The Interdisciplinary Center, Herzliya
Efi Arazi School of Computer Science
M.Sc. program - Research Track

Towards personalized melody learning and creative expression

by
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M.Sc. dissertation submitted in partial fulfillment of the M.Sc. degree, research track,
School of Computer Science requirements.
The Interdisciplinary Center, Herzliya

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Acknowledgments

Throughout the writing of this master's work, I received a great deal of support and assistance. I would first like to thank my supervisor, Dr. Revital Hollander. Dr. Hollander was invaluable in formulating the research questions and methodology and providing insightful feedback. You provided me with the tools to choose the right direction and complete my work. In addition, you were available all time, mornings, evenings, and weekends; I couldn't do it otherwise alongside working and having a family.

In addition, I would like to thank my parents for their support in my career and academic studies. You are always there for me.

Also, I would like to thank my friend, Or Peretz, who joined my journey as a colleague to the group but was always there for Consultations, chats, achievements, and disappointments.

Finally, I could not have completed this work without the support of my life partner, Shir, and my two amazing kids Tomer and Ori, who provided stimulating discussions and happy distractions to rest my mind outside of my research.

Abstract

The creative expression refers to a compositional richness and sophistication of how the creator's intents are expressed. Creative expression in music involves choosing from musical elements such as notes, melody, harmony, rhythm, structure, texture, sounds, instruments, processes, and organization. Expressive bounds naturally expand as the creator learns to utilize a greater variety of these musical elements. Still, the learning curve for utilization is steep, which leaves it for relatively few.

Our basic assumption is that everyone can create meaningful music and that creative expression can improve over time. The creator can be either a musician or a non-musician and may/may not have a background in playing an instrument or music theory.

There are many ways by which technology can be utilized in creative endeavors. Our approach notably emphasizes the importance of our main challenge, bridging a creator's personality, ability, knowledge, and creative intentions with computational formalisms of music technology. Our primary assumption is that personalized technology will help identify and realize the creator's creative intents and increase the creator's engagement and confidence in his creative musical abilities. As a result, we assumed that it would reduce the learning curve and break the barriers of creativity, especially among non-musicians that will be able to interact with digital personalized interfaces and create meaningful music.

This research focuses on studying the key features in melody playing that correspond with success in our experiments that can be used to create a profiler component that learns and analyzes user characteristics.

This research aims to explore the effectiveness and impact of melodic, rhythmic, and personal characteristics towards personalization in music creation and learning.

Our main objective was studying about the creator's learning and creation abilities using computational methods. We conducted an experiments with first-year students as participants in our experiments. They were asked to fill questionnaires and to play and interact with our application. All of these sessions were recorded, analyzed, and documented. We divided the data into several groups: demographic details, subjective reports, and documented interaction. We used data science and machine learning techniques for analysis. We based our main insights on unsupervised learning clustering methods with human validation. This study aims to characterize the most significant characteristics and features that increase novices' learning and playing a short melody using digital touch screen interfaces. We also studied how novices express themselves and improvise on the melody they learned. In addition, we explored digital interface efficiency as an educational tool.

Our research questions are:

1. What are the features which best fit to define a musical profile for a creator?
2. Can the learning time for creating meaningful content by a creator be shortened using technology and personal user interface?

3. What are the features that influence the most on new creator success or unsuccess with learning to play a short melody? Such as notes amount, rhythmic accuracy, repetitiveness, etc.
4. Does the UX or interface configuration are also a factors for success?

The analysis results show that using general-purpose applications and interfaces, people without a musical experience can produce meaningful and satisfying creations in a short time while we are breaking some physical barriers. We will show that certain features can distinguish between different groups of people in terms of successful and meaningful creation.

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1 Introduction

Can technology enhance creativity among people with little or no background in music? Music creation requires persistency and a skill set that has to be acquired and maintained. The learning curve for musical studies is very steep yet requires great effort for proficiency. The decisions that a person will make before he begins his studies will influence the skill set and features he will need to cultivate. Music creation requires that the person learn and adapt the characteristics of his musical tool (physical or computer). Music creation tools that exist today, such as DAWs (Digital Audio Workstation), Garage Band, and Guitar Hero, do not consider a minority and primarily functional personal parameters of the creator. We intend to create a personalized creator profile based on his taste, set of skills, and other individual features. The profile can be used in our tool in the decision-making, prediction, generation, and recommendation processes while interacting with the creator. By considering this profile, we would be able to assist the creator and help him express himself better. We assume this will increase his music creation engagement and improve one's creativity and creative processes. The following chapters are organized as follows: In section 1.1, we cover the scientific background on performance music analysis, section 2 describes our experiment method, in section 2.5, we present the experiment analysis and results. Section 3 includes the result summary, conclusions, and future work.

1.1 Scientific background

In this section, we summarize the literature on music analysis methods used to evaluate improvisation and performance.

1.1.1 Computational music analysis

One of the attributes distinguishing music from random sound sources is the hierarchical structure of music.

The musical structure is combining various events such as motifs, phrases, and sections. The musical structure helps to determine the overall layout of the composition. The goal of music structure analysis is to divide a given music representation into musical categories. The first principle for structure analysis s the *musical representation*; the complexity of the representation can influence the difficulty of identifying structures within the music. Second, segmentation may be based on various principles, including homogeneity, repetition, and novelty. The third principle considers different musical dimensions such as melody, harmony, rhythm, or timbre. The last principle depends on the musical context. The tasks of segmentation and structuring musical documents are essential for general analysis. The *segmentation* part refers to partitioning a document into a set of meaningful elements. The function of *structure analysis* handles understanding the relations between the different segments. The main challenge in structure analysis is that music has many different kinds of relations, including repetition, contrast, variation, and homogeneity [38]. *Repetitions* play a big part in music where sequences are repeated, according to Middelton et al.(1999) [21]. Another principle in music is a *variation* where parts are picked up again in transformed form. Finally, a section usually contains some *homogeneity* where the instrumentation, the tempo, or the harmonic material may be similar within the section. All of those principles must be considered in the temporal context. Music happens in time, and the *temporal order* is essential for understanding the meaningful entities. The *musical dimensions* are melody, harmony, instrumentation, and timbre. To study musical structures and their mutual relations, one idea is to convert the musical signal into a feature sequence and then compare every feature to every other feature in the sequence. these results in a *self-similarity matrix (SSM)*. We often see that repetitions generate path-like structures in the matrices [31].

1.1.2 String approximate matching approach for musical analysis

According to Cambouropoulos et al. (2001), there are many ways for representing music for processing patterns and sequences. When we are choosing string representation, we can apply string matching algorithms. As far as pattern matching is concerned, applications sometimes use approximate matching algorithms[8]. The task of approximate string matching is to find all locations at which a pattern string p of length m matches a substring of a text string t of length n with at most k differences. It is often common to use Levenshtein distance [28]. We used string approximation matching techniques to compare and identify musical patterns (or tries) in participants' playing.

1.1.3 SSM - Self-similarity matrices

In order to study musical structures, a common method is converting the musical sequence into a feature sequence. Then we can compare each feature with any other feature in the sequence. The results for this kind of comparison can be organized in a matrix shape and called Self Similarity Matrix or SSM. In SSM, repetitions tend to produce path-like structures and homogeneous regions that produce block-like structures. Formally if F is the feature space and $x, y \in F$ and s is the similarity measure, then:

$$\mathbf{S} \in \mathbb{R}^{N \times N}$$

$$s: F \; x \; F \rightarrow \mathrm{R}$$

$$S(n, m) = s(x_n, x_m)$$

We understand that the values range for every $x, y \in R$ is [0,1], where one is the maximum, and we get by feature self-similarity. The more exciting insights from SSM are the path-like and the block-like patterns. If a feature sequence remains constant for all musical segments, an entire block of high similarity appears in the matrix. In other words, homogeneity properties correspond to block-like structures. Suppose a sequence containing at least two repeating subsequences a path of a high similarity is created parallel to the main diagonal. In other words, repetitive properties correspond to path-like structures. We used self-similarity matrices for analyzing feature combination importance.

1.1.4 Performance Assessment

Brian C. Wesolowski and Stefanie A. Wind et al.(2018) pointed the following tests for Validity, Reliability, and Fairness in Music Testing [53]

1.1.4.1 Validity

According to American Educational Research Association (AERA) [2], Validity refers to the degree to which evidence and theory support the interpretations of the test scores for proposed uses of tests. Validity is, therefore, the most fundamental consideration in developing tests and evaluating tests. The process of validation involves accumulating relevant evidence to provide a sound scientific basis for the proposed score interpretations. (p. 11)

According to Wesolowski and Wind et al.(2018), tests were developed with specific objectives in mind. These tests include performance assessment at a given point in time or over a period of time. Every test can be supported with supported sub-tests or methods, including statistical analysis. Models for Validity: (A) The criterion-based model of Validity - Handles cases where statistical or computational measurements can be achieved (B) The content-based model of Validity suggests music experts' opinions. (C) The construct-based model of Validity is based on a set of axiomatic theorems connected by sets of empirical laws used to validate the observable data. (D) The unified model of Validity - This model considers the context of the tests. For example, it includes external factors.

1.1.4.2 Reliability

According to American Educational Research Association (AERA) [2], The general notion of reliability/precision is defined in consistency over replications of the testing procedure. Reliability/precision is high if the scores for each person are consistent over replications of the testing procedure and is low if the scores are not consistent over replications.

1.1.4.3 Fairness

A variety of factors can act as threats to fairness in a testing situation. The Standards (AERA et al., 2014) [2] identify four major categories of threats to fairness: (1) test content; (2) test context; (3) test response; and (4) opportunity to learn. Minimizing these threats is key to ensuring fair testing procedures threats to fairness related to testing content.

1.1.4.4 Techniques and frameworks

According to Reboursière, Lähdeoja, Drugman, Dupont, Picard-Limpens, Riche et al.(2012), Technique refers to a player's control of an instrument that makes the analysis instrument specific. Some Techniques and methods were researched and developed for learning about a player's skills and abilities [39]. Abeßer, J., Lukashevich, H., & Schuller, G et al. (2010) suggested a series of algorithms developed to detect guitar-playing techniques. They focused on feature extraction and classification algorithms for first distinguishing between right and left-handed players and then identifying the specific Technique [1].

According to Han et al.(2014), the most important thing in music study is the process of giving or getting feedback on performance. Han used a hierarchical approach and statistical methods to identify common mistakes of beginner flute players [20].

Luo did similar work for violin by YJ Luo, L Su, YH Yang, TS Chi et al.(2015) [29]

When music is played as it is written, most sounds will sound very much alike and lifeless. The art behind it is "shaping" the music to your imagination by varying several musical parameters like speeding up or down, for example.

Widmer et al.(1998) describe an application of machine learning to study musical expression and performance. One approach that he suggested is learning the structure level via knowledge-based abstraction. This approach abandons the note level approach and tries to find shapes and patterns at the structure level; Local expression patterns may be embedded within more prominent patterns. They pre-processed the data (melody) and segmented it into chunks to find the more exciting parts. Then, they were looking for melodic patterns and shapes within these parts. The second approach dealt with the melody at the note level. They have separated the problem into two different learning tasks: dynamic and the second is tempo. They have used the dynamic data to create a set of rules in a search tree and both dynamic data and numeric data (tempo) to create a numeric learner [54].

According to Wesolowski et al.(2019) [53], the assessment framework will use a set of tests and work not only for musicians. There is much research about the frameworks, and the assessment systems that should be created [51, 52]. According to Schindler et al.(2019), every design should consider few concepts: a) what are the knowledge and skills required; b) how it could be demonstrated; c) how tasks can be developed in such a way that the skill will be demonstrated [41].

1.1.4.5 Performance assessment

A measurement approach should consider the evaluation criteria and the assessment tool. According to Hallam and Batista et al.(2012) [19], there are a set of skills that can be acquired when learning to play an instrument. For example, an aural skill can be reflected by the ability of a player playing by ear and his sense of rhythmic accuracy [18] Eremenko, Morsi, Narang, and Serra et al. (2020) stated a method for automating the feedback of a computational musical system. Their goal was to provide a framework that will make an automated assessment system for a guitar player. They analyzed audio-based user's input using a computational model that maps the user creation to the requested criteria. The general pipeline is in the figure below:

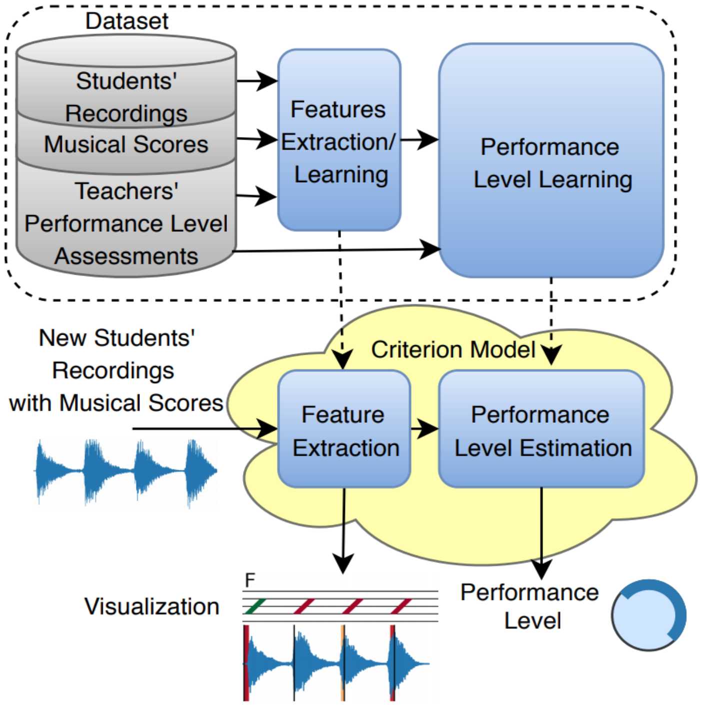

Figure 1 - Automotive assessment system pipeline - The proposed pipeline was suggested by Eremenko, Morsi, Narang, and Serra. It includes the model creation at the top. The bottom is the actual assessment.

For pitch and chords, they have used the pYIN method [30] for fundamental frequency extraction. They compared the obtained features with the reference recordings or the pre-defined guidelines for assessing the music performance. Most approaches for assessment include expert knowledge to extract hand-crafted features followed by classification. They have tried to estimate criteria automatically. For every measure selected, they used the appropriate audio features. Their machine is based on musically meaningful features. From a rhythmic perspective, they try to estimate how closely a student played by comparing the actual play and the expected metrical positions. In this research, the focus was on guitar playing and signal processing techniques. In their results, it seems that there is a difference between the auto vs. human assessment, probably due to the subjectivity of the evaluators. They stated that a system focused on specific student learning abilities should be created because each student has its way to learn. The design should be evaluated by measuring the improvement of the students. However, it was not presented [14].

