longer time.

Central to this approach is the theory that preferences for complexity in music overall follow an inverse parabolic or "inverted-U" shaped curve. An inverted-U relationship implies that music is processed and enjoyed similarly to challenges or games like a maze; if the maze is too easy or too complicated, the player wouldn't be as excited as compared to a challenge of moderate difficulty. This relationship between complexity and pleasure has been referred to as the "Berlyne Curve" or "Wundt curve" and it has been shown to be a preference for games or challenges across domains **[Sluckin et al., 2000]**. The background literature regarding this issue contained mixed results; studies have found inverted-U relationships in some cases and negative linear ones in others **[Burke & Gridley, 1990; Egermann et al., 2013; North & Hargreaves,**

1995; Orr & Ohlsson, 2005; Witek et al., 2016]. This premise is assumed to be true based on previous experiments in the Zatorre Lab with stimuli including the present ones, indicating a stronger negative quadratic relationship than a negative linear one, as seen in **Figure 1 [Neumann et al., 2017; Pearce 2005].**

Additionally, preferences at either end of the spectrum of information content are likely to change based upon individual characteristics. The question is, for each of these inter-individual differences in traits as measured by the questionnaires, how does their individual Liking vs. Complexity curve shift? Does the curve widen, get thinner, or is the entire curve shifted along the Complexity axis? These questions and more will be confronted later in the paper.

An integral distinction between the work that will be presented and much of the prior work investigating the relationship between musical complexity and preference is the means of quantifying complexity. Prior work, such as North & Hargreaves 1995 study, utilized subjective measures of complexity which involved participants judging the complexity of each excerpt which they also rated their preferences of. The issue with this subjective approach to complexity is that individual factors that influence perceived complexity —exactly the factors of interest in this experiment— are inseparable from the ratings made. Other studies have had a separate panel of judges rate aspects of complexity for each song and then averaged across these ratings **[Fung, C.V., 1996]**. The study to be presented, alternatively, involves a mathematical model that quantifies the likelihood of each note in a melody, and then denotes the resulting measurement as information content. By operationally defining complexity as formally quantified information content, this experiment ensures that participants' individual backgrounds and personalities are

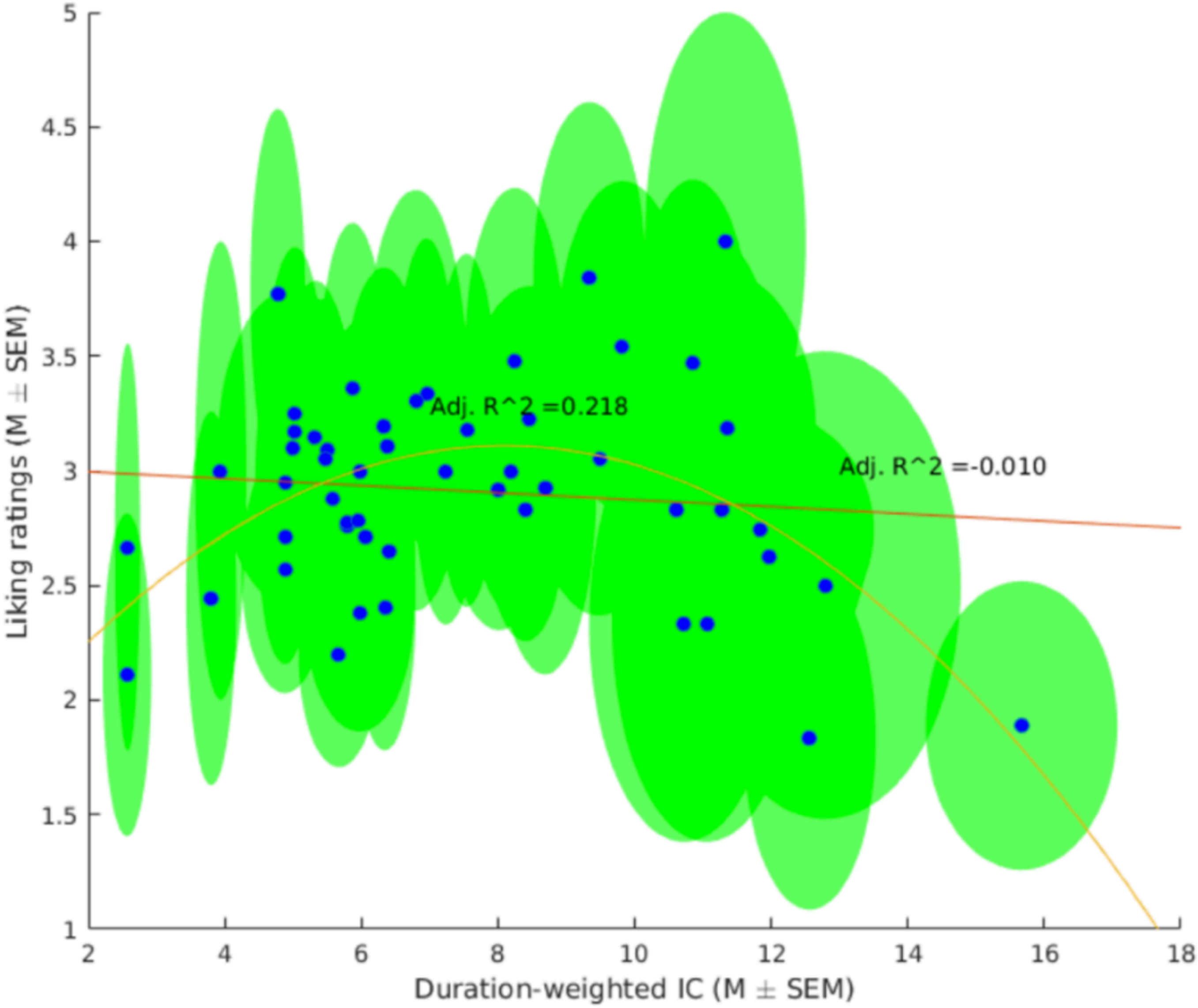

Figure 1: From Neumann et al., 2017: Test demonstrating superior quadratic versus linear relationship between DW-IC and liking ratings for 50 of the 55 stimuli

independent of the measure of complexity. This allows for between-subjects analyses with individual factors such as personality that would be compromised with a "subjective complexity" approach.

This work strictly pertains to the expectations of Western music, which is based on a 12-tone division of the octave and often relies on major and minor keys, that include 7 primary notes for each tonality (ex: C, D, E, F, G, A, & B for C major). There are many other musical cultures that rely on completely different sets of expectations, divisions of the octave, and scales that are not tested or modeled here and they are no less important. Furthermore, the model we used to quantify information content is trained on Western folk and classical melodies and thus does not necessarily apply to genres that have different sets of melodic expectations.

Lastly, with all of the information above in mind, what do we expect to see in regards to the effects of these independent variables? Firstly, we expect to see similar results to that of previous work positively correlating personality characteristics such as Openness to Experience, Neuroticism, and Agreeableness with complexity preference, specifically as increases in liking for high information content stimuli **[Dollinger, 1993; Rentfrow & Gosling, 2003]**. Furthermore, increased musical experience is presumed to coincide with higher overall information content preference. Lastly, it seems possible that higher reported reward from music overall would correlate with higher information content preference.

Methodology & Materials:

IDyOM:

An integral component of this project was the computational Information Dynamics of Music model, or IDyOM **[Pearce, 2005]**. The model analyzes a user-input sample of monophonic music in order to generate a distribution of probabilities for each musical transition. Similarly to past experiments, we used IDyOM to assign note transition probabilities based on two parameters: note pitch and inter-onset interval **[Gold et al., submitted; Neumann et al., 2017]**. The inter-onset interval is the duration from the start of one note to the start of another, while the note pitch corresponds with the 12 chromatic pitches (A-G), totaling 88 notes including octaves in Western music. This aims to recreate the melodic expectations of a Western music listener and provides a formalized measure of complexity for each of the musical excerpts. To do this, IDyOM relies on two sets of expectations, one modeled after the base set of expectations of a typical Western listener that we shall refer to as the "long-term model" and the other that generates and modulates expectations while 'listening' to a song as the "short-term model."

For the first note in a stimulus, IDyOM will have no information about the current song and will rely entirely on the long-term model, but by the last note it will have incorporated all of the song's newly presented short-term information and expectations. Additionally, IDyOM has a feature which, when multiple songs are inputed in succession, the information from earlier songs can be set to contribute to the long-term model that analyzes later songs, which can be turned on or off. While having this feature turned on is probably closer to the experience of a music listener incorporating new information to update expectations while listening, we turned off this feature and instead controlled for it by semi-randomizing the order in which participants heard the stimuli. In effect, we decided to prevent the short-term model from updating the long-term model after each excerpt in order to obtain more stable data that does not depend on stimulus ordering.

