

The Effect of Perceived Complexity and Formal Location
on Musical Preference

by

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Biographical Sketch

Ethan Lustig received his BA in Music Theory at the University of British Columbia before coming to the Eastman School of Music, University of Rochester for his MA and PhD in Music Theory. His research has been published in the academic peer-reviewed journals *Music Perception* and *Psychology of Music*, where, in collaboration with Prof. David Temperley (Eastman School of Music) and Prof. Ivan Tan (Brown University), he used statistical approaches to vocal melody, rhythm, and groove in popular music. Lustig has presented his research at four international conferences, including a collaboration with Joseph VanderStel (VP of Technology, Artusi) and Yujia Yan in Paris that presented a novel machine-learning/AI model for music composition to engineers from Google, Spotify, Pandora, Shazam, and dozens of other institutions. At the age of 22, he was awarded the prestigious Social Sciences and Humanities Research Council (SSHRC) of Canada Doctoral Fellowship, as well as the Sproull Fellowship from the University of Rochester.

At the Eastman School of Music, Lustig spent four years teaching music theory and aural skills to classrooms of first- and second-year undergraduate students; he also served for three years as Publicity Manager for the music theory journal, *Intégral*. Lustig is the editor of Greg Aranda's music theory encyclopedia, *The Architecture of Music*, available through Amazon, Barnes & Noble, and other platforms.

Lustig also has experience in Forensic Musicology, consulting for Beverly Hills law firm Johnson & Johnson, for whom he produced a technical, analytical report for a music infringement suit concerning a global Billboard Top 10 hit. He also served as chief Musicologist & Audio Engineer for innovative music technology company, Avec Audio.

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Abstract

Why do we like the music that we like? This seemingly simple question is surprisingly understudied. This dissertation aims to give some answers to this question, with a focus on analyzing the dataset of the FAV Corpus, a collection of pieces and excerpts that 140 survey participants gave as their favorite musical moments. Following a review of the literature on music preference, the study presents two hypotheses that pertain to the excerpts in the FAV Corpus. Both hypotheses are grounded in existing theory, and justified from multiple viewpoints, ranging from psychology, to evolutionary biology, to anecdotes by music scholars in diverse genres. The first hypothesis (the “C-S hypothesis”) predicts that the excerpts in the corpus will tend to be moments of decreased complexity. The second hypothesis (the “Returns hypothesis”) predicts that the excerpts will tend to be formal returns as well.

The C-S hypothesis is tested using an “AB/BC” paradigm with expert judges rating the perceived complexity of each stimulus. The result is that, surprisingly, participants’ favorite excerpts in the corpus were moments of *increased* complexity; this result holds stable regardless of level of training. The Returns hypothesis is tested via an “XYZ” paradigm with expert assignment of formal section labels to each piece. Participants’ favorite excerpts did not tend to be returns at a rate greater than chance; however, it was found that excerpt beginning times tend to align more closely with formal section beginnings than do randomly generated excerpts, suggesting that form is somewhat determinative in excerpt choices.

Analysis of the composers and genres in the FAV Corpus also reveals interesting information about the historical and stylistic tendencies of people’s favorite music, as do analyses of subjective participant comments. Finally, the study presents future possibilities, including potential directions in the spaces of machine learning and music information retrieval.

Contributors and Funding Sources

This work was supervised by a dissertation committee consisting of Professor David Temperley (advisor) and Professor Elizabeth West Marvin of the Department of Music Theory at the Eastman School of Music, and Professor Elise Piazza of the Department of Brain and Cognitive Sciences at the University of Rochester. Graduate study was supported by the Sproull Fellowship from the Eastman School of Music and a Doctoral Fellowship Award from the Social Sciences and Humanities Research Council of Canada.

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Chapter 1: Introduction

Why do we like the music that we like? Surprisingly little is known about this question. Relatively few studies have been devoted to issues of music liking, and almost none from a rigorous music-theoretic perspective. Previous studies have explored broad issues such as the correlation between personality dimensions and genre preferences (e.g. Rentfrow & Gosling, 2003), and how musical enjoyment is affected by exposure (the number of times a piece is heard) and musical training (e.g. Stevens & Latimer, 1991; Orr & Ohlsson, 2005). While such studies provide a useful theoretical foundation, they do not tell us what features characterize people's favorite songs or passages, or why. Even we music theorists ourselves seem to rarely reflect on the underlying rules and features that determine our own preferences in any systematic way—the assumption being that after a certain point, it is simply “a matter of taste” and beyond quantification. While music preference is certainly subjective and depends in part on extra-musical (i.e. social and personality) factors, there may also be underlying principles that shape and predict people's favorite and least favorite music. Teasing out these principles can contribute to our understanding of how we listen, as well as our understanding of musical structure itself.

If research on preferences for pieces of music has been relatively sparse, an even less studied question is why we prefer specific *sections* of those pieces. It is this question that the current dissertation explores. This dissertation presents a new corpus of people's favorite excerpts of music that I call the FAV Corpus. The corpus consists of recordings given by 140 participants as responses to a survey I created. In the survey, each participant was asked to choose three of their favorite pieces, in any style and time period, and then to identify their favorite 15-second excerpt within each piece and comment on their choice. The pieces and

excerpts are not only named and specified, but are also stored as audio files. Many pieces include formal analyses as well (see Chapter 5). It is my hope that this audio corpus of hundreds of favorite musical moments, as well as the pieces from which they come, will be of use to music researchers in the future.

The main focus of this dissertation is on analyzing the excerpts in relation to their surrounding context. Why did people choose these particular 15 seconds and not another excerpt from the piece? (While the question of why they chose this piece and not another is also interesting, that will not be explored here.) Chapter 3 presents two hypotheses attempting to explain this question. The first, and central, hypothesis is that the excerpts people chose as their favorites are generally lower in complexity than the preceding material: a move from complexity to simplicity is preferred, rather than the reverse. I will call this hypothesis the “C-S hypothesis”. A secondary hypothesis that follows from the C-S hypothesis is that these preferred excerpts will tend to be formal returns (the “Returns” hypothesis). Both hypotheses will be explored and justified in Chapter 3; Chapter 5 will test these hypotheses on the FAV Corpus.

This dissertation proceeds in five parts. Chapter 2 reviews the existing literature on musical liking, and identifies gaps in the existing research. Chapter 3 gives the research goals, hypotheses, and reasoning of the dissertation. Chapter 4 introduces and analyzes some features of the FAV Corpus and the survey study, such as the distribution of genres, and trends in the participants’ comments. Chapter 5 details the methodology of the data evaluation, testing the C-S and Returns hypotheses. For the C-S hypothesis, the AB/BC paradigm is introduced, and blind expert judges are used to rate the complexity of the passages along several music-theoretic domains. For the Returns hypothesis, the XYZ paradigm is introduced: the songs are analyzed and coded for formal section (X, Y, or Z), and the excerpts’ formal categories are compared to

random controls. The results of both tests are presented, discussed, and analyzed. Finally, Chapter 6 summarizes conclusions, discusses some pedagogical implications of the corpus, and gives future directions, both for expanding the survey study methodology to collect more and new types of data, and for extrapolating further on evaluation and analysis of the existing dataset.

Chapter 2: Previous Research on Music Liking

In this chapter, I summarize the existing literature as it pertains to the dissertation. Relevant issues include the effects of complexity on musical preference, effects of training, and the relationship between musical liking and emotion.

2.1 Complexity and liking

Liking is the extent to which someone enjoys a stimulus (i.e. a piece or passage of music, a lab-constructed tone sequence, etc.). This is typically measured using self-report scales (liking, pleasantness, preference, enjoyment, or pleasingness). In the case of my survey (see Chapter 4), the participants selected their favorite excerpts, rather than rating existing stimuli; we can assume that their liking for the excerpts was very high.¹ *Complexity* can be separated into objective and subjective aspects. The *objective complexity* of a stimulus can be formally defined using information theory, whereby any stimulus can be described in terms of its average information content, measured in bits (Crozier, 1981). Information (also known as uncertainty) is the negative logarithm of probability; as probability decreases, information increases (Shannon, 1948).² In contrast to objective complexity, *subjective complexity* (also known as perceived complexity) is the extent to which someone judges the stimulus as complex. Another way to think about the objective-subjective complexity distinction is in terms of its method of measurement: observed (using some quantitative and well-defined metric) versus perceived (self-

¹ There may be subtle differences in meanings between these various terms—“enjoyment,” “pleasantness,” “pleasingness,” “liking”, and “favorite.” I comment on this in section 2.4 below.

² Even objective complexity is subjective in a sense, since the probabilities assigned to events might differ between one listener and another.

reported) complexity respectively. In Chapter 5, this study uses the latter method, prompting judges to rate perceived complexity (based on a brief definition of complexity provided to them).

It should be noted that subjective and objective complexity measures are closely related, reflected both in strong positive correlations (0.84 in Stevens and Latimer, 1991; 0.95 in Velardo and Vallati, 2015) and in similar rank orderings of stimuli (Vitz, 1966; Heyduk, 1975). For the purposes of the present dissertation, this previously established tight mapping between subjective and objective complexity bodes well, as it suggests that a judge's subjective complexity ratings will most likely be an accurate proxy to the objective complexity features of the stimuli as well.

The relationship between musical complexity and liking has been widely discussed. One popular view is the *optimal complexity theory* associated with Berlyne (1972). Berlyne's full theory (also known as the two-factor arousal theory or the inverted-U hypothesis) involves physiological and aesthetic claims beyond the scope of this study. For our purposes, though, optimal complexity theory claims that we most prefer stimuli that are at an intermediate level of subjective complexity. If a stimulus is too complex, it is supra-optimal; if it is not complex enough, it is sub-optimal. This generates an inverted-U function of preference with respect to subjective complexity (Figure 1).

Many studies support the finding of an inverted-U function with respect to the relationship between complexity (or information) and liking. Vitz (1966) generated tone sequences at six levels of increasing variation. With each level of increasing variation, the sequences used more tones than the previous level, and increased either in the number of durations used, or the number of loudness levels used. He found an inverted-U function with respect to liking ratings and level of stimulus variation. This means that low-complexity and high-complexity stimuli were less liked than moderate-complexity stimuli. Heyduk (1975)

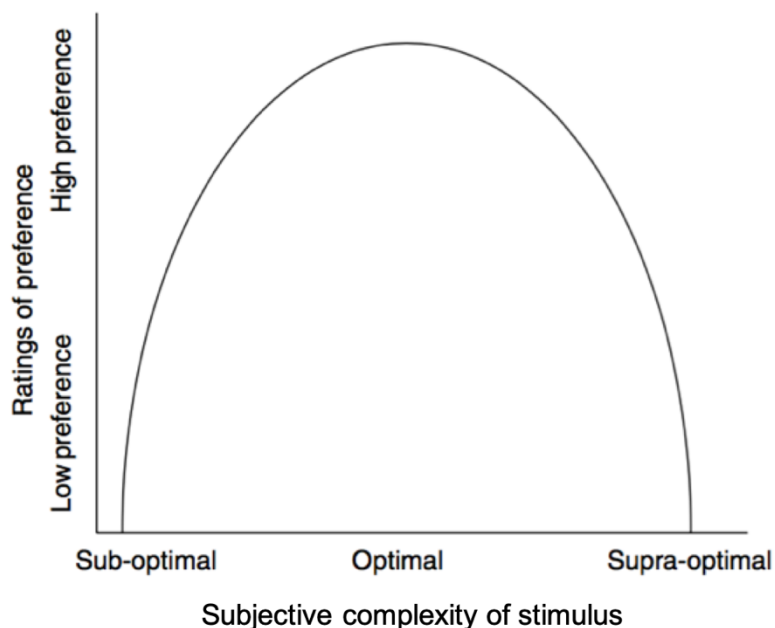


Figure 1. Inverted-U function of preference by subjective complexity. (Modified from Tan et al., 2006, p. 410)

created four 30-second solo piano pieces; with each piece the number of different chords and the amount of syncopation increased, therefore increasing their complexity. Like Vitz, Heyduk found that liking formed an inverted-U with respect to complexity. Crozier (1981) created tone sequences and manipulated them along two dimensions: variability (the total number of possible tones) and redundancy (the non-uniformity of the distribution: redundancy is high if one tone is much more probable than all the others) within each variability level.³ The variability and redundancy dimensions determined the amount of information per tone; decreasing the

³ Crozier's definition of "tone" includes pitch, dynamic, and durational levels. By this logic, a loud and a soft D3 are two different elements, and they are weighted as differently as are a D3 and an E3. This seems questionable. Fortunately, his result still holds even when we ignore his durational and dynamic levels and only consider pitch.

redundancy level or increasing the variability level led to an increase in the information of the tone sequence. Crozier, like Vitz and Heyduk, found that pleasingness ratings had an inverted-U with respect to information. Using some of the stimuli from Crozier (1974) (similar to those used in Crozier, 1981), Martindale and Moore (1989) also found that liking ratings formed an inverted-U with information. North and Hargreaves (1995) defined complexity to participants as how easy it is to predict what the music will do next and how many surprises the music contains. Stimuli were 30-second excerpts of pop music that were unrecognized by the participants. Once again, an inverted-U between subjective complexity and liking was found. Other studies that support this finding include Russell (1982), Smith and Melara (1990), and Velardo and Vallati (2015).

While this study does not explore optimal complexity as its focus, the important fact for our purposes is that complexity has been well-demonstrated to be a determinative and influential variable on musical liking.

2.2 Research on the effect of training on complexity judgments

The present dissertation (in the AB/BC paradigm discussed in Chapter 5) uses music experts to judge stimulus complexity. But is it valid or representative to use only experts to assess stimulus complexity? What is the relationship between training and complexity judgments?

Definitions of what constitutes “trained” vs. “untrained” have varied wildly: Vitz’s (1966) high musicality group had two or more years of training, while the expert group in a study by Orr and Ohlsson (2005) had an average of 28 years of training! Regardless, it has repeatedly been found that people across all training levels, however defined, tend to agree on the rank

ordering of stimuli from least to most complex (Vitz, 1966; Smith & Melara, 1990; Stevens & Latimer, 1991; Orr & Ohlsson, 2005; Velardo & Vallati, 2015). This finding supports the validity of the AB/BC blind judging paradigm of Chapter 5, because it suggests that complexity judgments by musical experts will accurately reflect and translate to the layperson as well. While evidence suggests that people with more musical training prefer a higher level of complexity (suggesting that the optimal complexity point for listeners shifts depending on their level of training, e.g. North and Hargreaves, 1995, pp. 83-87), the important fact for the present study is that the rank ordering of complexity judgments tends to be consistent across training levels.

There is also evidence that training may determine which musical variables are used to make complexity judgments. Conley (1981) had participants in three levels of training (non-music majors, sophomore music majors, and music graduates) rate the subjective complexity of Beethoven piano variations. Although complexity ratings were highly correlated between groups (.84-.94), the groups differed in the musical variables that they used to make their judgments. The rate of rhythmic activity was the most important variable for all three groups, accounting for 71-90% of subjective complexity ratings.⁴ However, factoring out this variable, for undergraduates the number of changes in rhythmic activity was a predictive variable, while for music graduates the number of different harmonies as well as the number of non-tonic/non-dominant harmonies were predictive.⁵ This difference between groups suggests that more expert

⁴ Variable 9, defined as the number of rhythmic events per minute. However, this is based on the opening pulse of the variation (even if the pulse changed, the calculation would be unaffected). The number also seems to be based on a metronome realization of the score, rather than on the actual recording used in the study. It ranged from 48 to 696 across the stimuli.

⁵ Variable 8 was defined as a shift from one rhythmic pattern to another. This ranged from 0 to 15 across the stimuli. Conley's definition of "harmony" (Variable 3) was root-based, such that a chord in root position and first inversion are not different harmonies. However, chromatic alterations do count as different harmonies, such that V and v are two different harmonies. The

listeners use both harmonic and rhythmic criteria in judging complexity, whereas less expert listeners use only rhythmic criteria. Stevens and Latimer (1991), in an extreme case, found that a rhythmically complex tonal piece was rated as more complex than a rhythmically simple atonal piece, at both levels of training (less than three years, more than six years). Thus, contrary to Conley's finding, both groups here privileged rhythmic over harmonic criteria in making their complexity judgments. (However, note that Stevens and Latimer's high training group is less trained than Conley's high training group.)

In summary, while people across all levels of training do tend to agree on the ordinal complexity of stimuli, there is some evidence that experts use different criteria in making their complexity judgments. Fortunately, the complexity judgments in Chapter 5 were made by musical experts (PhD music theory students) and the majority of the participants in the survey also had a high level of musical training, so we can assume that the two groups had similar intuitions about complexity.

2.3 Research on musical liking and emotion

Perceived emotion is the emotion attributed to the music, whereas felt emotion is the listener's response (Evans and Schubert, 2008). Evans and Schubert (2008) tested the relationship between perceived and felt emotion; a positive relationship (match) between the two variables occurred only 61% of the time. Interestingly, liking ratings were highest for stimuli with a match between felt and expressed emotion, suggesting that a match between felt and

number of non-tonic/non-dominant harmonies (i.e. roots other than scale degrees 1 or 5) was Variable 7, which ranged from two to 20 non-tonic/non-dominant harmonies across the stimuli.

expressed emotion is preferred by listeners to a mismatch. Sloboda (1991) notes that people tend to agree on judgments of perceived emotion, but this is not as true for felt emotion.

Felt emotion is more closely related to liking than is perceived emotion, because the former measures listener feelings rather than feelings attributed to the music itself. However, felt emotion is not the same as liking by any means; for example, people can and do enjoy music that makes them feel happy, sad, and any other emotions in between. Perhaps the most important factor for the emotion-liking relationship is that people's favorite music tends to elicit *strong* felt emotional responses, regardless of the type (i.e. happy, sad, etc.) of emotion. However, the emotion-liking relationship will not be explored further in this study, as the survey (Chapter 4) did not collect data on emotions.

Hargreaves and North, in their chapter on musical liking in the *Handbook of Music and Emotion*, remark that the literature on liking for music has developed largely in parallel to, rather than together with, research on emotional responses to music. They suggest that “the concept that may establish a bridgehead between liking for and emotional reactions to music is that of physiological arousal.”⁶ The most notable study in this regard is Sloboda (1991) (discussed in more detail in section [2.4](#)). In measuring thrills, Sloboda's study offers a rare bridge between emotion and liking research, via physiology. Sloboda's study is a “felt emotion” study (in contrast to “perceived emotion”). Harrison and Loui (2014) problematize “thrills” and “chills” and present a holistic model for experimenters in the psychophysiology of music. Bannister (2020) collects participant reports of musical chills, zeroing in on the emotional qualities associated with the experience.

⁶ Chapter 19, Section 19.2, page unknown (EPUB version).

Finally, a related project to the present dissertation (but with very different goals) should be noted: the Strong Experiences with Music (SEM) Project by Gabrielsson and Lindström-Wik (1993, 2003; Gabrielsson, 2010, 2011). The SEM project collects and analyzes over 1300 free descriptions of strong experiences with music. Participants were prompted to describe “the strongest, most intense experience of music that [they had] ever had” (Gabrielsson & Lindström-Wik, 2003, p. 163). The project’s focus on “strong experiences” is related to the current dissertation’s focus on favorite passages. Unlike this dissertation, however, the approach taken with the SEM Project is sociological. Rather than analyzing musical features, they chronicle the various social functions and uses of music, as well as the effects of personality and lifestyle on music taste.

2.4 Research on musical features and liking

Despite a wealth of existing music-theoretic metrics, surprisingly little work has been done to actually measure what specific stimulus features determine people’s musical preferences. Indeed, the paucity of work on this issue is a chief motivation for the present dissertation.

Sloboda (1991) had participants select pieces and specific passages that, in their experience, reliably evoked “thrills” (including chills, shivers, tears, and tingles). Sloboda’s study begins from the premise that pieces contain emotional valleys and peaks. His study is focused on the peaks, and what musical events induce them. He then maps musical devices to physical responses, finding that sequences and appoggiaturas tend to elicit tears, while surprising harmonies tend to elicit shivers. The most common self-reported physical responses to music were shivers down the spine, laughter, tears, and a lump in the throat. Most participants reported having the intense physical response to the whole movement, or a particular section of the piece.

Few of them experienced it in a more localized way: few felt it only in a particular bar, and fewer still in a single chord/moment. (This lends validation to the present study, in which I will discuss *sections* more than *moments*. See Chapter 3 for a justification of the section-based approach.)

Sloboda's fascinating study is in desperate need of a follow-up, and the present dissertation is inspired by his project of asking participants to select their favorite pieces and moments. Some key differences are that Sloboda only used classical music, asked about physical response, and required measure numbers with reference to a score; the present study uses music from many genres, asks about favorite (most liked) moments rather than physical responses, and uses an audio corpus of specific recordings. I also collected many more pieces and excerpts than Sloboda did (his study evaluates 38 passages), and analyze them more systematically.

Ilie and Thompson (2006) asked participants to rate the pleasantness (a related but different prompt than "liking" per se) of classical music recordings. In general, soft excerpts were rated as more pleasant than loud excerpts. At a fast tempo, low pitch height was rated as more pleasant than high pitch height; at a slow tempo, there was no effect of pitch height on pleasantness ratings. The lowest ratings of all went to music that was both loud and high-pitched.

In short, we know little about the specific musical devices or structural characteristics that contribute to liking and enjoyment, as it pertains to complexity or otherwise. This dissertation aims to fill this critical gap in the research.