Vidwans et al.(2017) tried to predict musicians' evaluation regarding Saxophone students playing in different work. He divided the features into three groups: 1) Baseline features - a set of low-level features, such as frequency. 2) Score-independent - represents the performance accuracy concerning pitch, dynamics, and rhythm. 3) Score-based - represents a set of features constructed after aligning the pitch contour using DTW (Dynamic time warping). The tuning frequency estimate subsequently shifts the pitch contour. In the end, he used Support Vector Regression with a linear kernel to predict expert ratings. He found a good correlation when examining rhythmic accuracy with a combination and Score-independent and Score-based features and less when using the other features. The main score-independent features were 1) Pitch-note steadiness, average pitch accuracy, percentage of in-tune notes. 2) Dynamics - amplitude deviation, amplitude envelope spikes. 3) Rhythm - timing accuracy. Overall - 24 features. The main scored-based features were - note steadiness, durations, DTW-based features, note insertion, and deletion ratio. Overall - 22 features [44].

Pati et al. (2018) applied convolutional and recurrent neural networks to predict expert ratings for wind instruments, like Flute, Alto Saxophone, and Bb Clarinet. The results show some promise; however, they offer limited scope for usage in a real music education context [37].

1.1.5 Creativity assessment models

Several authors have suggested different models and approaches for describing compositional processes using general theories for creative behavior. Aranosian et al.

(1981) [10], Emmerson et al. (1989) [13] Laske et al.(1989) [27], Roozendaal et al. (1993) [40], Baroni et al. (1999) [5] and Webster et al.(1987, 1989, 2002) [46, 47, 49] attempted to provide a model for creative thinking in music. A common approach is treating the creative event as a problem that needs to be solved [11]. General theories for creative process: Stage theory - The most common approach was developed by Wallas [45] that suggested four stages in creative activity: (1) preparation, (2) incubation, (3) illumination, and (4) verification. The preparation phase aims for the time before dealing with the problem how the person is analyzing the problem and preparing to deal with it. Incubation describes the time when the person is away from the problem. Illumination is the 'Flash insight' when a solution to the problem is achieved. The Verification phase may take the person back to the preparation or incubation phase. Gestalt theory - The idea of dividing creative thought into discrete stages is alien to the Gestalt school [12, 50]. Sub elements or sub-tasks are combined into one structure. The emphasis is on the organization and combination. Emerging systems theory - In this theory, the emphasis is on 'flashes of insights' according to Gruber et al. (1980) [15]. The theory is that ideas evolve. Gruber and Davis et al. (1988) [16] emphasized creative activities inside meaningful timeframes. Information processing theory - This theory aims to encapsulate these problems in testable computer programs, according to Newell et al. (1962, 1972) and Boden et al. (1994) [37, 32, 6]. It can be described as trial and error through the 'problem space' [33]. The problem-solver moves from this 'Initial state' to the 'Goal-state' by a rule system. According to Johnson-Laird et al.(1988, 1993), relativity is regarded as a form of problem-solving characterized by (1) the ill-defined nature of the problem; and (2) the notion of novelty or newness [24, 25].

2 Method

In this section, we describe the experiments we conducted in this study and the analysis method. We conducted two experiments with 152 participants: 72 in the first and 80 in the second. The participants did an interactive session with a musical application where they had to explore a new interface, learn to play a melody and then improvise and express new ideas. In addition, they filled up pre and post-questionnaires.

We used machine learning to analyze the interaction data, personal data, and behavior given by the participants. We analyzed and evaluated the user performance and interaction data computationally using DTW, absolute rhythmic features, and features that correspond to the time alignment of the melody that played. We computed melodic features, learning skills, and motivation levels. Each set of features comes from a different area and can represent other personal characteristics. We analyzed and learned from our first experiment and tested our conclusions on the second experiment.

2.1 Tools

2.1.1 Muzilator

Muzilator is a web platform for music interaction and creation, intended for both musicians and novices. Muzilator aims to improve the user's music creative expression, interaction, and creative skills. To achieve that, Muzilator provides intelligent musical interfaces to the user and interacts with him in a personalized manner. Muzilator can record interaction data, analyze, predict and generate interaction with the creator.

The Muzilator platform is designed in a plugin manner and exposes APIs for developers who can easily add their plugins to the platform. A plugin may have any functionality.

The Muzilator platform defines two types of plugins: Applications (App) and Libraries (Lib). Libraries can be: Controller, External Controller, Analyzers (Online/Offline Algorithms), Sound Engines, Profilers, etc. All plugins can communicate with each other with Muzilator channels. The channels (that are implemented in Post-Message Mechanism in Browser) can quickly transfer data from Plugin A to Plugin B if and only if there is a channel between those plugins.

The Muzilator Application is the main plugin responsible for loading libraries, connecting channels between plugins, connecting channels from the plugin to the current application, and handling the logic of a given application. Muzilator architecture design allows any web application to be uploaded to the platform as an independent plugin apart from applications. Each plugin can be developed by a different developer and can be integrated easily with other plugins. In this way, students can enhance their understanding of software design principles and experience sharing their software creations. Muzilator developers can benefit from being a part of a community of developers that create interactive applications (or parts of them).

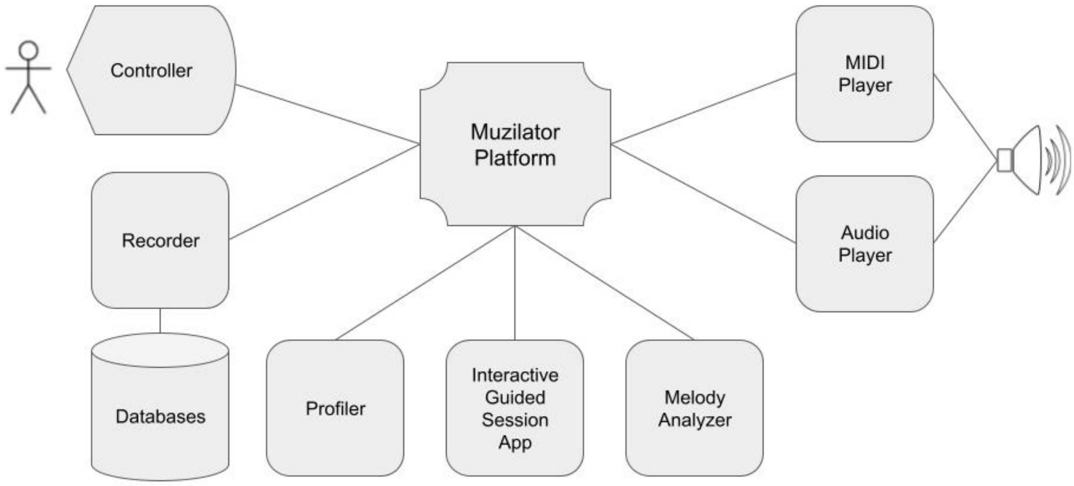

Figure 2 – An example of an application uploaded on Muzilator. The application uses Libs that are also uploaded on Muzilator and the Muzilator recorder that stores the data.

2.1.1.1 Components

Controller - It is the user interface for communication with the user. **Recorder** - Responsible for recording and logging all of the user activities. **Storage** - Database. **MIDI Player** - Responsible for playing MIDI notes. **Audio player** - Responsible for sound generation. **Melody analyzer** – Online, Offline, and real-time analysis for the user activities. **Profiler** - Responsible for evaluating the user musical profile, **Interactive guided session app** - The app used in the experiment. **Muzilator platform** - Responsible for connecting all of the components using messages and queues

2.1.2 Creative guided session

A creative guided session is an application that we wrote on top of the *Muzilator* framework. We designed this application to test the participant's abilities and creativity.

We designed and developed five different stages with different objectives. Each stage is aiming to test other skills. The stages are *Exploring, Learning, Mastering, Developing, Creating*. Description and objectives for each stage are described in the experiment chapter.

2.2 Experiment 1

2.2.1 Participants

In the first experiment, the participants were students from multiple disciplines of different ages between 21-27. All the participants are healthy and don't have any disabilities. 67% had no musical background while 33% did, 67% were males and 33% females, 83% were right-handed, 60% played the piano keyboard while 40% played. The average age was 23.

In the second experiment, the participants' ages were between 20 and 30.

2.2.2 Design

We designed the experiment as follows:

1. Pre-questionnaire
2. Interactive sessions with the "Creative guided session" app.
3. Post-questionnaire

2.2.3 Pre experiment

Before the experiment, the participants received a detailed brief that reviewed the experiment process, the different stages and objectives, the application that runs the experiment, and the controllers used. They have signed a consent form for participating in the experiment and filled a pre-questionnaire that included perceived creativity and competency evaluation, musical background, and demographics information.

2.2.4 Experiment 1 process

There were three sets of identical experiments, took place in January 2020. The experiment included two experimental conditions: piano keyboard:

- Miniature piano keyboard
- All the relevant notes were marked with stickers with the same colors as the touchpad represents the chorus of "Hey Jude" by the Beatles

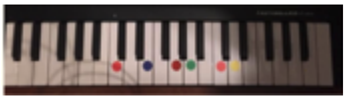

Figure 3 - Keyboard controller

- A computer application and a context-based interface were designed and developed by Dr. Hollander.
- Six circles with different colors representing the relevant notes and the chorus of "Hey Jude" by the Beatles.

Figure 4 - Touchpad controller

Pre and post-experiment described above. The experiment itself included six tasks of interactive guided sessions with application and interface. The participant must successfully finish one job to continue to the next. The six tasks and their objectives are:

1. **Exploration -** The participant explores the interface by playing notes without any clear guidance. **Objectives -** The participant must cover all of the notes that can be played with the controller or getting to 100 notes played.
2. **Learning -** The participant learns to play a short melody of a famous song chorus (Hey Jude by The Beatles). The application plays the melody once with additional blinking on the controller for better understanding. **Objectives -** The participant will be required to repeat the melody twice. The participant can ask for guidance and get another time the melody played with blinking.
3. **Mastering -** This stage is the same as the learning stage with a slight change. In this stage, the participant gets the melody and blinks along with the background melody, which defines the rhythm. **Objectives -** Repeating the melody twice, rhythm accuracy is analyzed as well.
4. **Developing 1 and Developing 2 -** The participant learns two different melody variations, changes in melody, and rhythm. **Objectives -** The participants are required to repeat the variations twice.
5. **Creation -** The participant plays freely with the background melody. **No objectives**

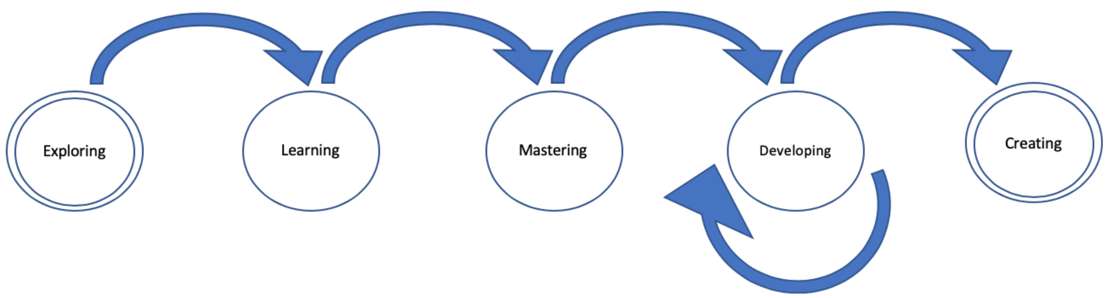

Figure 5 - Creative guided session state diagram for experiment 1

2.3 Experiment 2

The experiment took place in December 2020-January 2021. Eighty participants participated in the experiment, all novices with no musical background. 50% of the participants were males, and 50% were females. The experiment included four experimental conditions, C1, C2, C3, and C4, all with a touch screen interface using Android mobile devices. 50% of the participants did conditions C1 and C4, and 50% did conditions C2 and C3:

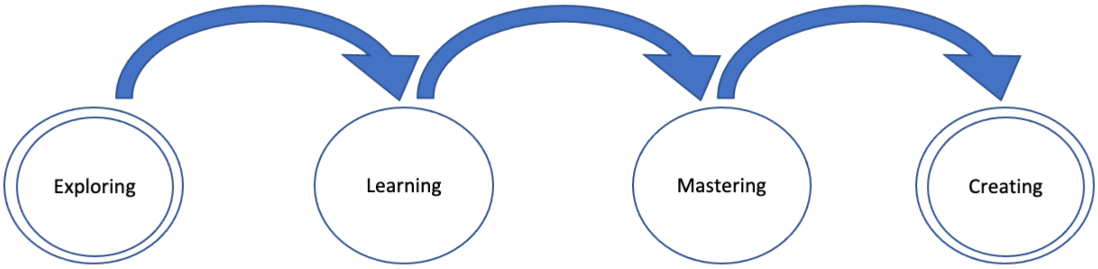

Figure 6 - Creative guided session state diagram for experiment 2

- A computer application and a context-based interface were designed and developed by Dr. Hollander.

1. "Hey Jude Line" - Six circles, organized in a line, with different colors representing the relevant notes and the chorus of "Hey Jude" by the Beatles.

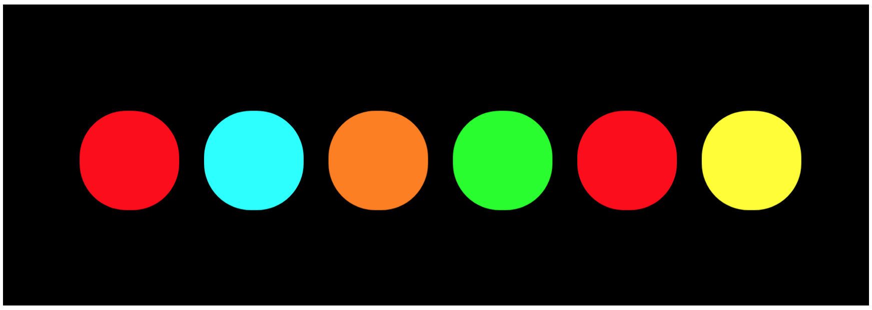

Figure 7 - Hey Jude line configuration – created similarly to the Piano keyboard configuration

2. "Hey Jude Cross" - Six circles, organized specifically for the song, with different colors representing the relevant notes and the chorus of "Hey Jude" by the Beatles.

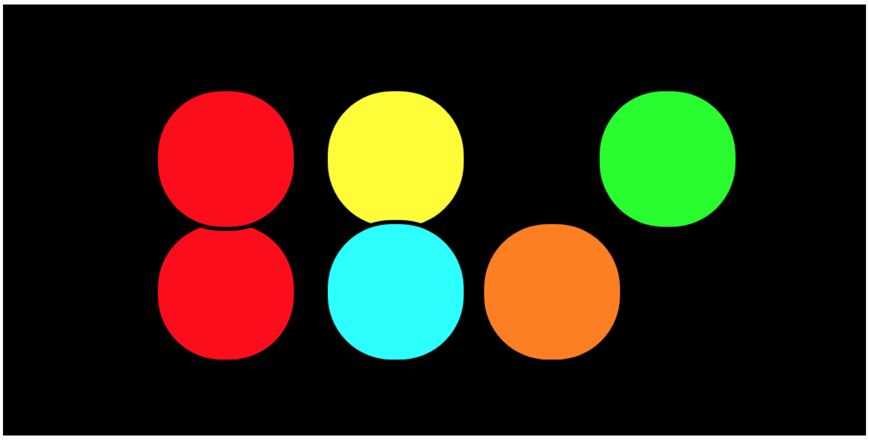

Figure 7 - Hey Jude cross configuration – created similarly to the Touchpad configuration

3. "Smoke on the Water Line" - Four circles, organized in a line, with different colors representing the relevant notes and the guitar reef of "Smoke on the Water" by Deep Purple.