The long-term model is created by introducing a large database of classical and folk melodies which the model uses to generate the probabilistic likelihood of any note transitioning to another note. The short-term part of the model gains information as the stimuli are presented and adjusts the probabilities accordingly. Furthermore, the more likely a note, the less information content that note has, where information content is the negative log (base 2) of probability: $IC = -\log_2(P)$.

For an example of how the long-term model works, at the beginning of interpreting a musical excerpt starting with the note 'C_4', IDyOM will expect an adjacent note such as "D_4" or

Filename	Song	Timbre Change Onset	Composer	Timbre	dwIC mean	dwIC SEM
Attentional1/10th	35 Exercises for Flute # 5	2.547 seconds	Ernesto Kohler	Flute	10.7095	1.4037
Attentional2/10th	Ballet of the Shepherds Pt. 2	7.508 seconds	Christoph Gluck	Flute	14.4635	1.3762
Attentional3/10th	Exercise 4	8.775 seconds	Baldwin Music	Flute	10.5668	1.0326
Attentional4/10th	Kopperia	12.293 seconds	Ali Project	Flute	8.1508	0.65729
Attentional5/10th	Opera 89, #6	15.000 seconds	Ernesto Kohler	Flute	4.9469	0.29518
Attentional6/10th	Fuku Jo So	18.750 seconds	Traditional Japanese	Flute	6.399	0.84569
Attentional7/10th	Ouji	21.727 seconds	Traditional Folk	Flute	4.4158	0.33798
Attentional8/10th	Sicilienne	24.390 seconds	Gabriel Faure	Flute	6.1666	0.63348
Attentional9/10th	Exercise 1	25.656 seconds	Baldwin Music	Flute	6.4671	0.7328

Table 1: Attentional stimuli & timbre changes

Used before?	Song	Excerpt Time	Composer	dwIC mean	dwIC SEM	Liking mean	Liking SEM
New	Caravan	0-30	Tizol & Ellington	17.91	0.70	NaN	NaN
New	Cowboy Song	0-30	Chinese Traditional	15.18	0.75	NaN	NaN
New	Le Jamf	45-1:15	Bobby Jasper	15.64	0.93	NaN	NaN
New	Maiden Voyage	2:50-3:20	Herbie Hancock	11.53	0.70	NaN	NaN
New	Sakura	0-30	Japanese Folk	4.23	0.43	NaN	NaN
Previous	18 Studies No 1	45-1:15	Anderson	5.57	0.42	2.88	0.72
Previous	18 Studies No 10	0-30	Anderson	5.87	0.49	3.36	0.72
Previous	18 Studies No 11	1:30-2:00	Anderson	2.57	0.35	2.11	0.70
Previous	18 Studies No. 18	50-1:20	Anderson	4.88	0.64	2.57	0.53
Previous	18 Studies No 6	0-30	Anderson	6.39	0.42	3.11	0.71
Previous	18 Studies No 6_2	1:00-1:30	Anderson	5.80	0.36	2.76	0.55
Previous	18 Studies No 8	1:30-2:00	Anderson	7.54	0.47	3.18	0.77
Previous	35 Exercises No 10	0-30	Kohler	5.02	0.30	3.17	0.75
Previous	35 Exercises No 11	1:00-1:30	Kohler	8.40	0.60	2.83	0.58
Previous	35 Exercises No 15	0-30	Kohler	5.97	0.59	3.00	0.65
Previous	35 Exercises No 3	7-37	Kohler	6.95	0.44	3.33	0.68
Previous	35 Exercises No 3_2	1:00-1:30	Kohler	5.50	0.40	3.09	0.66
Previous	Children Flute No 1-4	10-40	Children's Book	9.48	1.02	3.05	0.68
Previous	Dolly Suite Op56 No. 1	10-40	Faure	6.33	0.63	3.19	0.70
Previous	Entracte	45-1:15	Bizet	4.77	0.40	3.77	0.80
Previous	Fantasie 10	2:45-3:15	Teleman	7.24	0.48	3.00	0.67
Previous	Fantasie 12	1:57-2:27	Teleman	6.80	0.77	3.31	0.92
Previous	Fantasie_3	10-40	Teleman	4.88	0.44	2.95	0.68
Previous	Fantasie_3	45-1:15	Teleman	5.02	0.45	3.25	0.73
Previous	Fantasie_5	37-1:17	Teleman	6.05	0.61	2.71	0.55
Previous	Fantasie Op 79	30-1:00	Faure	6.40	0.38	2.65	0.64
Previous	Fantasiestucke	0-30	Schumann	11.35	1.31	3.18	0.68
Previous	Fantasiestucke_2	1:15-1:45	Schumann	11.98	1.40	2.63	0.54
Previous	Flute Concerto	5:50-6:20	Vivaldi	11.33	1.18	4.00	1.00
Previous	Flute Concerto_2	6:45-7:15	Vivaldi	9.34	0.83	3.84	0.77
Previous	Les Follies D'Espagne Var1-4	0-30	Marin Marais	10.86	0.88	3.47	0.80
Previous	Les Follies D'Espagne Var5-8	0-30	Marin Marais	8.01	0.78	2.91	0.61
Previous	Les Follies D'Espagne Var5-8_2	1:07-1:37	Marin Marais	8.25	0.74	3.48	0.76
Previous	Childrens Gavotte	0-30	Gossec	4.99	1.11	3.10	0.69
Previous	Le Rossignol En Amor	1:45-2:15	Flute	9.83	0.96	3.54	0.72
Previous	Mei	37-1:07	Kazuo Hukushima	15.67	1.41	1.89	0.63
Previous	Menuetto	50-120	Mozart	5.33	0.56	3.14	0.69
Previous	Menuetto_2	3:50-4:20	Mozart	5.67	0.59	2.20	0.49
Previous	Nocturne	0-30	Chopin	8.47	0.91	3.23	0.58
Previous	Nocturne_2	1:50-2:20	Chopin	8.69	0.75	2.92	0.81
Previous	Op 131 No 1	0-30	Gariboldi	5.78	0.57	2.78	0.53
Previous	Orchestral Suite No. 2	2:45-3:15	Bach	4.88	0.39	2.71	0.55
Previous	Orchestral Suite No. 2_2	0-30	Bach	5.95	0.43	2.78	0.58
Previous	Orchestral Suite No. 2_3	5:05-5:35	Bach	8.19	0.63	3.00	0.61
Previous	Solo De Concours	5:43-6:13	Messanger	6.34	0.45	2.40	0.62
Previous	Streams Of Kilnaspig	0-30	Traditional Irish	2.58	0.19	2.67	0.89
Previous	Syrinx	0-30	Debussy	11.83	1.68	2.74	0.53
Previous	Syrinx_2	3-1:00	Debussy	5.97	0.80	2.38	0.52
Previous	This Cruel War Is Over	60-90	Traditional American	3.94	0.38	3.00	1.00
Previous	Variatons	5:30-6:00	Weber	3.80	0.37	2.44	0.81
Previous	Variations_2	0-30	Weber	5.46	0.44	3.05	0.70
Previous	Con Alma	1:15-1:45	Dizzy Gillespie	12.56	0.97	1.83	0.75
Previous	Die Nachtigall	30-1:00	Alban Berg	11.05	1.38	2.33	0.95
Previous	Premiere Rhapsodie	2:55-3:25	Debussy	10.62	0.84	2.83	1.16
Previous	Traumgekront	0:15-0:45	Alban Berg	11.28	0.99	2.83	1.16
Previous	Alone Together	45-1:15	Arthur Schwartz	12.79	1.99	2.50	1.02
Previous	CityGate/Rumble	1:00-1:30	Chick Corea	10.73	1.39	2.33	0.95

Table 2: Stimulus information

“E4” more than a distant and out-of-key note such as “F#2.” In this case, there will still be a percentage likelihood of “F#2,” say two percent, but the likelihoods of “D4” or E4” are higher. Using this same example for the short-term model, imagine after starting with “C4,” an “E4” is played and then repeated 10 times. After each E4, the probability of another E4 becomes higher and that of every other note becomes lower. Finally, after 10 repetitions, when say a “G4” is played, the information content for that G is significantly higher than if the the passage were just “C4, E4, G4.”

In this experiment, the operational definition of complexity is the average of the information content of each note in a excerpt weighted by the notes’ durations as derived from IDyOM, denoted as mDW-IC for “mean Duration Weighted Information Content”. This was done in order to give more influence to the notes that last longer and accounted for closer approximation of the listening experience. With IDyOM, we are able to utilize a formalization of complexity that does not change between listeners, unlike subjective measures of complexity that rely on listeners’ ratings or that of a panel of judges.

Questionnaires:

Three questionnaires are used in this experiment: the Big Five Inventory (BFI) was used to assess personality characteristics, the Barcelona Music Reward Questionnaire (BMRQ) was used to quantify aspects of participants’ relationship with music beyond instrumentation, such as how they are rewarded by music, and the Goldsmith Musical Sophistical Index (GMSI) was used to gather a variety of measures of musical experience **[Caprara et al., 1993; Mas-Herrero et al., 2013; Müllensiefen et al., 2014]**.

