VISUALIZATION OF SOUNDS:

IMPROVING THE LISTENING EXPERIENCE THROUGH DIGITAL VISUALIZATION

by

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VISUALIZATION OF SOUNDS: IMPROVING THE LISTENING EXPERIENCE THROUGH DIGITAL VISUALIZATION

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Abstract

In this project we will observe the persuasiveness of visualization when pertaining to audio data. Specifically, we look at instrumental music composition and observe how visualization can facilitate the communication of a music-maker's state of mind. We first examine, through a research process, how visualization can facilitate the processing of information. Then, steps are taken using data bending and digital data visualization techniques – with minimal creative input – to generate animated visuals from the audio data. Finally, the digital visualizations are introduced to participants via a survey to measure how effective these visualizations were at translating intentionality.

Keywords - Data visualization, data bending, glitch effect, Blender, audio visualization, music, Photoshop, 3D modeling, texturing, blender animation, blender modifiers

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Introduction

Evergreen and Metzner (2013) said “Data visualization is often used in two main ways - as a tool to aid analysis or as a tool for communication” (p. 5). However, it can also be said that data visualization allows us to communicate information better *because* it facilitates analysis. As such, this paper explores the ways in which digital data visualization can be used to communicate the intentionality of audio compositions and reflect on rather these visuals can facilitate the analysis of that data. Thus, following a research process, *data bending* techniques were performed to translate audio compositions into images (den Heijer, 2013). These images were subsequently used to create 3D animations. It is important to note that the visuals were made with as little creative bias as possible to ensure that the intentionality of the music was not compromised. Furthermore, the *intentionality of music* – the information a musical composition means to communicate – is heavily reliant on perception, as is the case for most art forms (see Høffding & Schiavio, 2019). Thus, to avoid ambiguity in the interpretation of the research findings, we allow the composers of the audio to indicate what they intended on communicating in their compositions by picking, from a list of options, the *mind state* communicated in each song - the composer's emotional state or mood. Finally, participants are asked to take part in a visualization exercise during which they are asked to identify the *mind state* depicted in the visuals. Their answers are then compared to the composers to measure how effective the visuals are at communicating their intent.

Literature Review

Background

Processing Information Through the Senses

The broader objective of this research project was to identify an effective way to aid the understanding of sound through digital visualization. According to Jeong (2019, p. 22), when processing information, humans prioritize the sensory organs in the following order: Sight (70%), Hearing (20%), Smell (5%), Touch (4%), and Taste (1%) (Jeong, 2019). Sight is by far the most important sense for processing information because visual perception incorporates form, color, movement, and depth in the translation of information (Jeong, 2019). Hence, we noted the elements of visual perception as guiding principles in the development of the visualizations used in this research; and further investigated the benefits that can be found in using data visualization to communicate information.

Benefits of Data Visualization in Communicating Information

Evergreen and Metzner (2013) suggest that because the purpose of visualization is to educate, visuals should communicate data with the intention of supporting cognition (p. 6). In that way, effective data visualization could benefit in aiding the recall and retention of information. Furthermore, effective visuals will prevent information overload by communicating a message in a clear and straightforward manner. Thus, two main concepts of cognition - simplification and emphasis - are introduced to illustrate how data visualization can be used to support the brain's intake, interpretation, and retention of information (Evergreen & Metzner, 2013, p.18). The authors suggest that effective data visualization reduces *visual noise* - unnecessary colors, lines, decimals etc. - and *non-data ink* - anything that does not directly help the understanding of the data (Evergreen & Metzner, 2013, p. 6). Effective visualization also emphasizes the elements that are most likely to help the viewer interpret the data. Minimizing *visual noise* and *non-data ink* benefit data visualization because viewers are likely to abandon trying to understand a visualization if it is overly complex (Evergreen & Metzner, 2013). In addition to facilitating the understanding of information by simplifying and emphasizing data, visualizations can also aid in making the information communicated more persuasive. However, some factors can hinder the persuasiveness of visualizations (Pandey, Manivannan, Nov, Satterthwaite, & Bertini, 2014). For example, in their study, Pandey et al. (2014) used three different topics to test the effectiveness of visualization with tables and charts. The results demonstrated that charts were more persuasive than tables when viewers had a strong attitude about the topic, whereas, tables were more effective when participants had a strong attitude against the topic (Pandey et al., 2014). But, the research results did not clarify whether charts were more effective because of their visual appearance or due to the way the information was presented (Pandey et al., 2014). Furthermore, in measuring the persuasiveness of data visualizations, the authors focused solely on the attitude changes participants had on the topics (Pandey et al., 2014). Hence, they did not consider the degree of confidence participants had in their views of the topic prior to the visualizations versus their degree of confidence in their changed attitudes afterwards (Pandey et al., 2014). Still, we note that the *medium*, *topic* and the person's *degree of confidence* in their position on said topic, are factors that could impact how effectively data visualization can persuade. Thus, to maximise the effectiveness of the visualizations created in this research there was only one topic and medium introduced - music and 3D animation. Furthermore, the research survey will aim to evaluate the participants' degree of confidence in their attitude towards the music.

The Influence of Synesthesia

This research was highly inspired by synesthesia - a phenomenon only experienced by 1-4% of people (Simner et al, as cited in Zamm, Schlaug, Eagleman, & Loui, 2013). In their research, Safran and Sanda (2015) define synesthesia as "[…] an extraordinary perceptual phenomenon, in which individuals experience unusual percepts elicited by the activation of an unrelated sensory modality or by a cognitive process". They further classify synesthesia as either an acquired or developmental occurrence (Safran & Sanda, 2015). Acquired synesthesia can often be induced by drug use or neurologic conditions (Safran & Sanda, 2015). Whereas, developmental Synesthesia - the most frequent form of synesthesia - is intrinsic and often passed down (Safran & Sanda, 2015). The authors suggest that to test developmental synesthesia, it is imperative that the simulated events be prompted by a specific stimulus in a consistent manner (Safran & Sanda, 2015). The most common forms of synesthesia are Grapheme-Color synesthesia (64.4%), Time Unit-Color synesthesia (22.4%), and Sound-Color synesthesia (18.5%) – synesthetic events in which text and numbers, times and dates, and sounds are, respectively, perceived as colors (Safran & Sanda, 2015). Research seems to indicate that the rate of synesthetes is higher in artists than the general population (Barbiere, Vidal & Zellner 2007). However, music-color correspondences by artists who are synesthetes might be appreciated by consumers of that art who are not (Marks, as cited in Barbiere et al., 2007). For example, an artist with synesthesia may see a color when hearing music, whereas, their non-synesthetes fan may just feel the color "matches" the music well (Martino & Marks, 2001). Thus, even though most people are not synesthetes, they can experience cross-modal correspondences (Martino & Marks, 2001).

The four properties of visual perception demonstrate the way humans can be approached in the visualization of sounds, as synesthesia provides a framework for the creation of the visuals (Jeong, 2019). Thus, in this research we treated synesthesia as a form of data visualization, as audio data – the stimuli – was used in a systematic way to trigger visuals. For example, a music recording software was caused to generate image data from a song by converting a native Mp3 file into a .raw image format. Creating a computerized cross-modal correspondence experience where software was manipulated to visually perceive sound.

Methodology

Data Visualization Methodology

Considerations were taken to determine the best method of visualization. Some of the most popular data visualization techniques revolve around the stationary visual representation of data. However, with these forms of visualizations, it may be difficult to represent continuous changes within a song. So, the method of visualization selected had to allow for motion and animation in order to capture all possible shifts in a composition. Thus, to preserve the integrity of the audio data, animated visualizations were created via 3D modeling – a technique for producing 3D digital representations of any object or surface (Petty, n.d.). The process of creating the data visualizations consisted of three major phases: First, audio data was converted into a .raw format. Then, that new data format was used to generate images. Lastly, these images were brought over to a 3D modeling software to create the visualizations. Additional information on the technology used is available in Appendix A.