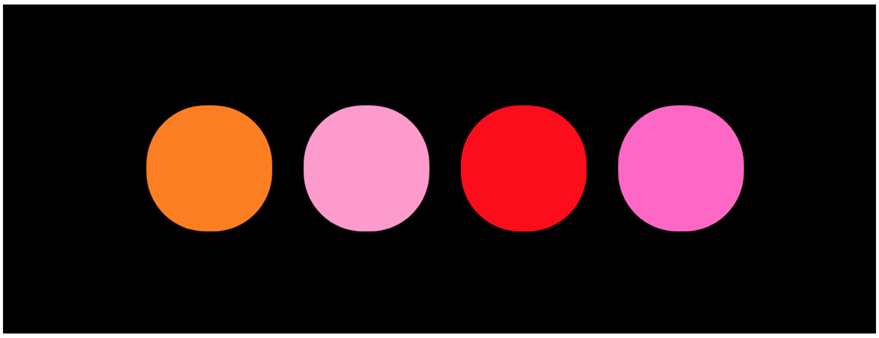

Figure 8 - Smoke on the water line configuration – created similarly to the Piano keyboard-configuration

4. "Smoke on the Water Cross" - Four circles, organized in a specific organization, with different colors representing the relevant notes and the guitar reef of" Smoke on the Water" by Deep Purple.

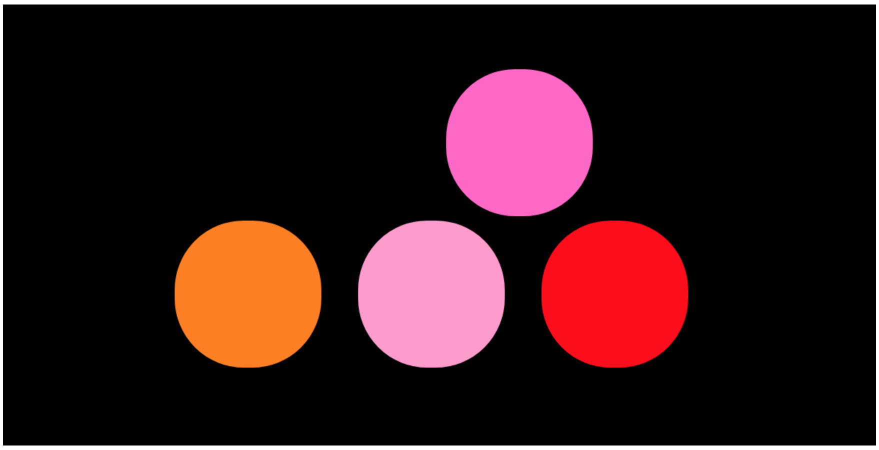

Figure 9 - Smoke on the water cross configuration – created similarly to the Touchpad configuration

2.4 Experiments configuration compare

Feature	First experiment	Second experiment
Amount participants	72	80
Musical background	2/3 Without and 1/3 with	No musical background at all
Interface	Hardware - keyboard	Software - app
Interface	Non-generic	Generic
Interface	Shared	Personal smartphone
Feedback	Without	With
Clues and hints	Without	With
Assistance	Without	With
Instructions	Self-explanatory, with instructions	Fully guided

Adjustments	None	Adjusted according to first experiment results

Table 1- Experiments configuration comparison

2.5 Analysis

2.5.1 Auto assessment model

Our goal for the analysis described in the current section was to build an auto-assessment model for evaluating a participant's creativity and musical profile.

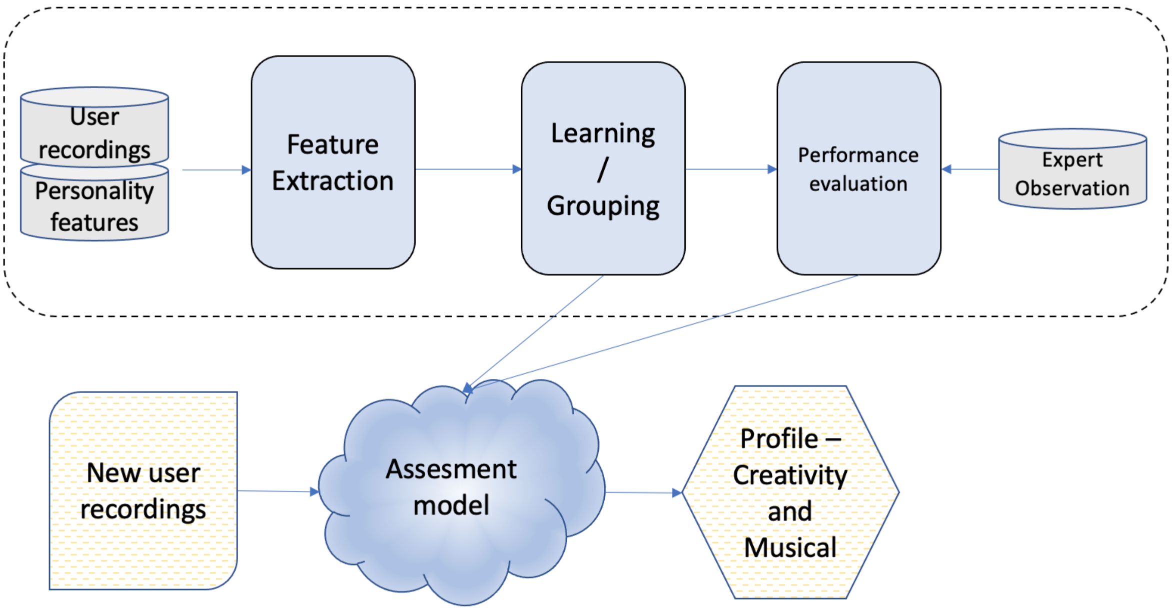

Figure 10 - Suggested assessment model

2.5.1.1 Model description

The top part is dealing with the creation of the model based on musical and personality features. At the bottom are the new recording classification and profile evaluation. The process starts with user recordings and personality features, the data is analyzed, and we are creating an unsupervised model to differentiate between the different groups of the participants. In the end, an expert musician is evaluating the other groups and checks whether this difference is expressed in the playing, and if it does, those features collected into the model

The analysis included several main phases. **Song reduction** for intermediate representation, **quantizing** the song the slightest closest beat and **meter analysis for rhythmic features, melodic features**

Song reduction – To reduce the complexity of the data so we could focus on our main features. The song is given as a set of messages log describing all the user activities to a sequence of structured notes from the schema:

- Pitch - note played.
- Timestamp of note-on and note-off

Segmentation – Song segmentation is essential in our research. As described above – each state of the experiment had its objectives and purposes; therefore, it has its analyzing methods and goals. We conducted the segmentation according to experiment states.

2.5.2 Definitions

Definition 3.1 A **Pitch pattern** *is a series* $[p_1,p_2,....,p_n]$ *of pitches of MIDI notes (integers in the interval [0,127[), or a rest (denoted by* ***rst)***

Definition 3.2 A **Rhythmic pattern** *is a series* $[r_1, r_2, \dots, r_n]$ *of durations in seconds of the notes in the pattern. For example: [0.5,0.25,0.5,1] is a pattern of durations of 4 notes: 0.5 second, 0.25 second, 0.5 second and 1 second.*

Definition 3.3 A Pattern length. *Given a pattern P= [p_1,p_2,....,p_n] denote by len(P) the length of P, where len(P)=n.*

Definition 3.4 A **Melody** *M = (P, R) is a pair of two patterns: where P= [p_1,p_2,....,p_n] is a* ***Pitch pattern*** *and R=*$[r_1, r_2, \dots, r_n]$ *is a* ***Rhythmic pattern*** *of the same length n.* $\forall i, 1 \leq i \leq n, r_i$ ***i****s the duration of note i with pitch* p_i *or a rest.*

Definition 3.5 Melodic motifs - *is a set of k melodic patterns* $\{P_1, P_2, \dots, P_k\}$ *where* $\forall i, 1 \leq i \leq n, P_i$ *is a subseries of a given melodic pattern P, and a natural constant k<n.*

Definition 3.*6 Rhythmic motifs -* *is a set of rhythmic patterns* $\{R_1, R_2, \dots, R_k\}$*, where* $\forall i, 1 \leq i \leq n, R_i$ *is a subseries of a given rhythmic pattern R, and a natural constant k<n.*

Definition 3.*7* ***Objective patterns*** *- Given a melody M=(P,R) of length n and a constant integer k,* $0 < k < n$*, objective patterns is a set* $\{M, M_1, \dots. M_k\}$*, where* $\forall i, 1 \leq i \leq n, Mi=$ (P_i, R_i) *and* P_i *is a subpattern of P and* R_i *is a subpattern of R. Objective patterns is in fact, a set of melodies where M is a given melody and* M_i *are specific parts of M.*

Definition 3.*8* ***Generated pattern*** *- A generated pattern is a melodic pattern or a rhythmic pattern that is generated by a user when he plays or improvises a melody.*

Definition 3.*9* ***Distance between patterns*** *- Given two patterns* P_1 *and* P_2 *of length N (Melodic or Rhythmic), the distance between* P_1 *and* P_2*, denoted by D (*P_1*,* P_2*), is the Levenstein distance between the string representation of the patterns.*

For example: P_1 *= [64,62,63,65],* P_2*, = [64,61,67,65], they can be represented as strings* S_1 *= abcd,* S_2 *= aefd, Levenstein distance between* S_1*,* S_2 *= 2. Note that* $0 \leq D(P_1, P_2) \leq N$.

Definition 3.10 Pattern Similarity Matrix (PSM), *Given a Melody (of a given existing song) and a set S =*$\{M_1, \dots M_n = M\}$ *of N given objective sub-patterns of M, and a melody U played by a user. The pattern similarity matrix PSM, is a matrix dimension N X N,* *where* $\forall j,\ 1 \le j\ \le N$ *PSM[i,j] is the number of patterns where the distance between* $M_k \in M$ *and* $u \in U$ *where Len(u) = Len(*M_K*) = j and the D(u,* M_K*) = i (The distance D is the Levenstein distance).*

Definition 3.11Pattern Repetitiveness Matrix (PRM), *Given a melody M played by the user. the pattern Repetitiveness matrix, is a matrix of dimension NXN, where* $\forall i, j,\ 1 \le i, j, \le N$*, PRM[i,j] is the number of patterns where the distance between* m_k, m_l $(k \le l) \in M$ *and* m_k, m_l *are subsequences of M is i and the length is j. PRM describes how repetitive the player/user is by calculating the number of repetitive patterns of all types: self-generated patterns and/or objective patterns.*

In order to evaluate the users' current ability to express creative ideas, in terms of creativity and repetitiveness, we analyzed the user's interaction both from melody and rhythmic perspectives. We computed PSM and PRM for both given and objective patterns.

Following are algorithms No. X and No. Y, that compute PSM and PRM, accordingly:

Computing the PSM:

- For every objective pattern s∈ S
    - Iterate over M
    - Compute the distance between patterns for every subsequence of M in the length of s and s.

Computing the PRM:

- For every i from MAXLENGTH to MINLENGTH
    - Iterate over M
    - Compute the distance between patterns for a, b subsequences of M.

Algorithm 1 Computing The PSM

```
Input: M(P,R) - Melody, S - Objective patterns set
Execution for P or R
res ← initZeros()
for all s ∈ S do
   for all i ∈ [ 0, Len(M) - Len(s) ] do
      d ← D(M[i,i+Len(s)],s)
      res[d][Len(s)] ← res[d][Len(s)] + 1
   end for
end for
return res
```

Algorithm 2 Computing the PRM

```
Input: M(P,R) - Melody
Execution for P or R
res ← initZeros()
for i ← MAXLENGTH to MINLENGTH do
   if Len(M) ≥ 2 * i then
      for all j ∈ [ i, Len(M)- i ] do
         d = D(M[0,i], M[j, j + i])
         res[d][i] = res[d][i] + 1
      end for
   end if
end for
return res
```

2.5.3 Rhythmic analysis

- Rhythmic quantizing – we created two quantized copies of every analyzed segment with respect to the minimal time difference in the segment and the whole session. We will use the [] notation on M for the subsequence of M.

Definition 3.12 *Let **minDiff** be the smallest difference in the whole segment.*

$$\forall i \in [2, segment[length]] : minDiff \leftarrow$$

$$\min(minDiif, |Sequence[i].time - Sequence[i-1].time|)$$

Definition 3.13 *Let* ***resolutionSet*** *be the beat fractions for measurement in our case.*

$$\frac{1}{2^t}, \frac{1}{2^{t+1}} \cdots \frac{1}{2^k}$$

Definition 3.14 *Let* ***resolution*** *be the largest element in resolutionSet which is smaller than minDiff*

$$\max(resolution \in resolutionSet) | resolution \leq minDiff$$

Definition 3.15 Performed sequence and Resolution are denoted by P and res accordingly. A_i refers to A_i's timestamp(note-on)**. Let the QuantizedSegemnt be as follows:**

$$Quantized[i] = \begin{cases} P_i + (res - (P_i \bmod res)) & (P_i \bmod res) \leq res/2 \\ P_i - (P_i \bmod res) & x > 0 \end{cases}$$

- Analysis for the reduced song conducted against the **QuantizedSegment**, the estimators described as follows. Quantized_I and Performed_i refers to their timestamp(note-on).
  - Relative average from beat –

$$\frac{\sum_0^n (Quantized_i - Performed_i)}{n}$$

  - Absolute average from beat –

$$\frac{\sum_0^n |(Quantized_i - Performed_i)|}{n}$$

  - Positive average from beat –

$$\frac{\sum_0^n \max(Quantized_i - Performed_i, 0)}{||positiveDiff||}$$

  - Negative average from beat –

$$\frac{\sum_0^n min(Quantized_i - Performed_i, 0)}{||negativeDiff||}$$

- Minimum positive diff average from beat –

$$\forall i \in [0, n] : diff \leftarrow (\min(\max(Quantized_i - Performed_i, 0), diff)$$

- Maximum positive diff average from beat –

$$\forall i \in [0, n] : diff \leftarrow (\max(\max(Quantized_i - Performed_i, 0), diff)$$

- Minimum diff for negative diffs –

$$\forall i \in [0, n] : diff \leftarrow (\min(\min(Quantized_i - Performed_i, 0), diff)$$

- Maximum diff for negative diffs –

$$\forall i \in [0, n] : diff \leftarrow (max(\min(Quantized_i - Performed_i, 0), diff)$$

- Scope – We focused the analysis on the Learning and Mastering stages.