The BFI is the leading personality trait questionnaire because it isolates five distinct and irreducible personality factors — Openness to Experience, Conscientiousness, Extraversion, Agreeableness, & Neuroticism — via factor analysis of the entire dictionary of personality-defining adjectives. The BMRQ is an important addition because it specifically measures how individuals are rewarded by music separate from musicianship. Without the BMRQ, we would be forced to rely more heavily on musical experience as a measure of musicality and therefore ignore the many individuals who have a deep relationship with music but do not play any instruments or sing. Lastly, The GMSI aids our experiment because it breaks down the concepts of "musicianship" or "musical experience" into many subcategories that can be analyzed together or separately.

Stimuli:

The musical excerpts used for this experiment included the 50 stimuli used in our prior experiments in addition to five new stimuli which were included to create a more equally distributed sampling of the information content spectrum. Results and information about both the original 50 and the full set of stimuli will be presented below, for information on the stimuli themselves see **Table 2**. The stimuli represent a wide range of complexity spanning across the information content spectrum derived from IDyOM, and this range can be seen in **Figure 1**.

The stimuli are all 30 +/- 2 seconds long, sampled from real compositions, and monophonic — only one note at a time — due to the complications of harmony and the limits of IDyOM. Furthermore, they were all standardized to 96 beats per minute in order to minimize effects of tempo differences between songs, although there is a possibility that note durations and subdivisions within the beats can give rise to feelings of different tempi. The realistic flute preset from within the digital synthesizer KONTAKT 5™ **[Native Instruments, Berlin, Germany]** was used for all stimuli and the reverberation was set to mimic a music studio and therefore appear less artificial.

A subset of 9 the stimuli were further manipulated in order to switch timbres during the excerpt. Each of these stimuli changed timbre at 1/10th, 2/10ths… up to 9/10ths through the music respectively in order to test participants attention during different portions of each excerpt as seen in **Table 1**. These trials were used to measure whether the participants were paying attention by measuring reaction times to the timbre change via how quickly they hit the "Enter" key. The randomly selected attentional stimulus used in the practice trials was removed from the experiment, while the remaining 8 attentional trials first appeared to be normal trials during the experiment, and participants only preemptively knew when it was going to be an attentional trial during the third practice trial before behavioral data collection begun. All participants ended up responding to the attentional tests within two seconds of the timbre change, on average, and therefore no subjects were removed from analyses for not paying attention and it is presumed that the attentional stimuli did what they were intended to do: keep participants actively engaged and attentive to the music.

Each of the excerpts are from real compositions that were available in MIDI form online. The MIDI information includes note pitch, velocity, and timing. The MIDI files were then converted into audio files in WAV format via KONTAKT 5 within the digital audio workstation Ableton Live™ **[Ableton, Berlin, Germany]** to make realistic-sounding stimuli. To further the humanlike features of the stimuli and increase ecological validity, I utilized Ableton's "Groove Pool" function with randomization set to 25 percent, where zero percent has no effect and 100 percent would randomly move each note approximately one subdivision of a beat away from the original onset. Lastly, I used the program Audacity™ to normalize the amplitude of all of the WAV files in order to ensure all stimuli were similar in volume.

The MIDI information used to generate the stimuli were found in free MIDI music databases from across the internet. I then ran the full MIDI files individually through IDyOM in order to visually inspect their note-by-note duration-weighted information content. I then cut 30-second segments from these larger pieces in order to get samples from across the spectrum of information content. Finally, I ran the newly sliced excerpts through IDyOM to measure their duration-weighted information content.

Participants:

44 participants were recruited from Montreal and the McGill community, primarily via Facebook and word of mouth. In order to qualify, interested participants had to present a list of their five favorite genres via email; if that list included jazz or atonal music, they were excluded due to the composition of the long-term model. 19 of 44 participants identified as male. Only one subject had all of their data excluded due to a misunderstanding of the 'familiarity' question during the behavioral portion of the experiment. Another participant withdrew from the study after approximately half of the listening portion was complete but their collected data was used in the analyses. Each participant was compensated 20 dollars for approximately an hour and a half of their time. All participants gave their informed consent before participating in this study in agreement with the McGill University ethics committee.

Inclusion criteria required participants to be at least the age of 18 and have healthy hearing. Exclusion criteria included no prior experience in any of the Zatorre lab's prior music expectation experiments due to exposure and familiarity with the stimuli, no neurological or psychiatric conditions, and genre preferences that did not include jazz or atonal music as mentioned above.

Experimental Procedure:

After participants qualified and scheduled their experiment online via Doodle™, they were invited to the Montreal Neurological Institute. Once they arrived, they were informed about the broad details of the experiment and had the opportunity to consent, after which they took the three questionnaires (BFI, BMRQ, & GMSI) online via a password-protected Google Form™ that took approximately 20 minutes.

After completing the questionnaires, they were brought into the Zatorre lab's audiometry booth in order to isolate them from distracting outside noise. Once in the chamber, participants were guided through three practice trials which were representative of the entire experiment. Before the practice trials, subjects were given an outline of the experiment and were shown the 1 to 7 Likert scale to be used to indicate liking ratings for the rest of the experiment. The scale is neutral at 4, very positive at 7, and very negative at 1.

The first two practice trials were the same; they began with approximately 30 seconds of flute music accompanied by a black screen with a fixation cross at the center to maintain their attention. The excerpts used in the practice trials were not repeated during the experiment. Participants were told to attentively focus on the music during these 30 seconds. Once the stimulus was complete, a prompt appeared asking whether the participant was familiar with the music just heard, inputting 'N' for no and 'Y' for yes. Participants were told that this did not mean they had to know the name of the piece, rather that they recognized it or not.

After the subject responded to the familiarity question, another prompt appeared asking them to rate their enjoyment of the excerpt on the Likert scale from 1 to 7. This was then repeated once for the second practice trial.

For the final practice trial, the participant was told that the trial would start the same as the first two, but at some time during the excerpt the timbre would abruptly switch from flute to piano. The excerpt used was randomly selected from one of the nine attentional stimuli and then excluded from the attention trials during the experiment. When the change occurred, subjects were instructed to hit the 'Enter' key as soon as possible. After the practice trials were completed, the participant had a final chance to ask questions regarding the experiment. After any questions were answered, the participant was left in the audiometry chamber to begin the data collection portion of the experiment.

The remainder of the experiment mainly involved trials akin to the first two practice trials, with intermittent attentional trials like the third practice trial spaced every 6 +/- 2 trials. This behavioral portion of the experiment took approximately 30 to 40 minutes. After the experiment was completed, subjects were debriefed and compensated.

In order to ensure participants' exposure to the full spectrum of information content that would be present in the experiment early on to ground their expectations, the stimuli were grouped into one of five levels of information content via MATLAB's "K-Means clustering" as seen in **Figure 2**. This resulted in 5 clusters, with 5 stimuli in the first, 23 in the second, 11 in the third, 12 in the fourth, and 4 in the fifth. For the first 5 trials of the experiment, the subject was subjected to one stimulus from each of the clusters, and then afterwards the remaining stimuli were ordered randomly.

MATLAB & Data Analysis:

Data analysis of the relationships between questionnaire results and overall preference indices were completed utilizing linear and quadratic regression, correlations, F tests and ANOVAs via SPSS™ and MATLAB™. More complex data analysis involving comparing quadratic versus linear models for this project were completed via MATLAB on scripts created by Ph.D candidate Benjamin Gold.

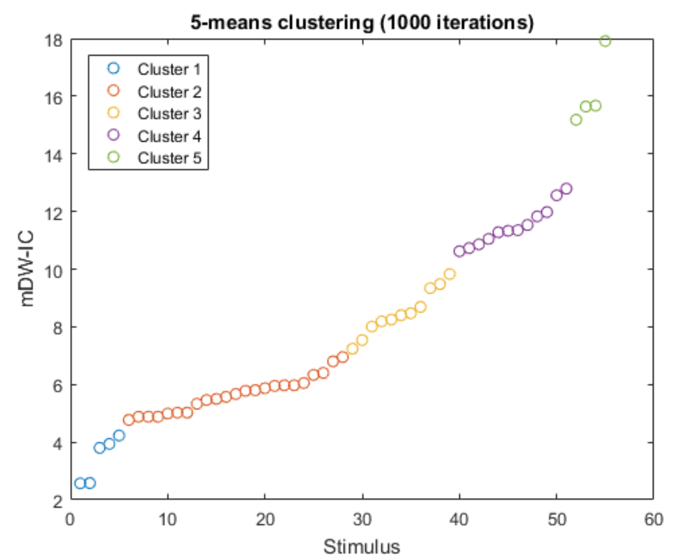

Figure 2:
K-Means Clustering of 55 Stimuli into 5 levels of DW-IC

Smoothing was applied to all behavioral data collected during the listening portion of the experiment (liking ratings and the corresponding information contents). This process utilized a “sliding window” technique in which the first smoothed value was the average of the first three actual data points, the second smoothed value was averaged across the second through fourth lowest data points, and so on in order to create more suitable data for quadratic and linear analyses. The ‘K-means’ clustering process arbitrarily chose 5 centers and then chose the closest center for each point. This K-means process was iterated 1000 times in order to reduce the risk of random disorder.

