A Personality-based Adaptive System for Visualizing Classical Music Performances

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ABSTRACT

To enhance the experience of listening to classical orchestra music, either in the concert hall or at home, we present a personalized system that integrates three visualization/interaction concepts: Score Follower (points to the current position in the score), Orchestra Layout (illustrates instruments that are currently playing and their dynamics), and Structure Visualization (visualizes structural elements such as themes or motifs). Motivated by previous literature that found evidence for connections between personality and music consumption and preference, we first assessed in a user study to which extent personality traits and music visualization preferences correlate. Measuring preference via pragmatic quality and personality traits according to the Big Five Inventory (BFI) questionnaire, we found substantial interconnections between them. These translate into rules relating certain personality traits (e.g., extraversion or agreeableness) to preference rankings of the visualizations.

In the proposed personality-based system, users are grouped into four clusters according to their answers to the most significant personality questions determined in the study. The order of the visualizations for a given user is adapted with respect to the ranking preferred by other users in the same cluster. Evaluation of the system was carried out by a second user study that showed a significantly higher normalized discounted cumulative gain (NDCG) for the personalized system in comparison to a system with randomized order of the visualizations.

CCS Concepts

•**Information systems** → **Music retrieval;** •**Applied computing** → **Sound and music computing;**

Keywords

music visualization, recommender systems, personality

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1. INTRODUCTION

Classical music is a great asset and cultural heritage. Nowadays, however, fewer and fewer people attend respective orchestra concerts. There is strong evidence that in particular the younger generation is reluctant to attend concerts, due to various reasons [13].[1] In the EU-FP7 funded project "Performances as Highly Enriched aNd Interactive Concert eXperiences" (PHENICX)[2], a central aim is to make classical music accessible to new audiences. One way to achieve this is to elaborate appealing, informative, and easy to use and understand systems to visualize and interact with multimodal information in order to support and enhance the listening experience. Taking into account the different individual preferences towards particular pieces of such information enables the creation of personalized systems to experience classical music performances.

In the work at hand, we present a system that provides a personalized view on different visualization and interaction techniques, based on personality traits of the listener. In particular, after a brief discussion of related work in Section 2, the three used visualization techniques are introduced in Section 3. In Section 4, we report a new user study in which we investigated the relationship between preferences towards these visualizations and the answers to 44 personality-related questions, according to the Big Five Inventory (BFI) [8] instrument. Section 5 presents the web-based user interface to the system that provides the user a recommendation for their personalized view on the visualizations. Section 6 details another user study which we carried out to assess the value of the recommendations the system provides to the listeners. Eventually, Section 7 summarizes the work and points to future directions.

The main novel contributions of this paper are (i) a user study to investigate the relationship between personality traits and visualization preferences for classical performances, (ii) the subsequent creation of a personality-based adaptive system that integrates the different visualization and interaction concepts and enhances the listening experience, and (iii) the evaluation of this system in terms of gain for the user.

2. RELATED LITERATURE

While we are not aware of any related work that uses personality traits to personalize or recommend visualizations, the psycholog-

[1] This also became evident in personal discussions between the authors and members and leaders of major classical orchestra, e.g., the Royal Concertgebouw Orchestra Amsterdam and the Philadelphia Orchestra.

[2] http://phenicx.upf.edu

ical concept of personality is a well studied one. It accounts for individual differences in a wide range of situations. Among many models, one of the most frequently used is the Five Factor Model (FFM) [11]. The model is composed of five factors, namely *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness*, and *Neuroticism*. Table 1 depicts adjectives that further describe each of the personality factors according to [11]. Each person can be modeled by these five factors by assigning a value to each factor, for instance, on a scale from 1 (low) to 5 (high). The assessment can be done through questionnaires [5] or unobtrusively from social media activity [9].