2.5.4 Features description

Feature	**Description**	Independent
Session Features	Computed in the whole session perspective	
Experiment completion	Was the session completed successfuly or not	Yes
Last stage completed	The last stage that was successfuly played by the participant	Yes
Hybrid Features	Computed in both session and each stage perspective	
Total amount notes	The total amount of notes that were played	Yes
Total time	The total time it took to complete(or quit)	Yes
Irrelevant notes	Total amount of "unsigned" notes	Yes
Incorrect notes	Total amount of notes that are not part of a correct pattern	Yes
Correct number of notes	Amount of notes that are part of correct pattern	Yes
PRM	See Definition 3.11	No
PSM	See Definition 3.10	No
Absolute average from beat	Computed regarding the whole stage	No
Relative average from beat	Computed regarding the whole stage	No
Absolute average from beat exact match	Computred only whithin pattern playing	No
Relative average from beat exact match	Computed only whithin pattern playing	No
Early/Late with respect to the beat	Computed regarding the whole stage	No
Max positive difference	Maximun positive difference from beat computed regarding the whole stage	No
Min positive difference	Minumum positive difference from beat computed regarding the whole stage	No
Max negative difference	Maximun negative difference from beat computed regarding the whole stage	No
Min negative difference	Minumun negative difference from beat computed regarding the whole stage	No
Stage Features	Computed only for stages	
Incorrect amount notes from beginning	Amount notes until first success	Yes
Tries amount	The amount of times that the participant has tried	Yes

Table 2 - describes the features that were computed for every session that was played.

- We computed the dependent features with respect to DTW (Dynamic time warping) with the corrected (to the beat) sequence.

- Session features - The session feature set is designed to measure accuracy and abilities for all 6-session stages.
- Hybrid features - computed for each stage and the whole session.
- Stage features – computed only for stages.
- There were a few questions in our mind when selecting the model; 1) Which stages contributed better to the trial purpose 2) How many classes are there in the group of participants. 3) How to evaluate and classify the different groups. 4) Using supervised or unsupervised methods. In this section, I will describe the different methods we tried for answering these questions.
- Classifying using the "Last stage played" feature. We tried analyzing the data with respect to this feature.

2.5.5 General exploration

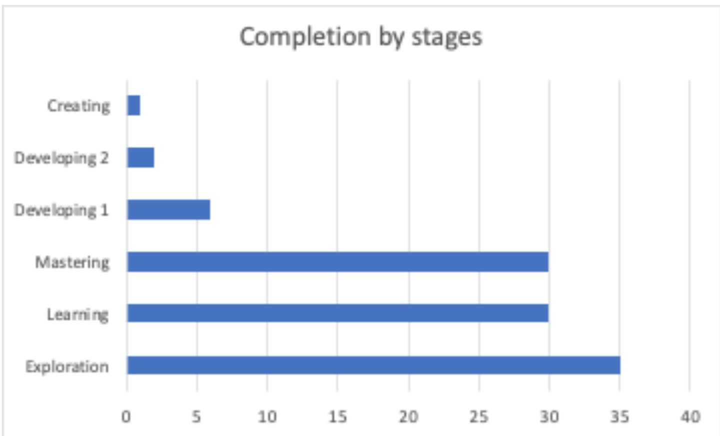

Figure 11 - This figure represents a histogram of the last played stage with respect to the number of participants. Most of the participants ended their session in the first three stages.

1) Total session time

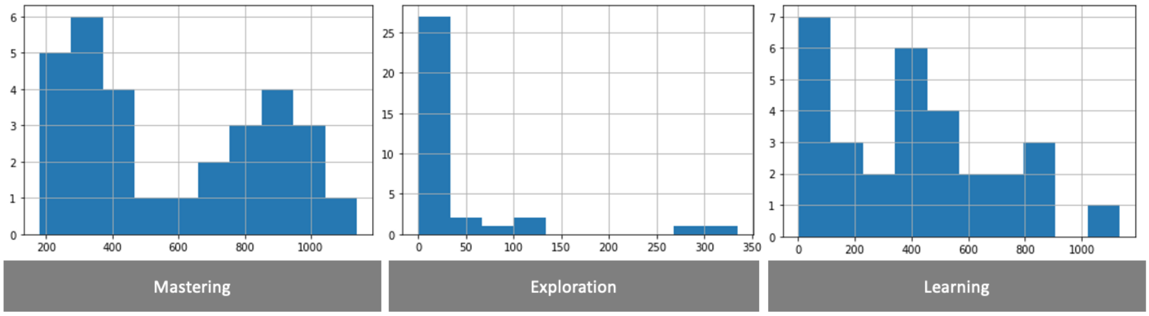

Figure 12 - Histograms for total session time in Exploration Learning Mastering stages. There is a big variance in times for those who finished Learning or Mastering

2) Learning selected features

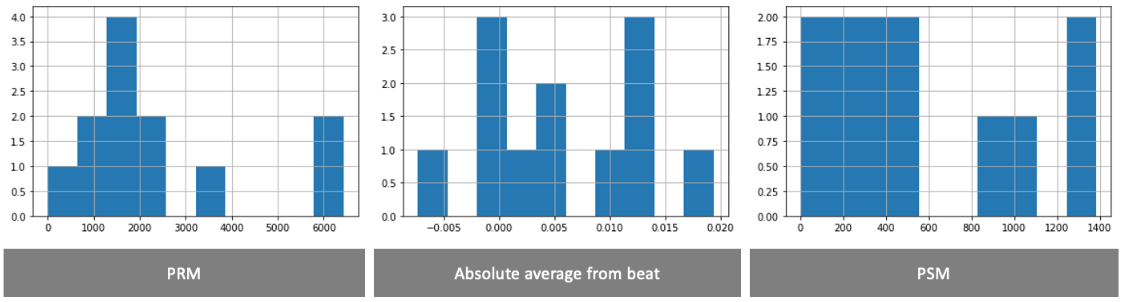

Figure 13 - Figure 13 - Histograms for PRM, PSM, Absolute average from beat for Learning stage. Most of the participants had similar repetitive and imitative scores. On average from the beat, there are many variances, and most of the participants were late.

3) Mastering selected features

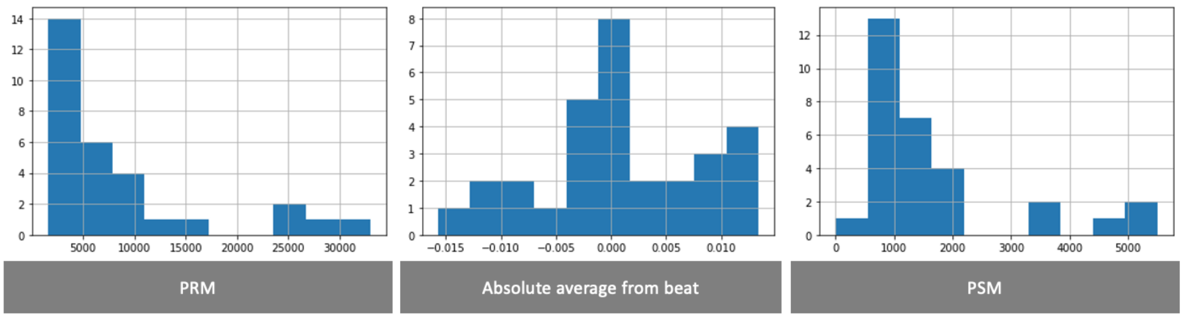

Figure 14 - Histograms for PRM, PSM, Absolute average from beat for the Mastering stage. Most of the participants had similar repetitive and imitative scores. On average from the beat, there are many variances, and most of the participants were early.

When we planned this experiment, we thought that more participants would complete the trial successfully. By assuming that the last stage played was more meaningful. The given result is that less than 10% had gone beyond the Mastering stage.

We examined selected features concerning the last stage played, and we got some insights.

- It is clear that the last stage played is not enough for predicting success or unsuccess in the trial.
- There is not enough data for using the stages beyond Mastering.
- There are different groups in the data - deeper investigation is required using other methods to decide how many affective groups there are.
- The classification which is based on statistical evaluation

  We were trying to determine which of the features is split well enough to divide the participants into several groups. Examining the split according to the distribution.

1) Selected features distribution for Learning stage(+PRM, PSM)

Feature	Learning Mean	Mastering Mean	Efficiency Learning	Efficiency Mastering
Incorrect notes from the beginning	56.35	13.03	-	-
Total time	163.80	73.71	+	-
Wrong notes amount	77.1	24.32	-	-
Absolute average from beat	0.05	0.05	+	-

Amount notes	131.02	50.06	-	-
PRM	30.19	11.34	+	+
PSM	6.48	3.07	+	+

Table 3 - Features efficiency summary for basic statistics division

2.5.5.1 Feature's contribution summary

The above table describes which features can split the data into several different groups. In addition, it also shows the efficiency of the split as evaluated by the musician by looking into participants divided by the average value where the base for comparison is the performance in each stage. The first two columns describe the statistical ability to use the feature, and the last two tell its actual efficiency when tested. The plus sign in the Learning and Mastering columns represents the ability to split the data accordingly and the other columns if the split satisfies in a performance perspective.

2.5.6 Grouping based on clustering with dimension reduction techniques

In this method, we decided to try an unsupervised learning approach. Our goal was to divide the group into some subgroups based on its features using clustering algorithms. After we had the groups solved, we tried to project some of the personality features computed from the questionnaires and correlate the clusters and the features scattering.

In addition to that, we used expert musician assessment to understand whether the scattering makes sense from a musical performance perspective. We used the K-Means algorithm and several sets of features and methods in several iterations to get the best grouping. We first try using 3D PCA using all of the features for a single-stage focusing on the Learning and Mastering stages.

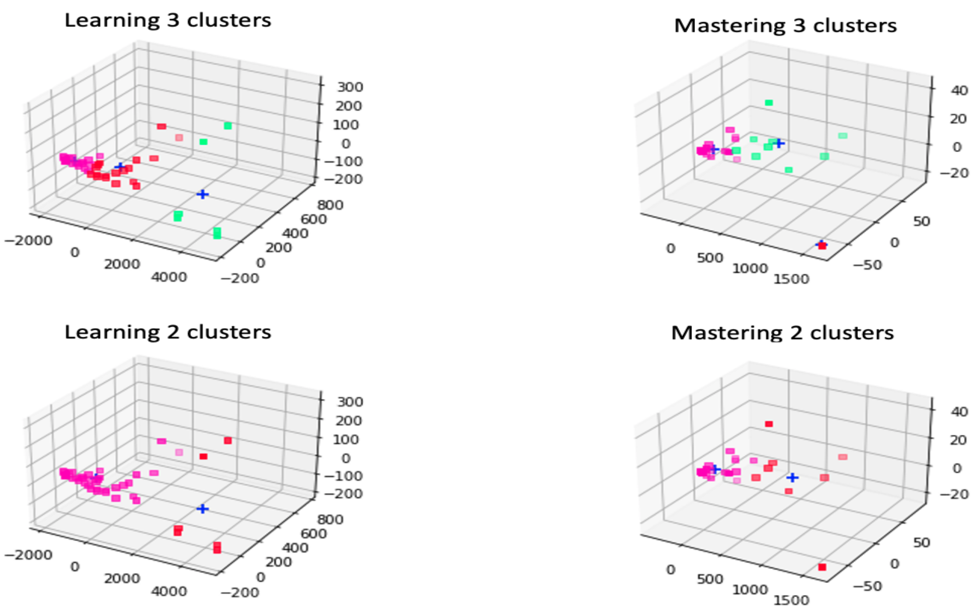

Figure 15 - Using 3D PCA and trying to divide the group into two and three different clusters. Two clusters grouping fits more to the data.

When examining these results, we see quickly that:

- Three different groups do not exist.
- The third dimension does not contribute to the division, and 2D PCA could be enough.

We then tried moving on to 2D PCA and projecting the personality features on the 2D division.

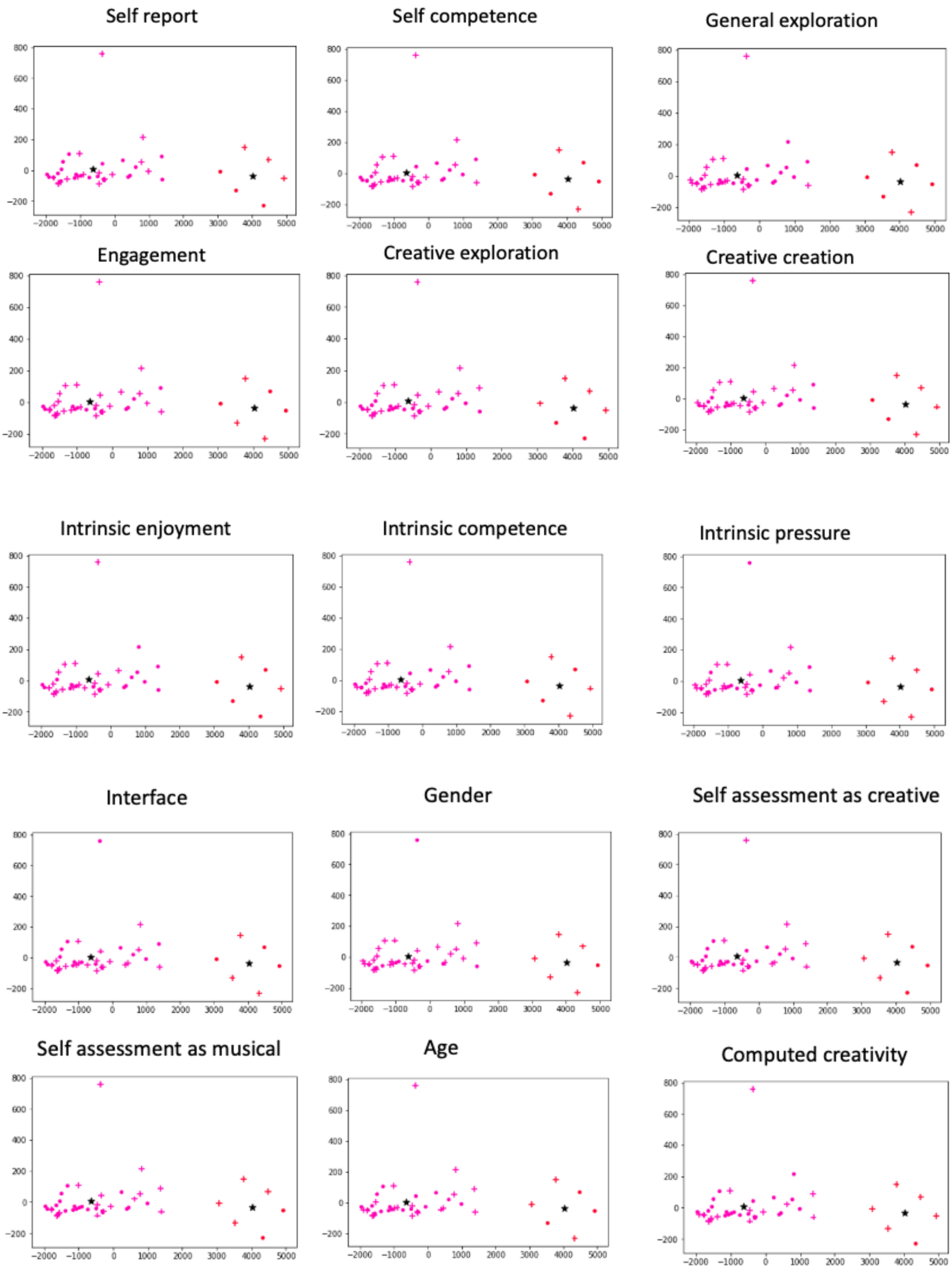

Figure 16 - The above scatter graphs represent a projection of a set of personality features on the Learning stage 2D division. For numerical features, the average is used, and for categorial - each one of the categories.