With regards to the quadratic versus linear analyses, we checked for whether a participant’s relationship between DW-IC and liking was a significantly linear or inverted quadratic relationship and then indicated which model better fit the data. Given that a participant’s data was significantly quadratic, an ‘Inflection Point’ was designated as the peak of the Inverted U. If a participant only had a significant linear relationship and no significant quadratic one, the inflection point data for that participant was entered as missing data.

Trials where participants indicated the excerpt as familiar were excluded from analyses due to the Mere-Exposure Effect, which would likely increased preference to those stimuli and therefore present a confound **[Bornstein, R. F., & D'agostino, P. R., 1992; Harmon-Jones, E. & Allen, J. J., 2001]**.

The primary independent variables analyzed were the BFI sub-scales (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), BMRQ sub-scales and total scores, and GMSI sub-scales and total scores. The dependent variables were the inflection points of quadratic liking ratings by duration-weighted information content (DW-IC), average liking ratings for the top 10 DW-IC stimuli, and average liking ratings for the 10 lowest DW-IC stimuli.

A subset of the full dataset was also analyzed in order to further explore the results. Analyses were run on the full collection of stimuli (n=55) for all participants in addition to a subset that were used in prior experiments, to be denoted below as the "previous stimuli" (n=50).

Hypotheses:

Based on the relevant music preferences literature and prior experiments in the Zatorre Lab, we first and foremost expected an inverted-U relationship between DW-IC and liking rating. While some studies have demonstrated a negative linear relationship between these two variables, prior data collected with 50 of the 55 stimuli included in the experiment demonstrated that an inverse-quadratic model better fit the data than a linear one.

With regards to the questionnaires, we expected Agreeableness to positively correlate with higher DW-IC preference **[Dollinger, 1993; Rentfrow & Gosling, 2003].** Similar effects were expected with Openness to Experience, although studies have shown mixed results regarding both indices **[Chamorro-Premuzic et al., 2010]**. Neuroticism was also expected to correlate positively with higher DW-IC preference **[Langmeyer et al., 2012; Dunn et al., 2012]**

Lastly, we expected a positive effect of musical training on the inflection point of participants' DW-IC x Liking Ratings **[Burke & Gridley, 1990; North & Hargreaves, 1995; Witek et al., 2016]**. Although, some studies have failed to show differences in complexity preferences between musicians and non-musicians **[Sauve et al., 2017].**

Results:

Full Stimulus Set Analyses

The following analyses were performed on the full stimulus set, which will be contrasted with analyses utilizing only the 50 previously used stimuli in the section below.

Firstly, with regards to the independent variables, a correlation table details the many bivariate correlations and relationships for all questionnaire measures, see **Figure 4** for details. With regards to the figure, significant relationships are denoted with a "*" and significant relationships post-Bonferroni correction for multiple bivariate tests are indicated with a "**".

With regards to the relationship between overall mean DW-IC (mDW-IC) and liking ratings of the stimuli, linear regression indicated a significant negative relationship ($F(1,53) = 11.10$, $p = 0.002$, Beta = -0.074, $p = 0.002$), and quadratic regression also displayed a significant negative relationship ($F(2,52) = 6.00$, $p = 0.005$, Beta_IC = 0.026 ($p = 0.808$), Beta_IC^2 =

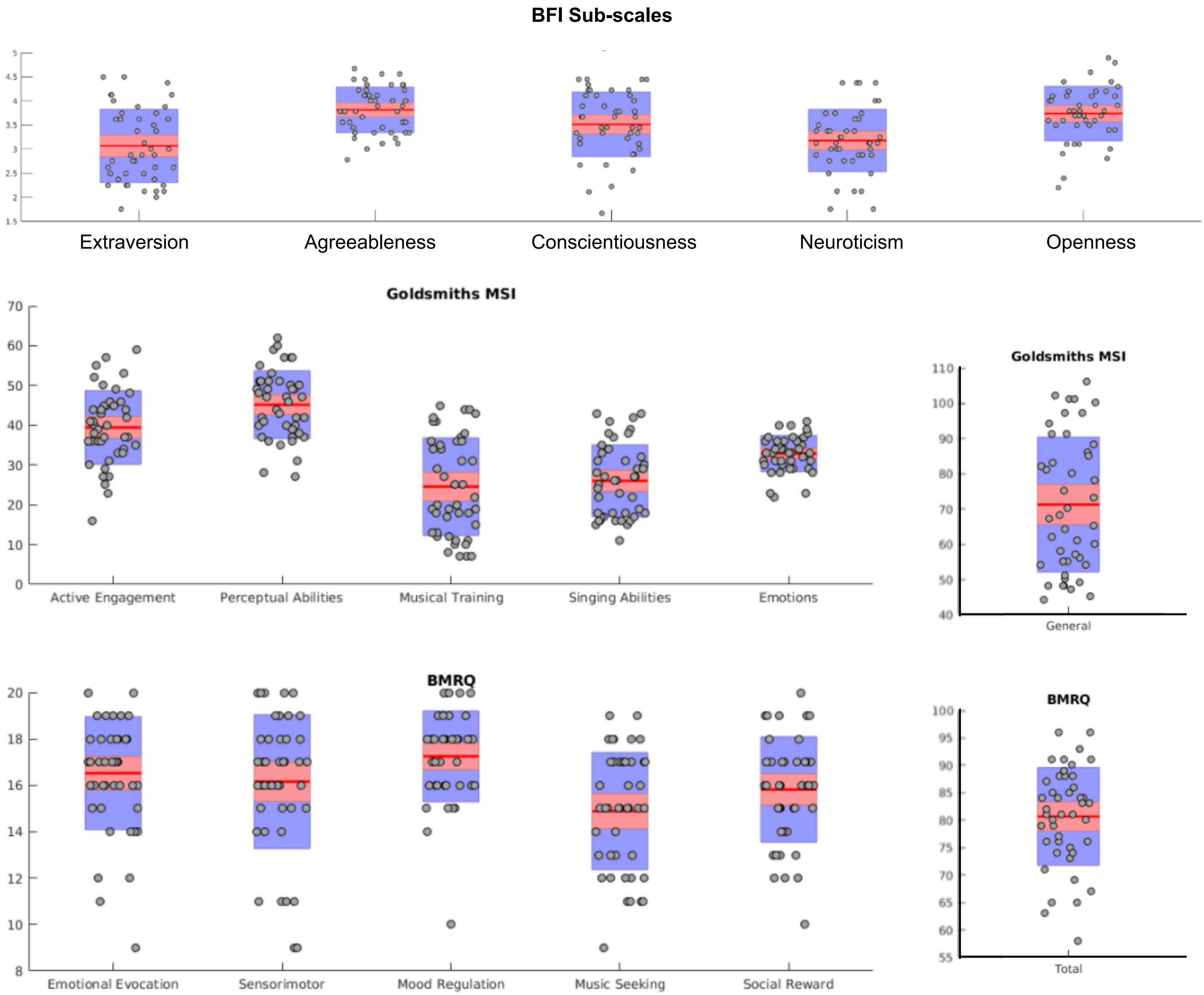

Figure 3: Distribution of questionnaire results (BFI. GMSI, & BMRQ) Red line represents the mean, salmon areas represent 95% confidence around mean, & blue areas represent 1 SD from the mean