Chapter 3: Unpacking the Hypotheses

The central claim and hypothesis of this dissertation is that the excerpts people chose as their favorites in my survey study (discussed further in Chapter 4) are generally *lower in complexity than the preceding material*: a move from complexity to simplicity is preferred, rather than the reverse. I call this hypothesis the “C-S hypothesis”. This will be tested using a novel “AB/BC” paradigm (described in Chapter 5) with blind judges rating the relative subjective complexity of passages. A secondary hypothesis that follows from the complexity-to-simplicity idea is that these *preferred excerpts will tend to be formal returns*; a novel “XYZ” paradigm will be presented in Chapter 5 for testing this latter hypothesis, which I call the “Returns hypothesis”.

To justify the C-S hypothesis, I will begin by turning to the idea of “contrastive valence” from Huron (2006). I will show how this basic idea is echoed in numerous, diverse sources both before and after him. Then, I will use these anecdotal observations from previous writers as a space to briefly untangle the interrelated concepts of complexity, ambiguity, unpredictability, and unfamiliarity (and their opposites). The Returns hypothesis will be explained in light of this discussion. Finally, while contrastive valence provides a basis for the C-S hypothesis, contrastive valence will not be sufficient in itself to explain why complex-to-simple should be uniquely pleasurable (rather than simple-to-complex). To answer this question of directionality I will argue from evolution and biology, via a discussion of reward and survival.

We must also consider that favorite or “peak” experiences (Maslow, 1964) might be due to elements (e.g. a vocal gesture, a drum fill) that are essentially independent of context; or they might depend on context in some way. This dissertation focuses on the latter—the contextual

reasons for these pleasurable musical experiences. In some cases, there may have been “context-free” factors affecting people’s choices but that possibility will not be explored here.

3.1 Contrastive valence

In a book chapter on musical expectancy and thrills, Huron and Margulis (2010) write: “Feeling states appear to be strongly influenced by contrast. If we initially feel bad and then feel good, the good feeling tends to be stronger than if the good experience occurred without the preceding bad feeling. Conversely, if we initially feel good and then feel bad, the bad feeling tends to feel worse.”⁷ This phenomenon has been demonstrated in the psychological literature (e.g. McGraw, 1999), as positive and negative hedonic contrast. Dating back to Fechner (1898 as cited in Beebe-Center, 1932/1965), hedonic contrast theory states that “stimuli are evaluated less positively if they follow good stimuli than otherwise [negative contrast]; stimuli are evaluated more positively if they follow bad stimuli than otherwise [positive contrast].” (Parker et al., 2008, p. 171) Positive and negative hedonic contrast have been amply demonstrated in many media such as colors, tastes, faces, and paintings. In their study, Parker et al. demonstrate the effect of hedonic contrast in music for the first time: they show that consonant melodies are liked more when they follow dissonant ones, and dissonant melodies are liked less when they follow consonant ones.

Positive hedonic contrast is essentially what Huron (2006) calls “contrastive valence”: where “pleasure is increased when a positive response follows a negative response.” (p. 39) The concept is general, as he roots it not in music perception per se, nor indeed in aesthetic perception, but in biology, evolution, and learning. Huron’s contrastive valence concept is

⁷ Chapter 21, Section 21.9.5, p. unknown (EPUB version).

grounded in earlier psychological theories like that of Solomon (1980), whose concept of “opponent process” Huron cites (2006, p. 383, fn. 8). Solomon’s theory states that when preceded by an unpleasant experience, the pleasantness of what follows is amplified; the physiological process creating displeasure enables an opposing, positive process.

To demonstrate contrastive valence, Huron (2006) gives the example of a suspension.

Consider first the pre-suspension moment (moment 1). As a I chord, it is quite stable and so may evoke no strong sense of continuation. Consequently, there is little feeling of anticipation and little tension. Consider next the moment when the suspended sonority appears (moment 2). The sonority is now more dissonant, so the reaction response has a comparatively negative valence...Finally, the anticipated moment of resolution occurs (moment 3)...the formerly dissonant sonority has been replaced by a chord with comparatively low sensory dissonance. Consequently, the reaction response will exhibit a relatively high positive valence. (pp. 309-310)

In their comprehensive review of research on chills in music, de Fleurian and Pearce (2020) find that, while contrastive valence has explanatory power as a model for chills, “contrastive valence doesn’t fully account for the experience of chills, notably by failing to provide an explanation for chills caused by the emotional expressiveness of music.” (p. 33) In other words, while contrastive valence can work well for discussing returns, contrast, and complexity differentials (all subjects of this dissertation), we must remember that another reason for chills (and musical liking) can be perceptions and experiences of emotional expressiveness, something that will not be explored here (see section [2.3](#) for a brief discussion of emotion).

The music research literature is rife with examples of the contrastive valence phenomenon, although it is rarely positioned in terms of that theory specifically. In his classic tome *Emotion and Meaning in Music*, Meyer (1956) discusses something very similar to Huron’s later idea of contrastive valence:

If the musical patterns are less clear than expected, then doubt and uncertainty as to the general significance, function, and outcome of the passage will result...[T]he mind rejects

and reacts against such uncomfortable states...The greater the buildup of suspense, of tension, the greater the emotional release upon resolution. (pp. 27-28)

Ball (2010) makes a similar claim:

Delaying a cadence, or creating uncertainty about any other learnt musical pattern, boosts the eventual reward (assuming that it comes at all)...And when the final tonic chord arrives...what would have been a mildly pleasant sense of completion becomes a flood of delight, even awe. (p. 285)

Solberg and Dibben (2019), in their study of physiological responses to peak experiences in EDM (electronic dance music), find that the "breakdown-buildup-drop" routine of the genre is especially pleasurable, because it creates a cycle of creating-denying-fulfilling expectations. The "drop" in particular is the most pleasurable part. This is congruent with the C-S hypothesis, because the EDM drop involves a reduction of complexity in a number of ways: the return of the kick drum, the full texture, and the lead synth or vocal all function to clarify (and therefore reduce the perceived complexity of) meter and form in EDM (Butler, 2006).

3.2 Untangling metaphors

Notice that the preceding examples intermingle a clarity-ambiguity dichotomy with a simplicity-complexity one. But how does the former dichotomy relate to the latter (the latter being the focus of this dissertation)? Clarity and ambiguity could be defined here as situations where there are fewer and more plausible interpretations of a stimulus, respectively. By this definition, the clearest stimulus in a given domain is one in which only one plausible hearing occurs for most listeners in that domain: for example, a stimulus for which all listeners identify the same time signature and downbeat location would be clear in the domain of meter, whereas a stimulus for which multiple interpretations and hearings abound with respect to the downbeat location and/or time signature would be metrically ambiguous. Germane here is the body of

work modeling the cognition of musical structures, often operationalized as they pertain to meter- and key-finding algorithms and tested using both clear and ambiguous inputs (see Lerdahl & Jackendoff, 1983; Temperley, 2001); as well as the body of more traditional music-theoretic work on metric dissonance (ambiguous insofar as it invokes conflicting metrical hearings) (e.g. Krebs, 1999) and tonal ambiguity (e.g. Hood, 2012).

Perhaps another way of framing the clarity-ambiguity dichotomy is in terms of yet another dichotomy: predictability-unpredictability. This brings the former dichotomy very close to the simplicity-complexity idea (recall that many studies have even defined complexity to participants as predictability). If the reader accepts my definition of ambiguity as something which projects multiple plausible interpretations and is therefore less predictable, it stands to reason that (all else equal) a more ambiguous stimulus will be a more complex one. By the same token, when the structure is more clear (i.e. with fewer plausible interpretations and therefore more predictable) the music seems less complex. In short, the less able we are to predict or make sense of a stimulus, the more complex it will seem to us. Thus, the dimensions of simplicity-complexity, clarity-ambiguity, and predictability-unpredictability are all strongly correlated.

Returning to the case study of the EDM drop: When it arrives, the relative clarity (i.e. unambiguity) of the underlying metrical structure is restored. In moments like these, I argue, we like clarity of structure, especially after ambiguity. The contrastive valence principle enhances our enjoyment of the return to clarity, just as I argue that it does for a return to its correlate, simplicity. An analogy from classical music would be a highly chromatic (and thus tonally ambiguous) passage followed by a tonally clear passage. Nelson (1999) writes about a similar phenomenon in Indian music, where the drummer deliberately obscures the meter with complex cross-rhythms:

Some sort of rhythmic shape emerges, but its relationship with the beat seems tense. When it resolves [meaning that the meter once again becomes clear], informed listeners, including the other performers, may nod their approval or briefly applaud. (p. 154)

Similarly, Clayton (2008) writes about how in Indian music, ambiguous “tihais” (cross-rhythms) leading up to the clarifying “sam” (hyperdownbeat) tend to be followed by applause (p. 3).

The quotes from Meyer and Ball in the previous section could also be seen as supporting a preference for ambiguity-to-clarity or unpredictability-to-predictability. Both authors write about the pleasure that occurs when “uncertainty” is “resolved” or removed; uncertainty could be viewed as another word for unpredictability. A final example of this phenomenon comes from classical music theory. Hatten (2004), in his extended discussion of the “arrival 6/4 chord”, describes how in the opening of Beethoven’s “Ghost” trio, an implied augmented-sixth chord (with its scale-degree b3) moving to a 6/4 chord (with its scale-degree natural 3) is a “breakthrough”, with its “positive, Picardy-third effect” and movement into the “glowing consonance of the major triad [the 6/4 chord]” (p. 24). Since the augmented-sixth chord is chromatic (and therefore less predictable) and the 6/4 chord is diatonic, this can be seen as a move from complexity to simplicity; in Hatten’s words, the “suspended *uncertainty* is resolved gloriously” (p. 25, emphasis added).

Though we could ponder further the relationship between familiarity, predictability, simplicity, and clarity on one hand, and their opposites unfamiliarity, unpredictability, complexity, and ambiguity on the other, the present study focuses on one such dichotomy: simplicity-complexity. A well-validated metric, complexity is the testing paradigm for this study’s central hypothesis (the C-S hypothesis). Specifically, perceived complexity will be judged in multiple musical domains using the AB/BC paradigm (see Chapter 5).

3.3 The Returns hypothesis unpacked

The Returns hypothesis predicts that the excerpts selected by participants in my survey will tend to be formal returns. A moment of return is by definition a moment of contrast; returns also tend to be moments of resolution, of clarification, of lower tension, and of lower perceived complexity relative to the preceding material. For one, returns are inherently more predictable than new material since a return presents familiar material from earlier in the piece; the repeated status of a returning section within a piece will reduce its perceived complexity through multiple exposures (for a discussion of how repeated exposure reduces perceived complexity, see Tan et al., 2006). However, even independently of the repeated status of returns, I would argue that many formal returns are still inherently more simple, predictable, and clear than their preceding sections. Two such examples are the chorus returning after a bridge in a pop song, and the recapitulation of a sonata-form piece. Anecdotally, both a chorus (when preceded by a bridge) and a recapitulation tend to be more tonally and metrically clear than the preceding sections. For instance, choruses and recapitulations are often preceded by a dominant pedal, and the arrival at the chorus or recapitulation often coincides with a return to the tonic. Also, the beginning of the chorus or the recapitulation often coincides with both a metrical and hypermetrical downbeat, a new phrase group, and a change of texture and instrumentation. All of these phenomena function to enhance the perceived clarity, simplicity, and predictability of the section, independent of its repeated status within the piece. Interestingly, speculative psychologist Abraham Maslow, in his 1964 book *Religions, Values, and Peak Experiences*, writes that “in peak-experiences, the dichotomies, polarities, and conflicts of life tend to be transcended or resolved. That is to say, there tends to be a moving toward the perception of unity and integration in the world.” (p. 65)

This sounds much like a tonal resolution, a formal return, or other types of musical closure, with their concomitant reductions in complexity and increases in predictability.

The basic claim is that the excerpts in the FAV Corpus will tend to be formal returns because returns are sections that involve both contrast and complexity reduction. (This claim will be tested using the XYZ paradigm in Chapter 5.) Moments of contrast are candidates for the contrastive valence principle to take effect; the following section will argue for why we might enjoy complexity reduction, justifying both the C-S and Returns hypotheses from evolutionary biology and psychology.

3.4 From contrastive valence and optimal complexity theory to the C-S and Returns hypotheses: An argument from evolutionary theory

Optimal complexity theory predicts that moderate complexity will be most enjoyable. Contrastive valence theory tells us that the move from *non-optimal* to optimal complexity will be especially enjoyable. By this view, either a decrease or an increase in complexity that takes us back to optimal (i.e. moderate) complexity could be equally pleasurable, as both involve a contrast and both end up at the optimal complexity point. In other words, these theories say nothing about what directionality of the complexity differential we might prefer. Neither theory is sufficient to justify the C-S hypothesis, which is more specific than either, predicting that *supra-optimal* to optimal complexity will be preferred more than *sub-optimal* to optimal complexity. The Returns hypothesis is also based in this notion. Although I have thus far defended my two hypotheses using conceptual reasoning and case studies, I have yet to present a rational, theoretical justification for the hypotheses. In this section, I will do so, giving an

evolutionary/biological argument from the sciences, supplemented with anecdotes from writers in the humanities.

Implicit in the C-S hypothesis is the idea that here (in the context of this particular temporal sequence of complex-to-simple, and all else being equal), “positive” and “negative” feelings map onto “lower” and “higher” complexity, respectively. If this hypothesis is correct, how might we explain the move from complex to simple as being uniquely pleasurable, more so than the move from simple to complex?

A foundational concept in psychology, evolutionary theory, and biology is that of *reward*:

Survival for most animals depends on minimizing contact with certain stimuli and maximizing contact with others. Contact is minimized when an animal experiences fear or anxiety...animals maintain contact with stimuli that they find rewarding in some way and ignore or avoid stimuli that they find neutral or aversive. According to this view, reward is a mechanism that evolved to help increase the adaptive fitness...of a species. (Kolb & Wishaw, 2005, pp. 433-436)

Similarly, Huron (2006) writes that “Positive feelings reward states deemed to be adaptive, and negative feelings punish us for states deemed to be maladaptive. The word ‘deemed’ here is important. Positive feelings are evoked not by results that are objectively adaptive, but by results that the brain, shaped by natural selection, presumes to be adaptive.” (p. 7)

But what do positive/negative feeling-states have to do with simplicity/complexity? I argue that, all else equal, supra-optimally complex environments are more dangerous for survival than sub-optimally complex ones. The former are unsafe, full of unknowns (perhaps predators or situations where it is difficult to find nutrients and mates), while the latter are simply boring or a waste of time. Also, complex environments require more processing power and energy to navigate, which is more taxing to the organism; a simple environment frees up more resources to focus on survival and reproduction. While the organism will not learn anything new from simple

environments, it will at least *understand* them. A move from a complex (i.e. dangerous) environment to a simple one signals a move to safety and an increased probability of survival (without which procreation, the ultimate goal of evolutionary design, cannot occur). Thus it stands to reason that we have evolved to find this move from complex to simple to be particularly rewarding: an organism's very survival (and concomitant procreation) is dependent on escaping dangerous (i.e. complex) environments when they present themselves.

In summary, I argue that we tend to prefer a move in the direction of complex to simple (the C-S hypothesis) because this is a vestigial trait in the reward system of animals, one that evolved to encourage us to escape complex (and thus dangerous) environments by creating pleasurable feelings as positive reinforcement for this behavior. This view receives further support from many statements by music scholars (see sections [3.1](#) and [3.2](#) above) implying that a move from complexity to simplicity is pleasurable.

This discussion should by no means be construed as suggesting that simple is always more enjoyable. In the wild, after all, if we took no risks and stayed only in the simplest of environments, we would learn little and ultimately fail to gain an evolutionary edge over the competition (be they other species or other individuals of the same species). Huron (2006) notes, "When all of the uncertainty is removed, the capacity for pleasure also seems to be diminished." (p. 39) That is to say, we need complexity in order to enjoy simplicity. We also know this empirically: preferred music tends to be optimally complex for a given listener, rather than listeners preferring music with as little complexity as possible (section [2.1](#)). Another explanation comes from Maslow:

Familiarization and repetition produces a lowering of the intensity and richness of consciousness, even though it also produces preference, security, comfort, etc. Familiarization, in a word, makes it unnecessary to attend, to think, to feel, to live fully,

to experience richly. This is true not only in the realm of religion but also in the realms of music, art, architecture, patriotism, even in nature itself. (1964, p. 34)

Here Maslow suggests a dichotomy between the familiar and repetitive, which he claims to induce “preference” on one hand – and the rich, intense, and (the implication being) *complex* on the other. By his view, much like Huron’s contrastive valence, the complex serves only as a sort of relief from the sameness of the familiar, as the familiar renders it “unnecessary to...live fully, to experience richly.”

Chapter 4: The FAV Corpus

4.1 The Survey

As discussed in Chapter 2, we know very little, from an empirical perspective, about the principles that govern people's musical taste. One way to begin answering this question is to examine people's favorite pieces and excerpts. Such a list could function as a corpus, creating a dataset for the analysis of patterns, and the testing of hypotheses. This corpus can function as a useful set of impactful stimuli for use in musical liking experiments. In the quest for such a collection of pieces and excerpts, I considered several possibilities. One potential source of data on people's favorite music is sales data (i.e. Billboard chart performance). However, looking to sales performance as an indication of people's favorite music is problematic for several reasons. First, chart performance, being a measure of radio play, streaming numbers, and so forth, is in part dependent on an artist's image, resources, marketing, and other extra-musical factors. Second, while high chart performance can indicate that a piece is *liked* by many, it cannot indicate whether a piece is *loved* by any. Third, I am interested in which specific musical sections are impactful for people, and chart performance only shows songs, not sections of songs.

Another potential source of people's favorite music could be lists of critically-acclaimed pieces, such as Rolling Stone's *Greatest Songs of All Time*. However, these lists tend to be based on the opinions of a select group of individuals; even when such lists do result from broad polling, they face the same problem as mentioned for sales data—namely that a piece voted highly by consensus is not necessarily any one person's favorite piece (c.f. democracy). Finally, as with sales data, critical lists do not specify sections of pieces.

Therefore, in order to better understand what pieces and musical sections people choose as their favorites, while avoiding the problems mentioned above, a survey was conducted. Appendix 1 shows the format of the survey, which asked each participant to identify “one of your most favorite songs/pieces/movements. It can be any style or time period”; they were instructed to provide a URL (web address) to a recording of the piece on YouTube or Spotify. (Hereafter I use the term “piece” to indicate any kind of piece of music.) They were further asked to “identify the 15-second excerpt that’s your favorite,” providing start- and endpoints for the excerpt in relation to the YouTube or Spotify recording. (The choice of 15 seconds was fairly arbitrary; I chose it because it roughly corresponds to the length of some of my favorite musical passages.) This process happens three times in the survey, and thus each participant gives three pieces, each with one 15-second excerpt. Following each selection, participants were prompted to write an open-format response to the following question: “Why do you love the excerpt? Try to be as specific and detailed as possible (music theory terms are encouraged but not required).” They were also asked to choose between one of *A* (“I enjoy this excerpt much more than the other parts of the piece”) or *B* (“I enjoy this excerpt about as much as the other parts of the piece”).

There were 140 participants in total, all undergraduate students at the University of Rochester. While the exact degree status of the participants was not collected, based on course enrollment data it is estimated that 119 or 85% of the participants were music majors at the Eastman School of Music, while the remainder were non-music majors enrolled in a music cognition course, which required basic music theory knowledge as a prerequisite. The participants reported an average of 11.08 years of formal musical training on an instrument (including voice) in their lifetime, ranging from 0 years to 23 years. There were 73 females, 63

males, and 4 preferred not to say. The average age of the participants was 19.7 years old, with a range of 17 to 29 years old. The survey received ethical approval by the Research Subjects Review Board (RSRB), which is the Institutional Review Board (IRB) of the University of Rochester.

4.2 The FAV Corpus

4.2.1 Formatting the corpus

The core of the corpus is the YouTube and Spotify URLs provided by the participants along with timepoints for their preferred 15-second excerpts. The recordings were extracted to WAV audio files and the timepoints normalized and converted (see below for a description of the process). As there were 140 participants, in principle, there are 420 responses (three pieces, along with the favorite excerpt from each piece, from each participant). However, in practice some participants were omitted as they failed to pass the attention check⁸ or used joke names. In other cases, individual pieces were excluded for a lack of a working URL, or excerpts were excluded due to the participant's neglecting to specify an excerpt from the piece. Once these exclusions are made, we are left with a corpus of 800 audio files: 402 pieces and 398 excerpts from those pieces.

The timepoints provided by participants were with reference to YouTube or Spotify URLs, but the 0:00 mark on these links did not always correspond to the true beginning of the piece. Therefore, the "URL" timepoints needed to be converted to "musical" timepoints.⁹ When

⁸ The attention check is Question 20 of the survey: "Sometimes people fill in online surveys without carefully reading the instructions. If you are paying attention, select C."