Activity 1: Data Bending

The first method used at this stage was data bending - the process of manipulating a media file of a certain format, using software meant to edit files of another format (Whitelaw, 2004). Data bending can be traced back to a technique in the 1970s referred to as *circuit-bending* (Hertz & Parikka, 2012). Hertz and Parikka (2012, p.426) have described *circuit bending* as a technique where synthesisers were used to transform battery-powered objects like toys into musical instruments and homemade audio generators. Thus, it is important to note that, given the nature of the data bending process, the audio files were inherently modified as they were transformed into .raw files. However, given that the data bending was done with similar audio files of the same length, and bent in an identical manner, it was assumed that the use of this method would yield reliable results. Thus, a free audio recording platform, Audacity 2.3.2, was used to turn audio files to a .raw format – see Appendix B. During the process, all audio files were re-saved as uncompressed .raw files and *encoded* – the act of converting into coded form – as follows:

Activity 1.1: Encoding

Binary digits or bits are the smallest unit of data in a computer and are represented by ones and zeros . Additionally, Sample Bit Depth (*n*) is the number of bits used to describe the data (Bit Depth., .n.d.). Thus, the higher the Bit Depth the more unique values are used to describe the audio file exported (Ahmed, 2012). For example, there would be a maximum sample value of 16,777,216 in a 24-bit file, while a 16-bit file would only contain up to 65,536 values (Data Representation, 2014). Thus, the higher the bit rate of the .raw file the more values will be used to accurately represent the audio data.

Activity 1.2: New Format Signed vs Unsigned Bits

Considerations had to be made as Audacity provided *encoding* options for signed and unsigned bits. Signed integers represent all numbers – zero, positive and negative – whereas, unsigned integers can only process positive numbers (Data Representation, 2014). However, the software provided no unsigned bits higher than 8-Bit. Thus, given that Bit Depth was a priority, in the creation of the data visualizations, only signed bits were selected.

Activity 1.3: A-law & U-law

According to Ben Joan (2010), A-law and U-law algorithms are mostly used for telephony systems. Furthermore, the main differences between the two are that U-law provides more Dynamic range – difference between the quietest and loudest sound – than A-Law (Joan, 2010). However, higher dynamic range leads to more distortion when sound input is very soft, making the A-law format the most desirable option of the two (Joan, 2010).

Thus, the Signed 32-bit encoding indicative of 4,294,967,295 values (Data Representation, n.d.). – and A-law encoding formats were selected to create two .raw files with the deepest available description of the audio file and the widest dynamic range on Audacity.

Although a straightforward process, this encoding approach of data bending was crucial for translating sounds into images.

Activity 2: Generating Glitch Images

Once the raw files were produced, the process of converting them into images was started using a *Glitch Art* technique - a "glitch" effect is created on an image when there is an error or a flaw in the file (Peña, 2017, p. 90). These errors can cause the images to appear differently, hence, creating a "glitch" in the image. A good example of the glitch effect, given by Leigh (2019), is the static image a TV can generate when it loses signal.

In this research however, the *Glitch Effect* is caused intentionally through the data bending process. In this manner, the images generated by the glitch are a direct representation of the .raw files, as opposed to a manipulated image (Mason, 2012). The below process was employed to generate the glitch art.

Activity 2.1: Using Photoshop to Create Images

Raw (.raw) files are computer files that are made up of uncompressed images (Sumner, 2014). They can be transcoded into other formats and are made up of 255 characters that account for every single combination of binary data (0/1) possible - in an array of 8 digits (Peña, 2017). When opening the .raw files on photoshop, the software reads a stream of bytes describing the color information in the image (File Formats, n.d). 3 color channels were selected – RGB: Red, Blue, Green – creating the images seen on Appendix B. The below methods were used to generate the images.

Activity 2.1.1: Photoshop Import. High pixel density and depth were favored features in the process of importing the files to photoshop. However, to be able to observe unbiased results, both the A-Law and 32-Bit .raw files had to be saved with the same dimensions. Whereas, the A-law files could only be opened at an 8-bit rate. Furthermore, because the images were going to be used to create a video, it was determined that a resolution of 1080px would create a more malleable video format.

Activity 2.1.2: Interleaved Vs Non-Interleaved. Lastly, considerations had to be made to create a *non-interleaved* or an *interleaved* image - data is interleaved when it is stored sequentially. However, given that the aim of this process was to provide the most complete representation of the audio files both options were selected. In conclusion, each A-law and 32-bit .raw file, was converted into an *interleaved* and *non-interleaved* 8-bit 1080px – making a total of four images per audio file.

Activity 3: Using Blender to create the MVP

Blender is an open-source 3D software that can be used for modeling, animation, data visualization and more. This software was used to create the visualizations because it is a free easy-to-use software through which 3D objects can be modified to respond to sounds and images/videos. Prior to starting the animation process, each song's glitch images were combined into video clips. This step was taken to ensure that the glitch effect was fully represented in the visualization process. With the tools available on Blender, two main animations were generated. Both animations were solely controlled by the video clips and the audio file's soundwaves.

Activity 3.1: Making Wave Animations

Three steps were taken to create the wave animation. First, a *Wave Modifier*[1], creating ripple-like motion, was used to animate a grid mesh (see Appendix B). By assigning a *Movie Texture* to the modifier, the glitch image clips were used to control the motion of the waves. When a *Movie Texture* is applied to the modifier, blender cycles through each frame and uses its RGB values to determine which vertices[2] to affect. In addition, to keep the textured animation cycling for the length of the audio data (1min), the *Movie Texture* was repeated horizontally and vertically, as well as in the XY positions. Second, the grid's *Material* - the surface qualities (colors, textures etc.) of the object – was used (Materials, n.d.). However, there was significant blurriness when applying the video clip to the *Material Properties* of the grid. So, to make the visualization sharper, the *Material* was assigned a high-resolution glitch image with a *Fluid* render type. Lastly, the *Bake Sound to F-Curves* keyframe was applied so that the audio file's soundwaves could generate the animation data that would control the waves' *Height* – see Appendix B.

Activity 3.2: Making Displace Animations

A *Displace Modifier* was used on an icosphere mesh to create this animation– see Appendix B. Icospheres - polyhedral spheres made up of triangles - were favored for this research because they are uniform in every direction. The glitch image clip was also used as a *Movie Texture* during the process. However, in the *Displace Modifier,* the texture's RGB values were used to move the mesh in the XYZ direction - the direction along which an object's vertices

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[1] In Blender, Modifiers change how objects are displayed and rendered through automatic operations that affect the object's geometry in a non-destructive way.
[2] In Blender, a vertex (vertices in plural) refers to a single point or position in a mesh's 3D space - the vertices of an object are stored as coordinates.

are displaced. During displacement, Red values are moved along the X axis, Green along the Y axis, Blue along the Z axis. Unlike the wave animation, the glitch image clip was also used in the *Material Properties*, so that the surface of the icosphere could cycle between images. Finally, *Bake Sound to F-Curves* was used to control the *Strength* of the displacement – see Appendix B. In Blender an F-Curve is created when animation properties are assigned to an object. The F-Curve is, thus, an interpolation between two animated properties. As a result, when using *Bake Sound to F-Curves,* the soundwaves of an audio file are used as the animation data that would control the curves.

To accurately test the effectiveness of the visualizations, the above process was repeated for each music file. Thus, a wave and displace animation - a total of eight digital visualizations – were presented to participants in the visualization exercise.

Activity 4: Surveying

To test the effectiveness of digital visualization in aiding the understanding of the intentionality of music, participants were presented with a visualization exercise and survey, see Appendix C for detailed results. The survey was separated into six sections: The first asked general questions to help measure participant's *degree of confidence* - how confident they are in their understanding of music. Each of the following four sections consisted of two visualizations – wave and displace animations – and a question asking participants to identify the *mind state* depicted in the visuals. To determine how to describe the composer's *mind state* we observed how Salas, Radovic & Turnbull (2011, p. 1) measured sentiment in their research. To measure sentiment, the authors grouped results into basic emotions and classified them as follows: Joy - which included happy, joyful, and energetic; sadness - sad, downhearted, and alone; anger - angry, hostile, and disgusted; fear - scared, afraid, and shaky (Salas et al., 2011). However, in this research, we measured participants' answers against that of the composers; so we avoided grouping moods and aimed to standardize responses. The music-makers identified the *mind state* they intended on communicating in each audio composition through a list of words - such as calm, sad, depressed, energetic, happy etc. - prior to the exercise. Then after each visualization participants were asked to select – from the same list of words – what they thought the composer's *mind states* were. In the fifth section, participants listened to the songs and again, attempted to identify the composer's *mind state* - this allowed for comparisons. In these sections the results were compared to determine if the data visualizations were effective in translating the audio data. Lastly, survey-takers were asked if they found the visualizations effective in aiding their understanding of the audio data.