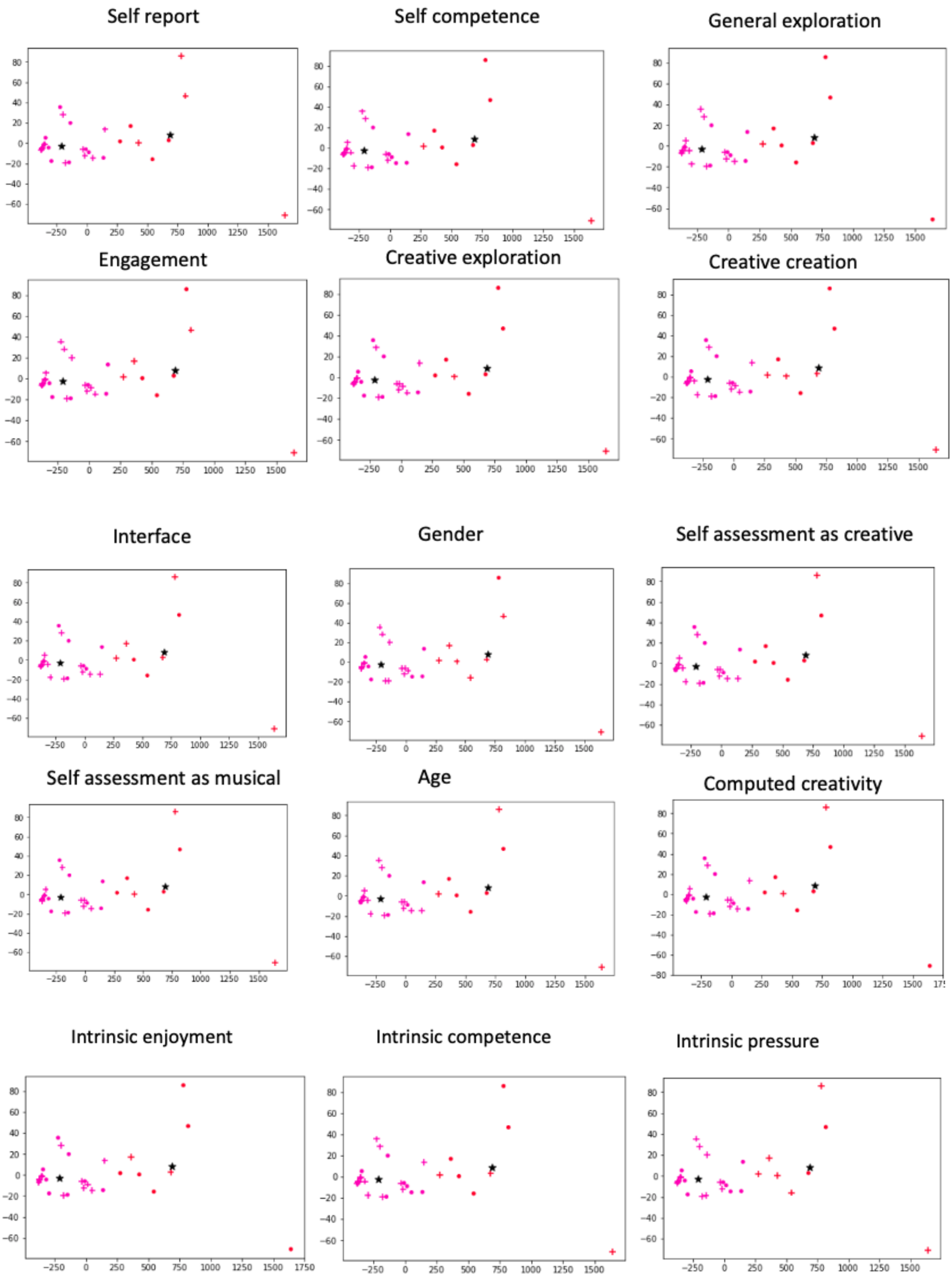

Figure 17 - The above scatter graphs represent a projection of a set of personality features on the Mastering stage 2D division. For numerical features, the average is used, and for categorial - each one of the categories.

By doing that, we saw that there is some correlation between those features and the clusters but:

1) There is no clear projection of one of the personality features on the data, which settles with the clusters created by the algorithm.
2) PCA shuffles the features in such a way that it's hard to isolate the influence of a single feature on the data.
3) We need a rougher cleaning of the data and outliers removal.

2.5.7 Grouping based on clustering using a subset of features

We decided to try every couple of computational features in the last approach focusing on the "main" clusters. By doing that, we could better understand feature influence and get a better resolution regarding the divisions. We used self-similarity matrices with Pearson correlation score (absolute value) as the distance method. Features with low correlation were used for clustering or linear separation. In addition, we projected the personality features on the scattered plots and found the ones that fit the most. Later we asked a professional musician to examine the different clusters and test whether this difference is expressed. If it does, those features were collected into the model.

Figure 18 - Correlation matrix for Learning stage

2.5.7.1 Learning stage features correlation

The darker squares represent the independent features that are more likely to work together for linear separation –

- Absolute average from beat in exact match - Incorrect notes amount
- Absolute average from beat in exact match - Relative average from beat
- Correct notes amount - PRM
- Correct notes amount - Relative average from beat

- Incorrect amount notes from beginning - Correct notes amount

Figure 19 - Correlation matrix for the Mastering stage

2.5.7.2 Mastering stage features correlation

Above is the correlation matrix for the Mastering stage. The darker squares represent the independent features that are more likely to work together for linear separation –

- Absolute average from beat - Absolute average from beat in exact match
- Absolute average from beat in exact match - Absolute average from beat
- Absolute average from beat in exact match - Tries amount

- Absolute average from beat in exact match - Relative average from beat
- Tries amount - Relative average from beat

Considering these Similarity matrices, we used the below features and projections:

We used a threshold of 70% for the first experiment and 60% for the second in terms of correlation score between the clusters and the projected feature to assume that they match.

2.5.7.3 Features Description

Computational Features	
Name	Melodic/Rhythmic/Other
Correct notes amount	Melodic
Incorrect notes amount from the beginning of the stage	Melodic
Amount Notes Played	Other
PSM	Melodic
PRM	Melodic
Absolute average from the beat	Rhythmic
Absolute average from the beat – In Specific Patterns	Rhythmic
Total time	Other

Table 4 - describes the computational features and measurements that were used for trying to separate the data linearly.

Projected Personality features	
Name	Scale – Average/Other
Interface	Touchpad/Piano Keyboard
Engagement	Average
Gender	Male/Female
General exploration	Average
Age	Average
Intrinsic competence	Average
Intrinsic enjoyment	Average
Intrinsic pressure	Average
Self-assessment - Musical	Average
Self-assessment - Creative	Average

Table 5 - describes the personality features and the meta-data that was projected on the computational data

The scattered plots below represent the features that created good separation (in both data and musical perspectives) with their best projected personal feature for the Learning stage.

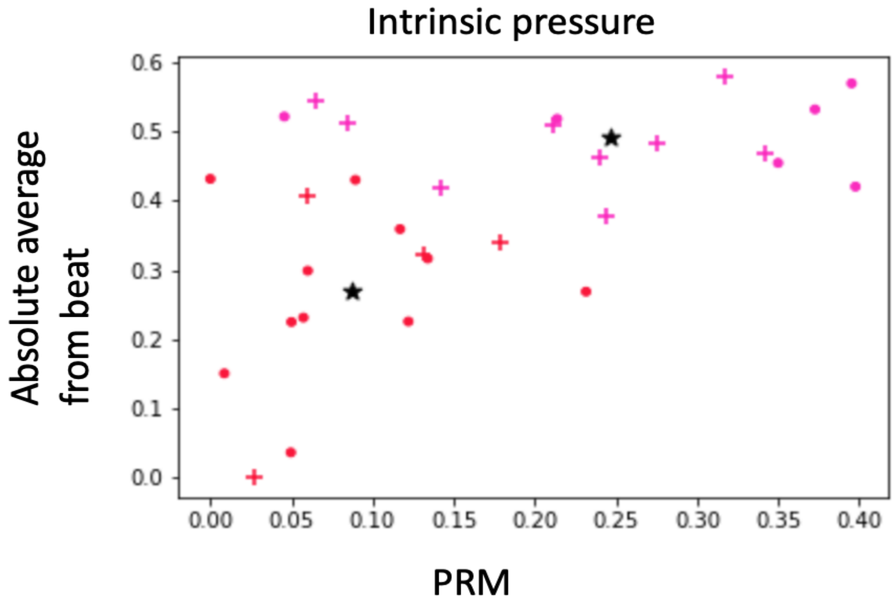

Figure 20 - Intrinsic pressure personality measurement projected well on clusters that were created using Absolute average from beat vs. PRM.

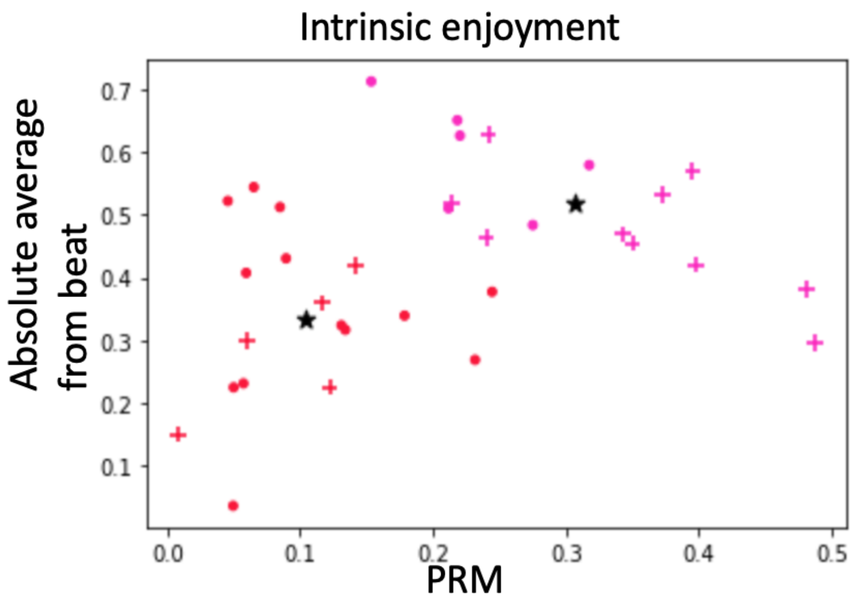

Figure 21 - Intrinsic enjoyment personality measurement projected well on clusters that were created using Absolute average from beat vs. PRM

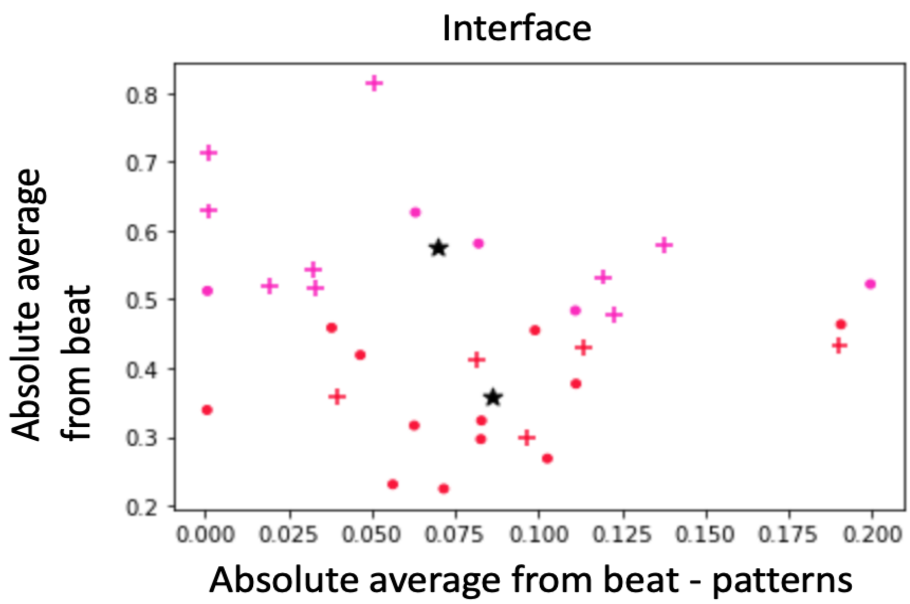

Figure 22 - Interface (+Touchpad,o keyboard) projected well on clusters that were created using Absolute average from beat vs. Absolute average from beat only in the correct playing

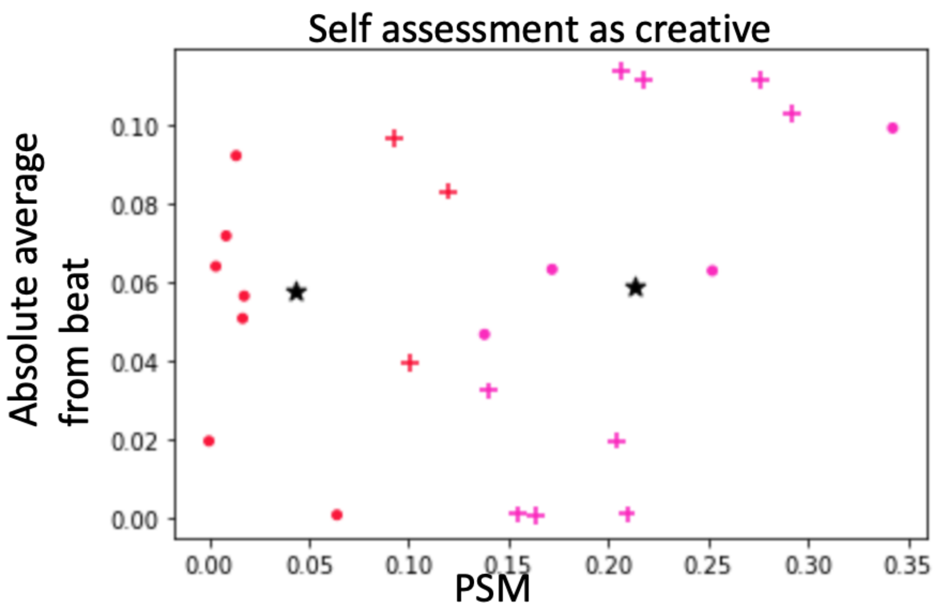

Figure 23 - Self-assessment as creative personality measurement projected well on clusters that were created using Absolute average from beat vs. PSM

The scattered plots below represent the features that created good separation (in both data and musical perspectives) with their best projected personal feature for the Mastering stage.