⁹ Many thanks to Adrian Go and Genevieve Jang for their assistance with this enormously time-intensive process of converting the URL timepoints to musical timepoints, normalizing the time windows, and extracting the audio from the URLs to disk.

a participant's timepoints are, for instance, 0:06-0:21, but the piece does not begin until 0:06 into the URL (be it preceded by silence, audience applause, titling, etc.), the musical timepoints are in fact 0:00-0:15 (the first 15 seconds of the piece). The beginning and ending point of the piece within each URL was noted to the nearest second, and this formed the basis of extracting the pieces from the URLs into audio files. Next, in cases where participants entered an excerpt time window that was not exactly 15 seconds, the timepoints needed to be normalized. In these cases the midpoint of the time window was calculated and the 15 seconds determined from this calculation. For example, consider a participant specifying 0:00-0:18, which is 18 seconds rather than the required 15 seconds (three seconds too long). The solution to this was to take the midpoint (0:09) and to subtract the extra three seconds from both sides—beginning the excerpt two seconds later and ending it one second earlier (or vice versa—this decision of whether to give the longer duration to the beginning or end was determined by using a random number generator that produces either a 0 or 1). (In cases where the provided timespan was an uneven number of seconds and thus the midpoint was not an integer value of seconds but rather a fractional value (i.e. 7.5 seconds), the random number generator determined whether to round up or down.) The result would be that the participant's entry of 0:00-0:18 was normalized to 0:02-0:17. In cases where the provided timespan was shorter than 15 seconds, the same process was applied, except that seconds from the piece were added to the timespan rather than subtracted. For instance, a participant-provided 0:30-0:40 would be normalized to 0:28-0:43 (or 0:27-0:42 depending on the random number generation). Finally, in cases where the midpoint of the excerpt was at 0:07 or earlier, the timespan was simply normalized to 0:00-0:15; the corresponding operation was applied to cases where the midpoint of the excerpt was within 7 seconds of the end of the piece (normalized to the last fifteen seconds of the piece).

Appendix 2 shows the FAV Corpus, in the form of a list organized by participant number and piece number. The excerpt times are given as well as the artist or composer and piece title. (For some pieces participants did not provide excerpts and thus there is a piece but no corresponding excerpt.) The corpus consists of two types of audio files—musAudio files, which are complete pieces extracted from the URLs, and excerptAudio files, which consist of the 15-second (normalized and converted) excerpts from the pieces. The musAudio files are named in the format musAudioX_Y, where X = participant number and Y = song number (1 through 3). The excerptAudio files are named in the same way. For example, in Appendix 2 the Kendrick Lamar song in the third row corresponds to the file musAudio2_1 while the excerpt chosen by the participant would be found in the file excerptAudio2_1.

4.2.2 Genre analysis of the corpus

Coding the pieces in the corpus by genre reveals interesting information. First, each piece was labeled as one of three broad genres—classical, pop, or jazz. While most genre assignments were straightforward, some judgment calls were involved. Problems included pieces that straddled the line between jazz fusion and rock-with-jazz-aspects, songs of the musical theater variety (some of which I interpreted to be pop with music-theater leanings, such as Voctave – “Disney Love Medley,” 128_3, and others which I felt were closer to classical music than pop, such as Sondheim’s “No More” from *Into the Woods*, 23_3), and compositions that fuse jazz and classical elements (such as big band arrangements). Figure 2 shows the distribution of these broad genres in the corpus, revealing that the leading genre in the corpus is classical music (49.5% of pieces), an unsurprising result given that an estimated 85% of the participants were

music majors at a conservatory. The next most common genre is pop (41.8%), followed by jazz (8.7%).

Figure 3 shows the classical pieces in the corpus, broken down into historical eras: Baroque, Classical, Romantic, and 20th/21st century. Some judgment calls were involved with this assignment as well. Beethoven was considered Classical; Mahler pieces were considered Romantic, despite the composer having lived into the 20th c.; the opposite was applied for Debussy. A historical rather than aesthetic approach was taken, wherein the year of the piece's publication and the years in which the composer was predominantly active were determinative.¹⁰ For instance, a neo-Romantic or folk-style piece composed by a 20th-century composer was still categorized as being from the 20th/21st century era. As a result, the 20th/21st century category is, from an aesthetic perspective, inflated in Figure 3, in the sense that this category includes many pieces in reactionary styles, rather than pieces in distinctly post-1900 styles (such as atonality, pointillism, texturalism, minimalism, etc.); some of these pieces would not necessarily have sounded out of place in the Romantic 19th century. Nonetheless, this history- rather than style-based assignment is to me the only neutral way to tally the results, and after all, it reflects the diversity of styles that did coexist in the 20th century (and that continue to exist in contemporary classical music in the present century).

¹⁰ The Baroque era was 1600-1749; the Classical era was 1750-1819; the Romantic era was 1820-1899; the 20th/21st century era was 1900-present.

Distribution of Genres in Corpus

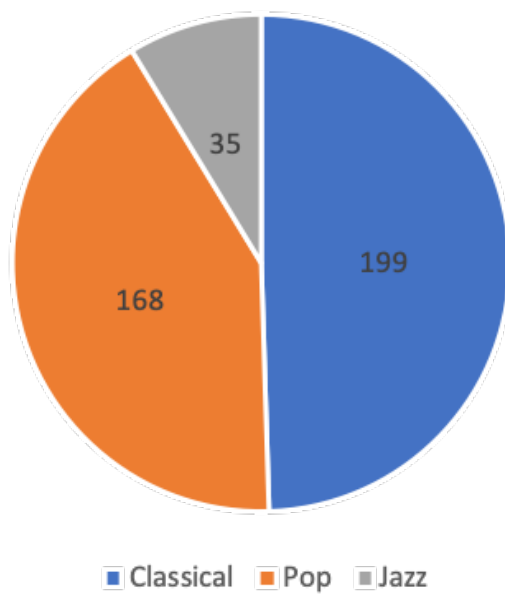


Figure 2

Distribution of Classical Music Eras in Corpus

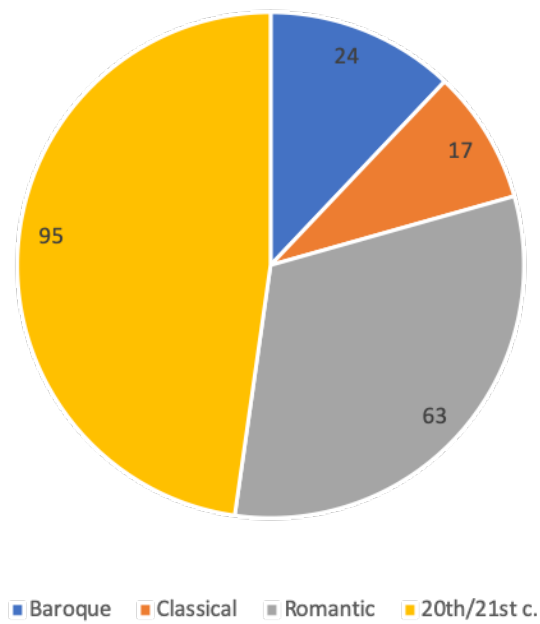


Figure 3

The preceding discussion explains why of the 199 classical music pieces in the corpus, 95 of them (47.7%) were 20th or 21st century pieces. However, of these, only one piece was from the Second Viennese School (Berg, Piano Sonata Op. 1, 136_1); no pieces by Schoenberg or Webern were given by participants, despite an estimated 85% of participants being music majors at a conservatory. (The pedagogical implications of this seeming mismatch between the weight afforded atonal music in college curricula versus their relative lack of representation in the corpus will be discussed in section [6.2](#).) The second most common category of piece was Romantic (63 or 31.7%), followed by Baroque (24 or 12.1%) and finally Classical (17 or 8.5%). (No pieces from the pre-Baroque era appear in the survey results, and this finding will also be discussed in section [6.2](#).)

Figure 4 shows the distribution within the corpus of artists or composers for which more than one piece was chosen by participants. What is immediately apparent is that classical composers dominate the chart. Many pieces were chosen by Bach (17), Brahms (14), Beethoven (12), and so forth; meanwhile, the most songs chosen by any one pop artist is six (Kendrick Lamar). The classical eras of Baroque, Classical, and Romantic are made up of a small set of big-ticket historical composers; meanwhile, the pop, jazz, and 20th/21st c. classical genres show much diversity of artists and composers. (For further discussion of this topic, see section [6.2](#).)

Composers/Artists with More than One Piece in the Corpus

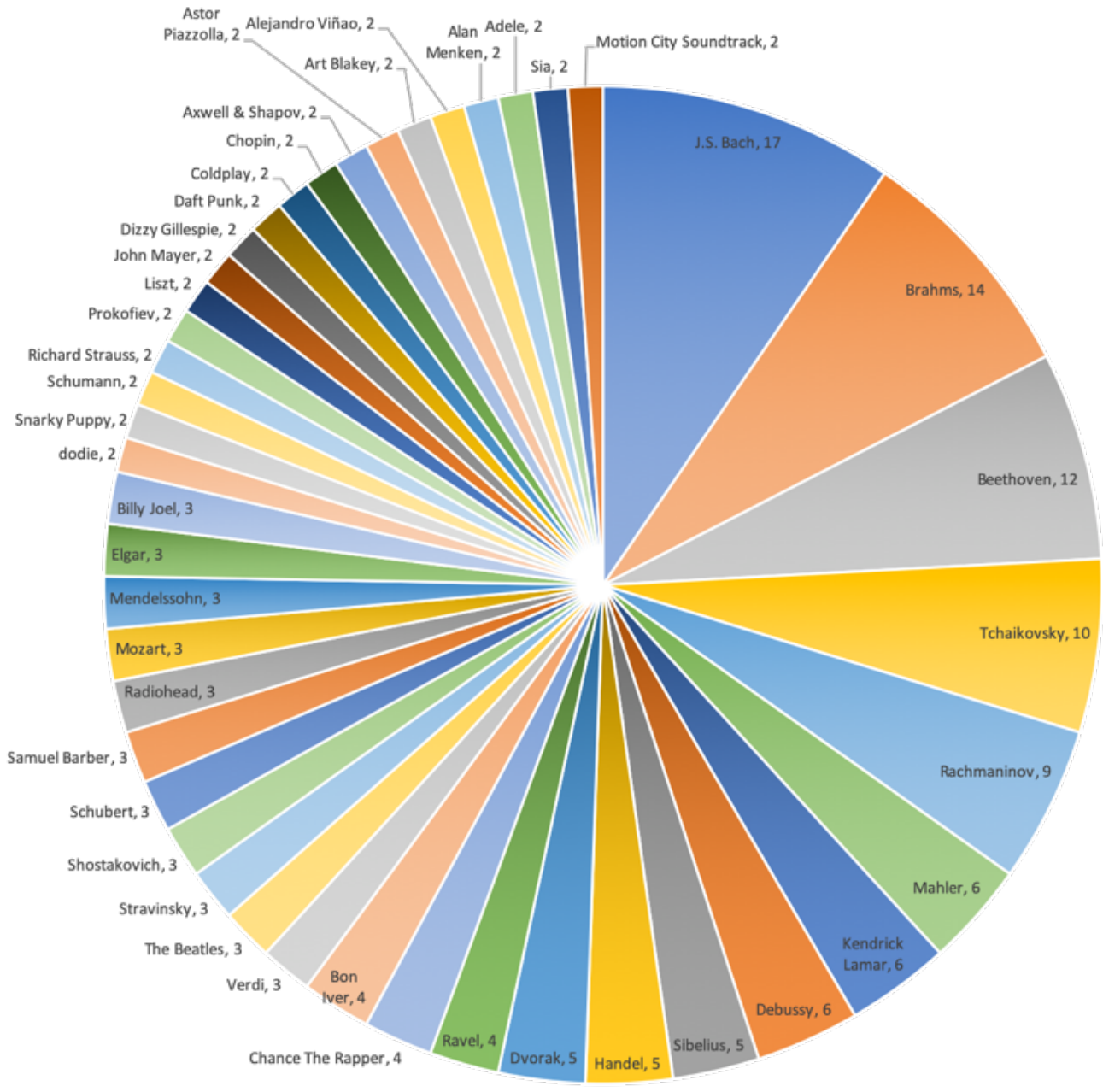


Figure 4

4.2.3 Comment analysis of the corpus

In answering the survey question, “Why do you love the excerpt?” participants gave many diverse reasons. Many cited purely musical parameters; some examples are shown below.

Harmony

“That is the best chord progression I have ever heard.”^{11 12}

Rhythm and meter

“The chords, played evenly, seem to be falling consistently on beats 1, 2, 3, and 4.

However, the chords actually fall half a beat earlier, on the upbeats...It's almost like an optical illusion. Your brain hears one thing, when you know it's something entirely different...With this song, you have to fight your own brainwaves to hear the song as it was originally intended, which makes the song so much more complex...”¹³

Melody

“It is the first theme of the sonata. The melody is quite simple, and yet elegant and gorgeous.”¹⁴

Timbre

“I like the intensity and low timbre of the violin...”¹⁵

¹¹ In what follows, all time windows given in these footnotes are with reference to the corresponding musAudio file in the corpus; or the excerpt alone can be listened to (indicated by the filename in each case).

¹² Mahler, Symphony No. 2, 5th movt, 7:02-7:17 (excerptAudio4_3).

¹³ Radiohead, “Videotape”, 0:19-0:34 (excerptAudio103_3).

¹⁴ Beethoven, Piano Sonata, Op. 110, 1st mvt., 0:25-0:40 (excerptAudio121_1).

¹⁵ Britten, Violin Concerto, 2nd mvt., 0:41-0:56 (excerptAudio37_3).

Dissonance treatment

“Kehlani adds a second voice to harmonize with her melody over some very clean and expressive 7th chords. She also changes the melody and adds 9-8 suspensions, which are my favorite because of how emotional they feel.”¹⁶

Formal return or contrast

“This is the last chorus and it is such a release from the bridge. It is different from the rest of the choruses and the rest of the piece, and it's a jam.”¹⁷

“...the mismatched instrumentals make it sound chaotic to the point of near cacophony as the music crescendos. I really like the chaos as it seems like the song is just descending into chaos, only to have it suddenly brought together in harmony with a power chord hit together by the whole band as they go back to the chorus. The descent into chaos and sudden bringing back of the music and playing together makes a really cool effect as well as denying my expectations by ending so abruptly mid-phrase.”¹⁸

Other comments cited technical aspects of the performance as it relates to their own instrument:

“The reason I love this excerpt is not really for theoretical reasons (at least as they [pertain] to harmony). I love this part because, as a guitarist myself, I recognize that playing such a fast section involving tapping takes great technical facility. In Layman's terms, SHREDS!”¹⁹

¹⁶ Kehlani, "Honey", 1:30-1:45 (excerptAudio110_1).

¹⁷ Kiah Victoria, "Hollow", 2:49-3:04 (excerptAudio128_3).

¹⁸ Motion City Soundtrack, "The Future Freaks Me Out", 3:00-3:15 (excerptAudio135_2).

¹⁹ CHON, "Knot", 1:28-1:43 (excerptAudio2_2).

Some based their response simply on how the music made them feel (i.e. felt emotion):

“The beat in this song is sick. I have listened to it more times than I can count, simply because it makes me feel great.”²⁰

Others took a more neutral approach, describing the mood or atmosphere of the excerpt independently of their own emotional response (i.e. perceived emotion):

“Intimacy combined with masterful and genuine playing. The negative space, silence, surrounding the music is utilized to create that atmosphere.”²¹

Finally, some participants cited associations with lyrics:

“The imagery in the lyrics here is so vivid, it's hard not to get emotional. I relate to this song; in high school I had a friend whose brother drowned in the same river that his father had drowned in about a dozen years before. This song takes me back to that place.”²²

(This last quote also shows the effect of autobiographical associations, something that appeared in just a few of the comments.)

²⁰ Foggieraw, "U Can't Be My Baby", 0:50-1:05 (excerptAudio137_3).

²¹ Debussy, "Clair de lune", 4:16-4:31 (excerptAudio52_1).

²² Slaid Cleaves, "Lydia", 3:22-3:37 (excerptAudio53_2).

While the preceding discussion gives some anecdotal impressions and observations, a more systematic and data-driven approach to analyzing the participant comments was needed. A content analysis of the comments was performed by two coders. The first coder, Professor Temperley, identified 15 recurrent themes in the comments, and labeled each comment as to the themes reflected in it. The second coder (a theory PhD student) then coded the comments using the same set of themes. The 15 themes were as follows, along with their definitions as provided to the second coder:

LYR = Lyrics.

BIO = Autobiographical connection. References to the respondent's past experience with the piece or excerpt, or incidents in their life that it reminds them of for any reason.

MEL = Melody. The main melody in this particular part of the piece. Also includes improvised solos, e.g. in jazz.

VIR = Virtuosity. This category also includes proficiency, i.e. playing a very difficult passage accurately; or intonation.

INT = Interpretation. Aspects such as expressive timing, or general statements about the beauty/expressiveness of a performance or quality of a performer.

DYN(+/-) = Dynamics.

RH = Rhythm. Includes references to general rhythmic feel, e.g. “groove”.

MET = Meter. This category includes references to tempo.

HAR = Harmony. Harmonic progression, function, or chord quality; also tonality (e.g. modulation), mode (major/minor), and dissonance/consonance.

INS = Instrumentation. Instrument choice or instrument combinations; general uses of an instrument (e.g. “I like the clarinet in a high register”); special timbral effects prescribed by the composer, e.g. extended techniques; synthesized parts in popular music textures.

TIM = Timbre. This theme is invoked when credited to a performer (e.g. a singer’s tone), or synthesized/electronic sounds that are not a consistent part of the texture.

TEX = Texture. A catch-all category including aspects of pitch-rhythmic patterns other than melody, such as details of accompaniment or bass lines, chord voicings, or polyphonic patterns.

EN(+/-) = Energy. Energy level in music is thought to be conveyed by parameters such as dynamics, register, rhythmic activity, and textural thickness; an increase in any of these dimensions could create a rise in energy. However, when a change is described in more

specific terms (e.g. dynamics) it should be coded in that way—EN should be reserved for more general descriptions of energy change or level, e.g. “buildup” or “climax”.

RET = Return. When earlier thematic material returns.

COM(+/-) = Complexity. This category also includes direct or indirect references to its opposite, simplicity.

Each coder assigned as many or as few themes as were relevant to each comment.

“Relevant” here means that a theme is explanatory in a participant’s liking of the excerpt.

Because the participant comments are not simply open-ended responses, but rather are answers to the specific prompt, “Why do you love the excerpt?”, we can *usually* think of a theme’s presence in the comments as an explanatory factor in the liking of an excerpt. However, while in many cases the correct theme assignment is obvious and explicit (e.g. “I like the melody” would receive a MEL), in some cases, the mere presence of a theme in the comment does not mean that the theme is a reason for their liking of the excerpt. For example, if the respondent writes “I love the violin melody”, it seems likely that what the respondent likes is the melody, not the fact that it was played on a violin. Therefore, MEL would be assigned, but INS or TIM would probably not be germane assignments. On the other hand, if the respondent wrote “I love the tone of the violin melody”, then certainly INS and/or TIM and/or INT would become relevant assignments, and MEL may not be a relevant assignment, despite the word “melody” being used in the response.

Three themes—DYN, EN, and COM—are “parametric” and could be marked with a + or - to indicate an increase or decrease, or simply a high or low level. For instance, a reference to a crescendo or a *fortissimo* could be DYN+. (Coders were also free to omit a + or – from a thematic assignment.) If both an increase and decrease are indicated in the response, this could be marked with a “+/-”.

One goal of this content analysis was to determine the relative weight of different factors in participants’ excerpt choices. All else equal, themes that are more common in the comments can be assumed to be more generally determinative of liking. A few caveats are that, first, self-report only reveals what a participant can access via their explicit awareness; and second, even if a participant had all the vocabulary, tools, and training to explain their liking, they will tend to write about whatever is most “heuristically available” to them rather than necessarily digging deep for the underlying reasons. Nonetheless, the written responses constitute a very valuable dataset that begs investigation.

Table 1 shows Cohen’s Kappa (κ) (a measure of reliability ranging from 0.0 to 1.0) for the two coders’ thematic assignments.²³ As can be seen, agreement between coders varies greatly across themes—from 0.37 to 0.80 depending on the theme.

²³ In the table, DYN, EN, and COM are each collapsed between the versions with +, -, +/-, and no parametric marker.

Table 1. Cohen's Kappa values between the two coders for each thematic assignment.

Theme	κ
LYR	0.80
BIO	0.59
MEL	0.48
VIR	0.37
INT	0.45
DYN	0.68
RH	0.73
MET	0.60
HAR	0.75
INS	0.51
TIM	0.49
TEX	0.48
EN	0.51
RET	0.49
COM	0.62

Which themes featured the most prominently in the participant comments? Figure 5 shows the percentage of the comments that each theme appeared in (the count of each theme, averaged between the two coders, as a proportion of the total number of responses).²⁴ The most common themes are Melody, Harmony, Texture, and Instrumentation, in that order. It is interesting to see that over 1/3 (34.2%) of the participant comments cited melody as a reason for their liking of the excerpt. Given the predominance of the Melody and Harmony (27.7%) themes in the comments, the pitch domain is a commonly-cited reason for why these excerpts are participants' favorites. However, sonic factors appear to be perhaps an even more important consideration, with 27.6% of comments citing Texture, 24.3% citing Instrumentation, and 12.5% citing Timbre. Rhythm receives comparatively short shrift (19.4% of comments mention

²⁴ In the figure, DYN, EN, and COM are collapsed between the versions with +, -, +/-, and no parametric marker.

Rhythm), while Meter receives a mere 4.6%. While it may seem that Rhythm features in a substantial number of comments, 19% to me seems surprisingly low, given the amount of attention that rhythm receives in the discourse of music, as well as in the theoretical and practical training of musicians across basically every genre. One possibility is that some rhythmic comments addressed expressive timing or “feel”, which might fall under the theme of Interpretation rather than Rhythm. However, anecdotally, from examining the comments this seems unlikely; and besides, Interpretation is only cited in 6% of the comments.