Evaluation

Research Findings

Measuring Confidence Levels

Ninety-five percent (Appendix C, p 24) of survey participants - in a sample size of 24 people - found music to be an important aspect of their lives. Furthermore, results show that most participants listen to multiple music genres (95.7%) (p 25) and tend to enjoy the same music as their friends (69.6%) (p 24). Still, a large majority reported exposing their friends to new music (91.3%) (p 24). However, only 30% of them identified as artists or musicians (p 25). These findings lead us to conclude that the participant group is made of music enthusiasts, who are confident enough in their taste, that they seek to influence others.

Data Visualization Survey Results

To ensure that participants visualized the animations on a per song basis, the visualizations were presented in different "Rooms" each representing an audio composition. Results were as follows:

Room 1: Results. The composer of this audio file classified the mind state they were communicating as *Calm.* However, most people depicted the mind state of the composition as *Energetic* (62.5%) (p 26). In fact, only 20.8% recognized the mind state of the composer - the second most popular answer (p 26). However, when presented with the audio data, 70.8% of participants were able to recognize the implication of the music as it was intended (p 28).

Room 2: Results. The composer of this audio file classified the mind state they were communicating as *Calm* and *Sad.* However, very few people identified these mind states through visualizations. Instead, 41.7% of participants classified the song as *Energetic* (p 26). In the audio portion of the survey participants still demonstrated a relatively low understanding of the song – *Calm* (33.3%), *Sad* (25%), and *Depressed* (16.7%) (p 28). Given that a depressive state could easily be interpreted as sadness, we note *Depressed* as an accurate depiction of the artist's mood.

Room 3: Results. Although the composer classified this song as *Energetic,* only 20.8% of people recognized that mind state (p 27). In fact, the most perceived state was *Calm* - 33.3% of the results (p 27). Like the first two rooms, the composer's mind state was only communicated through the audio - as 54.2% of people finally identified the song as *Energetic* (p 29).

Room 4: Results. This room was the most successful of the four. The composer had classified their mind state as *Energetic* and *Happy*, and 70.8% of people understood that mood (p 26). The Participant's understanding of the music was further confirmed as 79%, perceived the music as *Energetic* once they heard it (p 29).

The Effectiveness of the Visualizations

Aside from the fourth room, the differences in the information perceived in the visualizations and music were drastic. Thus, we infer that the visualizations produced, did not efficiently *translate* the audio data. Furthermore, the visualizations did not adequately *communicate* the intentionality of the music.

The Perceived Effectiveness of The Visualizations

Furthermore, when analyzing the *perceived* effectiveness of the visualization exercise, results show that most people were not very confident about the accuracy of their answers - 45.8% selected 3, on a scale of 5 (p 30). However, despite results showing otherwise, 50% of people believed the digital visualizations were helpful in their comprehension of the audio compositions (p 30). The digital data visualizations presented on the survey can be seen here "https://www.youtube.com/".

Conclusion

A major takeaway of this research is that the audio to visual data translation, for the most part, was a one-to-one process. Yet, the audio elements of the songs were not amplified enough in the visualizations to allow participants to connect them to the visuals. So, if the visualizations were an accurate representation of the audio - as the process suggests; then, there may have been a mental disconnect between what was perceived as a visual cue and what was perceived as a visualization of sound. This can be explained by Masahiro Mori's (2012) *uncanny valley* hypothesis. The hypothesis suggests that the human brain cannot wrap itself around humanlike movements applied to artificial characters - as it usually creates a sense of unease (Mori, 2012, p. 99). Instead, Mori suggests that to get a positive response to humanlike movement, designers should aim to be less literal by exaggerating or defying human likeness (Mori, 2012, p. 100). Secondly, the visualizations generated in this research were only a measure of volume and pitch; so other elements that make up music - such as melody, timber, harmony etc. - were not captured. Thus, it is possible that a composer's mind state be better communicated through - or in addition to - those missing elements. Hence, some next steps could include exploring whether over-amplifying the audio data presented in the visuals, could allow participants to better connect the digital visualizations to the audio. As well as, examining how the other elements of music missing in this research could be visualized. And determining rather visualizing them would improve the accuracy of the mind states perceived in the digital visualization of music data.

Appendix A – Description of Technology Used

Description of Technologies Used Throughout the Development Process

Technology Category	Technology	Description
Programs	Audacity 2.4.2	A multi-track audio editor and recorder.
	Adobe Photoshop CC	An imaging and graphic design software.
	Blender 8.83	An open-source 3D software for modeling, animation, and more.
Graphics	.raw	A file format for uncompressed images.

Appendix B – The Design and Development Process

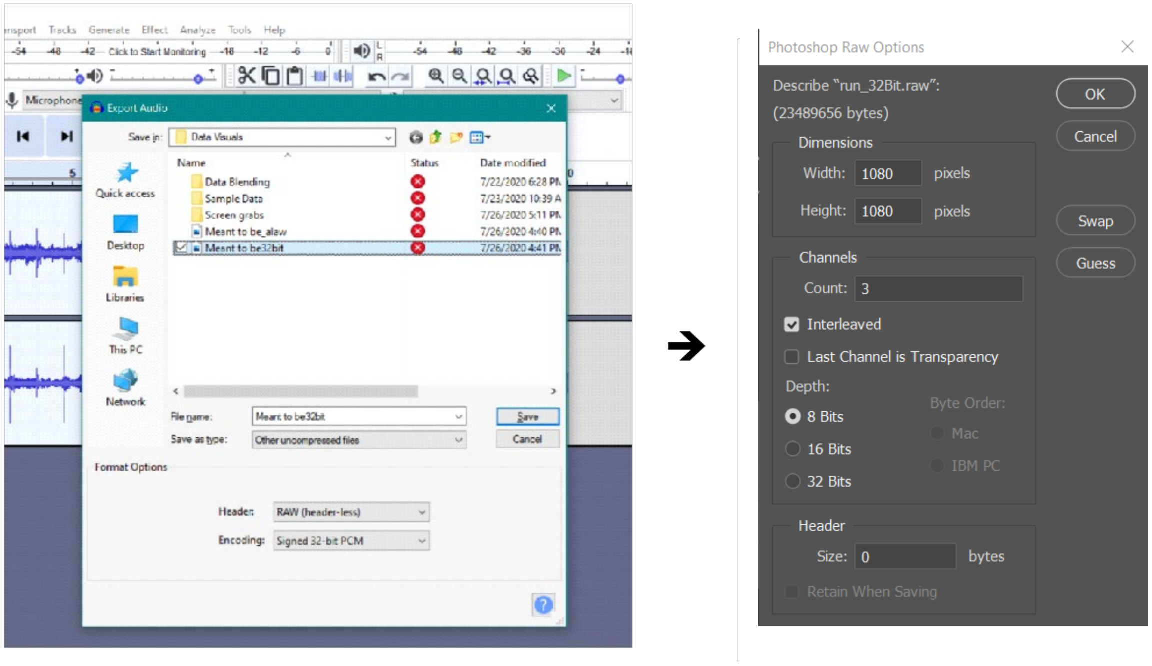

Figure B-1. The Design and Development Process. Screenshots of the Data Bending process as the audio data is saved as a .raw file on Audacity and opened on Photoshop.