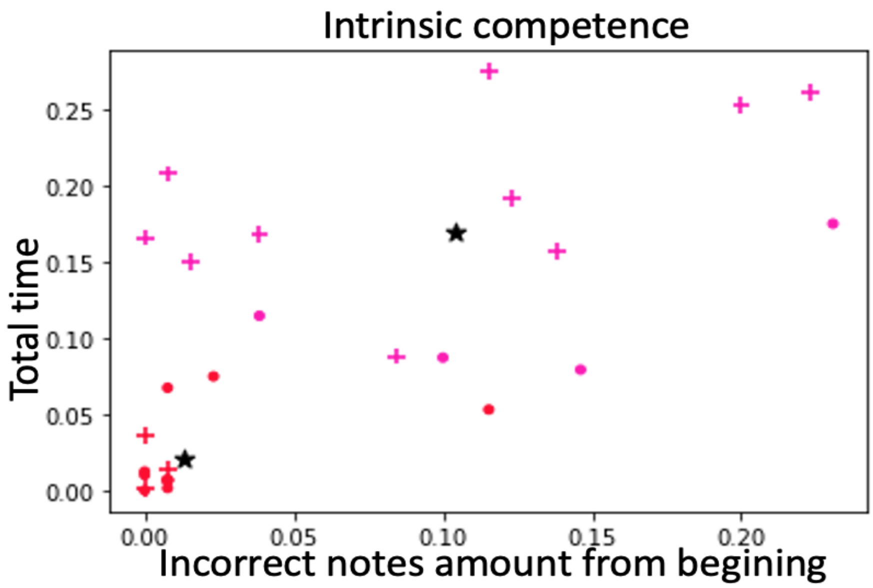

Figure 24 - Intrinsic competence personality measurement projected well on clusters that were created using Total time vs. incorrect notes amount from the beginning of the stage

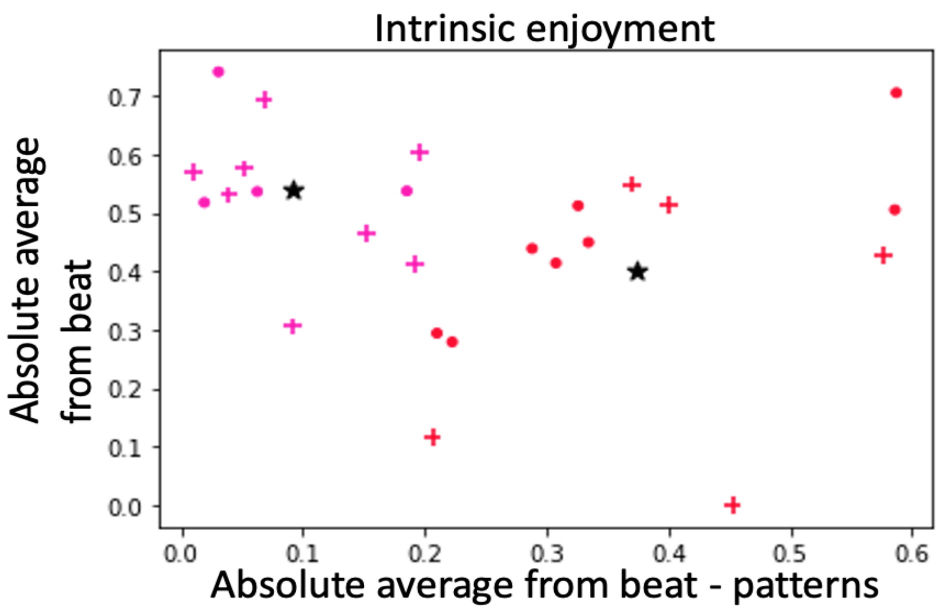

Figure 25 - Intrinsic enjoyment personality measurement projected well on clusters that were created using Absolute average from beat vs. Absolute average from beat only in the correct playing

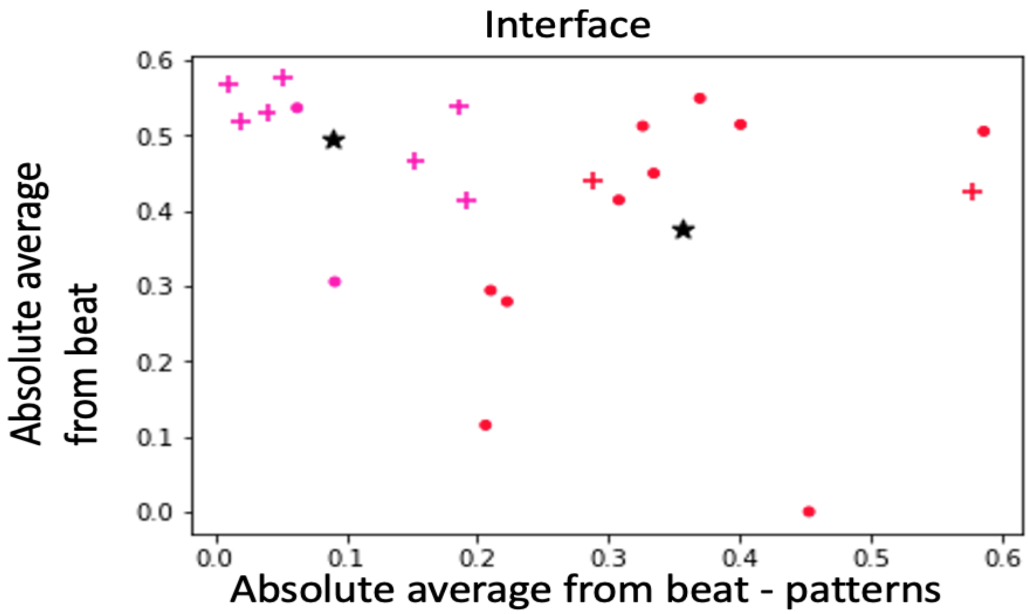

Figure 26 - Interface (+Touchpad,o keyboard) projected well on clusters that were created using Absolute average from beat vs. Absolute average from beat only in the correct playing

The same method was used to analyze the second experiment, and the charts are as follows:

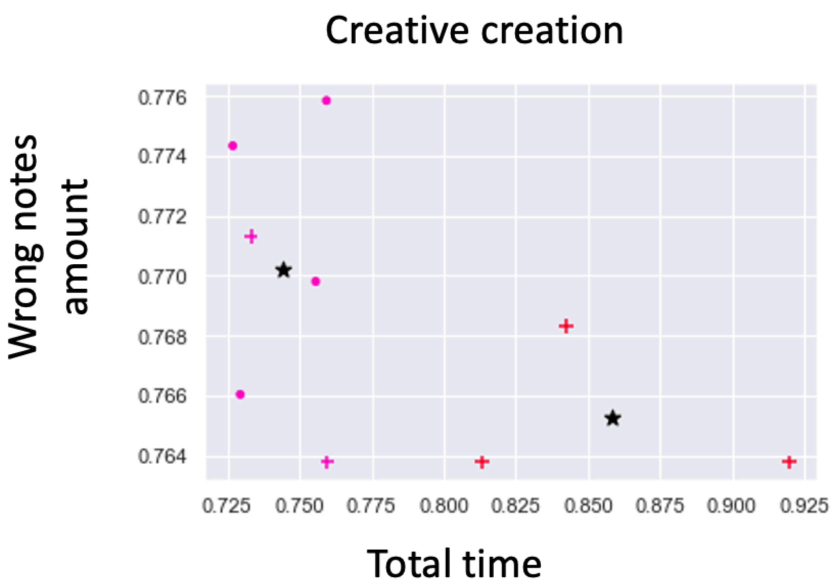

Figure 27 - Creative creation personality measurement projected well on clusters that were created using wrong notes amount vs. total time

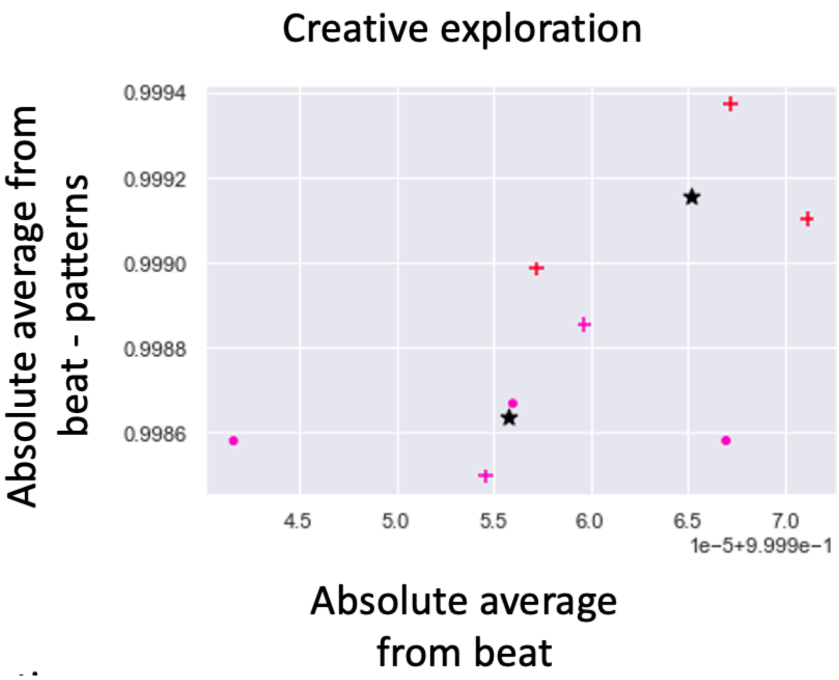

Figure 28 - Creative exploration personality measurement projected well on clusters that were created using an absolute average from beat. vs. absolute average from beat only the in correct playing

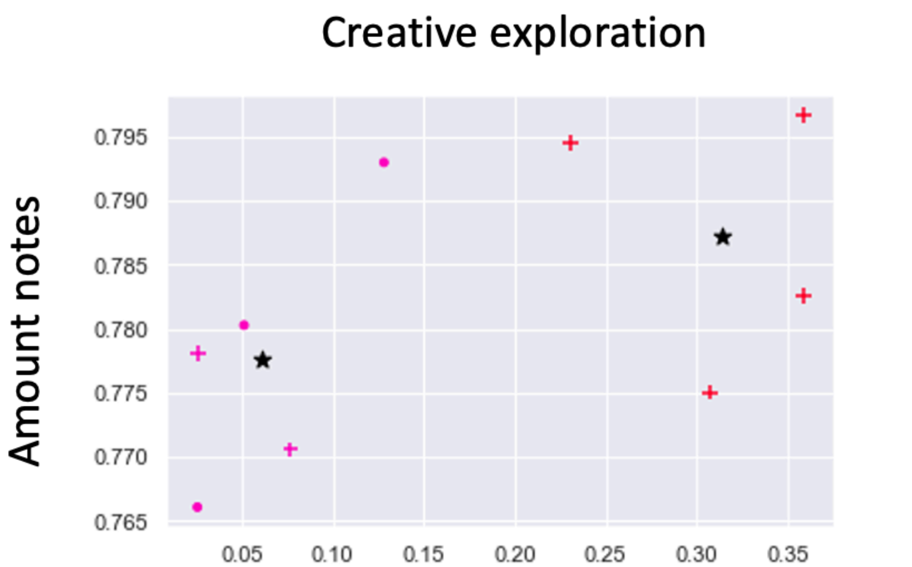

Figure 29 - Creative exploration personality measurement projected well on clusters that were created using amount notes vs. incorrect notes amount from the beginning of the stage

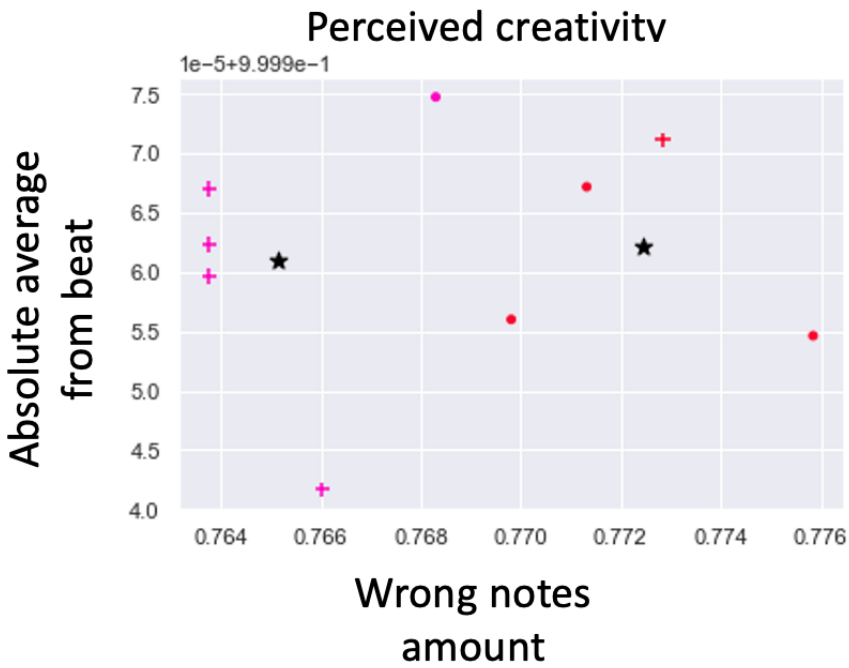

Figure 30 - Perceived creativity personality measurement projected well on clusters that were created using an absolute average from beat vs. wrong notes amount

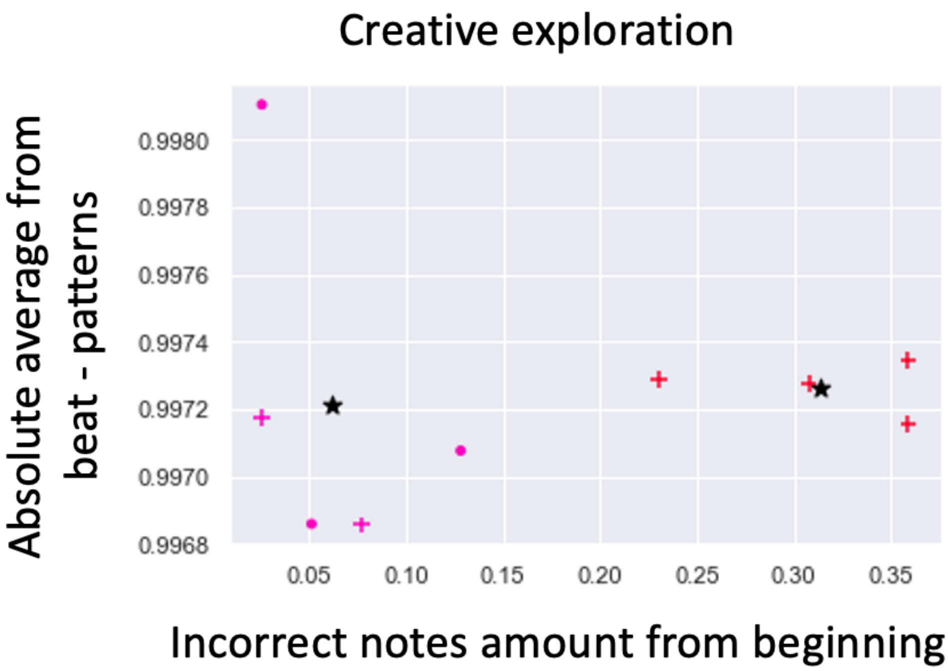

Figure 31 - Creative exploration personality measurement projected well on clusters that were created using an absolute average from beat only in correct playing. vs. incorrect notes amount from the beginning of the stage