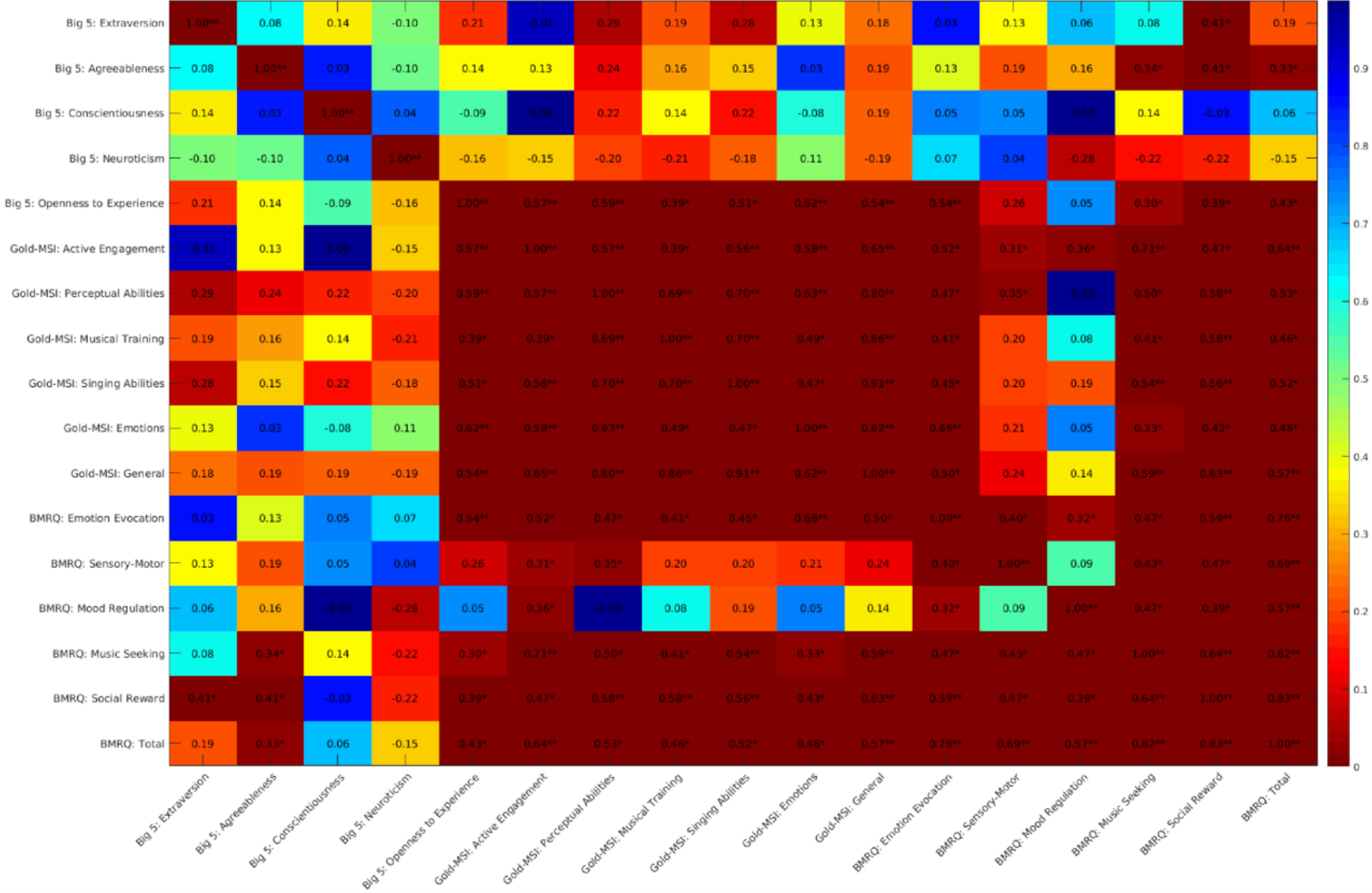

Figure 4: Correlation matrix: All questionnaire measures (BFI, GMSI, & BMRQ.
"" indicates significance without corrections, "**" represents significance after Bonferroni corrections*

0.335) as seen in **Figures 7 & 8**. These two regressions were compared via a likelihood ratio test, which demonstrated insignificant improvement of the more complex quadratic model over the linear one (χ^2 (2, N = 48) = 0.99, p = 0.319).

Furthermore, stepwise linear regression of all questionnaire variables were used to describe the liking of the ten lowest-IC stimuli, which demonstrated a significant negative relationship with Neuroticism (F(1,40) = 5.69, p = 0.022, Beta = -0.417, p = 0.022), see **Figure 11.** The same statistical test was used to test whether any independent variables were correlated with liking of the bottom ten lowest-IC stimuli, which showed no independent variables significantly explained the individual differences in dependent measures.

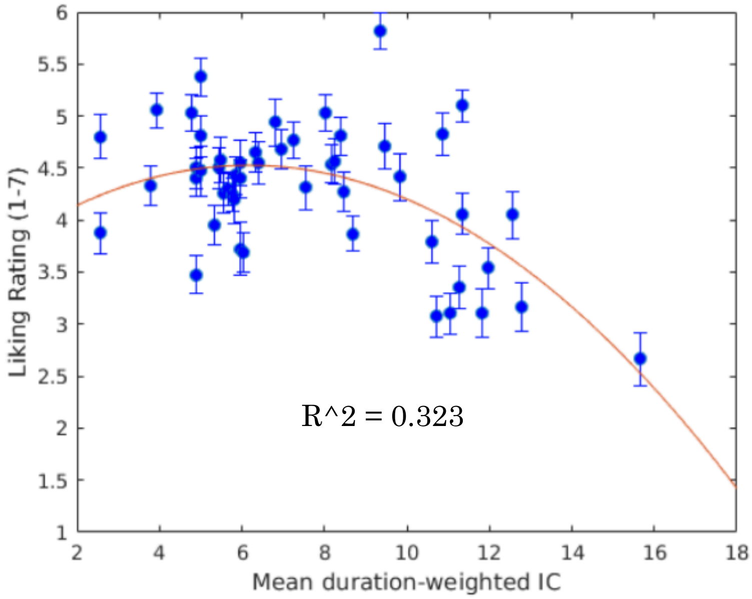

Figure 5: Quadratic regression: mDW-IC and liking ratings, only previous stimuli
R^2 = 0.323, p < 0.0001, N = 47

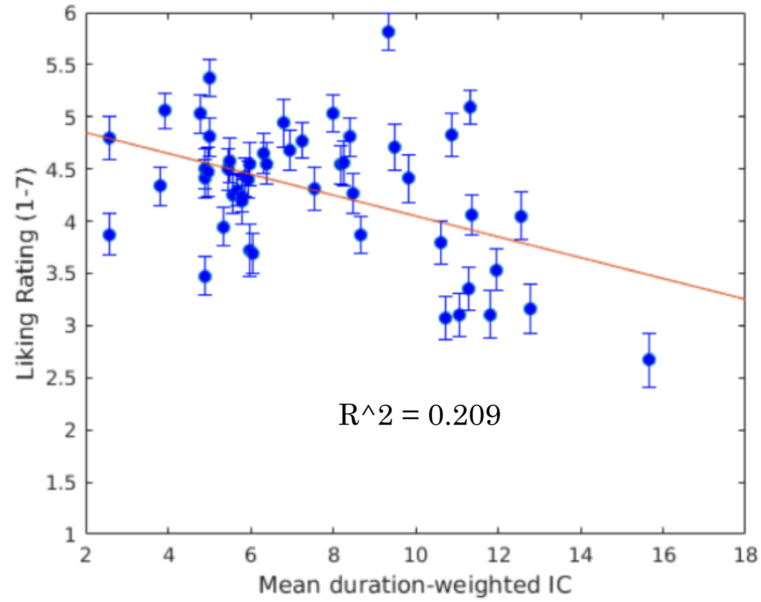

Figure 6: Linear regression: mDW-IC and liking ratings, only previous stimuli
R^2 = 0.209, p < 0.001, N = 48

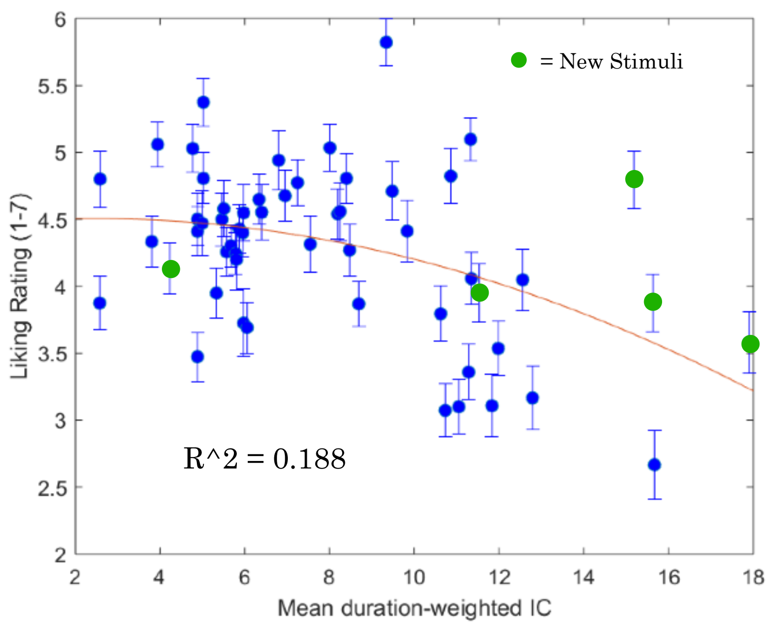

Figure 7: Quadratic regression: mDW-IC and liking ratings, all stimuli
R^2 = .188, p = .005 N = 53