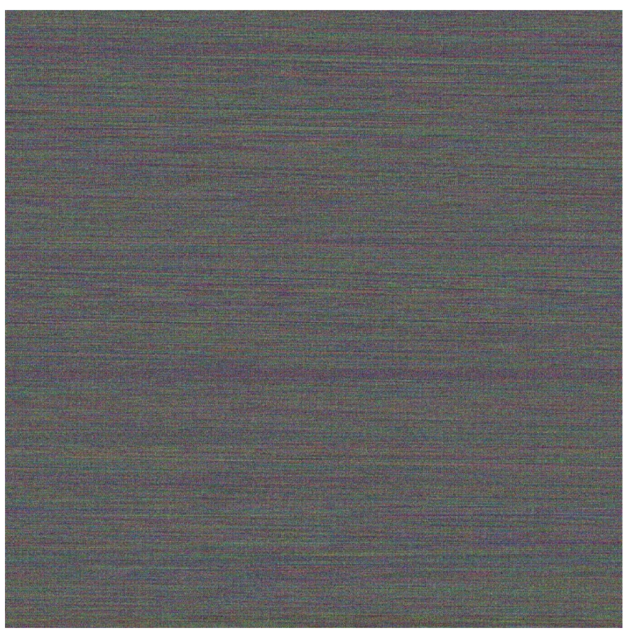

Figure B-2. The Design and Development Process. Glitch Image generated from opening .raw files on Photoshop.

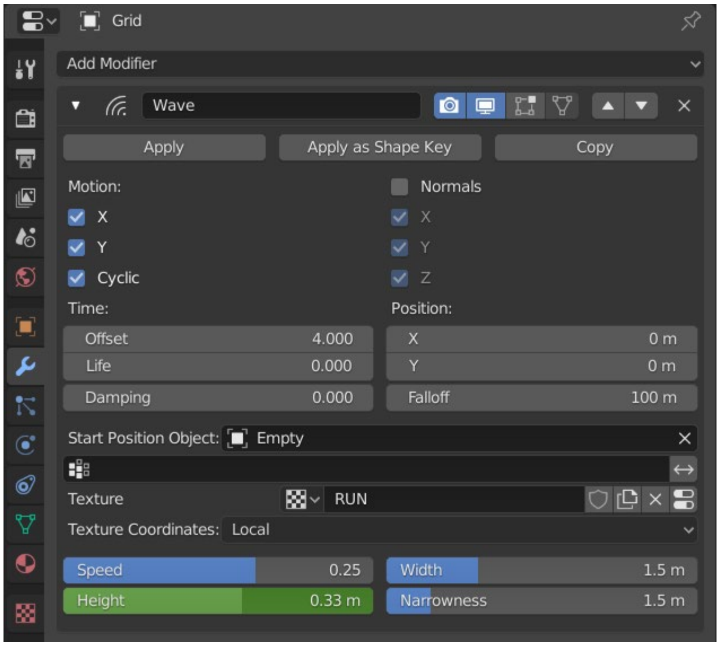

Figure B-3. The Design and Development Process. Screenshot of Wave Modifier properties used to create the wave animation on Blender 2.42.

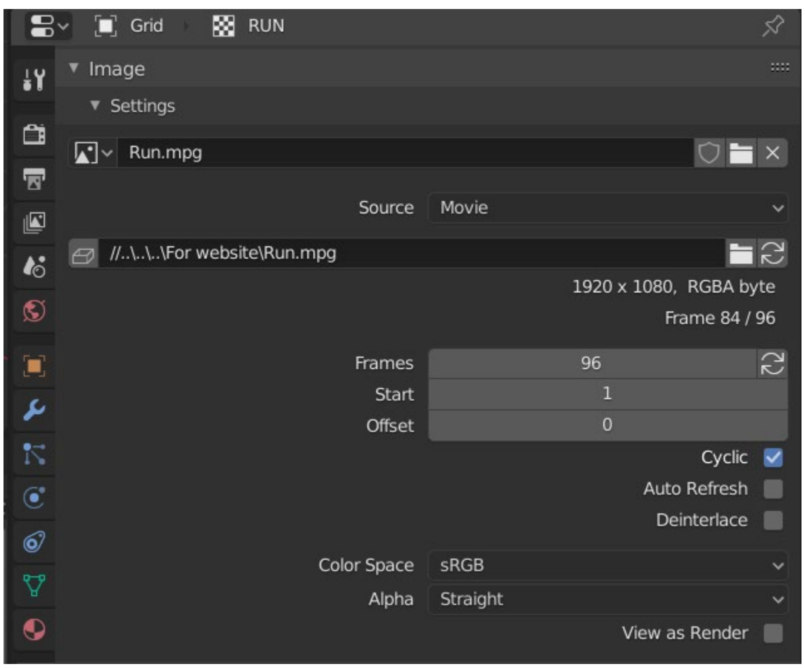

Figure B-4. The Design and Development Process. Screenshot of Wave Materials properties used to create the wave animation on Blender 2.42.

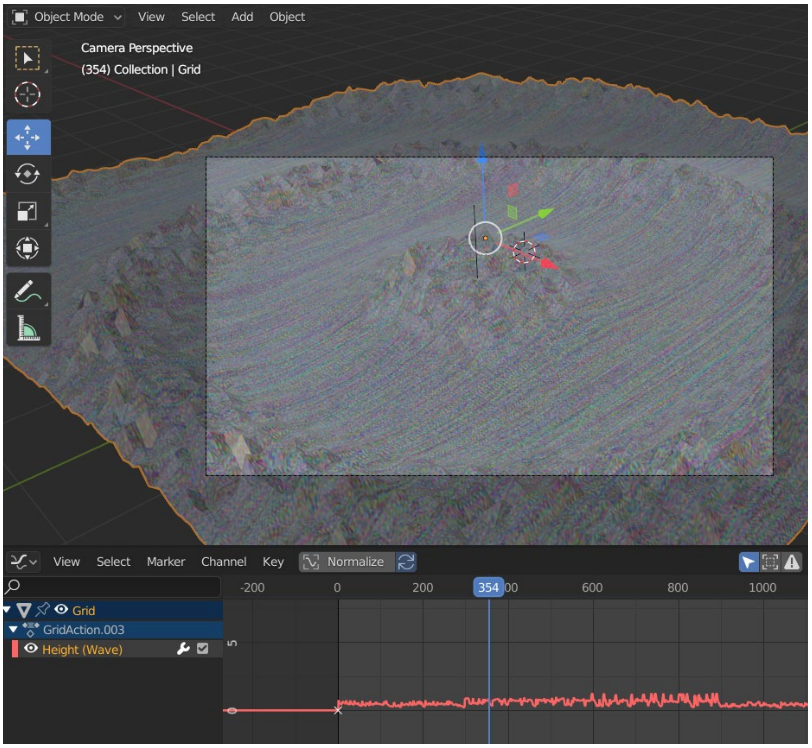

Figure B-5. The Design and Development Process. Screenshot of the Bake Sound to F-Curve keyframe as it uses soundwaves to control the Height of the wave animation on Blender 2.42.

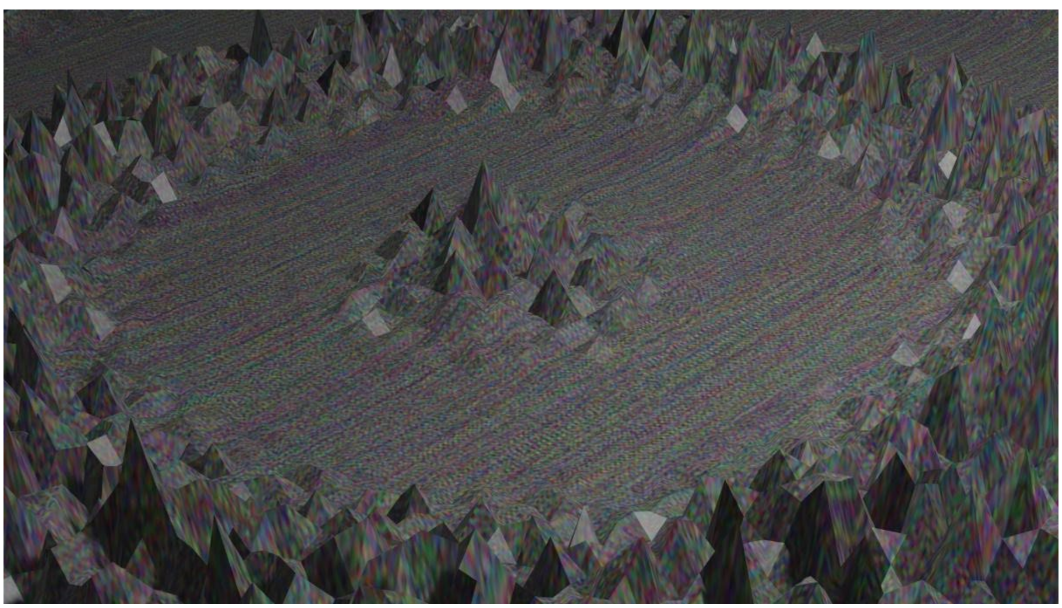
Figure B-6. The Design and Development Process. Rendered image of wave animation.