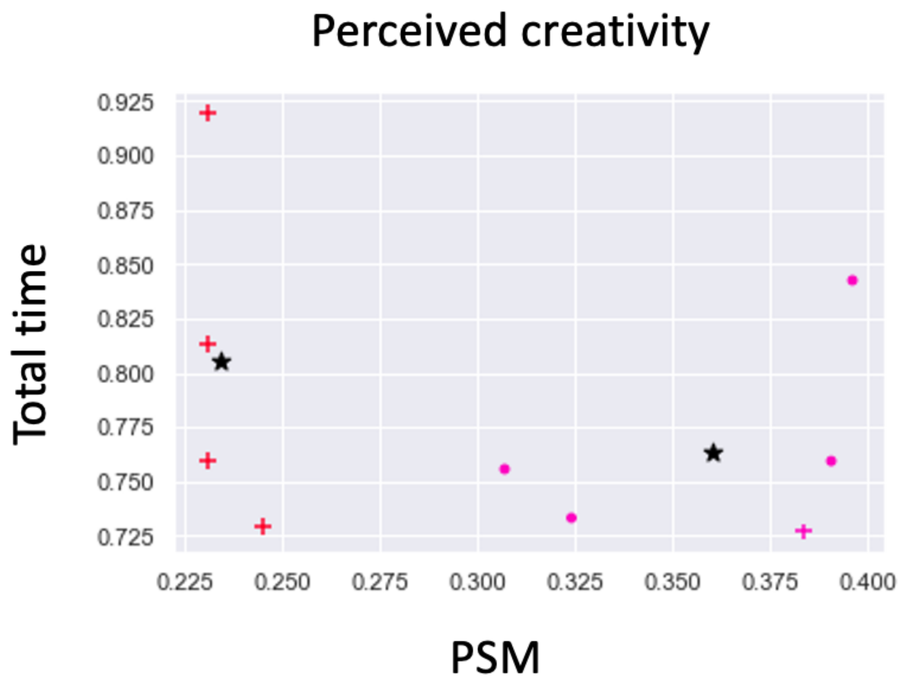

Figure 32 - Perceived creativity personality measurement projected well on clusters that were created using total time vs. PSM

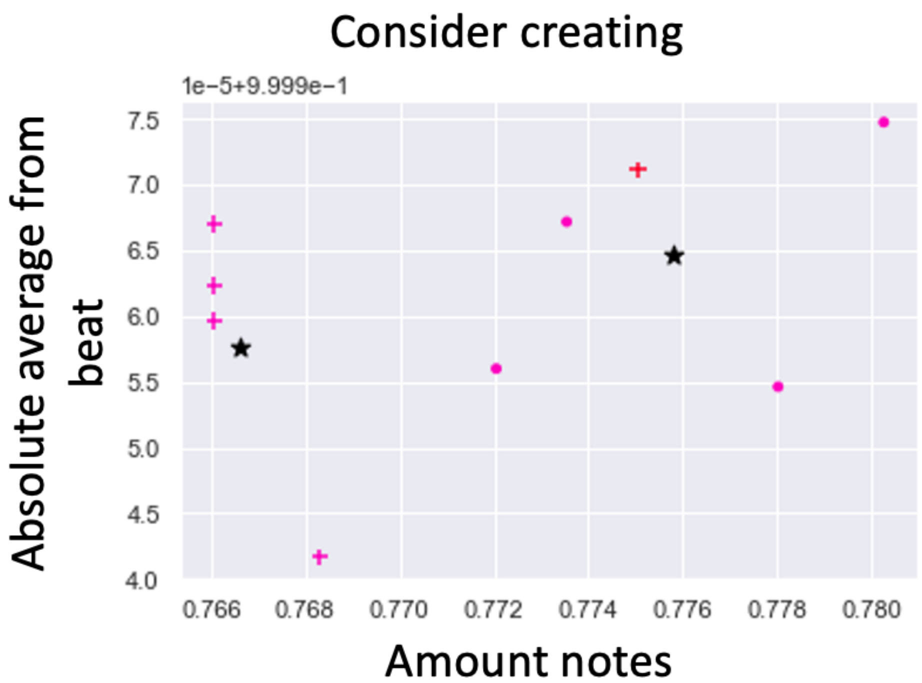

Figure 33 - self-evaluation as creative personality measurement projected well on clusters that were created using an absolute average from beat. vs. amount notes

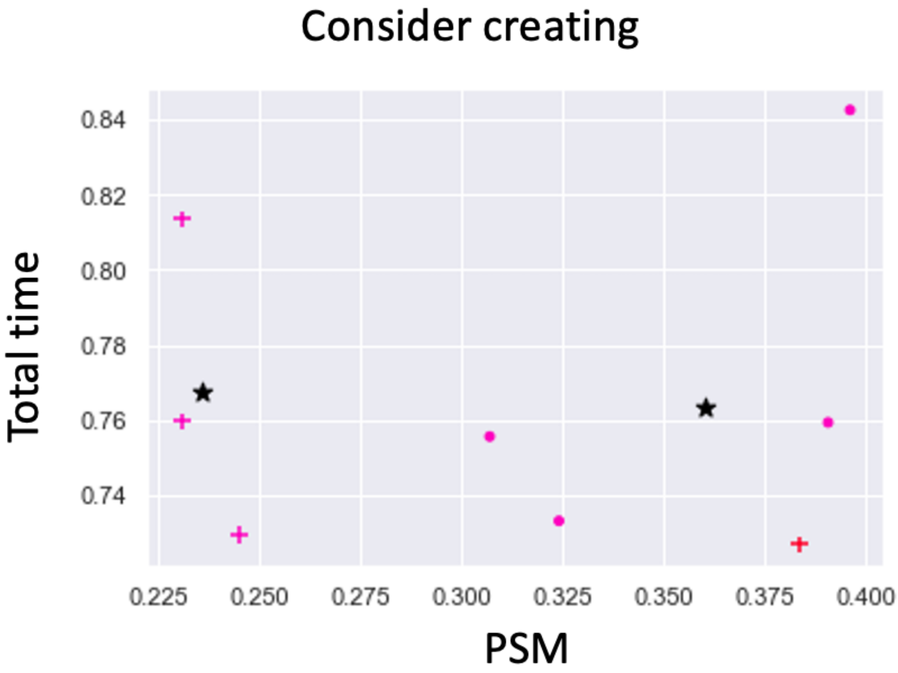

Figure 34 - self-evaluation as creative personality measurement projected well on clusters that were created using total time vs. PSM

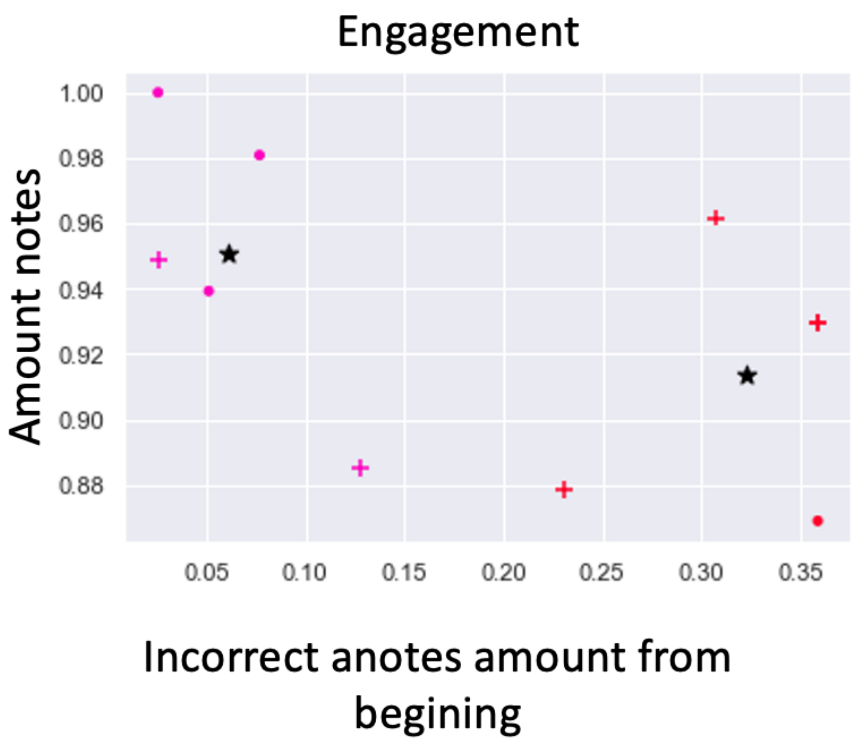

Figure 35 - Engagement personality measurement projected well on clusters that were created using amount notes vs. incorrect notes amount from the beginning of the stage

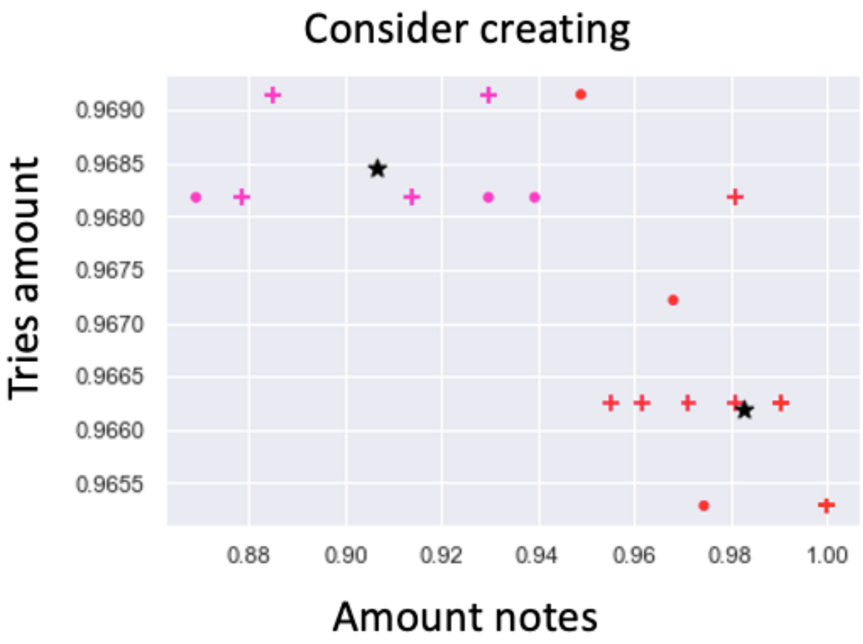

Figure 36 - Self-assessment as creative personality measurement projected well on clusters that were created using amount notes vs. tries amount

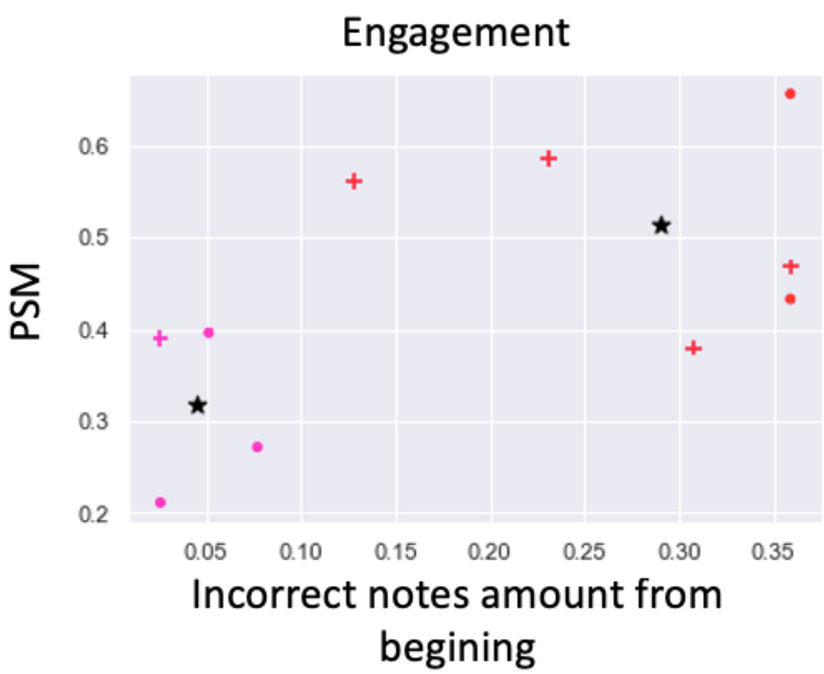

Figure 37 - Engagement personality measurement projected well on clusters that were created using incorrect notes amount from the beginning of the stage vs. PSM

2.5.8 Experiments comparison

Mean	First Learning	Second Learning	P value	First Mastering	Second Mastering	P value
Incorrect notes the from beginning	56.35	6.83	P < 0.001	13.03	5.2	P = 0.18
Total time	163.80	90.33	P = 0.008	73.71	158.1	P = 0.11
Absolute average from beat	0.05	0.06	P < 0.001	0.05	0.07	P < 0.001
Amount notes	131.02	54.28	P = 0.06	50.06	88.73	P = 0.1
PRM	30.19	56.18	P = 0.15	11.34	62.54	P = 0.04
PSM	6.48	15.13	P = 0.43	3.07	12.98	P < 0.001

Table 6 – We see the comparison between the Learning and Mastering stages in the two experiments. We can see that Learning parameters were improved almost in every criterion.

Reflection in clustering analysis	First	Second
Incorrect notes from the beginning	High	High
Total time	High	Low
Wrong notes amount	Low	High
Absolute average from beat	High	High
Amount notes	Low	High
PRM	High	High
PSM	High	High

Table 7 – Features representation in clustering analysis. It can be seen that most of the features had a significant role in both of the experiments.

3 Conclusions and future work

This section includes the results summary for both experiments in computational and personal perspective for Learning and Mastering stages.

3.1 Learning

1) The essential features, as reflected from the analysis, are:
    - PRM – Those who had higher PRM scores were more pressured and enjoyed more.
    - PSM - Those who had higher PSM scores were more creative and less engaged.
    - Absolute average from the beat – Those who were less accurate was more pressured. Keyboard players were more accurate.
    - Absolute average from the beat, in correct play - Touchpad players were more accurate. Those who had bigger differences were less creative and less engaged.
    - Incorrect notes amount from the beginning of a stage – Those who had a higher number of incorrect notes from the beginning were less engaged and more creative.
2) In the Learning stage, the ones that were more repetitive and could follow the experiment guidelines better were more creative and enjoyed more. They played more notes, taking more time, but they were more accurate within the correct playing time. PSM and PRM in the Learning stage correlate well with the participant's last stage (0.63, 0.6) and can predict the experiment's success.

3.2 Mastering

1) The essential features, as reflected from the analysis, are:
    - PSM – Those with higher PSM scores were less creative, less explorative, and had lower self-competence.
    - Incorrect notes amount from the beginning of a stage – Those who had a higher number of incorrect notes from the beginning were less engaged, less creative, and had lower intrinsic competence.
    - Absolute average from the beat – Those who were less accurate was less creative. Touchpad players were less accurate.
    - Amount notes – Those who played more notes had lower self-competence and were less explorative.

3.3 Conclusions

1) The first experiment included some participants who had musical backgrounds, while there were all without any previous experience in the second one. Still, we showed that the learning curve in the second experiment was better. Total time for learning was deducted from 163 seconds on average to 90 seconds (P-value = 0.008), The number of incorrect notes that was played until first success was deducted from 56 to 6 (P-value < 0.001), and the number of notes that was required deducted from 131 to 54 (P-value < 0.001). With the proper configuration and environment, people without musical knowledge can learn to play a short melody within a short time range.
2) In the first experiment, we saw that the most influencing features for success were repetitiveness, replication, rhythmic accuracy; on the second - replication and rhythmic accuracy.