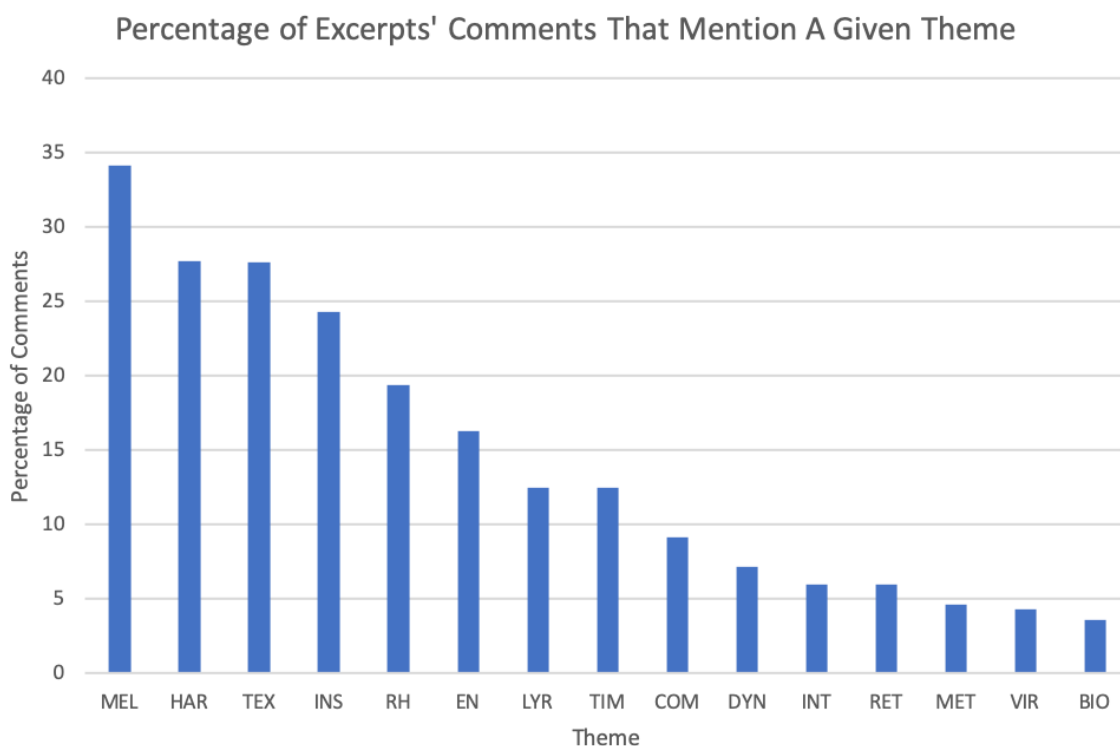


Figure 5

Complexity, while one of the central concepts of this dissertation, was only mentioned in 9.2% of comments, while the related concept of Energy appeared in 16.3% of comments. Return, another central concept of the dissertation, appears in only 6% of the comments. The aspects associated with the performer or other concepts outside of what is traditionally considered the

"music itself"—Virtuosity, Interpretation, Lyrics, and the Autobiographical—appear in 4-13% of the comments. (I suspect that if the participants had all been total non-musicians, the Autobiographical and Lyrics categories might take first and second place.)

Although the COM(+/-) theme did not account for many comments, it is interesting to note that both coders coded many more COM- (a decrease in complexity) than COM+ (an increase in complexity). While there were 6.5 instances of COM+ in the comments, there were 22 instances of COM- (these counts are averaged across the two coders' analyses). This result seems to support the C-S hypothesis, that the favorite excerpts in the corpus will tend to be moments of decreased complexity. However, the comments have many more mentions of EN+ (energy gain) than EN- (energy loss): 35.5 versus 2.5, respectively. The comments therefore point to a preference for complexity *decrease* but also for energy *increase*. Intuitively, this may seem like a contradiction. Musical energy is often associated with factors such as increased textural density and rhythmic activity (Gabrielsson & Lindström, 2001; Daynes, 2011), which would also tend to increase complexity. However, a process that involves an energy increase, such as the EDM build-up discussed in Chapter 3, need not involve a complexity increase as well; sometimes the most perceptually complex moments are when the texture is the sparsest (and thus the energy is low), offering less cues for disambiguation. However, a simpler explanation is that the presence in the comments of more COM- than COM+ along with more EN+ than EN- reflects two entirely different types of situations, rather than phenomena that coexist within the same comments. Indeed, of the 44 instances of COM- and 71 instances of EN+ coded between the two coders, in only *one* of the comments do both COM- and EN+ codings co-occur. Therefore, it would seem that two different phenomena are operational, and they account for two different subsets of the comments: when comments feature EN+ it likely reflects moments such

as build-ups, whereas when comments feature COM- it could reflect the satisfaction of complexity decrease predicted by the C-S hypothesis, as detailed in Chapter 3.

Another way to analyze the comments is by tallying word frequencies. Figure 6 presents frequency counts for the (musical) words that occur at least 20 times in the comments.²⁵ The count of each “word” represented in the figure is the sum total for that literal word along with grammatical variants. For instance, the 100 instances of “melody” results from “melody”, “melodic”, “melody’s”, “melodically”, and “melodies”. “Build” includes “build”, “build-up”, “building”, “builds”, and “buildups”. In two cases (sudden/unexpected/surprise; singer/vocal), different words (along with their grammatical variants) were clustered together under one concept. As seen in Figure 6, the pitch domain reigns supreme. “Melody” is the most common word in the comments, occurring 100 times; “chord” appears 67 times; “harmony” appears 50 times. While “rhythm” occurs a respectable 47 times (with “meter” occurring only eight times, not making it into the figure), we see here the same linguistic predominance of pitch over rhythm that was observed in Figure 5 for the comments’ thematic tendencies.

“Feeling” is the fourth-most common word in the comments, reflecting the importance of emotion to listeners, as well as capturing information not covered by the thematic analysis of the comments. Another aspect not captured by the thematic analysis is the prominence of “singer/vocalist”, which is the second-most common word in the comments, beating out every other musical term except for “melody”. As found earlier with the tendency towards EN+ (energy gain) over EN- (energy loss), “build” is the eighth-most common word in the comments, suggesting that many participants selected passages of increasing energy or intensity. Notably,

²⁵ In addition to one-word frequencies, I also conducted a count of phrases (two-word, three-word, and four-word phrases), but this yielded nothing of interest not covered by the one-word search.

also, “simple” and related words are frequent in the comments (32 occurrences), much more so than “complex” and its variants (11 occurrences); this, again, points to a decrease in complexity as a factor in listeners’ preferences.

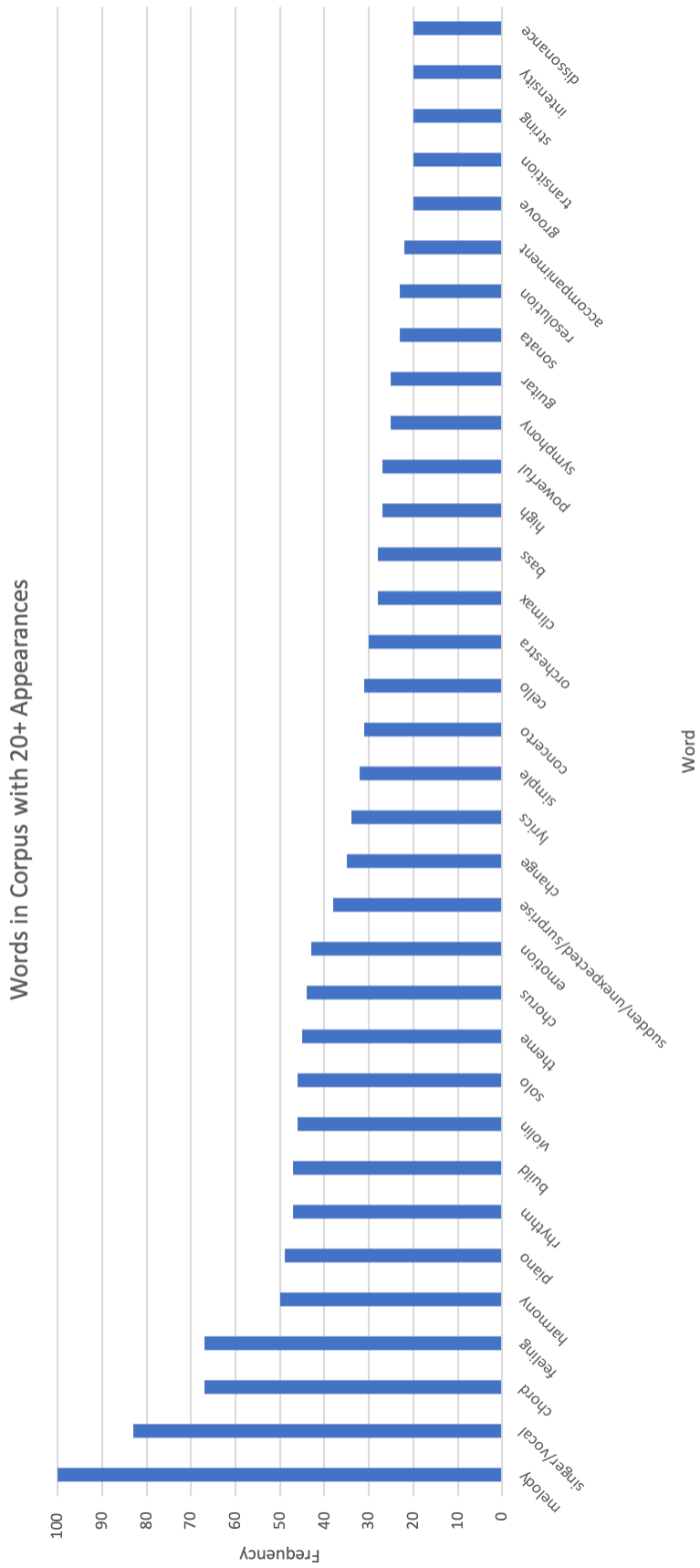


Figure 6

4.2.4 Subsets of the corpus

While all the data in the FAV Corpus is valuable for future study, the remainder of the dissertation focuses on subsets of the provided corpus. First, I only include excerpts where participants chose “A. I enjoy this excerpt much more than the other parts of the piece”, excluding excerpts where they chose “B. I enjoy this excerpt about as much as the other parts of the piece.” The reasoning behind this exclusion is to focus only on the unequivocally impactful excerpts—indeed so impactful that even in an already preferred piece, and even when the survey already instructed the participant to select “the 15-second excerpt that’s your favorite”, these excerpts were a second time confirmed by the participant as being much more enjoyable than the other parts of the piece. The excerpts that participants enjoyed about as much as other parts of the piece risk being token or arbitrary timepoints, liked equally to any other excerpts in the pieces, rather than indications of genuinely impactful passages. Second, in order to conduct the AB/BC paradigm discussed in section 5.1, which is the central test of the dissertation’s chief hypothesis, it was necessary to exclude excerpts that begin before 0:15, as this does not allow for the creation of a preceding 15-second “A” clip; similarly, I excluded excerpts that end within less than 15 seconds of the end of the piece, as this disallows creation of a following 15-second “C” clip. With these exclusions, we are left with a subset of the FAV Corpus consisting of 113 pieces and 113 excerpts from those pieces, which forms the basis of the AB/BC experiment in section 5.1. Appendix 2 shows members of this subset via a check mark in the “AB/BC” column. Meanwhile, the XYZ paradigm presented in section 5.2 includes no such constraint on excerpt ending times; this subset of the corpus is larger, consisting of 127 pieces and 127 clips from those pieces: all of the clips that received an “A. I enjoy this excerpt much more than the other

parts of the piece”, and the pieces that were analyzeable into meaningful formal sections.

Appendix 2 shows members of this subset via a check mark in the “XYZ” column.

Chapter 5: Testing the Hypotheses

5.1 Testing the C-S hypothesis: The AB/BC paradigm

5.1.1 The AB/BC Paradigm: Methodology

As described in Chapter 3, the “C-S hypothesis” is that the excerpts (marked as people’s favorite 15-second musical moments) in the corpus will tend to be generally lower in complexity than the preceding material in the piece; a move from complexity to simplicity will be preferred. In order to test this hypothesis, a paradigm was needed in which each excerpt’s complexity could be compared to the complexity of the music preceding it. However, it was not enough to simply present judges with the excerpt along with the preceding 15 seconds, and ask them to compare the complexity of the two audio clips; such an approach would risk order effects as a potential confound. For instance, under such a paradigm, the second clip (the excerpt) could be consistently rated as less complex than the first clip (the 15 seconds preceding the excerpt)—seemingly confirming the C-S hypothesis—but that result could simply be an artefact of judges perceiving the music as decreasing in complexity over time as they became more familiar with the music.

The solution to this issue of order effects was to design an “AB/BC” paradigm. The underlying logic of this paradigm is that two 30-second clips are created from each piece in the FAV Corpus. (As explained in section [4.2.4](#), the current test only uses excerpts where a) the participants indicated a strong preference for the chosen excerpt over the rest of the piece; and b) the excerpt begins after the first 15 seconds of the piece, or ends before the last 15 seconds of the piece. These are indicated with a check mark in the “AB/BC” column of Appendix 2.²⁶) The first

²⁶ Many thanks to Haleila Harrison for assisting in creating the A, B, and C clips.

clip (AB) consists of the 15-second excerpt chosen by the participant as their favorite excerpt in the piece (“B”), preceded by the 15 seconds immediately before it (“A”). The second clip (BC) consists of the same favorite 15-second excerpt (“B”), except *followed* by the 15 seconds immediately after it (“C”). See Figure 7:

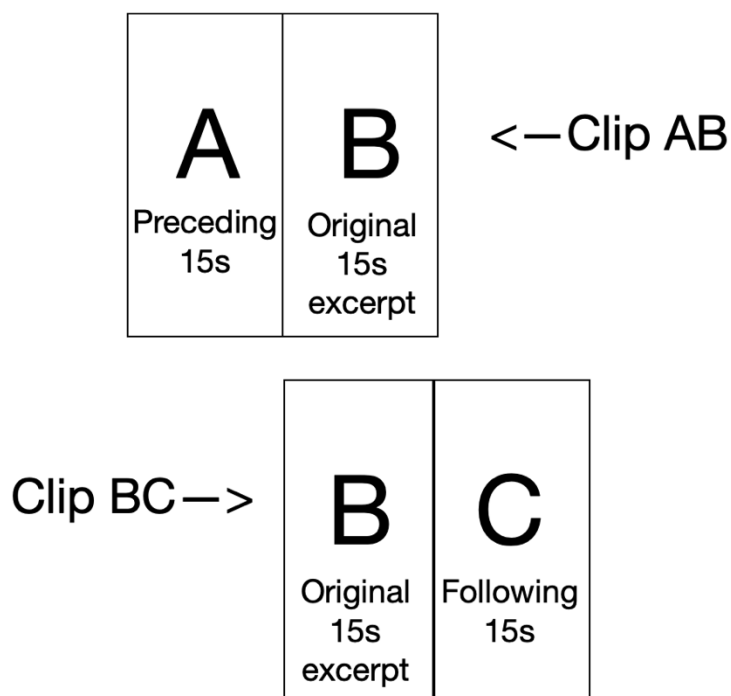


Figure 7

The AB/BC paradigm allows for the excerpt to sometimes be in the first position of the comparison, and sometimes in the second position. Therefore, the average complexity rating of the excerpt will be unlikely to be confounded by an order effect. (However, in the results and discussion presented in section [5.1.2](#), I do test further for order effects.)

Four judges were employed, and all were musical experts at a post-graduate level (doctoral students in music theory). Judges 1 and 2 compared A and B clips for half of the excerpts, and B and C clips for the other half of the excerpts; Judges 3 and 4 did the reverse.

(However, the B and C clips were renamed as A and B respectively, such that the judges saw only A and B clips throughout; judges were also unaware of the experimental hypothesis.) The judges were asked to make a comparative determination of the relative complexity between clips A and B (which are in reality either A and B, or B and C) along various musical domains. For each excerpt, they were provided with two audio files: a 15-second A clip and a 15-second B clip. Their task was to listen and decide which of clips A or B is more complex in four domains: Rhythm & meter, harmony, melody, and texture. For example, a judge might decide that clip A is more complex in its rhythm & meter, harmony, and texture, but clip B is more complex in its melody.

Judges were not provided with specific examples or definitions of the various musical domains, nor were they given examples or definitions of rhythmic, harmonic, melodic, or textural complexity. However, complexity itself was defined for them, albeit in general terms. The regrettably few researchers who have defined perceived complexity to judges (North & Hargreaves, 1995; Orr & Ohlsson, 2005) have been consistent in defining it as the extent to which you can predict what will happen next in the music. This is a nice definition, as it mostly corresponds to the information-theoretic definition of objective complexity, where high probability (predictability) equals low information. However, technically, in information-theoretic terms complexity depends not only on the predictability of events, but also on their temporal density. For example, imagine an unpitched temporal sequence of four quarter-note onsets vs. a sequence of sixteen 16th-note onsets (both at the same tempo). Anecdotally, both patterns seem equally simple and predictable. However, there are far more possible patterns of sixteen 16th-notes than there are of four quarter-notes, so the probability of each 16th-note

pattern will be lower; thus the 16th-note pattern will be higher in information (Temperley, 2018, pp. 142-5; Temperley, 2019).

At any rate, a definition of perceived complexity as predictability was not tenable for the present study for the simple reason that the stimuli are not lab-constructed but rather are real-world pieces that judges may already be familiar with to varying degrees. Therefore, an unbiased assessment of a percept such as predictability would be impossible to make if a judge is already familiar with a passage; any question about predictability would be confounded by potential real-world past exposure to a piece (i.e. familiarity). Even a familiarity check cannot remedy this issue, as subconscious exposure to a piece is not out of the question.

Therefore, while predictability was incorporated into the judges' instructions as a factor to consider, it was not made the central feature of the definition of complexity. Instead, complexity was mostly defined to judges in phenomenological terms, in the spirit of the inquiry into subjective perception of complexity. The instruction and definition was: "Your task is to judge the relative complexity of the two excerpts A and B, in each of the musical dimensions in the sheet (e.g. melody, texture, etc.). While you are welcome to use your own intuitive judgments of complexity, we suggest considering the following criteria: 1) normativeness/predictability within the style (more normative = less complex), 2) repetitiveness within the excerpt (more repetitive = less complex), and 3) density of events per unit time (higher density = more complex)." Judges were allowed to listen to the individual clips as many times as they wished. Judges also gave a confidence rating (1 = low, 2 = medium, 3 = high) for each judgment.

To pre-emptively address the critique that using judges (rather than some sort of computational analysis) introduces human bias and subjectivity, I would say three things. First,

recall from section [2.2](#) that human judgments of complexity correlate very strongly with computational metrics of complexity. Second, while judgments of relative complexity undoubtedly do vary between listeners to some extent, anecdotally, to give a rather extreme example, consider that nobody would claim or perceive the opening of Mozart's K. 545 to be equal in harmonic complexity to Scriabin's Prelude No. 11 from his Op. 11 (also an Allegro piece for solo piano). Third, only those cases where both judges concur will be included in the analysis in section [5.1.2](#).

The results of the AB/BC paradigm (discussed shortly in section [5.1.2](#)) provide us with a testable and quantifiable approach to the subjective complexity of the participants' favorite excerpts (B) relative to the material immediately preceding (A) those excerpts, conveniently teased out into multiple music-theoretic domains. From here, the hypothesis can be tested statistically. If the hypothesis is correct for all domains, then for all domains clip A will be, on average, significantly higher in complexity than clip B in the majority of cases (Chi-squared tests will be used for all comparisons discussed here, assuming a significance threshold of .05). (In more computational terms, let $c()$ denote the complexity of an excerpt. If the C-S hypothesis is true for all domains, then $c(A) > c(B)$ in all domains.) If the hypothesis is correct for only some domains (i.e. it is correct for harmony but not for melody, etc.), then for only those domains clip A will be higher in complexity than clip B in the majority of cases. If the hypothesis is false for all domains, then for all domains clip A will be lower in complexity than clip B, and this will tell us that in fact the *reverse* of the hypothesis is suggested—that people's favorite excerpts are moments of *higher* perceived complexity relative to the preceding material. The final possibility is that no significant result will emerge.

However, it is not sufficient to say that if $c(A) > c(B)$ in a domain, then the hypothesis is true for that domain. This is because A needs to be consistently more complex than B by a greater amount than B is to C in order for the $c(A)$ vs. $c(B)$ relationship to be strong and meaningful; otherwise it may simply represent a bias towards giving a higher complexity rating to the first 15 seconds of a clip (i.e. if judges were to give $c(A) > c(B)$ and $c(B) > c(C)$). The C clip therefore serves as a control condition. We need to see that the proportion of A's chosen in the AB comparison is significantly greater than the proportion of B's chosen in the BC comparison. Therefore, the final and more rigorous formulation of the hypothesis has two parts: it is predicted that

$$c(A) > c(B)$$

and

$$(c(A) / (c(A) + c(B))) > (c(B) / (c(B) + c(C)))$$

in a given musical domain (rhythm and meter, harmony, melody, and texture).