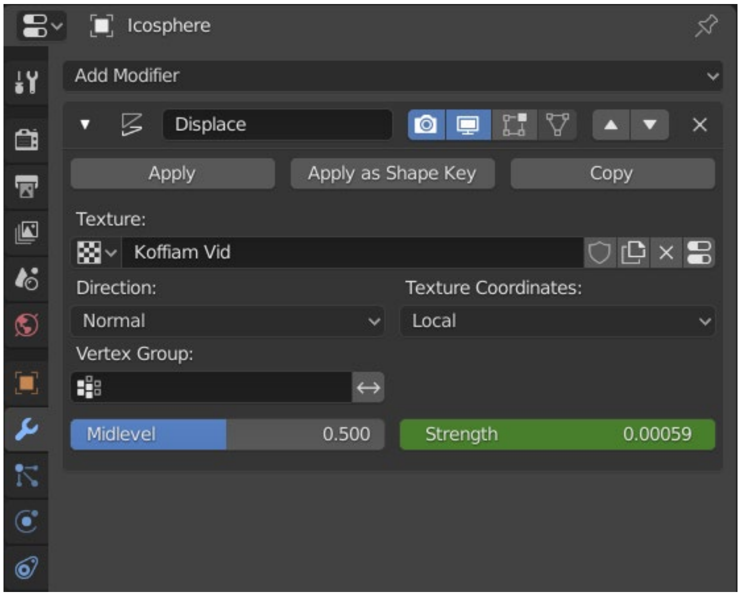

Figure B-7. The Design and Development Process. Screenshot of Displace Modifier properties used to create the displace animation on Blender 2.42

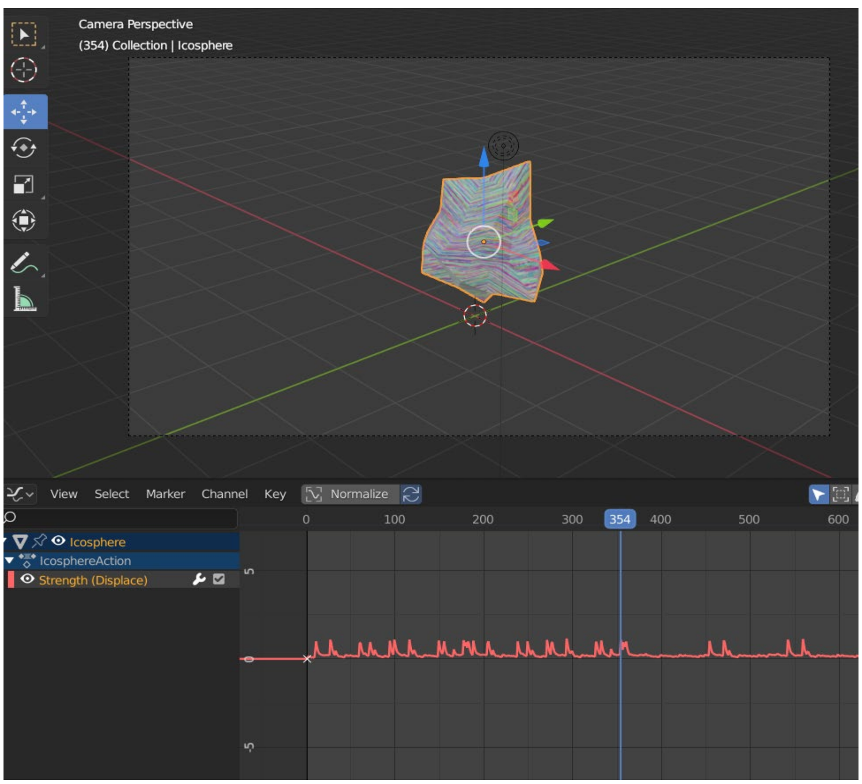

Figure B-8. The Design and Development Process. Screenshot of the Bake Sound to F-Curve keyframe as it uses soundwaves to control the Strength of the displace animation on Blender 2.42

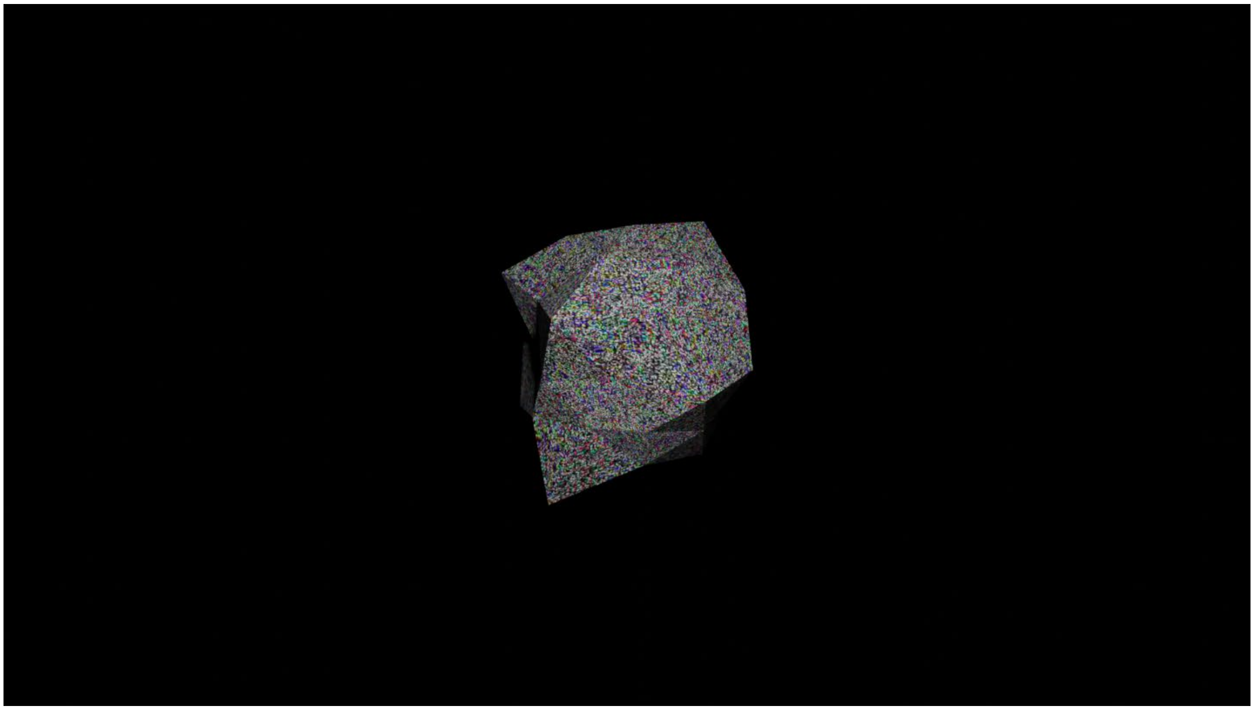

Figure B-9. The Design and Development Process. Rendered image of displace animation.