3) Playing with the touchpad was more accurate than comparing it to the keyboard. Generic, personal and less biased instruments or interfaces can improve the learning curve.
4) In the Mastering stage, the less able ones to follow the experiment guidelines were less creative, explorative, and had lower self-competence. They play more notes, it took them more time and needed more tries to complete the stage, but they were more accurate. PSM and PRM in the Learning stage correlate well with the participant's last stage (0.65, 0.53) and can predict the experiment's success.
5) In conclusion, repetitiveness and imitation ability in the Learning and Mastering stages can predict the experiment's success. While they correlate with creativity in the Learning stage, it’s the opposite of the Mastering stage. We assume that those who performed better in the Learning stage felt secure to improvise and break the boundaries in the Mastering stage (which is more interesting), and that’s why their scores were less good.
6) We suggested the assessment model described in figure 10. This model defines the pipeline for performance assessment, including data cleaning, feature extraction, clustering, and psychologist observations projection as ground truth. We proved these relations and those insights described above. As for now, we set the foundations for building the prediction model by mapping these relations. As future work, we can create the actual model to predict the participant’s musical features based on his psychologist observations or vice versa.

3.4 Future work

In our experiments, we had five different stages for the first experiment and four for the second. The first one is for exploration; it is the case when the participant meets his instrument for the first time without any previous knowledge. The 4’th (in the first experiment) is for development; it included built-in changes in the melody; this stage was too hard at the first experiment; therefore, it has been removed. The last one is for the original creation. In this work, we put our main effort into studying a musical task's learning process; we didn’t consider the preparation for the process during the exploration stage and the creative outcome during the original creation stage. Those stages are less structured while they don’t have any relative objectives. Future work can include the first interaction with a new instrument and the musical structure elements implemented in that interaction. In addition, we can try to understand why the complexity of adding rhythm in the background of the playing is bigger than changing notes in the melody (Transitions from Learning to Mastering and Mastering to Developing). The last stage in our experiment included original creation. It can also be a future topic for research regarding the creative ability that can be achieved with an unknown instrument.

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5 Appendix

5.1 Pre Questionnaire

- Age
- Gender 1 - Male, 2 - Female
- Musical_Background (1-5 scale: 1- no background, 2 - beginner, 3 - intermediate, 4 - advanced, 5 - expert, 0 - no data, Derived from musical background)
- Degree and name of faculty
- Mother tongue
- Dominant hand 1 - R, 2 - L
- General Perceived Creativity (1-7 Scale: 1 = Very Unlikely; 7 = Very Likely)
- Mean: 5.56 = Most of the participants lean towards moderately likely to have perceived creativity
- SD: 1.05
- Self - evaluation of subjective report on:
    - i) Creativity - “Do you consider yourself creative?”
    - ii) Exploration - “Do you like to explore new things?”
    - iii) Musicality - “Do you consider yourself a musical person?”

5.2 Post Questionnaire

The interface used in the experiment (Touchpad = 1 / Keyboard = 2)

Please rate your music preferences

(1-5 Scale: 1 = Do not prefer, 2 = Prefer a great deal)

- Electronic music
- Hip hop
- Pop
- Jazz
- Classical
- Rock
- Alternative rock
- Progressive rock
- Rhythm and Blues
- Country
- World music
- Israeli music
- Eastern Israeli music (Mizrahi)

1. **General Perceived Creativity**
2. **Subjective reports or personal reflections**

   (1-6 Scale:1 = Strongly Disagree; 6 = Strongly Agree)

   Mean: 4.26 = Most participants lean in the middle between feeling relaxed and tense, finding the activity complex or easy

   SD: 0.85

- Questions regarding how participants felt during the activity (relaxed, tense), as well as how they perceived the activity (complex, easy, amusing).

3. **Self Competence**

(1-7 Scale:1 = Strongly Disagree; 7 = Strongly Agree)

Mean: 5.18 = Most participants somewhat agree to being self-competent

SD: 1.23

- Sense of competence, where people perceive their capabilities and expectations towards their performance.
- How our cognition, thoughts, and emotions play a significant role in our learning through the effects of personal, behavioural, and environmental processes.
- In our study: we want to see how participants perceived their abilities and performance after working with the musical interface.

4. **General Exploration**

(1-5 Scale: 1 - Definitely not, 5 - definitely yes)

Mean: 3.93 = Most participants feel somewhat neutral to somewhat agreeing being generally explorative

SD: 0.62

- Measures an individual's general explorative nature
- In our study: we want to examine if the participant is generally explorative regardless of the activity: seeking new information in new situations, their openness to new experiences

5. **Engagement**

(1-5 Scale: 1 - Strongly Disagree, 5 - Strongly Agree)

Mean: 3.27 = Most participants felt neutral

SD: 0.49

- User's engagement using the musical interface
- The extensive involvement of one's attention and emotions in the task at hand.
- In our study: we want to find out if being engaged in the activity helps the participant's learning and mastery of new and complex experiences.

6. **Creative Engagement**

(1-7 Scale: 1 - Strongly Agree, 2 - Strongly Disagree)

User's engagement towards the activity/prototype through the following:

- **Creative Exploration**

  Mean: 4.44 = Neutral

  SD: 0.85

  - The action or the pursuit of unfamiliar objects, places, or activities.
  - In our study: we want to know how explorative participants were, or if they felt they came up with something creative while they were exploring the musical interface.

- **Creative Creation**

  Mean: 4.35 = Neutral

  SD: 0.81

  - The process of which new ideas are created.

- In our study: are the participants able to express themselves through the musical interface? Are they able to find new ways to express themselves?

7. **General Questions**

(1-5 Scale: 1 - Definitely not, 5 - Definitely yes)

Mean: 3.41 = Neutral

SD: 0.79

- Additional questions we want to ask the participant without making them open-ended questions:
    - Do you have a good mathematical understanding?
    - Did you enjoy learning the song?
    - Did you enjoy improvising with the song?
    - Did you feel that the interface helped you be more expressive?
    - Did you feel that the interface helped you be more creative?
    - Did you feel that you came up with new musical ideas?

8. **Intrinsic Motivation**

(1-7 Scale: 1 - Strongly Disagree, 7 - Strongly Agree)

Doing something due to interest to learn, understand, adapt and accomplish personal rewards such as knowledge.

User’s internal motivation through the following:

- **Interest/Enjoyment**

  Mean: 4.70 = Most participants felt neutral, but leaning towards somewhat agree to having enjoyed the task

SD: 1.31

- Did the participant enjoy the task?
- In our study: the aspect of enjoyment is important as it influences an individual's intrinsic motivation, which in turn, may positively affect their performance and overall experience with the musical interface.

- **Perceived Competence**

  Mean: 4.49 = Neutral

  SD: 1.35

  - How did the participant perceive themselves and their performance with the task?
  - In our study: perceiving oneself as competent is another important element regarding intrinsic motivation. How the participant views themselves before, during, and after the task affects their willingness, performance and experience.

- **Pressure/Tension**

  Mean: 2.94 = Most participants somewhat disagree to feeling pressure or tension while doing the activity

  SD: 1.27

  - How did the participant feel while doing the task?
  - In our study: it is also important to understand participants' emotional/physiological states while they are completing the task. These states either enhances or hinders their abilities in performing well or their overall experience with the activity.

9. Flow

(1-7 Scale: 1 - Strongly Disagree, 7 - Strongly Disagree)

Mean: 4.21 = Neutral

SD: 0.68

- The mental state of being fully absorbed, along with the enjoyment one feels during an activity.
- In our study: similar to engagement, we want to find out if being absorbed in the activity helps the participant's learning and mastery of new and complex experiences. Additionally, when an individual is absorbed in what they do, is their enjoyment with the task also enhanced (despite the complexities)?

-

	Variable	Scale	Definition & The Study
1	**General Perceived Creativity**	1-6	Questions asking participants whether they perceive themselves as creative, musical and if they like to explore new things.
2	**Subjective reports**	1-6	Questions regarding how participants felt during the activity (relaxed, tense), as well as how they perceived the activity (complex, easy, amusing).

3	**Self Competence** (Williams & Deci, 1996)	1-7	Sense of competence, where people perceive their capabilities and expectations towards their performance. - How our cognition, thoughts, and emotions play a significant role in our learning through the effects of personal, behavioural, and environmental processes. - In our study: we want to see how participants perceived their abilities and performance after working with the musical interface.
4	**General Exploration** (Kashdan et al., 2009)	1-5	Measures an individual's general explorative nature - In our study: we want to examine if the participant is generally explorative regardless of the activity: seeking new information in new situations, their openness to new experiences
5	**Engagement** (O'Brien, Cairns & Hall, 2018)	1-5	User's engagement using the musical interface - The extensive involvement of one's attention and emotions in the task at hand. - In our study: we want to find out if being engaged in the activity helps the participant's learning and mastery of new and complex experiences.

6	**Creative Engagement** (Wu & Bryan-Kinns, 2019)	1-7	User’s engagement towards the activity/prototype through the following: **a. Exploration Session** The action or the pursuit of unfamiliar objects, places, or activities. - In our study: we want to know how explorative participants were, or if they felt they came up with something creative while they were exploring the musical interface. **b. Creation Session** The process of which new ideas are created. - In our study: are the participants able to express themselves through the musical interface? Are they able to find new ways to express themselves?
7	**General Questions**	1-5	Additional questions we want to ask the participant without making them open-ended questions - For example, if they enjoy learning and playing? If they have a good mathematical understanding? Questions regarding how the interface has helped them be more creative and expressive.

8	**Intrinsic Motivation** (Deci, Eghrari, Patrick & Leone, 1994; Ryan, 1982)	1-7	Doing something due to interest to learn, understand, adapt and accomplish personal rewards such as knowledge. User's internal motivation through the following: **a. Interest/Enjoyment** Did the participant enjoy the task? - In our study: the aspect of enjoyment is important as it influences an individual's intrinsic motivation, which in turn, may positively affect their performance and overall experience with the musical interface. **b. Perceived Competence** How did the participant perceive themselves and their performance with the task? - In our study: perceiving oneself as competent is another important element regarding intrinsic motivation. How the participant views themselves before, during, and after the task affects their willingness, performance and experience. **c. Pressure/Tension** How did the participant feel while doing the task?

			- In our study: it is also important to understand participants' emotional/physiological states while they are completing the task. These states either enhances or hinders their abilities in performing well or their overall experience with the activity.
9	**Flow** (Engeser & Rheinberg, 2008)	1-7	The mental state of being fully absorbed, along with the enjoyment one feels during an activity. - In our study: similar to engagement, we want to find out if being absorbed in the activity helps the participant's learning and mastery of new and complex experiences. Additionally, when an individual is absorbed in what they do, is their enjoyment with the task also enhanced (despite the complexities)?

תקציר העבודה

ביטוי יצירתי מתייחס למידת העושר והתחכום שבהן מובאות לידי ביטוי כוונותיו של היוצר. ביטוי יצירתי בנגינה, משלב בחירה מתוך מגוון רחב של אלמנטים מוזיקליים כמו תווים, מלודיה, הרמוניה, קצב, מבנה, מרקם, צליל, כלים, תהליכים וארגון. גבולות יכולת הביטוי באופן טבעי מוגבלים ומתרחבים ככל שהיוצר לומד להשתמש במגוון יותר רחב של אותם אלמנטים הנ"ל ועקומת הלמידה הנדרשת היא חדה, מה שמשאיר הרבה אנשים מחוץ למעגל הזה. ההנחה הבסיסית שלנו הינה שכל אחד יוכל לייצר מוזיקה שתהיה בעלת משמעות עבורו ושכושר הביטוי היצירתי יוכל להשתפר עם הזמן. היוצר יוכל להיות מוזיקאי אם חסר כל ניסיון במוזיקה כלל, נגינה או תאוריה. ישנן הרבה דרכים בהן טכנולוגיה ניתנת לשימוש על מנת לתרום לשיפור היצירתיות. הגישה שלנו מדגימה את החשיבות של האתגר המרכזי שלנו, לגשר בין אישיות, מסוגלות, ידע, רצונות וכוונות ואלמנטים חישוביים פורמליים של טכנולוגיות מוזיקליות. במילים אחרות, הטכנולוגיה תעזור לנו לנתח ולזהות את כוונותיו של היוצרת לצמצם את עקומת הלמידה ואף לשבור מחסומים של יצירתיות, בעיקר בקרב חסרי ניסיון מוזיקלי. ההנחה העיקרית שלנו שניתן באמצעים טכנולוגיים לצמצם את החסמים ולבנות יותר מחויבות וביטחון עצמי בתהליך הביטוי היצירתי וכתוצאה מכך, היוצר יהיה מסוגל להביע את עצמו בצורה מוזיקלית במהלך אינטראקציה עם פלטפורמת ה "עזרים החכמים" שיצרנו על מנת להגיע לתוצרים שיהיו בעלי משמעות בשבילו. בעבודה זו – המיקוד הוא ברכיב הפרופיל (איור 2) והמטרה היא לחקור את ההשפעה של התאמה אישית של תהליך הלמידה ויצירת מוזיקה על התוצר. דרך הפעולה שלנו הייתה ללמוד את יכולות הנגינה ואת היצירתיות של משתמש באמצעות גישות חישוביות. נעזרנו בסטודנטים שישתתפו בניסויים וישתמשו באפליקציה ייעודית שנבנתה עבור הניסוי. הם נדרשו למלא שאלונים לפני ואחרי הניסוי. כל הפעולות שלהם באפליקציה תועדו ונותחו. המידע שנאסף מחולק לפרטים דמוגרפיים, הערכה עצמית של המשתמש ואינטראקציה מוקלטת. השתמשנו בגישות של מדעי הנתונים ולמידת מכונה לניתוח וגיבשנו את עיקרי מסקנותינו מגישה של למידה בלתי מודרכת עם אשרור התוצאות על ידי מומחה. המטרה של מחקר זה הוא לאתר את המאפיינים החשובים ביותר שמשפיעים על היכולת של נגנים מתחילים ללמוד לנגן מלודיה קצרה באמצעות אינטראקציה עם אפליקציה על מסך מגע. בנוסף מדדנו גם את היכולת של נגנים מתחילים לבטא את עצמם ולאלתר על בסיס מה שכבר נלמד. בנוסף נבדקה יעילות הפלטפורמה ככלי לימודי.

השאלות העיקריות שהתמודדנו איתן הן:

1. מהם המדדים שעל פי הם נכון לאפיין פרופיל מוזיקלי של יוצר?
2. האם שימוש בטכנולוגיה והתאמה אישית של חווית משתמש ניתן לצמצם את הזמן הנדרש ליצירה בעלת משמעות עבור היוצר.
3. מהם המאפיינים המנבאים הצלחה של משתמש חדש? למשל, מספר תווים, דיוק בקצב, חזרתיות ועוד.
4. האם אופי הממשק או הקונפיגורציה שלו משפיעה על ההצלחה של המשתמשים ומתאימה להם?

המסקנות יראו שעל ידי שימוש באפליקציה כזאת, אנשים בלי ניסיון מוזיקלי יכולים לייצר נגינה משמעותית ומספקת תוך זמן יחסית קצר. אנחנו נציג את המאפיינים שמבדילים בין הקבוצות השונות בהיבטי הצלחה ונגינה משמעותית.

המרכז הבינתחומי בהרצליה

בית-ספר אפי ארזי למדעי המחשב
התכנית לתואר שני (M.Sc.) - מסלול מחקרי

לקראת למידה והבעה מוזיקלית של מלודיה מותאמת אישית

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יולי 2021