5.1.2 The AB/BC paradigm: Results & Discussion

Recall that each stimulus pair (A and B, or B and C) was compared by two judges. The judges agreed on 59% to 67% of the total comparisons, depending on the domain. Table 2 shows, for each domain, the number of cases in which both judges concurred, along with their percentages. (In order to have the strongest possible data, only those cases where both judges concurred were analyzed in what follows.) However, Cohen's Kappa (κ) paints a more detailed picture (by controlling for the probability of agreements happening by chance alone). Table 3 shows the Kappa values for Judges 1 and 2, and for Judges 3 and 4, broken down into domains. The bottom row shows the average Kappa value for each domain; the right-most column shows

the average Kappa value for Judges 1 and 2, and for Judges 3 and 4. The bottom-right cell shows the overall average (derived from the two judge-averages, or from the four domain-averages). As can be seen, the average agreement in the four domains ranged from $\kappa = 0.19$ to $\kappa = 0.34$; this is considered “fair” agreement (where 0.41-0.60 is considered “moderate”); Judges 1 and 2 had an average agreement of $\kappa = 0.32$; Judges 3 and 4 had $\kappa = 0.21$. Therefore, both judge-pairs exhibited “fair” agreement. Overall agreement was $\kappa = 0.27$, also considered “fair” agreement. (Despite this relatively low κ value, a clear and highly significant result did emerge, as will be discussed below.)

Table 2. Concurrences between judges in their complexity judgments.

	Rhythm & meter	Harmony	Melody	Texture
Concurrences	138	134	149	151
Comparisons	226	226	226	226
%	61.1%	59.3%	65.9%	66.8%

Table 3. Cohen’s Kappa values in the AB/BC judgments.

	Rhythm & meter	Harmony	Melody	Texture	Average
Judges 1 & 2	0.27	0.43	0.33	0.26	0.32
Judges 3 & 4	0.17	-0.06	0.31	0.42	0.21
Average	0.22	0.19	0.32	0.34	0.27

To test the hypothesis, a one-way Chi-squared test was performed comparing the number of A's and B's chosen in the A vs. B cases, with an expected distribution of .5/.5; the corresponding test was performed comparing the number of B's and C's chosen in the B vs. C cases. This was applied separately for each domain. Figure 8 shows the results of the AB/BC paradigm in two bar graphs, first for the A vs. B clips, and then for the B vs. C clips.²⁷ The Y axis shows the number of times a clip was judged as more complex than the comparison clip. In the domains of harmony and texture, a pattern emerged where B was significantly more complex than A, and C was significantly more complex than B. Therefore, for these two domains, the perceived complexity is: C>B>A. Meanwhile, for rhythm/meter and melody, B was significantly more complex than A, while B and C did not have a statistically significant difference between them. Therefore, the representation for these two domains is: (B=C)>A. Note that in all four domains, A was the least complex.

²⁷ A vs. B:

Rhythm and meter: $\chi^2(0) = 11.17$ ($p < .001$);

Harmony: $\chi^2(0) = 35.03$ ($p < .00000001$);

Melody: $\chi^2(0) = 36.10$ ($p < .00000001$);

Texture: $\chi^2(0) = 89.67$ ($p < .00000001$).

B vs. C:

Rhythm and meter: $\chi^2(0) = 0.03$ ($p = 0.85$);

Harmony: $\chi^2(0) = 9.53$ ($p < .01$);

Melody: $\chi^2(0) = 2.35$ ($p < 0.13$);

Texture: $\chi^2(0) = 14.24$ ($p < .001$).

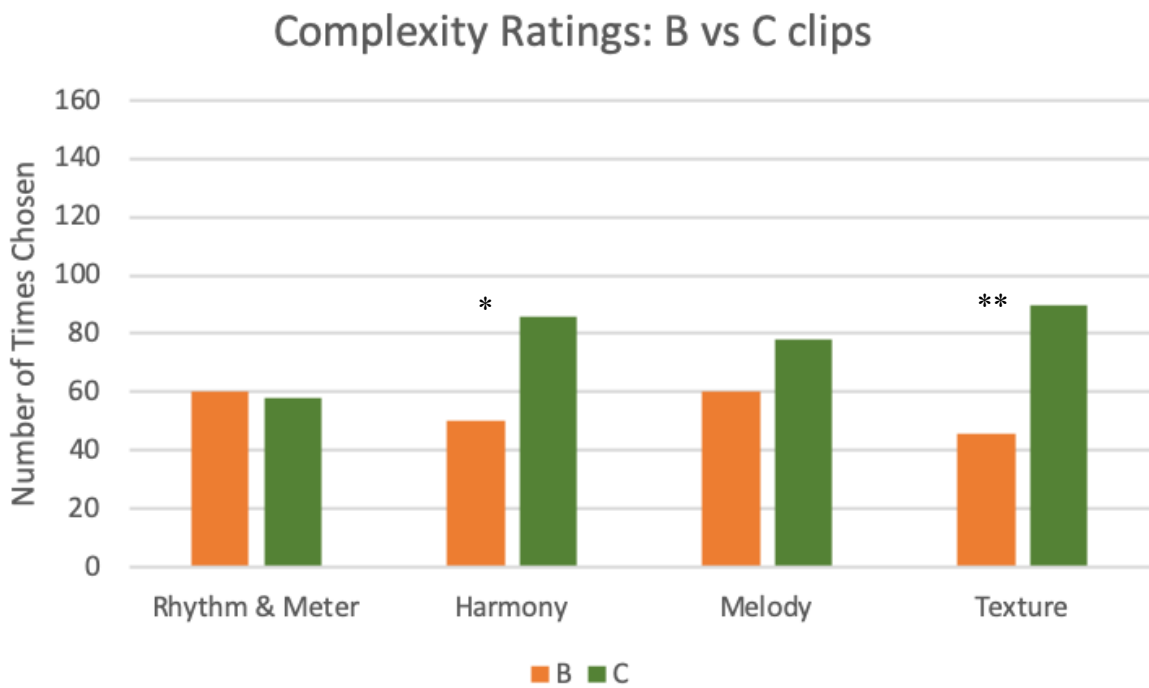
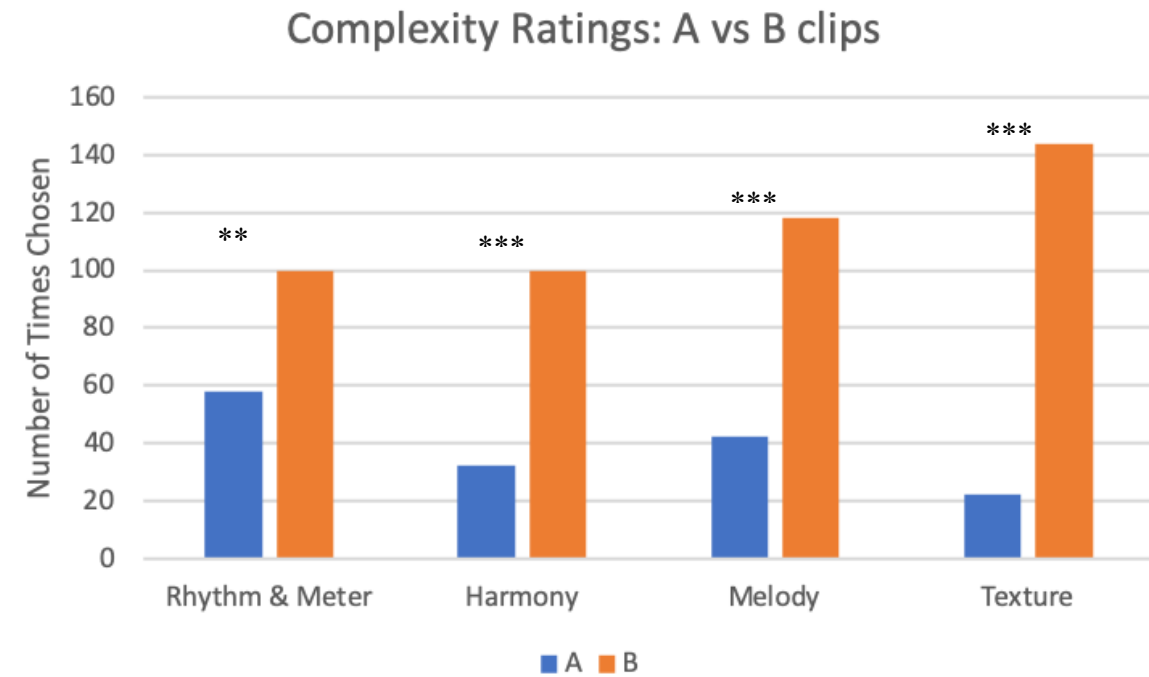


Figure 8

* $p < .01$, ** $p < .001$, *** $p < .00000001$

Recall that the C-S hypothesis was operationalized, in its first part, as $c(A) > c(B)$ (where $c()$ denotes the complexity of a clip in a given domain). The strongest confirmation of the hypothesis would be if this were true for all domains. In fact, the opposite has occurred for all domains: $c(B) > c(A)$. This result provides strong evidence of a disconfirmation of the hypothesis and of a proclivity (at least for these subjects, many of whom were music majors with a high amount of training) for increased complexity relative to the immediately preceding material. In other words, the 15-second excerpts which participants in the survey gave as their favorite moments, are significantly more rhythmically, melodically, harmonically, and texturally complex than the immediately preceding 15 seconds. It would appear, then, that instead of a C-S (complexity decrease) process, what is operational here is an S-C (complexity increase) process.

Depending on the domain, the C clips were rated as equally complex to B (rhythm/meter and melody) or as more complex than B (harmony and texture). Therefore, no definitive (i.e. cross-domain) pattern emerges with respect to the B vs. C relationship, suggesting that the material preceding the B clips (i.e. the A clips) may be more determinative in why the B clips were favored than the material following the B clips (i.e. the C clips). Because of the finding that $c(B) > c(A)$ in all four musical domains, the first part of the C-S hypothesis's formulation ($c(A) > c(B)$) has been unsupported. Next, let us test the second part of the hypothesis's formulation: that $(c(A) / (c(A) + c(B))) > (c(B) / (c(B) + c(C)))$. A 2x2 Chi-squared test comparing the AB to BC relationships yields a statistically significant result, for all four domains: $(c(A) / (c(A) + c(B))) < (c(B) / (c(B) + c(C)))$.²⁸ Therefore the "S-C" pattern was significantly stronger for the AB pairs than for the BC pairs. If the results of the first test were

²⁸ Rhythm and meter: $\chi^2(1) = 5.52$ ($p < .05$); harmony: $\chi^2(1) = 4.95$ ($p < .05$); melody: $\chi^2(1) = 9.77$ ($p < .01$); texture: $\chi^2(1) = 18.13$ ($p < .0001$).

simply due to a bias among judges to rate the second excerpt as more complex, we would expect the C clips to be rated as significantly more complex than the B clips, in all domains, in a manner similar to the A-B relationship; but in fact, the B>A pattern is significantly stronger than the C>B pattern. Furthermore, given that previous research suggests that perceived complexity decreases with exposure (Tan et al., 2006), it stands to reason that if anything, and all else equal, there would be a tendency to give a *lower* complexity rating to the second member of a pair – i.e. the B in an AB pair, or the C in a BC pair—not a higher rating.

In summary, it would appear that participants' favorite excerpts were moments of increased complexity from what came immediately before, rather than decreased complexity (as had been predicted in Chapter 3). How can we explain this result? One potential explanation is that the participants are not representative of the taste of the layperson, as an estimated 85% were music majors with a lot of training. Therefore, the C-S hypothesis may be true for non-musicians, but false for musicians. In other words, perhaps non-musicians prefer moments of decreased complexity while it is a unique preference among musicians to “geek out” to moments of increased complexity. If this were true, then we would expect to find a positive correlation between a participant's self-reported years of musical training and a tendency to prefer excerpts that exhibit a complexity increase, or an “S-C” process.

To answer this question, the judges' ratings of the comparative complexity of the A vs. B clips were coded as follows. If A was deemed more complex, a -1 was assigned; if B was more complex, a 1 was assigned. The judges' ratings across the four musical domains were then averaged to produce a single value ranging from -1.0 to 1.0 for each excerpt. We can think of this value as an “S-C” score: an indication of the extent to which complexity increase occurs in an excerpt (the B clip). A lower value towards -1.0 means that complexity decrease is preferred

(A tends to be more complex than B); a higher value towards +1.0 means that complexity increase is preferred (B tends to be more complex than A).

These “S-C” scores were then averaged across the excerpts for each participant.²⁹ Thus each participant now has a final, single “S-C” score. The hypothesis is that a participant’s years of training and their “S-C” score will be positively correlated: as years of training increase, so too will the tendency to prefer complexity increase. However, the correlation was not statistically significant ($r = -0.11$, $p = 0.34$, $N = 76$), suggesting that there is in fact no meaningful relationship between years of training and an S-C (or C-S, for that matter) process.

Another explanation for the S-C, rather than C-S, result is that the judging method was somehow flawed; however, only cases where both judges concurred were analyzed, and there is plenty of evidence that people tend to agree on ordinal rankings of perceived stimulus complexity (see section [2.2](#)). Nonetheless, it should be acknowledged that the extent of concurrence between judges (Tables 2 and 3) is rather low, suggesting a great deal of variance in the complexity judgments. But the most tenable explanation is that, independently of the truth or falsehood of the C-S hypothesis, other musical parameter(s) account for and explain more powerfully people’s favorite excerpts, as we saw in section [4.2.3](#) where the comments were far more likely to cite aspects such as melody, harmony, or instrumentation than complexity. It is also possible that form plays an important role; this will be tested below via the XYZ paradigm of section [5.2](#). In other words, the complexity differential between clips A and B—though it yielded a highly significant result—could be a red herring that is tangential to, rather than determinative of, the real reasons underlying people’s choice of excerpt. The final explanation is

²⁹ As explained in section [5.1](#), the AB/BC test used only a subset of the excerpts in the corpus. Here, we only include the participants who were represented by at least one excerpt in that subset; there were 76 such participants.

that, not only is the C-S hypothesis false, but its opposite is true: that instead of a C-S (complexity decrease) process, what is preferred for most people is an S-C (complexity increase) process. If this is correct, the truth value of the multiple, similar “contrastive” theories discussed in Chapter 3—contrastive valence, hedonic contrast, and opponent-process theory—is unscathed; the only difference is that in the context of these theorized temporal processes, “good” would appear to map onto “complex” and “bad” would appear to map onto “simple”, rather than the hypothesized opposite. However, in view of the many comments from music theorists and others (cited in Chapter 3) suggesting that a shift from complexity to simplicity is pleasurable, it is quite surprising to obtain the opposite result.

While confidence ratings were collected for each complexity judgment, these were not incorporated into the analysis of the results. Future analyses could apply weightings commensurate to the confidence level, or omit low-confidence ratings from the analysis. In fact, the confidence ratings in themselves would be an interesting object of study, to see what types of musical situations or which domains create low or high confidence for complexity judgments.

5.2 Testing the Returns hypothesis: The XYZ paradigm

5.2.1 The XYZ paradigm: Methodology

As discussed in Chapter 3, the secondary hypothesis of this dissertation, the “Returns hypothesis”, predicts that people’s favorite excerpts (i.e. the excerpts in the FAV Corpus) will tend to be formal returns. Note that although the Returns hypothesis follows (in terms of thought) from the C-S hypothesis, the verification or falsification of the two hypotheses can be independent. In other words, it is possible that listeners prefer returning material but not a move from complex to simple, or that listeners prefer complex-to-simple moves but have no preference towards returns specifically. Therefore, the apparent falsification of the C-S hypothesis in the previous section still allows for the possibility that the Returns hypothesis is correct.

In order to test the Returns hypothesis, 127 pieces from the FAV Corpus (shown as check marks in the “XYZ” column of Appendix 2) were formally analyzed by a musical expert.³⁰ As described in section 4.2.4, the inclusion criteria for a piece from the corpus to receive a formal analysis were that its corresponding excerpt received an “A” on question 7 (“I enjoy this excerpt much more than the other parts of the piece”), and that the piece was analyzeable into meaningful formal sections. (Several pieces proved impossible to analyze formally, because there was no large-scale repetition and no clear moments of change demarcating reasonably-sized sections. Some of these were contemporary pieces; others were Baroque pieces, e.g. imitative textures with a rapid or seamless alternation between subject entries and episodes.)

³⁰ It would have been desirable to use an expert with no knowledge of the study; however, the formal analysis process proved to be quite time-consuming, and paying an expert to do it exceeded our financial resources. Therefore the formal analyses were done by Professor David Temperley. While he had general knowledge of the experiment and the hypothesis, he did not consult the participants’ favorite excerpts while doing the formal analyses.

The method for the formal analyses was as follows. The recordings of the pieces were broken into sections to the nearest second, and given formal labels (i.e. for each piece, a text file listing the beginning timepoint and label of each section). For instance, the text file for 32_2 (the fourth movement of Beethoven's Symphony No. 7) contains:

0:00 P
0:40 TR
1:02 S
1:52 P
2:29 TR
2:50 S
3:40 DEV
5:13 P
5:37 TR
5:58 S
6:57 CO
8:29 END

It was assumed that each section continued until the beginning of the next section (i.e. each piece is exhaustively partitioned into sections). As an arbitrary constraint to simplify the analysis, no section was allowed to be less than 15 seconds long. Two main criteria were used for determining the location of formal sections: change and repetition. A significant change in any musical parameter (i.e. harmony, melody, instrumentation, texture, meter, rhythmic pattern) was considered to make a good candidate for a section break. Repetition could also define sections: for instance, the form of a jazz piece is often defined by a repeating chord progression, such that when one iteration of the progression ends and another one begins, this can define a new section beginning. Each section label consists of a series of letters, followed by an optional number. In some cases, neutral labels (such as A, B, C, etc.) are used. In other cases, more meaningful labels are used: for instance, many analyses of pop songs use labels like IN (introduction), V (verse), PC (pre-chorus), CH (chorus), BR (bridge), and IS (instrumental); for

classical works in sonata form, common labels include P (primary theme area), TR (transition), S (secondary theme area), DEV (development), and CO (coda). Repetition of the same label signifies exact or slightly modified repetition (e.g. V and V for verses 1 and 2 of a pop song, with different lyrics and some changes in instrumentation, but mostly similar melody and harmony); for more substantially modified repetitions, numbers were used (e.g. V1 and V2 for two verses that have substantially modified melody or harmony). For quite dissimilar iterations of a section type, "X" and "Y" were added to a section label. For example, two very different instrumental sections in a song could be labelled as ISX and ISY (in the statistical analysis that follows, such labels were treated as completely distinct). Some situations warranted a hierarchical analysis of the form, with smaller sections nested inside larger ones. In these cases, symbols like A_a and A_b were used to indicate smaller sections within A. (Further distinctions were shown in a manner such as A_a1 and A_a2.)

These formal labels provided by expert analysis were then converted into more general labels, with each section coded as either X (new material), Y (returning material), or Z (variation or continuation of preceding material, where "continuation" means one section immediately following another of the same type). While the location and labeling of formal sections involved judgment calls, the conversion from the formal labels to the XYZ format was strict and computational. The first appearance of a letter (or string of letters) becomes an X; the subsequent appearance of that identical letter (or string of letters) becomes a Y; the re-appearance of a letter but with a different number appended to it becomes a Z. A few examples follow. A rondo, initially encoded as A B A C A B A, would be coded as X X Y X Y Y Y. A verse-chorus-bridge form V C V C B C would be coded as X X Y Y X Y; alternatively, if it was felt that Verse 2 was sufficiently modified from Verse 1, the formal labels would be V1 C V2 C B C, and Verse 2

would thus receive a “Z” denoting a modified repetition of a previous section: X X Z Y X Y. A variations form (i.e. A1 A2 A3...) would be coded as X Z Z...