Appendix C – Digital Visualization Survey

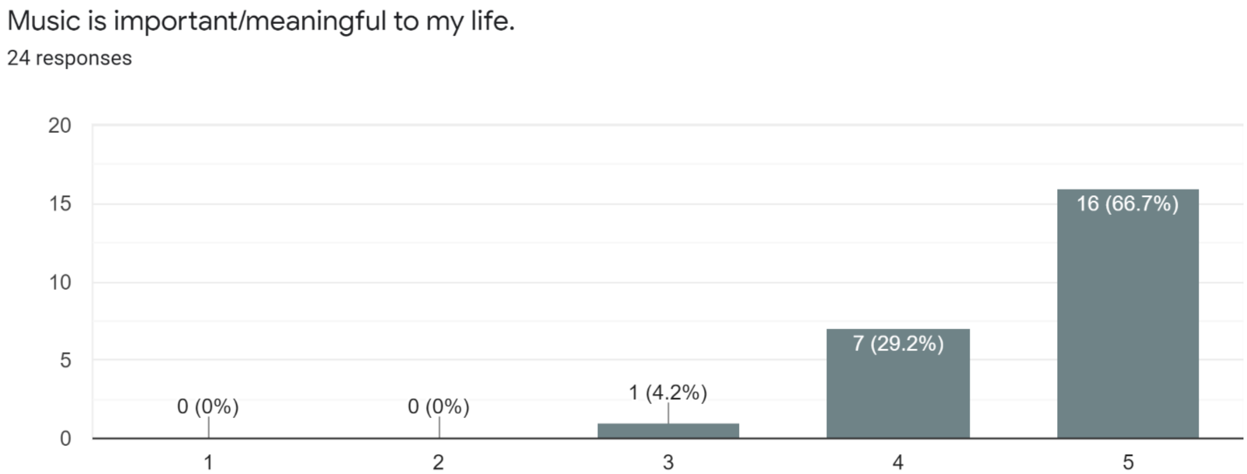

Figure C-1. Digital Visualization Survey. This bar graph represents the results from the stated "Yes" or "No" question.

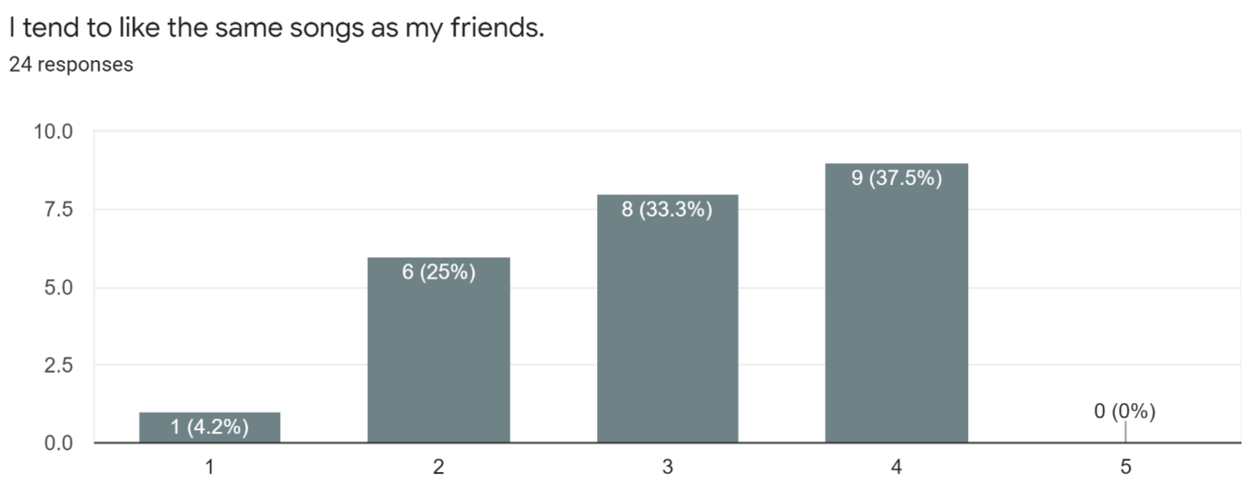

Figure C-2. Digital Visualization Survey. This bar graph represents the results from the stated question on a scale of "Never" to "Always".

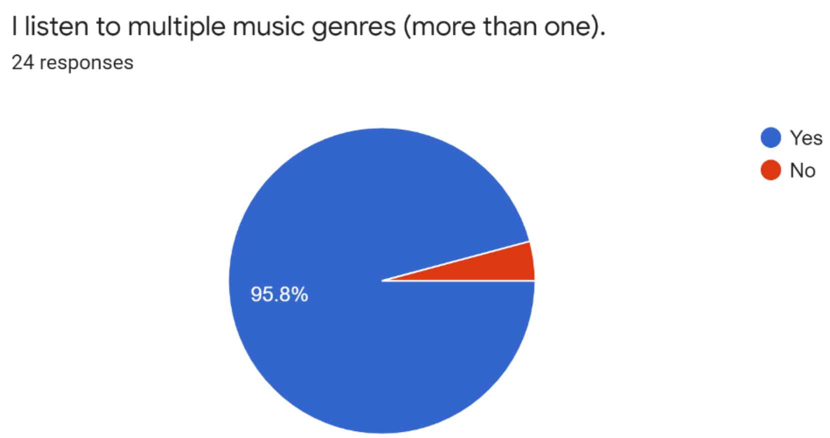

Figure C-3. Digital Visualization Survey. This pie chart represents the results of the stated question.

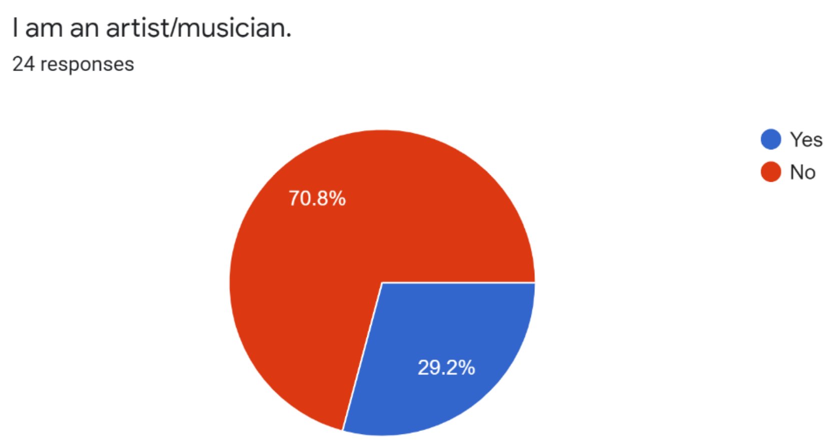

Figure C-4. Digital Visualization Survey. This pie chart represents the results of the stated question.

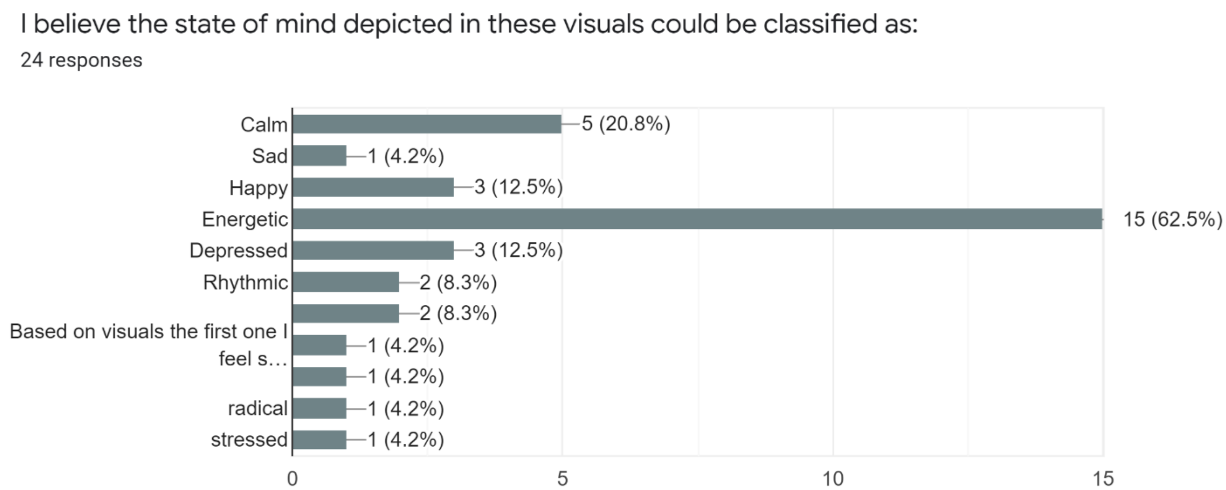

Figure C-5. Digital Data Visualization Survey. This bar graph represents the results of the stated question.