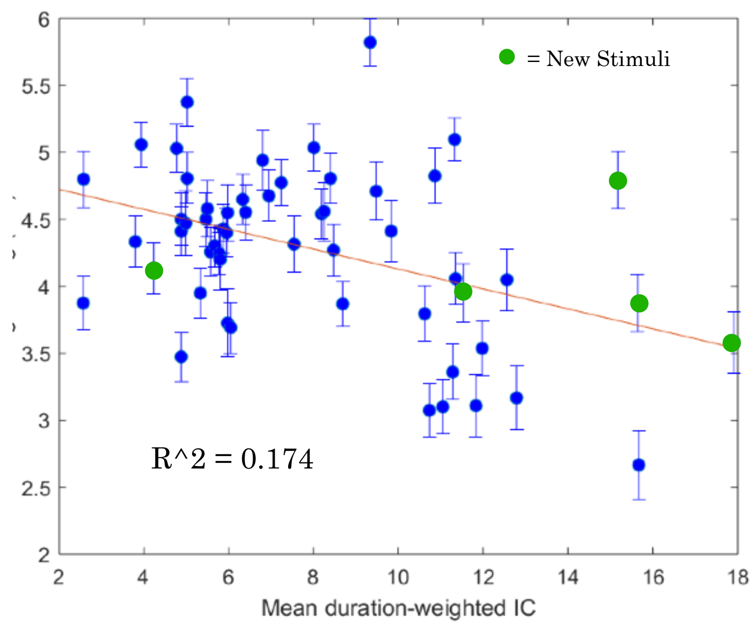

Figure 8: Linear Regression: mDW-IC and liking ratings, all stimuli
R^2 = 0.174, p = .002, N = 53

Although, Agreeableness positively approached significance when compared with liking ratings of the 10 lowest DW-IC stimuli via stepwise linear regression ($R^2 = .0725$, $F(1, 40) = 3.13$, $p = .0846$, Beta = .406) as seen in **Figure 10.**

Lastly, stepwise linear regression was also used to attempt to explain variance in the inflection point of the quadratic curve via the questionnaire results. This analysis indicated that no independent variables significantly explained the differences in inflection points of the quadratic curves.

50 Previous Stimulus Analyses

The following analyses were performed by utilizing listeners' responses to only the 50 previously used stimuli while removing the 5 new stimuli (as indicated in green on **Table 2** and **Figures 7 & 8**). These analyses were done separately in order to investigate the differences the 5 newly-added stimuli had on liking ratings of the remaining 50.

Linear regression between the overall mDW-IC and liking ratings of the 50 stimuli indicated a significant negative linear relationship ($F(1,48) = 12.70$, $p < 0.001$, Beta = -0.100, $p < 0.001$). Quadratic regression of the same relationship indicated a significant negative relationship too ($F(2,47) = 11.20$, $p < 0.001$, Beta_IC = 0.274 ($p = 0.049$), Beta_IC^2 = -0.022 ($p = 0.007$)). Similarly to the full dataset analysis, these two models were compared via a likelihood ratio test, which unlike the prior likelihood ratio test, demonstrated that the quadratic model was significantly better than the linear model (χ^2 (1, N = 48) = 7,78, $p = 0.005$), see **Figures 5 & 6**.

Stepwise linear regression of questionnaire variables with liking of the ten highest-IC stimuli indicated a significant positive relationship with Agreeableness ($F(1,41) = 4.46$, $p = 0.041$, Beta = 0.625, $p = 0.04$), see **Figure 9**.

Stepwise linear regression of questionnaire variables to describe the liking of the ten lowest-IC stimuli indicated a significant negative correlation with Neuroticism ($F(1,40) = 4.71$, $p = 0.036$, Beta = -0.371, $p = 0.036$).

Finally, stepwise linear regression indicated that none of the independent variables significantly explained the inflection points of the quadratic curves, including no personality measures or measures of musicianship.

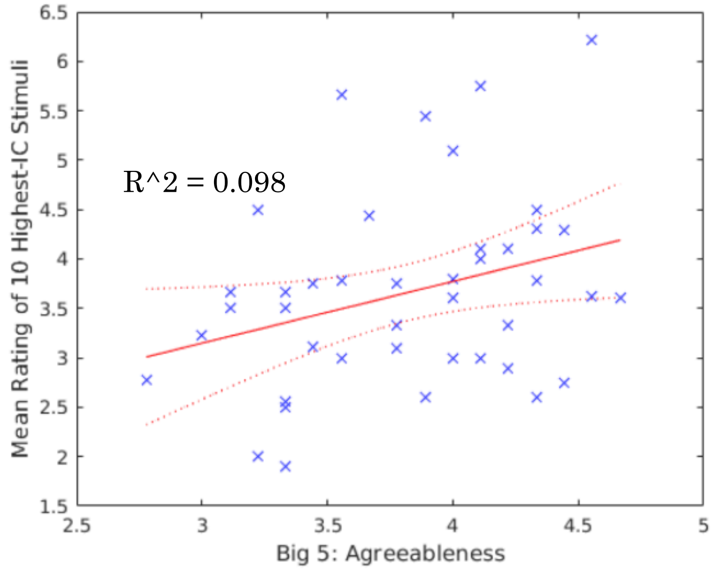

Figure 9: Stepwise linear regression: Agreeableness and mean liking ratings of top 10 DW-IC stimuli, previous stimuli
$R^2 = .098$, $p = .0409$, $N = 41$

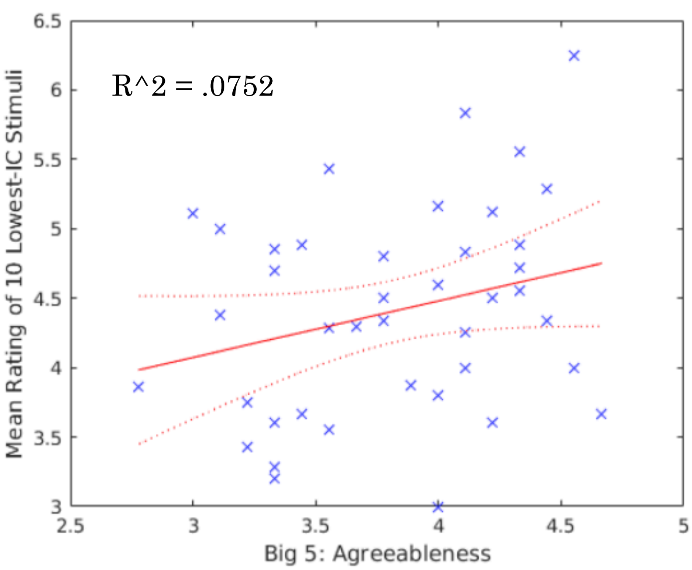

Figure 10: Stepwise linear regression: Agreeableness and mean liking ratings of bottom 10 DW-IC stimuli, all stimuli
$R^2 = .0725$, $p = .0846$, $N = 40$

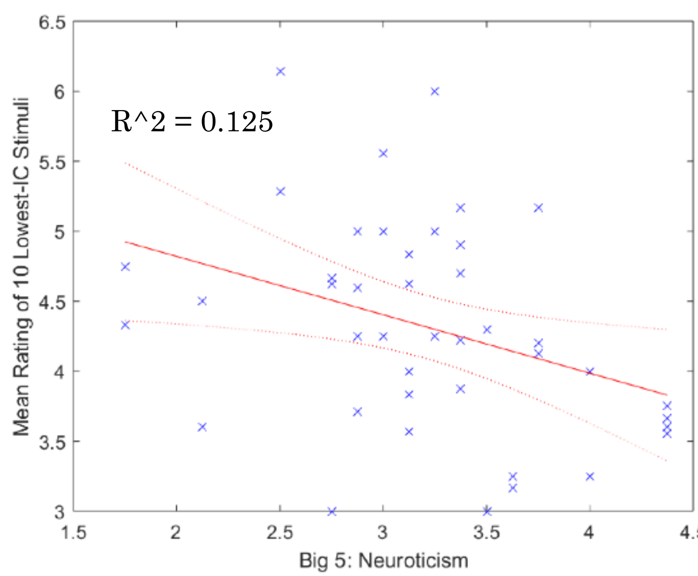

Figure 11: Stepwise linear regression: Neuroticism and mean liking ratings of bottom 10 DW-IC stimuli, all stimuli
$R^2 = .125$, $p = .022$, $N = 40$

Discussion:

The relationship between individual differences in musical preferences and the personality traits and experiences that underlie them are still unknown. Moreover, with regards to complexity, these factors are just beginning to be investigated and at this point no scientific investigation into them, including this work, is more than correlational **[Nave et al., 2018; Renfrow & Gosling, 2003].** With robustly valid and reliable questionnaires such as the Big 5 Inventory to quantify individual personality differences, contemporary music software to emulate and manipulate humanlike-music, and computational models to examine the expectations associated with these preferences, questions in the deeply subjective domain of individual musical pleasure can finally begin to be illuminated. The unscientific work that was relegated to philosophers and composers for millennia can now be taken on by psychologists and neuroscientists, transforming the introspective and phenomenological into the quantifiable.