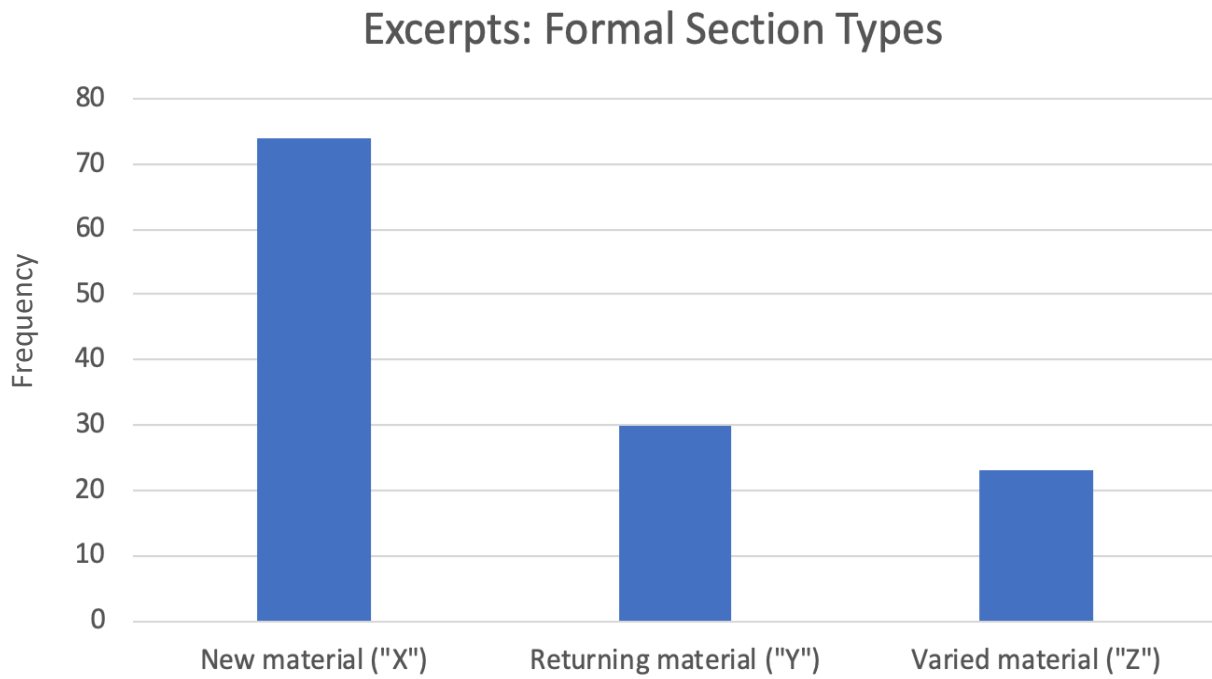
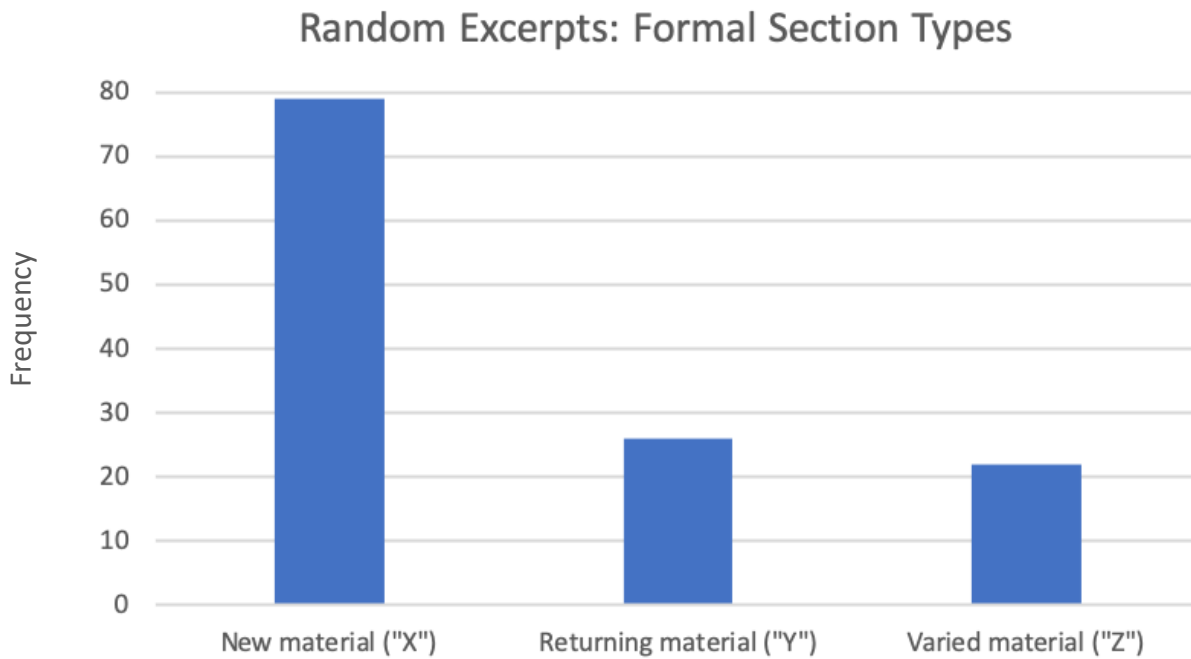
The aim of this XYZ coding of formal sections is to determine whether subjects’ preferred excerpts were formal returns (or occurred within formal return sections)—i.e. Y sections—at a rate significantly greater than chance (where “chance” would be selecting a random 15-second excerpt from the same piece). Thus, we find the formal section to which the 15-second favorite excerpt belongs (or has the most overlap); we assign the excerpt an X, Y, or Z depending on the X/Y/Z status of that formal section. We then compare the X/Y/Z distribution of the excerpts, with that of randomly selected 15-second excerpts from the same pieces.³¹ If the Returns hypothesis is true, the number of Y’s for the favorite excerpts should be significantly higher than those of the random excerpts: in other words, it should be unlikely that the chosen excerpts would be returns by chance alone. If the reverse of the hypothesis is true (that people tend to prefer excerpts that are new material), then the number of Y’s for the favorite excerpts should be significantly lower than those of the random excerpts. Finally, no significant difference between the values will suggest that people prefer neither new nor returning material.

5.2.2 The XYZ paradigm: Results & Discussion

Figure 9 shows the distribution of formal types (X, Y, or Z) among the 127 excerpts. We can see the preponderance of “X” or new material compared to “Y” or returning material and “Z” or varied material. Figure 10 shows the corresponding data for the random excerpts. Figure 10 shows us that a random timepoint in the corpus (or at least, in this subset of 127 pieces) is

³¹ Specifically, for each piece, a timepoint was randomly generated within the range 0:00 to end-0:15 inclusive, allowing for the creation of a hypothetical 15-second excerpt that did not exceed the end of the piece.

also much more likely to land inside a formal section presenting new material, than inside a section presenting returning material. As can be seen by comparing Figures 9 and 10, there is little difference between the formal section types of the favorite excerpts vs. the random excerpts. A Chi-squared test confirms that there is no significant difference between the distribution of formal section types in the favorite excerpts vs. the random excerpts, $\chi^2(2) = 0.47$ ($p = 0.79$).

**Figure 9****Figure 10**

In other words, there is no significant difference between the formal section types of participants' chosen excerpts and randomly generated excerpts from those same pieces. It appears that formal type was thus not determinative in participants' choices of excerpt. The Returns hypothesis appears to be disconfirmed: returns (Y) were far less predominant than new sections (X), and this result is congruent with that found in randomly generated excerpts from the same pieces.

However, we must consider that the predominance of the X (new) category could be due to a problematic conflation *within* the X category of two separate types of formal sections. Consider that we can draw a distinction between X sections that are unique, and X sections that are initial instances of a repeating section. Unique X sections are sections which are not repeated later in the piece. These unique sections are heard once in the whole piece; for example, a bridge. While the unique sections are still "new material", there is some triviality to this assignment, as it is not possible for a unique section to get the chance to become a Y (return) because it only occurs once in a piece. In contrast, the other type of X section is that which is the first instance of a section that later recurs; for example, Verse 1 or Chorus 1. If we omit from our X's the unique sections, and only consider the remaining X's versus the Y's, we now have a distinction between *initial* (1st) instances of a repeating section (i.e. the X's minus the unique X's) and *non-initial* (2nd to nth) instances of a repeating section (i.e. the 'Y' excerpts). Under this new analysis, of the 127 excerpts, only 28 were initial instances of a repeating section (repeating X's), while 30 were non-initial instances (Y's). We now see about the same number of Y's to X's, and we also see that a great many of the X's from Figure 9 (46, to be exact) were unique sections. Meanwhile, the random excerpts exhibit a very similar distribution: 30 repeating X's and 26 Y's.

A Chi-squared test again confirms that there is no significant difference between this distribution of formal types in the favorite excerpts vs. the random excerpts.³²

It is worth considering the following: if all of the instances of a section were perceptually equivalent to participants, the easiest thing for them to do would be to choose the first instance (X). Therefore, the fact that they chose any non-initial instances at all is interesting in itself. I suspect that the decision to choose a non-initial instance of a section rather than its first appearance in the piece stems from the principle of development. By this I mean, ordinarily a section will appear with more embellishment, energy, or complexity with each reoccurrence. This is particularly true for choruses in pop music, and for most verses in that style as well. (Choruses and verses make up a sizeable 18% of the 127 preferred excerpts.)³³ We also know from the discussion in section [5.1.2](#) that the participants in the survey appeared to prefer passages with increased complexity, at least on a local (i.e. 30-second) scale; therefore, it stands to reason that they would opt for a non-initial instance of a section if that meant a further increase in complexity on a larger (i.e. piece-wide) scale. Whether the non-initial instances were chosen due to being formal returns *per se*, or due to being higher in complexity, energy, or some other dimension, is unclear and suggests an intriguing direction for future research.

Another hypothesis worth testing is the extent to which excerpts align with formal section beginnings. If formal section type was determinative in participants' choices of excerpt, then the beginning of an excerpt should align more closely to a sectional beginning than chance alone. To answer this question, a t-test was performed comparing, for each piece, the temporal distance (in seconds) from an excerpt's beginning to the nearest formal section beginning, with the temporal

³² $\chi^2(2) = 0.32$ ($p = 0.57$).

³³ 23 total: 13 choruses, 7 verses, 2 verse-refrain units, and 1 verse-chorus unit.

distance from a randomly generated excerpt's beginning to its nearest formal section beginning.³⁴ (Temporal distance is defined as the absolute value of the time difference between the excerpt beginning and the nearest formal section beginning.) The excerpt beginnings were on average 10.72 seconds away from a formal section beginning (SD = 19.47), while the random excerpt beginnings were on average 14.56 seconds away (SD = 13.44) ($t(252) = -1.83, p = 0.07$). Approaching significance, this finding suggests that the selected excerpts are somewhat closer to section beginnings than chance alone.

Figure 11 shows the data visually: the frequencies of the temporal distances of excerpt beginnings to the nearest section beginnings, bucketed into ranges of width 5 (0-5, 5-10, etc.). (The X-axis label represents the maximum value (inclusive) of each bucket.) As can be seen, the most frequent situation (62 of the excerpts or 48.8%) is for an excerpt to begin within 5 seconds of a section beginning. Save for one outlier clocking in at 191 seconds away from a section beginning, all of the excerpts begin within 0 to 51 seconds of a section beginning. Figure 12 shows the corresponding information for the random timepoints. Omitting the outlier piece from the excerpts and also from the random timepoints gives a highly significant result: the excerpt beginnings now have an average temporal distance from the nearest section beginning of 9.29 seconds (SD = 10.96), while the random excerpts have a distance of 14.07 seconds (SD = 12.31) ($t(250) = -3.25, p = 0.001$). Therefore, with the outlier omitted, on average, the participant excerpts tend to be about 9 seconds away from a section beginning. By contrast, a randomly selected timepoint tends to be about 14 seconds away from a section beginning. This difference, though highly significant, is admittedly small (Cohen's d is 0.41, which is considered a small to

³⁴ For the temporal distance calculation, as with the X/Y/Z paradigm, for each piece, a timepoint was randomly generated within the range 0:00 to end-0:15 inclusive, allowing for the creation of a comparable hypothetical timepoint to the actual excerpt's beginning timepoint.

medium effect size); and while it serves to suggest that section beginnings were somewhat determinative in participants' choices, there is far from a tight mapping between section beginning and excerpt.

A final possibility is that the timings of the sections in the expert's analysis do not reflect the section timings in the minds of the participants; however, it seems unlikely that opinions on formal section beginning-times between people should differ by more than a few seconds, especially given the predominance in the corpus of such uncontroversial sections as verse, chorus, or the return to a theme. The most plausible conclusion is that form was somewhat determinative, but not foremost in participant's minds, when deciding on where to begin their favorite excerpt.

Excerpts: Distance from Formal Section Beginning

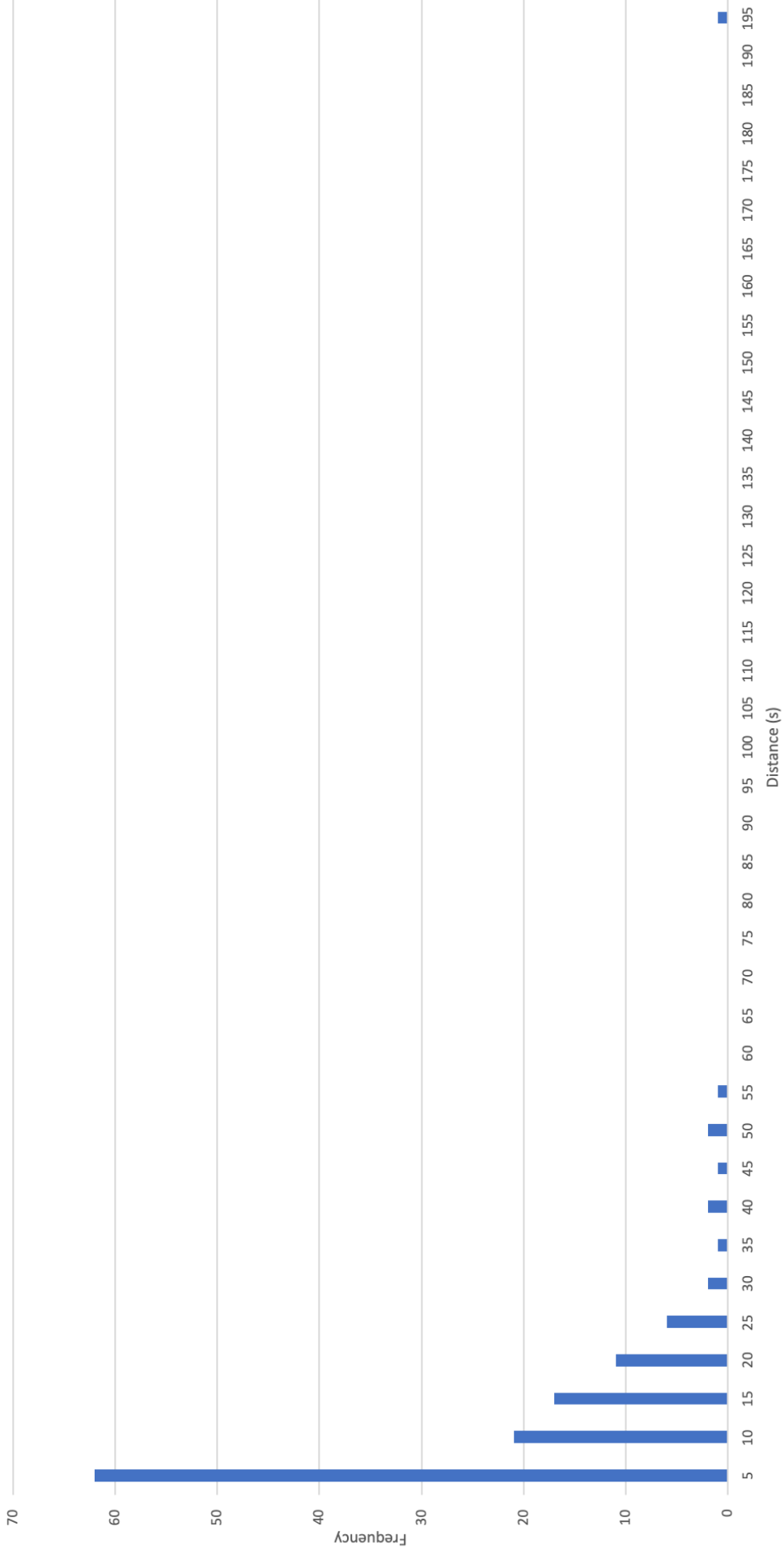


Figure 11

Random Excerpts: Distance from Formal Section Beginning

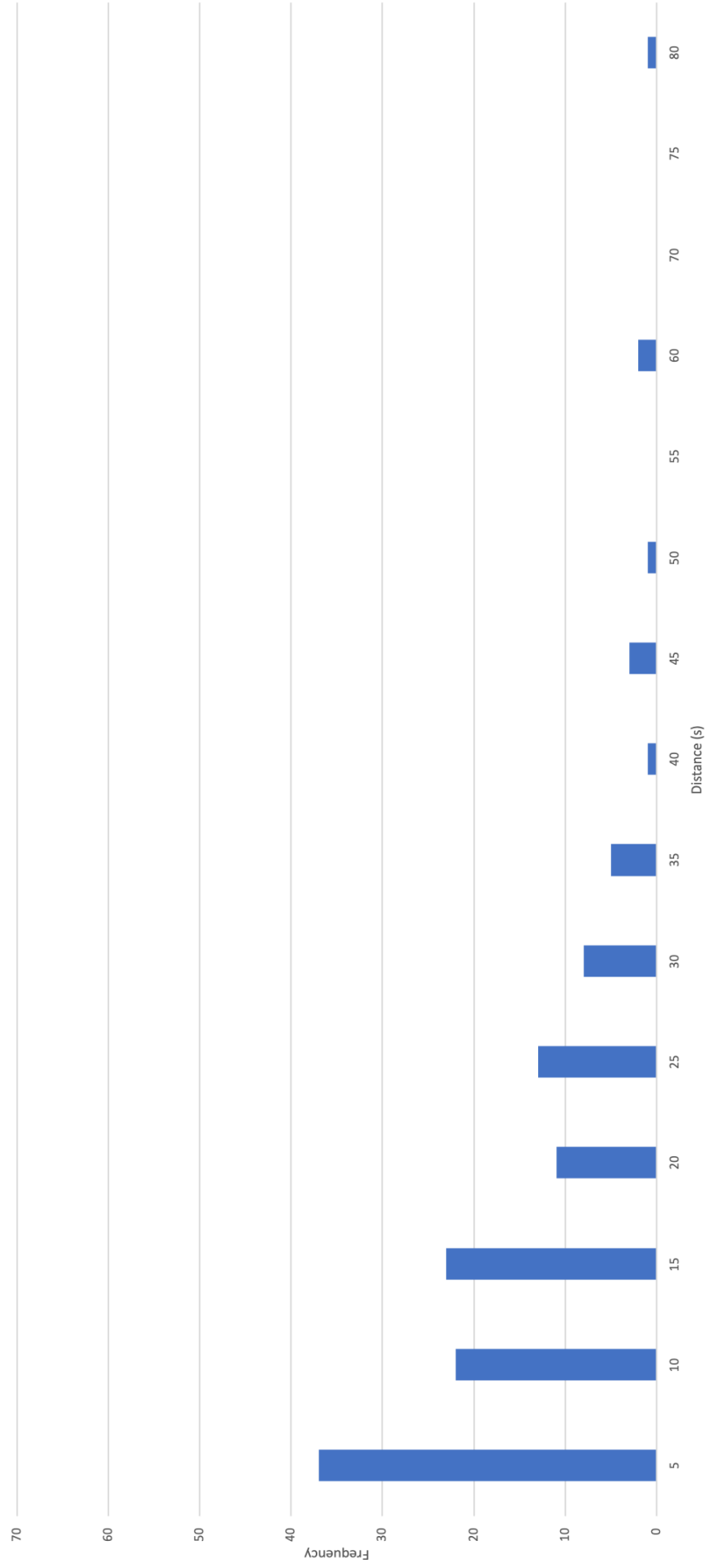


Figure 12

Chapter 6: Conclusions and Future Directions

In this chapter, I will summarize the findings of the dissertation, discuss some pedagogical implications of the corpus, and give suggestions for future research directions.

6.1 Conclusions

Chapter 2 demonstrated through review of the literature that complexity is a variable that can play an important role in musical liking. Chapter 3 presented the C-S hypothesis, the claim that people's favorite musical excerpts would tend to involve complexity reduction (in other words, that the material in the excerpt would be lower in complexity than the preceding material). In Chapter 3 this hypothesis was justified through many anecdotes from music scholarship, in genres ranging from classical to Indian to EDM; I also gave a more rational justification for the C-S hypothesis via evolutionary psychology, namely the claim that the reward system of humans evolved to incentivize us to escape complex (i.e. dangerous) environments in favor of simple (i.e. safe) ones, and that this vestigial trait would carry over to music taste as well. In Chapter 5, this hypothesis was tested using a corpus of favorite 15-second excerpts (the FAV Corpus), given by respondents to a survey; the complexity of each excerpt (in relation to the previous or subsequent passage) was judged by musical experts.

Given the wealth of evidence and reasoning that seemingly supports the C-S hypothesis, the result in Chapter 5—that the excerpts in the FAV Corpus were in fact more often passages of *increased* complexity—was surprising. No significant correlation was found between years of training and a preference for complexity increase, suggesting that the observed S-C pattern was not simply due to the participants' special training as music students. While it does appear that

listeners tend to prefer complexity increase, there may be aspects other than complexity that better explain musical preference. The thematic and frequency analyses of the comments in Chapter 4, for instance, demonstrated several aspects—chiefly pitch (melody and harmony), sonics (instrumentation, texture, and timbre), vocals, and feelings—that all featured much more prominently in participants’ comments than did complexity (or simplicity). Therefore, these parameters may be more reliable determinants/predictors of musical preference than complexity.

The secondary hypothesis of the study, the Returns hypothesis, predicted that the favorite excerpts would tend to coincide with formal returns (Chapter 3). Instead, the result was that the participants’ favorite excerpts did not differ in formal category from random controls (see Chapter 5). Both the favorite excerpts and the randomly generated excerpts from the same pieces tended to be new material (‘X’) more often than returning material (‘Y’); a further distinction was drawn between initial and non-initial instances of repeating sections, but even so, no difference emerged between the chosen excerpts and the random controls. Finally, Chapter 5 also showed that formal boundaries were somewhat determinative in excerpt choices, as the excerpt beginnings were more likely to align with a section beginning than were random controls.

6.2 Implications of the FAV Corpus for music theory pedagogy

In section 4.2.2 we observed several somewhat surprising trends regarding the eras of the classical music selections within the FAV Corpus, which have potential implications for music theory pedagogy. In what follows, my intent is not to give opinions about how pedagogy ought to be done, but rather to give some thoughts to consider in light of the data.

First, there were no pieces from the pre-Baroque era in the corpus. Given that an estimated 85% of participants were in a music conservatory, and that music history curricula

often dedicate a full semester to this era, this finding is surprising. Many students participate in early music ensembles, yet it would seem that (for this sample of participants, at least) pre-Baroque pieces are not among their personal favorites. Second, it was observed that while 48% of the classical pieces in the corpus are 20th/21st century pieces, only one of these 199 pieces was from the Second Viennese School of atonal/twelve-tone composers (Schoenberg, Webern, and Berg). Most college music theory curricula dedicate at least one full semester to post-tonal music, and typically the bulk of this semester is focused on set-class theory and twelve-tone techniques, with the core repertoire consisting of the Second Viennese School. Therefore, as seen with pre-Baroque music, there appears to be a mismatch between the weight given to these composers in the curriculum, and their place in students' favorite music.