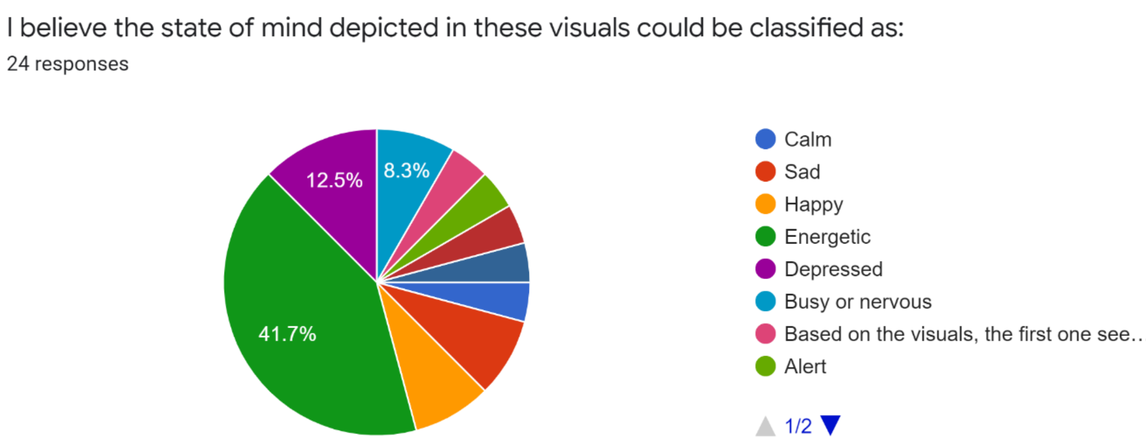

Figure C-6. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

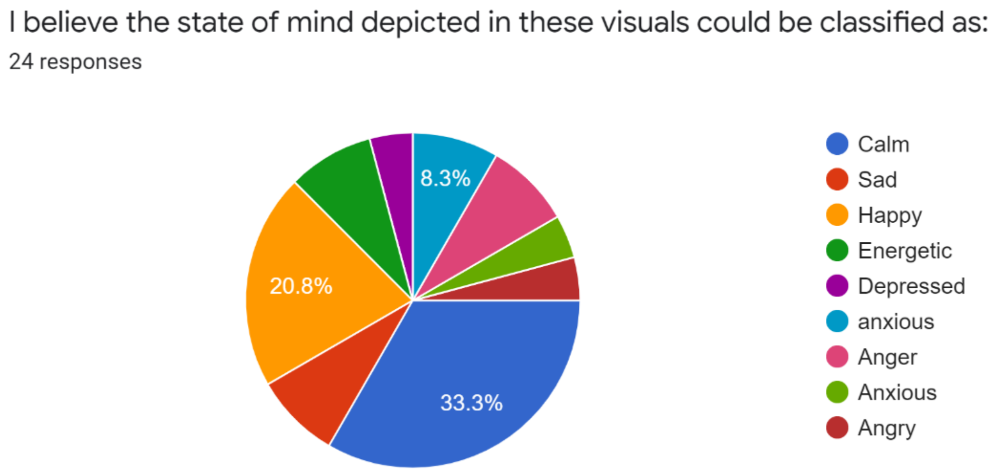

Figure C-7. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

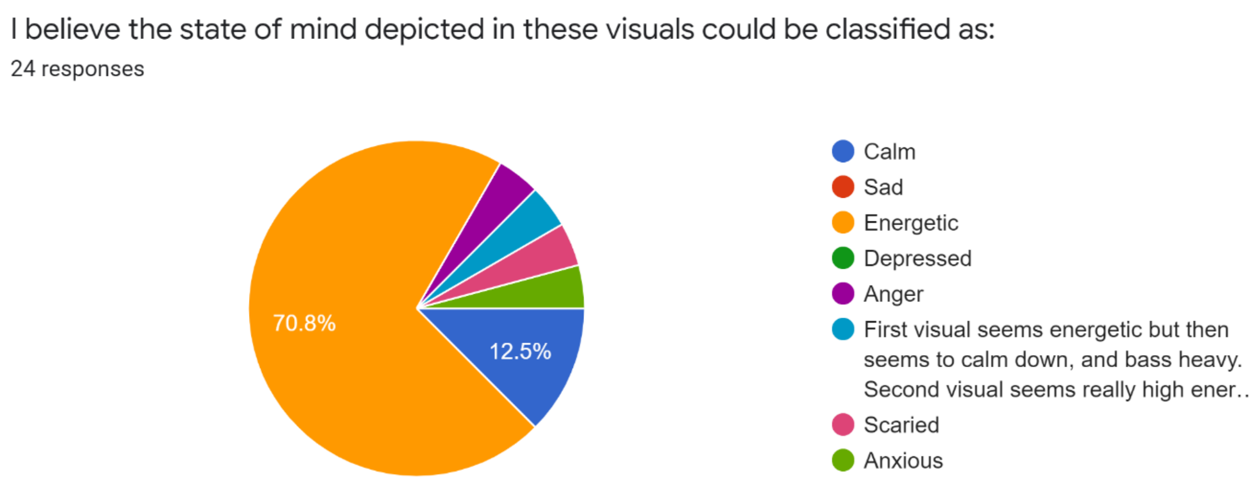

Figure C-8. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

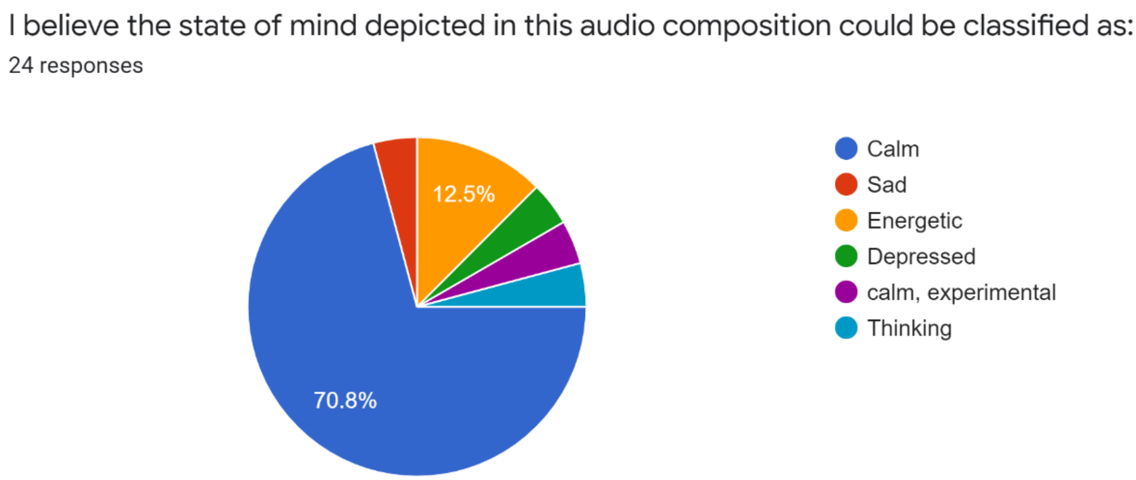

Figure C-9. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

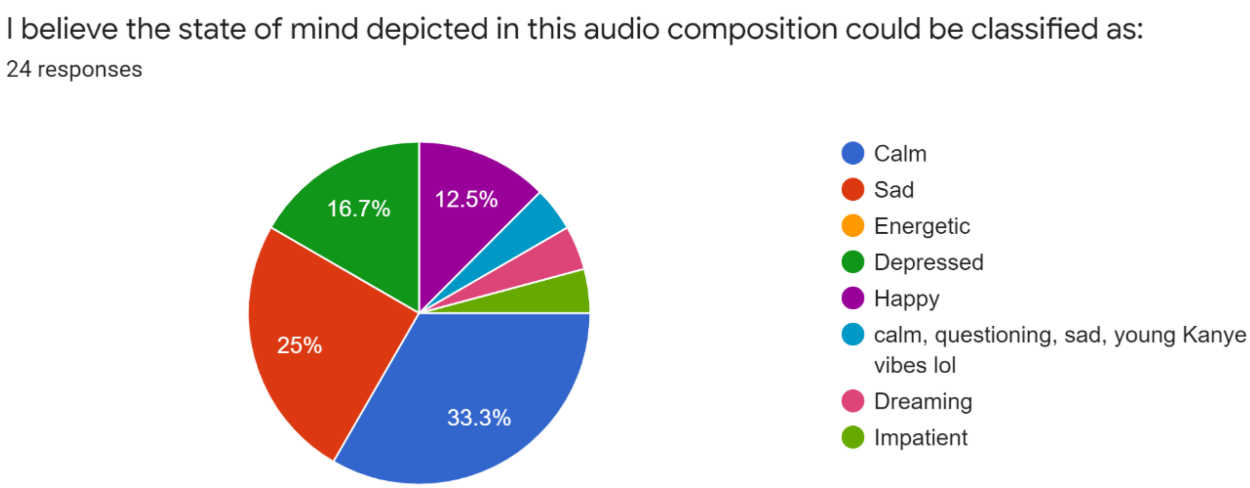

Figure C-10. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

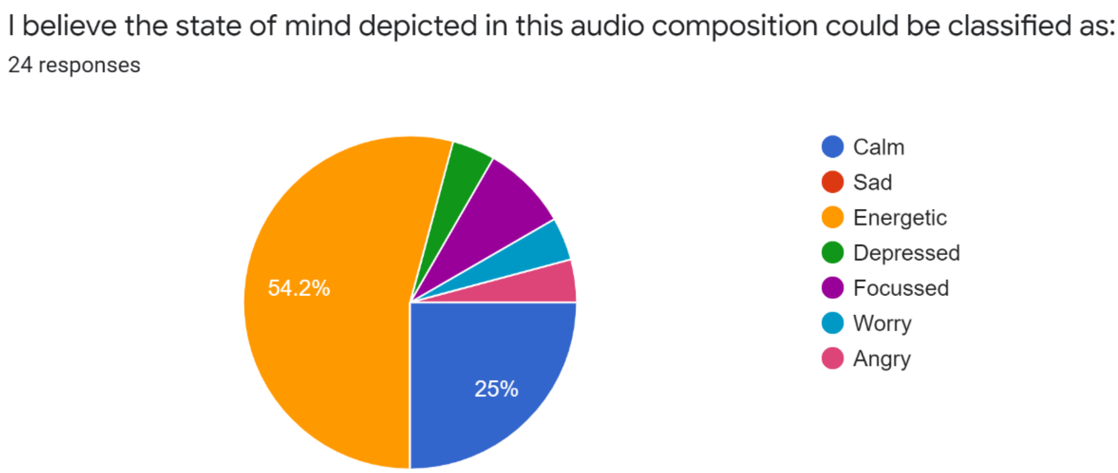