Results from this experiment indicated a number of significant correlations between personality characteristics and music preferences that partially replicate prior experiments and open the door to explore previously-unreported relationships. Agreeableness and Neuroticism were statistically significantly correlated with increases in liking of the most complex stimuli and dislike of the simplest stimuli respectively. Furthermore, the overall liking rating vs. mean DW-IC analyses support the inverted-U hypothesis on one hand, and an overall negative linear effect on the other hand when looking at the full set of stimuli. While these results regarding complexity preference seem to be contradictory, they may offer a more nuanced insight into the true nature of this puzzling phenomenon. Lastly, the lack of significant relationships between individual differences in musicianship or musical reward and the dependent variables was unexpected and challenge the intuition that increased musical experience correlates with complexity preference.

Outcomes with respect to Agreeableness replicated prior work indicating larger affective responses to complex music stimuli, in addition to the result that approached significance which may indicate an increase in liking of all music, if not specifically the most complex music. **[Lading et al., 2012].** Trait Neuroticism, alternatively, did not exhibit the expected relationship although what appeared was something similar; instead of correlating with increasing liking for complex music, Neuroticism correlated with decreasing liking of simple music [**Dunn et al., 2012; Langmeyer et al., 2012].** Openness to Experience, however, did not exhibit correlations with complexity preference as it has in previous work **[Nave et al., 2018; Rentfrow et al., 2003].** Openness to Experience results replicated Mas-Herrero and colleagues work when comparing the BMRQ with the BFI, with statistically significant correlations between BMRQ total score, and BMRQ Social Reward and Music Seeking sub-scales. Lastly, Openness to Experience was also statistically significantly correlated with almost every one of the GMSI sub-scales even after Bonferroni correction, indicating substantial overlap between the measures.

The two sets of analyses done in this experiment differed based upon whether they included the 5 stimuli that were added in order to increase the range of information content. The overall relationship between complexity and preference was better modeled by a quadratic or linear model depending on whether these songs were excluded or not. The new stimuli were primarily found from jazz songs in order to have exceptionally high information content but may have presented issues with IDyOM, which is trained exclusively on folk and classical melodies. Additionally, it is possible that the inclusion of these stimuli stretched the boundaries of what listeners deemed "extreme" information content during the experiment. This could have widened their complexity vs. liking curve and thus made other less extreme stimuli more preferable, as shown in prior experiments in the Zatorre lab **[Neumann et al., 2017]**. Nonetheless, having the ability to look at both datasets was valuable and provided insights that were impossible otherwise.

A key takeaway from the main results of this experiment is the possibility for an asymmetry in the inverted-U relationship between liking and complexity. It appears that the inverted-U curve may be biased towards lower information content music such that simpler stimuli are more preferable than more complex stimuli equidistant from the mean of the sample, with maximal preference still in the center of the curve. Alternatively, this revision of the inverted-U hypothesis could be an aberration from the stimuli presented due to restriction of only including composed music. The stimulus set lacked sequences of pitches so simple that they are unrecognizable as "music," such as the repetition of a single note or simple linear scales, which may explain the bias towards lower information content music. If this lack of extremely simple stimuli is what drove the effect, it is possible that we are only seeing a portion of the total inverted-U curve, with the leftmost portion cut off.

Personality trait results from this experiment, specifically those regarding Agreeableness and Neuroticism, present novel relationships that deserve further investigation. Agreeableness seemed to widen the liking vs. complexity curve, increasing the liking rating of the most complex stimuli and possibly increasing preference for simple excerpts too. Although, the increased low-complexity preference correlation with Agreeableness should be approached with caution due to a p-value that failed to reach significance ($p = .0846$). Neuroticism's correlation with dislike of simple music indirectly supports the background literature while being slightly different from it. Prior work indicated an increased preference for genres deemed more complex, such as classical music and jazz, but never relating to complexity more generally. Increased usage of the emotional regulation aspect of music has been shown to correlate with increased Neuroticism, although the correlation between Neuroticism and the Mood Regulation sub-scale of the BMRQ was not significant.

The lack of significant correlations between dependent variables and measures of musicianship and musical reward were perhaps the most surprising result of this experiment. As stated in the Introduction, intuitionally, it was proposed that musically experienced individuals would prefer more complex music. The data collected directly contradicts this claim. Instead of musically experienced individuals preferring more complex music than their non-musician counterparts due to their intense musical experience, it may be their personality characteristics and preexisting penchant for complex music that drives their preferences. Future studies could focus on sampling participants with extreme amounts of music exposure, by recruiting participants who are professional musicians and those with no experience at all, to further examine this relationship.

In terms of possible confounds for the results of this work, the remaining seven factors in Juslin's BRECVEMA model (besides musical expectation) may have played a role despite attempts to control for them **[Juslin et al., 2008; Juslin & Västfjäll 2010].** Rhythmic entrainment, the "R" of BRECVEMA, may have been more or less present in some of the stimuli and could have played a role in liking. Excerpts with a rhythm easier to lock into and move with were likely more enjoyable **[Witek et al., 2016]**. Additionally, (emotional) Contagion, or the

"C," which entails taking on the emotion of the music, was not sufficiently controlled for. Pieces range in emotional tone and were not controlled for whether they were in major keys, minor keys, or some other modality. The degree to which emotions were aroused by the music could very possibly influence preferences, as emotion evocation is a key part of positive musical affect **[Mas-Herrero et al., 2013]**. Finally, Aesthetic Judgment, the "A," of BRECVEMA, is the personal stylistic preferences each individual brings to the experiment based on their personal musical history. Despite efforts to control for this by presenting a variety of genres and artists whilst maintaining the timbre, tempo, and style of the stimuli to minimize the variance caused by this, it is nonetheless an unavoidable confounding influence that should not be ignored when examining the results of this experiment.

Personality characteristics, despite the robust test-retest reliability of the BFI, are sometimes subject to change within-individuals based upon the situational context **[Fleeson, 2001; Steck & Machotka, 1975]**. Individuals have been shown to temporarily score higher on Conscientiousness when in academic settings, on Agreeableness with friends, and on Neuroticism when acutely stressed **[MacAdams & Pals, 2006]**. The controlled and systematic nature of this experiment could have temporarily influenced these personality traits and how these traits interact with preferences for musical complexity. Even though this variance may exert a similar effect on all participants, there may be interacting effects or individual differences in these changes that could have confounded the results.

Future work investigating the nature of complexity preferences in music should aim to control for the confounds mentioned above, such as by utilizing music from a larger variety of genres in order to more accurately represent the range of musical influences and expectations of

Western listeners. Furthermore, improvements to the IDyOM model could incorporate relevant modern melodic expectations, such as those by major popular artists like the Beatles, jazz artists like Miles Davis, and even more contemporary and influential artists like Beyonce. All of these composers and musicians influence the expectations that participants bring into the laboratory environment and the optimal model to investigate these expectations would include as many influential sources as possible.

Additionally, including even simpler excerpts in the stimulus set may lead to a better understanding of the relationship between liking and complexity. The point in which the information content of an excerpt goes from elementary, unmusical patterns to what listeners consider to be "music" was not sufficiently sampled and is an area ripe for investigation. Furthermore, the inverted-U hypothesis detailing the relationship between complexity and liking is still inconclusive and deserves further investigation. The possibility of an asymmetrical inverted-U has been presented by this work and future experiments could test whether that hypothesis is factual or merely an artifact of the data collected.

Conclusion:

In line with results from other recent work, it seems that musical preferences are at least correlated with, if not mediated by, personality characteristics. This experiment, specifically aimed at investigating the differences in musical complexity preference between individuals, demonstrated significant correlations between Neuroticism and Agreeableness with preferences for low and high complexity stimuli respectively. Differences in musical experience and music reward, however, failed to significantly correlate with any of the dependent variables relating to musical complexity and liking. These novel results leave more questions unanswered than answered, but refine hypotheses regarding the overall relationship between musical complexity and preferences and interactions between personality traits and complexity preferences. The enigmatic and unique experience of pleasure each individual has while listening to any piece of music is still largely unexplained, although this work takes a step in the direction of understanding and quantifying the previously unquantifiable.