It's worth considering potential reasons for this relative lack of early music and atonal music in the corpus, despite both of those genres receiving dedicated attention in both music theory and history curricula. (The following explanations are not mutually exclusive.) The first explanation is that students prefer the sound of major-minor tonality which extends all the way from Bach to today's pop music; pre-Baroque music has many important differences from standard tonality (Lester, 1989), while atonal music by its very premise avoids tonality. The second explanation is that, for whatever reason, these two eras receive relatively little exposure in concert programmes, classical radio, online playlists, and so forth;³⁵ therefore, in their childhood, and prior to arriving at a music conservatory at age 17 or 18, students have very little exposure to these two eras, and thus their music preference has already been dictated to some degree. Related to this idea of exposure is the third explanation: of the 140 participants, 20

³⁵ While atonality is often used in horror movie scores, this is an incidental use and not the main listening focus.

(14.3%) were in their first semester of first-year theory, while another 99 (70.7%) were in their first semester of second-year theory; the remaining 21 (15.0%) were taking a music cognition course and assumed to be non-music majors.³⁶ Therefore, it's entirely possible that these students simply weren't yet exposed to much atonal or early music, and even if so, they hadn't had sufficient time to familiarize themselves. In other words, with 3rd-, 4th-year, or graduate students as participants, the survey results might be entirely different with respect to early and atonal music. This third explanation seems to be the best and simplest one, and the lack of early and atonal music in the corpus should not be taken as evidence that students do not like it, but rather that younger students have not yet been exposed to it.

Another seeming mismatch between music theory curricula and the survey results was that pieces from the Classical era (defined as 1750-1819) constitute only 8.5% of the classical pieces in the corpus. This is surprising, given that Classical pieces are very common in the life of a budding music conservatory student (some of the first pieces they learn for their instrument), constituting an enormous amount of early exposure to this era for the average music major. (Nor are the likes of Mozart, Haydn, and Beethoven without a large fanbase in the classical world, if concert programmes are any indicator.) Nonetheless, Romantic pieces (31.7% of the classical selections) dwarf Classical pieces (8.5%) in the classical category of the survey. Particularly implicative for music theory pedagogy is that the entire tonal music curriculum is arguably based on models and repertoire of the Classical music era; yet this may be divergent from the eras that students' most impactful favorite pieces appear to belong to. *If* one's goal is to teach tonal music

³⁶ While it's possible that in a few cases the first- or second-year students were retaking the course, or were older or transfer students with prior exposure to atonal studies, the general point remains.

theory using pieces that excite students the most, the present data suggests that Romantic-era repertoire might better achieve that goal.

Finally, it was observed in section 4.2.2 that the classical eras of Baroque, Classical, and Romantic are made up of a small number of famous composers, while the pop, jazz, and 20th/21st c. classical genres have a lot of diversity of artists and composers. In my opinion, this result is unsurprising, as it suggests that with historical distance, a time period becomes reduced and simplified to a few composers. Consider that in Mozart's day, there were many active, respected, and disseminated composers; yet today, the vast majority of Classical music that is listened to or performed is by Haydn, Mozart, or Beethoven. This situation is not for lack of access either, as music libraries are full of thousands of scores by virtually-forgotten historical composers, and many of these pieces have been recorded and made available online. I believe that this process of reduction over time is a combination of collective memory with the pedagogical process of simplifying for the institutions of the course, textbook, and exam. (To be clear, I am neither arguing for nor against courses, textbooks, and exams; rather, I am only observing that a simplification process normally occurs in order to fit the needs of standardized testing.) I would argue that this same process will, in the future, apply to our own era just as it applies to past ones. By the year 2200, perhaps most people will only know of, or listen to, a handful of artists from the 20th century.

6.3 Future directions

In terms of future directions, the first avenue of exploration could be expanding the existing dataset. The survey could be re-run online, and globally, with many more participants, increasing sample size and statistical power. Instead of three songs and excerpts, many more

songs and excerpts could be requested from each participant, allowing for better trend analysis *within* participants, so as to potentially identify different listener-types.

As the corpus grows in size, the potential for using machine learning (which tends to excel with large datasets) to analyze the data becomes more viable. An acoustical signal-analysis-based approach could be effectively combined with a symbolic, music-theoretic approach (the latter taken in the present dissertation). The meeting of the continuous (i.e. acoustical) and discrete (i.e. symbolic) worlds of data analysis can be very powerful. The many tools available in the field of music information retrieval, for instance, could be incorporated into an analysis of the corpus, to determine which audio features (e.g. spectral flux, dissonance, loudness, etc.) are determinative of the favorite excerpts as compared to random controls from the same pieces.

Even without venturing outside of the symbolic space, there is immense potential for further coding and analysis of corpus features such as scale-degree distributions, metric position, harmonic root patterns, and so forth, akin to the statistical work applied to the Rolling Stone Corpus (de Clercq & Temperley, 2011; Tan, Lustig, & Temperley, 2019). Supplementing this computational approach to the corpus could be a more humanistic, analytical approach in which more speculative and traditional analysis is conducted to attempt to understand why these particular excerpts are so powerful. For instance, given the overwhelming emphasis on pitch (melody and harmony) in participants' comments, it would be interesting to determine the melodic and harmonic structures characteristic of the excerpts in the FAV Corpus; and what distinguishes the pitch material of a favorite excerpt from a non-favorite excerpt in the same piece.

Another intriguing area is the correlation of personality type with music taste (e.g. Rentfrow & Gosling, 2003). An expanded iteration of the survey could perhaps include a personality inventory; indeed, socio-economic data could be collected to build a more holistic model of music taste as well.

It was suggested in Chapter 5 that perhaps the FAV Corpus is better explained not by complexity differentials, but rather by percepts such as energy; specifically, energy gain (i.e. build-ups). Indeed, the comment analyses in Chapter 4 found that the EN theme occurred almost twice as frequently as the COM theme. Future analyses of the corpus could use human judges or acoustical methods to see what role, if any, energy plays in the corpus. Emotion (via the word “feeling”) was also very prominent in the frequency analysis of the comments. Teasing apart the effects of complexity, energy, and emotion on musical preference will be an interesting avenue for further research, as we continue to answer the question: why do we like the music that we like?

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Appendix 1: Survey

A Survey of Music Taste

You will be asked to identify three of your favorite excerpts of music. Each excerpt can be in any style and from any time period. You will be asked to find recordings of the pieces on the internet (e.g. on YouTube or Spotify) and identify the excerpt that you have in mind.

Duration: ~15 min.

Click "I want to proceed" to consent to the survey.

* Required

1. *

Mark only one oval.

I want to proceed.

1/3

2. Step 1: Find *

In YouTube or Spotify, find one of your most favorite songs/pieces/movements. It can be any style or time period.

Mark only one oval.

Done

3. Step 2: Link *

Link to the music - provide a URL link so we can listen too. If it's a YouTube video: Copy the link from your browser's address bar. If it's a Spotify song: Right-click on the song and click "share", then click "copy link to clipboard"

1/3

4. Step 3: Listen! *

Listen to the entire piece.

Mark only one oval.

Done

1/3

5. Step 4: Excerpt *

Identify the 15-second excerpt that's your favorite (e.g. 1:50-2:05). (If your favorite part is longer than 15 seconds, choose any 15 seconds within it. If it is shorter than 15 seconds, choose any 15-second excerpt that contains it.)

6. Step 5: Describe *

Why do you love the excerpt? Try to be as specific and detailed as possible (music theory terms are encouraged but not required).

7. Step 6: How does the excerpt compare to the rest of the piece? *

Mark only one oval.

A. I enjoy this excerpt much more than the other parts of the piece.

B. I enjoy this excerpt about as much as the other parts of the piece.

2/3

8. Step 1: Find *

In YouTube or Spotify, find one of your most favorite songs/pieces/movements. It can be any style or time period.

Mark only one oval.

Done

9. Step 2: Link *

Link to the music - provide a URL link so we can listen too. If it's a YouTube video: Copy the link from your browser's address bar. If it's a Spotify song: Right-click on the song and click "share", then click "copy link to clipboard"

2/3

10. Step 3: Listen! *

Listen to the entire piece.

Mark only one oval.

Done

2/3

11. Step 4: Excerpt *

Identify the 15-second excerpt that's your favorite (e.g. 1:50-2:05). (If your favorite part is longer than 15 seconds, choose any 15 seconds within it. If it is shorter than 15 seconds, choose any 15-second excerpt that contains it.)

12. Step 5: Describe *

Why do you love the excerpt? Try to be as specific and detailed as possible (music theory terms are encouraged but not required).

13. Step 6: How does the excerpt compare to the rest of the piece? *

Mark only one oval.

- A. I enjoy this excerpt much more than the other parts of the piece.
- B. I enjoy this excerpt about as much as the other parts of the piece.

3/3

14. Step 1: Find *

In YouTube or Spotify, find one of your most favorite songs/pieces/movements. It can be any style or time period.

Mark only one oval.

- Done

15. Step 2: Link *

Link to the music - provide a URL link so we can listen too. If it's a YouTube video: Copy the link from your browser's address bar. If it's a Spotify song: Right-click on the song and click "share", then click "copy link to clipboard"

3/3

16. Step 3: Listen! *

Listen to the entire piece.

Mark only one oval.

Done

3/3

17. Step 4: Excerpt *

Identify the 15-second excerpt that's your favorite (e.g. 1:50-2:05). (If your favorite part is longer than 15 seconds, choose any 15 seconds within it. If it is shorter than 15 seconds, choose any 15-second excerpt that contains it.)

18. Step 5: Describe *

Why do you love the excerpt? Try to be as specific and detailed as possible (music theory terms are encouraged but not required).

19. Step 6: How does the excerpt compare to the rest of the piece? *

Mark only one oval.

- A. I enjoy this excerpt much more than the other parts of the piece.
- B. I enjoy this excerpt about as much as the other parts of the piece.

20. *

Sometimes people fill in online surveys without carefully reading the instructions. If you are paying attention, please select C.

Mark only one oval.

- A. Definitely
- B. Maybe
- C. Not at all
- D. Unsure

A few final questions

21. How many years of formal training on a musical instrument (including voice) have you had during your lifetime? *

22. What is your gender? *

Mark only one oval.

- Male
- Female
- Prefer not to say

23. What is your age? *

24. Enter your first and last name: *

Your name will be used for record-keeping only and will not be associated with your responses in any way.

25. Any other comments on the study (criticisms, suggestions for improvement?)

Appendix 2: Pieces and Excerpts in the FAV Corpus

Piece 1

P #	Composer/artist	Piece	From	To	AB/BC	XYZ
1	Shostakovich	3rd mvt - String Quartet No. 3 in F major Op. 73	2:16	2:31		
2	Kendrick Lamar	LOVE	1:39	1:54		
3	Prokofiev	1st mvt - Violin Concerto No. 2, op. 63 in G minor	0:02	0:17		√
4	Mahler	5th mvt - Symphony No.2 in C minor	8:15	8:30	√	√
5	Handel	Oh sleep, why dost thou leave me?	1:42	1:57		
6	William Steinberg	Jeannie With The Light Brown Hair	1:02	1:17	√	√
7	EXO	Forever	0:52	1:07		
8	Coldplay	Speed of Sound	0:00	0:15		
10	Love and Theft	Thinking of You (And Me)	1:56	2:11		
11	Camille Saint-Saëns	Danse Macabre	1:33	1:48		
12	Sivan Cohen Elias	Still Life with Squares	10:06	10:21		
13	Jem	It's Amazing	3:15	3:30		
15	Ahmad Jamal Trio (Bernie Baum, Stephen Weiss)	Music! Music! Music!	2:28	2:43		
16	Tennyson	Body Language	0:54	1:09		
17	Bartok	1st mvt - Viola Concerto	0:08	0:23		
18	Pascal Le Boeuf	Alpha	4:08	4:23		
19	The Beatles	Here Comes the Sun	0:42	0:57		
20	Blue Swede	Hooked on a Feeling	0:24	0:39	√	√
21	K Will	Melting	0:54	1:09		
22	Mahler	4th mvt - Symphony No.5	3:01	3:16		
23	Dry the River	Weights & Measures	3:55	4:10		
24	Lany	Super Far	1:40	1:55		
25	Ravel	Une barque sur l'océan from Miroirs	0:19	0:34		
26	Calle 13	Muerte En Hawaii	2:03	2:18		
27	Keith Urban	Blue Ain't Your Color	0:36	0:51	√	√
28	J.S. Bach	Prelude - Cello Suite No.6	2:29	2:44		

29	The All-American Rejects	Move Along	0:45	1:00		
30	Tom Kitt	"Everything Else" from Next to Normal	1:12	1:27		
31	Tame Impala	The Less I Know The Better	1:06	1:21		
32	Hiatus Kaiyote	Molasses	2:08	2:23		
33	Lorde	Liability	0:49	1:04		
35	Ernst	Variations on "The Last Rose of Summer"	3:08	3:23		
37	Verdi	Libera me (Libera me) - Requiem	2:21	2:36		
38	Sleeping at Last	Saturn	3:16	3:31		
40	Chance The Rapper	How Great	3:05	3:20		
41	Bon Iver	The Wolves	4:01	4:16	√	√
42	Gluck	Che faro senza Euridice from Orfeo ed Euridice	3:18	3:33		
43	Daft Punk	Digital Love	0:12	0:27		
44	Slum Sociable	Don't Come Back Another 100 Times	0:57	1:12		
45	Hozier	In a Week	4:07	4:22		
46	James Arthur	If Only	2:40	2:55	√	√
47	Invalids	Strengths	4:18	4:33	√	√
48	Debussy	Clair de Lune	0:14	0:29		
49	Astor Piazzolla	Libertango	2:05	2:20		
50	Kendrick Lamar	Alright	1:46	2:01		
51	Brahms	2nd mvt - Piano Concerto No.1	1:39	1:54		
52	Debussy	Clair de Lune	4:16	4:31		√
53	Aesop Rock	Rings	0:38	0:53		
54	Beethoven	1st mvt - Violin Concerto in D Major, Op. 61	18:43	18:58		
55	Stevie Wonder (arranged by Jacob Collier)	Don't You Worry 'Bout A Thing	3:49	4:04		
56	Billy Joel	The Stranger	1:14	1:29		
57	John Mackey	Xerxes	1:14	1:29	√	√
58	Johnny Cash	You Are My Sunshine	0:45	1:00		
59	J.S. Bach	Gavotte - Cello Suite No.6	1:07	1:22		

60	周興哲	以後別做朋友 (Don't Be Friends Anymore)	1:15	1:30		
61	Rachmaninov	3rd mvt - Symphony No.2 in E minor, Op.27	0:00	0:15		
62	Beethoven	2nd mvt - Piano Concerto No.5	6:23	6:38		
63	Paul Lansky	1st mvt - Three Moves for Marimba	3:23	3:38	√	√
64	Sibelius	4th mvt - Symphony No.2 in D major, Op.43	1:12	1:27		
65	Dvorak	1st mvt - Cello Concerto in B minor, Op. 104	14:34	14:49		
66	Elgar	1st mvt - Cello Concerto in E minor Op.85	2:25	2:40		
67	Herbie Hancock	Butterfly	1:10	1:25		
68	Brady Wiggins (Fractal)	Duality	0:00	0:15		
69	Schnittke	Choir Concerto 3 - God, Grant Deliverance From Sin	3:47	4:02		
70	Brahms	2nd mvt - Symphony No. 2 in D, Op. 73	3:30	3:45	√	√
71	Damien Rice	The Blower's Daughter	3:48	4:03		
72	Miles Davis	Round About Midnight	0:50	1:05		
73	Handel	Judas Maccabaeus, HWV 63: Sing Unto God	0:35	0:50		
74	Rachmaninov	"O ne rydai, mai Paolo", from Francesca da Rimini, Op. 25	1:59	2:14		
75	John Coltrane	My Favorite Things	9:00	9:15		
76	Adam Anders/ Nikki Hassman	Can I Have This Dance	0:59	1:14		
77	Handel	In War and Peace	4:00	4:15		
78	Elgar	1st mvt - Cello Concerto in E minor, Op. 85	7:09	7:24		
79	Elliott Smith	Everything Means Nothing to Me	1:10	1:25		
80	Chet Faker	Talk is Cheap	1:33	1:48		
81	Alan Menken	Bells of Notre Dame	2:55	3:10		
82	J.S. Bach	Chaconne from Partita No. 2 BWV 1004	5:47	6:02		
83	Samuel Barber	Agnus Dei	5:53	6:08	√	√
84	James Vincent McMorrow	Look Out	1:55	2:10	√	√
85	Brahms	Intermezzo in A major, Op. 118 No. 2	4:44	4:59		

86	Robyn	Dancing On My Own	1:06	1:21		
87	Sibelius	1st mvt - Violin Concerto in D minor, Op.47	4:06	4:21		
88	Taylor Eigsti	Play With Me	0:53	1:08		
89	Villa-Lobos	Ciranda das sete notas	9:42	9:57	√	√
90	Rachmaninov	2nd mvt - Piano Concerto No. 2 in C minor, Op.18	8:10	8:25		
91	J.S. Bach	Matthäus Passion BWV 244	2:29	2:44		
92	Nikolai Medtner	3rd mvt - Piano Quintet in C major	8:18	8:33		
93	Sara Bareilles	Say You're Sorry	2:53	3:08		
94	Gray Matter	Footsteps	1:10	1:25		√
95	Ustad Nusrat Fateh Ali Khan	Afreen Afreen	3:07	3:22	√	√
96	Rachmaninov	3rd mvt - Symphony No. 2 Op. 27	6:51	7:06	√	√
97	Robert Randolph & the Family Band	Ain't Nothing Wrong with That	1:41	1:56		
98	Andrew Bird	Two Sisters	3:30	3:45		
99	Richard Strauss	Act 3 - "Marie Theres'!" - "Hab' mir's gelobt" from Der Rosenkavalier	4:30	4:45	√	√
100	Ottorino Respighi / Antonio Pappano	Pini di Roma, 4th movt	4:53	5:08		
101	J.S. Bach	Johannes-Passion, "Ruht wohl, ihr heiligen Gebeine"	0:29	0:44		
102	The Weeknd	Secrets	3:20	3:35	√	√
103	Bizet	Pastorale from 20 Melodies, Op.21 No.9	2:26	2:41	√	√
104	Bob Marley	Could You Be Loved	0:00	0:15		
105	Hindemith	Kleine Kammermusik for Wind Quintet, Op. 24/2	6:55	7:10	√	√
106	Schumann	2nd mvt - Quintet in E flat, Op. 44	3:16	3:31		
107	Axwell & Shapov	Belong	1:31	1:46		
108	Beethoven	1st mvt - Symphony No. 3 "Eroica"	11:32	11:47		
109	Ravel	Pavane pour une infante défunte from Miroirs	0:07	0:22		
110	Kehlani	Honey	1:30	1:45	√	√

111	John Powell	Coming Back Around	1:35	1:50		
112	Mahler	3rd mvt. - Symphony No. 5	14:17	14:32	√	√
113	Beethoven	1st mvt - String Quartet op. 132	3:55	4:10		
114	Beethoven	2nd mvt - Symphony No 7 in A major, Op 92	2:28	2:43		
115	Ravel	1st mvt - Violin Sonata No.2	3:30	3:45		
116	Frank Ocean	Self Control	2:15	2:30		
117	Quincy Jones	Soul Bossa Nova	0:35	0:50		
118	Art Blakey	Ugetsu	1:07	1:22		
119	Axwell & Ingrosso	Sun is Shining	1:27	1:42		
120	Eddie Vedder	Guaranteed	0:57	1:12		
121	Beethoven	1st mvt - Piano Sonata No.31 in A flat Op.110	0:25	0:40		
122	Brahms	1st mvt - Symphony No. 1	0:55	1:10		
123	Bon Iver	Wash.	2:29	2:44	√	√
124	Samuel Barber	2nd mvt - Violin Concerto Op.14	0:14	0:29		√
126	Jacques Ibert	Concertino da Camera for Alto Saxophone and Orchestra	3:40	3:55		
127	J.S. Bach	Aria Da Capo - Goldberg Variations	3:25	3:40		
128	Alan Menken / Stephen Laurence Schwartz	"Out There" from Hunchback of Notre Dame Musical	4:06	4:21		
129	Ernesto Lecuona	6th mvt - Suite Andalucia	0:13	0:28		
130	Brahms	Intermezzo, Op. 118, No. 2 in A major	3:19	3:34	√	√
131	Tchaikovsky	Romeo and Juliet (Rostropovitch, NYE 1990 concert)	14:53	15:08		
132	Brahms	Intermezzo, Op. 118, No. 2 in A major	0:00	0:15		√
133	Herbert Howells	Long, long ago	4:48	5:03		
134	J.S. Bach	Chaconne from Partita No.2 BWV 1004	0:01	0:16		
135	Motion City Soundtrack	Disappear	2:10	2:25		
136	Berg	Piano Sonata, Op.1	6:17	6:32		
137	Prokofiev	3rd mvt - Flute Sonata No.2 in D major, Op.94	1:09	1:24		
138	Phillip Bimstein	A Little Bit About My Cows	0:40	0:55		
139	Kendrick Lamar	Pride	4:02	4:17		