Figure C-11. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

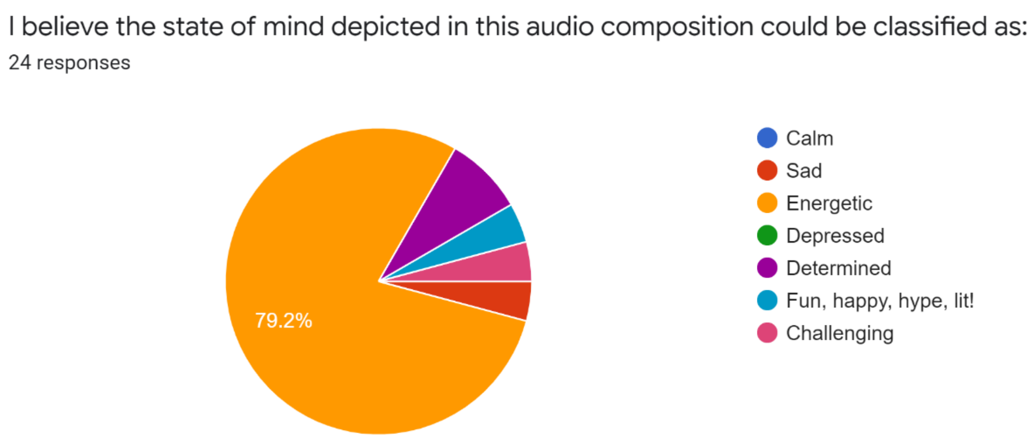

Figure C-12. Digital Data Visualization Survey. This pie chart represents the results of the stated question.

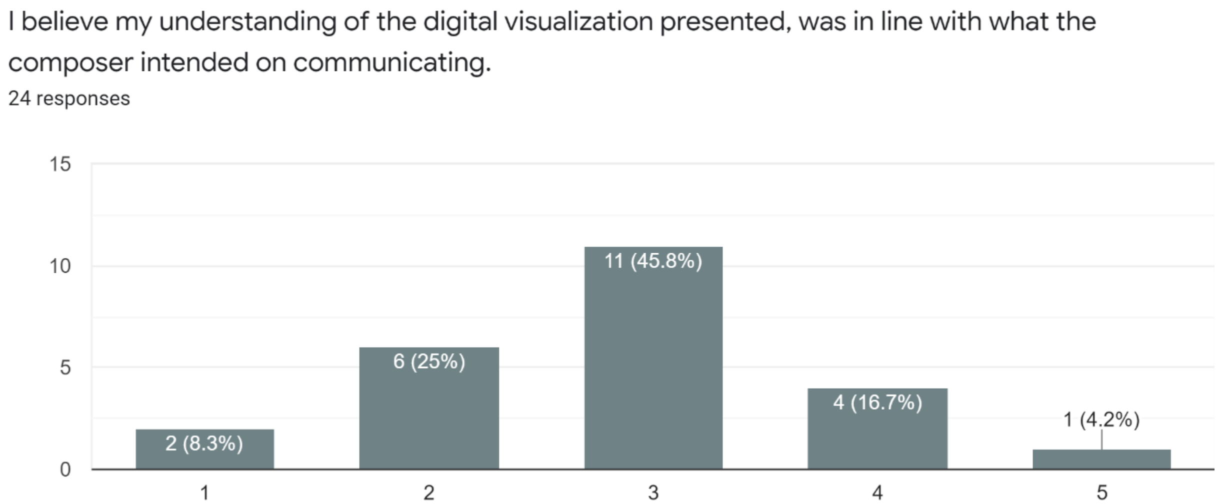

Figure C-13. Digital Visualization Survey. This bar graph represents the results from the stated question on a scale of "Unsure" to "Sure".

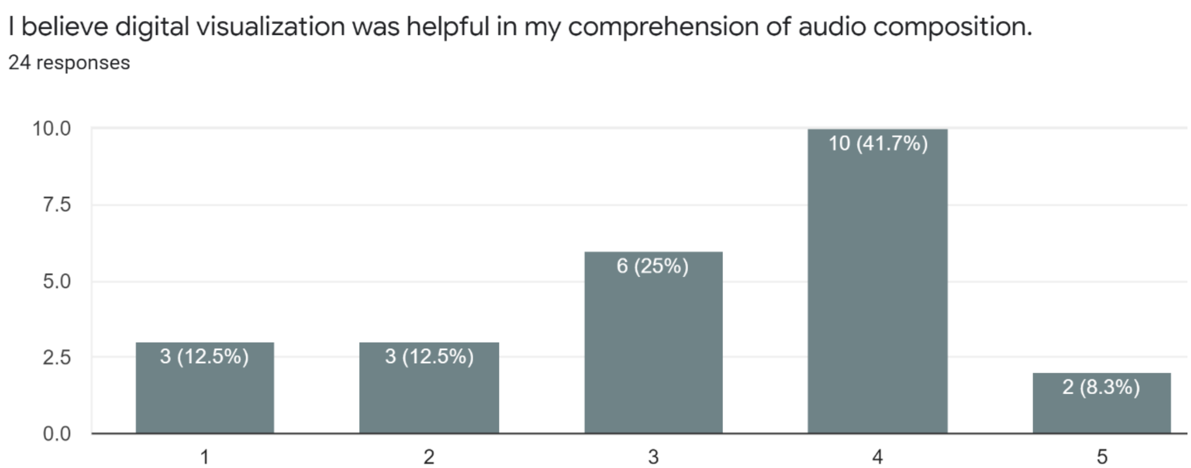

Figure C-14. Digital Visualization Survey. This bar graph represents the results from the stated question on a scale of "Unsure" to "Sure".

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