References:

- Baroni, M., Maguire, S., & Drabkin, W. (1983). The concept of musical grammar. *Music Analysis,* 2(2), 175-208.
- Bornstein, R. F., & D'agostino, P. R. (1992). Stimulus recognition and the mere exposure effect. *Journal of personality and social psychology*, 63(4), 545.
- Burke, M. J., & Gridley, M. C. (1990). Musical preferences as a function of stimulus complexity and listeners' sophistication. P*erceptual and Motor Skills,* 71(2), 687-690.
- Caprara, G. V., Barbaranelli, C., Borgogni, L., & Perugini, M. (1993). The "Big Five Questionnaire": A new questionnaire to assess the five factor model. *Personality and individual Differences,* 15(3), 281-288.
- Chamorro-Premuzic, Tomas; Swami, Viren; Furnham, Adrian; Maakip, Ismail (1 January 2009). "The Big Five Personality Traits and Uses of Music". *Journal of Individual Differences.* 30 (1): 20–27. doi:10.1027/1614-0001.30.1.20.
- Chamorro-Premuzic, T., Fagan, P., & Furnham, A. (2010). Personality and uses of music as predictors of preferences for music consensually classified as happy, sad, complex, and social. P*sychology of Aesthetics, Creativity, and the Arts,* 4(4), 205-213.
- Dollinger, S. J. (1993). Research note: Personality and music preference: Extraversion and excitement seeking or openness to experience?. *Psychology of music,* 21(1), 73-77.
- Dunn, P. G., de Ruyter, B., & Bouwhuis, D. G. (2012). Toward a better understanding of the relation between music preference, listening behavior, and personality. *Psychology of Music*, 40(4), 411-428.
- Egermann, H., Pearce, M. T., Wiggins, G. A., and McAdams, S. (2013). Probabilistic models of expectation violation predict psychophysiological emotional responses to live concert music. *Cogn. Affect. Behav. Neurosci.* 13(3), 533-553. doi: 10.3758/s13415-013-0161-y
- Fleeson, William (2001). "Towards a structure- and process-integrated view of personality: Traits as density distributions of states". *Journal of Personality and Social Psychology*. 80: 1011–1027. doi:10.1037/0022-3514.80.6.1011.

- Fung, C. V. (1996). Musicians' and nonmusicians' preferences for world musics: Relation to musical characteristics and familiarity. *Journal of Research in Music Education,* 44(1), 60-83.
- Gordon, J., & Gridley, M. C. (2013). Musical preferences as a function of stimulus complexity of piano jazz. *Creativity Research Journal,* 25(1), 143-146.
- Harmon-Jones, E., & Allen, J. J. (2001). The role of affect in the mere exposure effect: Evidence from psychophysiological and individual differences approaches. *Personality and Social Psychology Bulletin,* 27(7), 889-898.
- Huron, D. B. (2006). Sweet anticipation: Music and the psychology of expectation. MIT press.
- John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (pp. 102-138). New York, NY, US: Guilford Press.
- Juslin, P. N. "From Everyday Emotions to Aesthetic Emotions: Towards a Unified Theory of Musical Emotions." (2013) *Physics of Life Reviews,* 05 Sept. 2013.
- Juslin, P. N., & Västfjäll, D. (2008). Emotional responses to music: the need to consider underlying mechanisms. *The Behavioral and Brain Sciences*, 31(5), 559-575-621. https://doi.org/10.1017/S0140525X08005293
- Koelsch, S. (2014). Brain correlates of music-evoked emotions. *Nat. Rev. Neurosc*i. 15, 170-180. doi: 10.1038/nrn3666.F
- Ladinig, Olivia; Schellenberg, E. Glenn (2012). "Liking unfamiliar music: Effects of felt emotion and individual differences". *Psychology of Aesthetics, Creativity, and the Arts.* 6 (2): 146–154. doi:10.1037/a0024671.
- Langmeyer, A., Guglhör-Rudan, A., & Tarnai, C. (2012). What do music preferences reveal about personality?. *Journal of Individual Differences.*
- Lerdahl, F., & Jackendoff, R. S. (1985). A generative theory of tonal music. *MIT press.*
- Mas-Herrero, E., Marco-Pallares, J., Lorenzo-Seva, U., Zatorre, R. J., & Rodriguez-Fornells, A. (2013). Individual differences in music reward experiences. *Music Perception: An Interdisciplinary Journal,* 31(2), 118-138.

- Mullensiefen, D., Gingras, B., Musil, J., & Stewart, L. (2014). Goldsmiths Musical Sophistication Index. *PsycTESTS* Dataset. doi:10.1037/t42817-000
- Nave, G., Minxha, J., Greenberg, D. M., Kosinski, M., Stillwell, D., & Rentfrow, J. (2018). Musical preferences predict personality: evidence from active listening and facebook likes. *Psychological science*, 0956797618761659.
- Neumann, K. A., Gold, B. P., Zatorre, R. J. (2017). An Information Content Model of Subjective Pleasure in Monophonic Music Listening. *MPSI McGill Undergraduate Psychology Research Journal*
- North, A. C., & Hargreaves, D. J. (1995). Subjective complexity, familiarity, and liking for popular music. Psychomusicology*: A Journal of Research in Music Cognition*, 14(1-2), 77.
- Orr, M. G., & Ohlsson, S. (2005). Relationship between complexity and liking as a function of expertise. *Music Perception: An Interdisciplinary Journal*, 22(4), 583-611.
- Pearce, M. T. (2005). The construction and evaluation of statistical models of melodic structure in music perception and composition (Doctoral dissertation, City University London).
- Pearce, M. T., & Wiggins, G. A. (2006). Expectation in melody: The influence of context and learning. *Music Perception: An Interdisciplinary Journal,* 23(5), 377-405.
- Pearce, M. T., & Wiggins, G. A. (2012). Auditory expectation: The information dynamics of music perception and cognition. *Topics in Cognitive Science,* 4(4), 625-652.
- Pearce, M. T., Ruiz, M. H., Kapasi, S., Wiggins, G. A., and Bhattacharya, J. (2010). Unsupervised statistical learning underpins computational, behavioural, and neural manifestations of musical expectation. *NeuroImage* 50(1), 302-313. doi: 10.1016 j.neuroimage.2009.12.019.
- Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: The structure and personality correlates of music preferences. J*ournal of Personality and Social Psychology, 84(6), 1236–1256*. https://doi.org/10.1037/0022-3514.84.6.1236

- Salimpoor, V. N., Benovoy, M., Larcher, K., Dagher, A., & Zatorre, R. J. (2011). Anatomically distinct dopamine release during anticipation and experience of peak emotion to music. *Nature Neuroscience,* 14(2), 257-262. doi:10.1038/nn.2726
- Salimpoor, V. N., van den Bosch, I., Kovacevic, N., McIntosh, A. R., Dagher, A., & Zatorre, R. J. (2013). Interactions between the nucleus accumbens and auditory cortices predict music reward value. *Science*, *340*(6129), 216-219.
- Sauvé, S. , Sayed, A., Dean, R. T., Pearce, M. T. (2017). Effects of pitch and timing expectancy on musical emotion. *Unpublished Manuscript.*
- Sloboda, J. A. (1991). Music Structure and Emotional Response: Some Empirical Findings. *Psychology of music, 19(2), 110-120.*
- Sluckin, W., Colman A., Hargreaves D. (2000). "Novelty and Human Aesthetic Preferences." *British Journal of Psychology. Novelty and Human Aesthetic Preferences, Jan. 2000. Web. 10 May 2017.*
- Steck, L., Machotka, P. (1975) Preference for musical complexity: Effects of context *Journal of Experimental Psychology: Human Perception and Performance, 104, 170–174*
- Steinbeis, N., Koelsch, S., & Sloboda, J. A. (2006). The Role of Harmonic Expectancy Violations in Musical Emotions: Evidence from Subjective, Physiological, and Neural Responses. *Journal of Cognitive Neuroscience 18(8)*, 1380-1393. doi:10.1162/jocn.2006.18.8.1380
- Vuust,. P, and Kringelbach, M. (2010) "The Pleasure of Making Sense of Music.": SSRN. *Interdisciplinary Science Reviews,* 04 Sept. 2010
- Witek, Maria A. G., Eric F. Clarke, Mikkel Wallentin, Morten L. Kringelbach, and Peter Vuust. (2016) "Syncopation, Body-Movement and Pleasure in Groove Music." *PLOS ONE. Public Library of Science*, 16 Apr. 2016.
- Vuust, Peter, and Morten Kringelbach. (2010) "The Pleasure of Making Sense of Music.":: SSRN. *Interdisciplinary Science Reviews,* 04 Sept. 2010.

Statement of Contribution

Despite the fact that this was my independent thesis project, the work done for this semester's research course was only possible with the assistance and mentorship by Ph.D candidate Ben Gold. Mr. Gold wrote the code used to analyze the data for this project. My work this semester included designing & conducting the experiment, data analysis, subject recruitment, creation of stimuli, and assisting others in the lab. The majority of the lab work this year involved planning, scheduling, and collecting the data from 44 participants which each took approximately 2 hours per experiment. My project also was designed in part to replicate and validate prior work on musical expectation. Additionally, this project would not have been possible without Dr. Marcus Pearce's IDyOM model of information content in monophonic music and his collaboration. Lastly, but not least, this project would have been impossible without the guidance and resources of Dr. Robert Zatorre. This experiment and other work this semester is based heavily upon the work that was done during my past research projects and previous experiments done by Mr. Gold and the rest of the Zatorre Lab.