140	Sigmund Romberg/ Oscar Hammerstein II	Softly, as in a Morning Sunrise	0:00	0:15		
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Piece 2

P #	Composer/artist	Piece	From	To	AB/BC	XYZ
1	Sibelius	op. 47 Mvt. I	14:57	15:12	√	√
2	CHON	Knot	1:28	1:43	√	√
3	Brahms	Violin and Piano Sonata No 1 in G major, 2nd movt	2:43	2:58	√	√
4	Tchaikovsky	Symphony No 5 in E minor IV: Finale	9:33	9:48	√	√
5	Roberta Alexander	Tell Me, Oh Blue, Blue Sky	1:40	1:55	√	√
6	Liszt	Hungarian Rhapsody No 12 Mvt. 1	9:07	9:22	√	√
7	B1A4	A Lie	0:35	0:50	√	√
8	Don Henley	The End of the Innocence	3:08	3:23		
10	Five for Fighting	Road to You	1:03	1:18		
11	Tchaikovsky	Romeo & Juliet	6:26	6:41	√	√
12	Kate Soper	Nadja	23:20	23:35		
13	The Bird and the Bee	You're a Cad	2:00	2:15		
15	Radiohead	Mr. Magpie	2:03	2:18		
16	VULFPECK	Birds of a Feather, We Rock Together	0:11	0:26		
17	Brahms	Violin Sonata No 1 in G Major Mvt. I	1:39	1:54	√	√
18	John Psathas, Pedro Carneiro	One Study	1:19	1:34		
19	Elvis Presley	Can't Help Falling in Love	0:19	0:34	√	√
20	Mahler	Symphony No. 2 M. V	6:42	6:57	√	√
21	Chopin	Andante Spianato e Grande Polonaise	4:47	5:02	√	√
22	Samuel Barber	Adagio for Strings	5:26	5:41	√	√
23	The Mountain Goats	Up the Wolves	2:50	3:05		
24	John Mayer	City Love	0:00	0:15		
25	Schubert	Quintet in C Major	11:50	12:05		
26	Frank Sinatra	Come Fly With Me	1:29	1:44	√	√
27	Michael Bublé	Nobody But Me	1:30	1:45	√	√
28	Rachmaninov	Cello Sonata in G Minor IV: Allegro mosso	3:31	3:46		
29	Demi Lovato	Tell Me You Love Me	0:47	1:02	√	√
30	Stravinsky	Petrushka	1:56	2:11		
31	Empire of the Sun	Celebrate	1:02	1:17		
32	Beethoven	Symphony No. 7 M. IV	2:07	2:22	√	√
33	Omnipotent Youth Society	Kill the One From Shijiazhuang	3:25	3:40	√	√

35	Birdy	Skinny Love	none	none		
37	Dvorák	Symphony No. 8 M. I	0:00	0:15		
38	Don McLean	American Pie	6:39	6:54		
39	Anderson .Paak	The Bird	2:45	3:00	√	√
40	Beyoncé	Superpower	1:46	2:01		
41	Dvorák	Symphony No. 9 M. I	3:31	3:46	√	√
42	Marilyn Horne	Beautiful Dreamer (Stephen Foster)	0:53	1:08		
43	Justice	D.A.N.C.E	2:25	2:40	√	√
44	Shallou	Begin	2:28	2:43		
45	Debussy	Doctor Gradus ad Parnassum	0:01	0:16		
46	Denée Bonton	No One Else	0:55	1:10		
47	Delta Sleep	So Say We All	2:36	2:51		
48	Tchaikovsky	Violin Concerto in D Major M. I	6:21	6:36	√	√
49	Purcell	King Arthur, "What Power Art Thou?"	1:00	1:15		
50	Kendrick Lamar	HUMBLE.	1:59	2:14		
51	Adele	Make You Feel My Love	0:56	1:11	√	√
52	CLARA	My Kinda Lovin	2:28	2:43		
53	Slaid Cleaves	Lydia	3:22	3:37	√	√
54	J.S. Bach	Suite No. 6 in D Major, Gavotte I/II	3:28	3:43		√
55	Father John Misty	When You're Smiling and Astride Me	4:07	4:22		
56	The Police	Roxanne	2:09	2:24		
57	Frank Ticheli	Angels in the Architecture	6:58	7:13	√	√
58	Sia	Chandelier	0:57	1:12		
59	Lianne La Havas	Say a Little Prayer	0:37	0:52		
60	MINO, ZICO	Okey Dokey MV	0:00	0:15		
61	Rachmaninov	Piano Concerto No. 2 in C Minor M. II	8:24	8:39		
62	Beethoven	Violin Concerto in D Major M. I	12:21	12:36	√	√
63	Alexej Gerassimez	Asventuras for Snare Drum	3:58	4:13	√	√
64	Marcel Grandjany	The Colorado Trail: Fantaisie for Harp	2:55	3:10		
65	Mendelssohn	Violin Concerto in e minor M. II	0:58	1:13		
66	Alexander Glazunov	Violin Concerto in a minor M. II	0:01	0:16		√
67	Kendrick Lamar	You Ain't Gotta Lie (Momma Said)	2:15	2:30		
68	Freddie Hubbard	Little Sunflower	4:38	4:53		
69	J.S. Bach	Mass in b minor: Agnus Dei: Dona Nobis Pacem	3:00	3:15	√	
70	Brahms	4 Serious Songs: Song IV	0:47	1:02		

71	Arturo Márquez	Danzón No. 2	6:14	6:29		
72	Chance the Rapper	Acid Rain	0:55	1:10		
73	Iain Burnside	When I am Dead, My Dearest	1:05	1:20		
74	Traditional	Vagiorko Mai/ Do You Love Me?	1:25	1:40		
75	Mac Miller	My Favorite Part	0:00	0:15		
76	DJ Khaled	I'm the One	0:16	0:31		
77	Beethoven	Sonata No. 12 in Ab Major M. I	1:42	1:57	√	√
78	Grieg	Sonata for Piano and Cello in A minor M. I	3:31	3:46		
79	John Ludington	Let Me Show You	1:40	1:55		
80	Bon Iver	715 - CrΣΣks	1:32	1:47		
81	Kate Shindle	The Mad Hatter	2:05	2:20	√	√
82	Selena Gomez	Bad Liar	0:47	1:02		
83	Andre Thomas	Credo	4:45	5:00		
84	NEIKED	Sexual	2:30	2:45	√	√
85	Liszt	Ballade No. 2	9:38	9:53		
86	Lady Gaga	The Cure	0:47	1:02		
87	The Beatles	Here Comes the Sun	0:15	0:30		
88	Kendrick Scott Oracle	Cycling Through Reality	8:27	8:42		
89	Elgar	Romance for Bassoon and Orchestra	1:59	2:14		
90	Mozart	Rondo in A minor	0:00	0:15		√
91	Dvorák	Symphony No. 9 M. II	9:47	10:02	√	√
92	Richard Strauss	Tod und Verklärung	3:02	3:17		
93	dodie	Intertwined	1:50	2:05		
94	Fred Hersch	Con Alma	0:20	0:35	√	√
95	J Balvin, Willy William	Mi Gente	1:25	1:40		
96	Rachmaninov	Vocalise	5:58	6:13		
97	Trombone Shout Band	Song Unknown	0:11	0:26		
98	Pablo de Sarasate	Zigeunerweisen	0:02	0:17		
99	Brahms	Fünf Lieder M. I Botschaft	1:22	1:37		
100	deadmau5	Strobe	6:37	6:52	√	√
101	J. F. Fasch	Trumpet Concerto in D Major M. II Largo	0:00	0:15		
102	John Mayer	Daughters	3:30	3:45		
103	Hall Johnson	Ain't Got Time to Die	0:26	0:41		
104	Radiohead	Everything in its Right Place	0:00	0:15		

105	Jean Constantin	Main Theme and Police Car - The 400 Blows	0:40	0:55	√	√
106	Brahms	Viola Sonata No. 2 M. II	2:13	2:28	√	√
107	Axwell & Shapov	Belong (Axwell & Years Remode)	1:30	1:45		
108	Mahler	Um Mitternacht	5:04	5:19	√	√
109	J.S. Bach	Zion hört die Wächter singen	3:25	3:40		
110	Erich Korngold	Tomorrow (When You Are Gone)	2:52	3:07	√	√
111	Stravinsky	Firebird Suite Finale [Fantasia 2000]	0:23	0:38		
112	Tchaikovsky	Symphony No. 6 M. IV	6:12	6:27		
113	J.S. Bach	Cello Suite No. 5 M. III	1:36	1:51		
114	Rachmaninov	Symphony No. 2 M. IV	12:54	13:09	√	√
115	Debussy	Violin Sonata M. I	0:00	0:15		√
116	Rihanna	Close To You	1:49	2:04		
117	War	Low Rider	2:52	3:07		
118	Art Blakey & The Jazz Messengers	Pensativa (Fischer)	0:56	1:11	√	√
119	Brahms	Piano Quintet in F Minor M. I	0:00	0:15		
120	Led Zeppelin	Going To California	2:36	2:51	√	√
121	Ravel	Ondine M. I	0:57	1:12		
122	Watsky	Tiny Glowing Screens Pt. 2	0:48	1:03		
123	Bon Iver	Holocene	4:34	4:49	√	√
124	Sibelius	Symphony No. 1 M. II	9:45	10:00	√	√
126	J.S. Bach	Cello Suite No. 5 M. I	6:53	7:08		
127	Beethoven	Piano Sonata No. 32 M. II	15:31	15:46	√	√
128	Alan Menken	Beauty and the Beast (Finale)	0:06	0:21		√
129	Scott Joplin	Maple Leaf Rag	0:00	0:15		√
130	Brahms	Violin Sonata No. 2 M. I	1:52	2:07	√	√
131	Astor Piazzolla	Tango Preparense	0:00	0:15		
132	J. Massenet	"Thais" Meditation	0:00	0:15		
133	G. Finzi	Clear and Gentle Stream	1:12	1:27		
134	Steve Reich	Sextet	0:43	0:58		
135	Motion City Soundtrack	The Future Freaks Me Out	3:00	3:15	√	√
136	J.S. Bach	French Suite No. 5 M. 3	0:00	0:15		√
137	Milo	Note to Mrs	0:10	0:25		
138	Christopher Theofanidis	Bassoon Concerto: I. alone, inward	1:08	1:23	√	√
139	Kid Cudi	Cosmic Warrior	0:28	0:43	√	√

140	Yo Yo Ma	Quarter Chicken Dark	3:09	3:24	√	√
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Piece 3

P #	Composer/artist	Piece	From	To	AB/BC	XYZ
1	Arashi	Tsunagu	1:43	1:58		
2	Austin Peralta	Capricornus	2:36	2:51	√	√
3	Sibelius	Violin Concerto 1st movt	0:00	0:15		√
4	Mahler	Symphony 2, 5th movt	7:02	7:17	√	√
5	Kesha	Woman	0:55	1:10		
6	Camille	Le Festin	1:14	1:29	√	√
7	SHINee	One minute back	1:12	1:27		
8	Tom Petty & The Heartbreakers	American Girl	0:00	0:15		
10	Zac Brown Band	Loving You Easy	1:46	2:01	√	√
11	Rimsky-Korsakov	Russian Easter Festival Overture, Op. 36	0:17	0:32		
12	Matthias Pintscher	Mar'eh	5:09	5:24		
13	Kate Nash	Lullaby for an insomniac	2:28	2:43	√	√
15	Dizzy Gillespie	Groovin' High	3:32	3:47		
16	Chance the Rapper	Unreleased track on Stephen Colbert show	0:48	1:03		
17	Tchaikovsky	Violin Concerto, Op. 35, 1st movt	3:44	3:59		
18	Alejandro Viñao	Burritt Variations	3:33	3:48		
19	Pixies	Where is my mind	1:55	2:10	√	√
20	The Beatles	Blackbird (Rehearsal Take)	0:00	0:15		
21	Verdi	La Forza del Destino (Overture)	1:24	1:39	√	√
22	Kodaline	All I Want (Live)	3:54	4:09	√	√
23	Sondheim	"No More" from Into The Woods	2:55	3:10		
24	Pearl Jam	elderly woman behind the counter in a small town	1:59	2:14		
25	Fritz Kreisler	Caprice Viennois, Op. 2	3:33	3:48		
26	Rossano Galante	Transcendent Journey	4:22	4:37	√	√
27	medley/source unknown - "Nat King Cole and Patti Page - blue Skies (1958)"		0:28	0:43		√
28	Monteverdi	Lamento della ninfa	0:31	0:46		
29	We The Kings	Check Yes Juliet	0:45	1:00		
30	Shostakovich	String Quartet No. 8, Op. 110, end of 1st/beg of 2nd movt	none	none		
31	Daft Punk	Digital Love	3:26	3:41		
32	Thundercat	Show you the way	1:36	1:51		

33	Tom Odell	I know	2:21	2:36		
35	Ingrid Michaelson	You and I	0:35	0:50		
37	Britten	Violin Concerto, Op. 15, Mvt 2	0:41	0:56	√	√
38	Dvorak	New World Symphony, Movt 1	1:59	2:14		
39	Iron Maiden	Phantom of the opera	2:46	3:01		
40	Adele	Turning Tables	2:45	3:00	√	
41	All Time Low	Remembering Sunday	3:20	3:35		√
42	High School Musical Soundtrack	Gotta Go My Own Way (composers: Dodd & Watts)	1:50	2:05		
43	Wagner	Tannhauser Overture	13:08	13:23	√	√
44	Grad Party	Feeling	0:58	1:13		
45	Dr. Dog	That Old Black Hole	0:49	1:04	√	√
46	Ricky Ian Gordon	Wild Swans	2:00	2:15		
47	Yvette Young	Adventure Spirit	4:00	4:15		
48	Aaron Parks	Nemesis	1:09	1:24		
49	Leichenwetter	Chor der Toten - Live	3:30	3:45		
50	Kendrick Lamar	M.A.A.D. City	0:10	0:25		
51	Chopin	Op. 22, 2nd movt	3:45	4:00	√	√
52	Rzewski	Which side are you on?	15:05	15:20	√	√
53	The Leonid Garin Ensemble	Хороши вечера на Оби (composed by Fattach)	0:32	0:47	√	√
54	Eugène Ysaÿe	Violin Sonata, Op. 27, No. 5: Danse rustique	5:01	5:16		
55	Bruno Mars	Versace on the floor	3:02	3:17		
56	Prince	When doves cry	0:00	0:15		
57	Eric Whitacre & Guy Sigsworth/Virtual Choir 4	Fly to paradise	1:53	2:08	√	√
58	Marcy Heisler & Zina Goldrich	Alto's Lament	1:08	1:23		
59	Victor Feldman & Miles Davis (perf. by Miles Davis quintet)	Joshua	0:32	0:47	√	
60	JC	說散就散	0:47	1:02		
61	Beethoven	Piano Sonata 7, 1st movt	0:29	0:44	√	√
62	Schubert	Quintet in CM, Op. 163, 1st movt	2:11	2:26	√	√
63	Yasuo Sueyoshi	Mirage for Marimba	2:59	3:14	√	
64	Eagles	Wasted time	1:50	2:05		
65	Mendelssohn	Piano Trio No. 2, 1st movt	0:00	0:15		

66	Violin and piano, by Hubray, based on Bizet	Carmen Fantasie	3:35	3:50		
67	Brad Mehldau Trio	Blackbird (Lennon-McCartney)	0:30	0:45	√	√
68	Haywyre	Synergy	2:07	2:22		
69	Death Grips	Hacker	0:19	0:34		
70	Rachmaninov	Piano Concerto 2, 3rd movt	1:08	1:23		
71	Vivaldi	Four Seasons, Winter, 1st movt	0:39	0:54	√	√
72	Milhaud	Suite Francaise, 4th movt	0:00	0:15		√
73	The Ink Spots & Ella Fitzgerald	I'm beginning to see the light	1:25	1:40		
74	Mozart	Serenade in Bb, K361, iii	0:31	0:46		
75	Baritone Explosion (comp. by John Coltrane)	Blue Train	1:05	1:20		
76	Logic	1-800-273-8255	1:05	1:20		
78	Tchaikovsky	Valse Sentimentale, Op. 51 No. 6 (appears to be an abridged piano and violin version)	0:00	0:15		
79	Chet Atkins and Merle Travis (composed by Gus Kahn, Isham Jones)	I'll see you in my dreams	2:33	2:48		
80	Snarky Puppy	Outlier (from live DVD, "We Like it here")	4:30	4:45		
81	Jeff Williams and Casey Lee Williams	Red Like Roses Part II (from RWBY: Volume 1 Soundtrack)	1:23	1:38	√	√
82	Mozart	Sonata for Two Pianos, K448, i	1:33	1:48		
83	Handel	"Sta nell'Ircana" from Alcina	3:19	3:34	√	√
84	Meg Mac (composed by Bill Withers)	Grandma's Hands	2:19	2:34	√	√
85	Beach Fossils	Sleep Apnea	0:11	0:26		
86	Danny L Harle	Super Natural	0:49	1:04		
87	Sia	The Greatest	0:43	0:58		
88	Ben Wendel Quartet	Still Play (live at the Blue Whale in Los Angeles, CA on January 23rd, 2015)	2:15	2:30		
89	Dutilleux	Cortege from Sarabande et Cortege	0:40	0:55		
90	Linkin Park	One More Light	1:24	1:39		
91	Tauren Wells	Hills and Valleys	0:50	1:05		
92	Shostakovich	Piano quintet in G Minor, Op. 57, 1st movt	3:08	3:23	√	√
93	dodie	Intertwined	0:00	0:15		

94	Ben Wendel with Julian Lage	The Seasons: July	1:23	1:38	√	√
95	Stromae	Ave Cesaria	1:01	1:16		
96	J.S. Bach	"Mache, dich, mein herze, rein" from St Matthew Passion, BWV 244	0:47	1:02		
97	Charlotte NC Citywide Hymn Choir	Unknown song, performed for Black History Month	0:29	0:44		
98	Gucci Mane	5 Million Intro	0:15	0:30		
99	Coldplay	Fix You	2:57	3:12		
100	Porter Robinson & Madeon	Shelter	2:50	3:05	√	√
101	Debussy	Arabesque 1	2:55	3:10		
102	Stan Kenton (Comp. by Ernesto Lecuana)	Malaguena [from 1995 Best Of CD]	3:41	3:56		
103	Radiohead	Videotape	0:19	0:34		
104	Snarky Puppy	Lingus [from live DVD, "We like it here"]	7:03	7:18	√	√
105	Billy Joel	Vienna	1:13	1:28		
106	Mendelssohn	Violin Concerto in Em, Op. 64, 1st movt	5:37	5:52	√	√
107	Kaskade	Summer nights remix	2:15	2:30		
108	Verdi	"Dammi tu forza, o cielo!" Violetta's scene from La Traviata, Act II (treating the "movement"/"song" as being pp. 173-181 of Ricordi piano vocal score Printing #133060)	3:08	3:23		
109	J.S. Bach	Fugue from Toccata and Fugue in Dm, BWV 565	5:38	5:53		
110	Chance The Rapper	Finish Line/ Drown	5:38	5:53	√	√
111	AJR	Weak	2:35	2:50		
112	Elgar/ VOCES8	Lux Aeterna	2:14	2:29		
113	Schubert	Piano Trio No.1 in B flat, Op.99, 2nd mvt	1:33	1:48		
114	李偲菘	我怀念的	none	none		
115	Debussy	Violin Sonata, 1st mvt	4:22	4:37		
116	Brockhampton	Fight	0:55	1:10		
117	Dizzy Gillespie	Fiesta Mojo	2:43	2:58		
118	Art Blakey	Skylark (comp. Carmichael and Mercer)	3:15	3:30	√	√
120	Billy Joel	Vienna	1:39	1:54		
121	J.S. Bach	Aria - Goldberg Variations	0:00	0:15		

122	Grace VanderWaal	Moonlight	0:18	0:33	√	√
123	Bear's Den	Elysium	3:07	3:22		√
124	Stravinsky	Finale - Firebird Suite	1:26	1:41	√	√
126	Handel	Arrival of the queen of sheba	1:06	1:21		
127	Brahms	1st mvt - Violin Sonata No.1 in G Major, Op.78	10:17	10:32		
128	Kiah Victoria	Hollow	2:49	3:04	√	√
129	Elpidio Ramírez/ Pedro Galindo	La Malaguena (Salerosa) from Once Upon a Time in Mexico	0:51	1:06	√	√
130	Dvorák	Song My Mother Taught Me	1:58	2:13		√
131	Aram Khachaturian	Sabre Dance from Gayan Suite No. 3	0:53	1:08		
132	Beethoven	Cello Sonata No. 3, 1st movt	1:09	1:24	√	√
133	Girlyman	This is Me	3:55	4:10		
134	Alejandro Viñao	Khan Variations	8:38	8:53		
135	Modern Baseball	Holy Ghost + Wedding Singer [technically two songs on the album, but it appears fans sometimes treat the two as one]	0:47	1:02	√	√
136	Schumann	Sonata No. 1 in F-Sharp Minor, 3rd movt	0:01	0:16		
137	Foggieraw	U Can't Be My Baby	0:50	1:05	√	√
138	Voctave	Disney Love Medley	3:34	3:49	√	√
139	Justin Vernon, Bryce Dessner, and Aaron Dessner	Love More	4:20	4:35		
140	Miles Davis (comp. Rogers and Hart)	My Funny Valentine (Live at philharmonic hall, NY, Feb 1964)	2:31	2:46		