On a higher level, the work at hand also connects to the analysis of the relationship between music in general and personality. Related studies investigated the connection between personality and music genre preferences [16], between personality and the use of music by people [2], and between personality and the way people organize music [3]. Exhibiting a stronger connection to the work at hand, due to their focus on classical music, Tkalčič et al. conducted a user study to relate personal characteristics (personality and musical knowledge) to preferences for digital program notes, in particular to preferences for different multimedia material related to classical music [18]. More precisely, the authors investigated *musical background* variables, such as frequency of concert attendance, playing an instrument, or weekly hours spent on listening to classical music, *musical preference* (according to 18 genres), and *personality* using the Ten Items Personality Inventory (TIPI) questionnaire [5]. On the content side, the 165 participants in the study were asked to rate the interestingness and novelty of a variety of multimedia material (text, images, and audio) related to composer, piece, and performer. In addition to correlations between personality traits and several of the musical background variables, Tkalčič et al. found that people with high openness, agreeableness, conscientiousness, or extraversion tend to consume more material, find it more interesting and novel. In contrast, people scoring high on neuroticism tend to consume less material, find it less interesting or novel.

3. VISUALIZATION OF CLASSICAL MUSIC PERFORMANCES

Within the PHENICX project, we developed various concepts and respective implementations of visualization and interaction techniques for classical music performances. Three of these concepts were selected for the personalized system at hand, given that: (i) they were consistently reported as positive in preliminary user studies [12]. , (ii) they enhance different musical dimensions and complement each other, and (iii) they were seen useful by users with different backgrounds. The chosen visualizations are briefly introduced in the following. Although interactive functionalities are described and implemented for all of them, methodological reasons constrained the reported studies to passive visualizations.

3.1 Score Follower

Music scores provide arguably the richest musical information about a composition, as the actual music they represent can be fully recreated from them. Based on audio-to-score alignment techniques [1, 4] , our system allows to match (follow) the orchestral performance over time with a visual representation of the score. To this end, the audio signal from the actual performance is time-aligned with a digital encoding of the score, and the currently played position is highlighted in the score at the bar level. The listener can either follow the score in real time along with the performance in the concert hall or offline. In the latter case, the user can interact

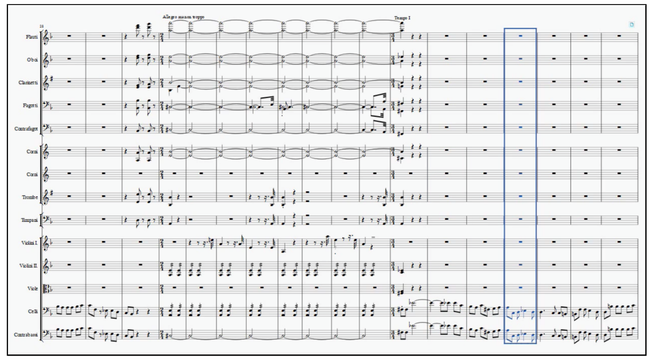

Figure 1: The *Score Follower* visualization. The blue box indicates the bar currently played by the orchestra.

with the score for navigating the music, by means of selecting a bar in the score which positions the playback time accordingly. A screenshot of the Score Follower, as used in the reported system, is depicted in Figure 1. Preceding qualitative user studies conducted among people with different levels of musical expertise and education showed that even novices who are not able to read scores appreciate this kind of visualization and find it useful.

3.2 Orchestra Layout

A general reported drawback of the Score Follower is the overwhelming amount of information it conveys, as well as the requirement of musical literacy to fully understand it. A useful simplification of the score is to account only for the instrumental sections playing at the current time. By avoiding the music notation and the explicit visual reference to time (x-axis in the score), the Orchestra Layout visualization focuses on simpler perceptual cues easily understandable by wider audiences, such as instrumental timbre, while adding relevant information about spatialization of the sound. A screenshot of the Orchestra Layout visualization, as used in the reported system, is depicted in Figure 2. The visual design consists of an schematic spatial arrangement of the orchestra as seen from a very high angle. Using again audio-to-score alignment techniques, each individual musician is highlighted only when he or she actually plays. Furthermore, the dynamics of each instrumental section is computed by means of source separation techniques [14], so as the individual intensities can be dynamically represented along with the music. Higher dynamics translate to higher color intensities. Furthermore, below the legend for the instrument groups on the top of the visualization, pitch information for each group is displayed in a highly simplified way: the vertical position of the bars below each group illustrates pitch. As interactive functionality in the offline scenario, also powered by the aforementioned source separation, the user can select any instrumental section from the layout and enhance its corresponding audio signal in a spatialized way, so as focusing the attention to the chosen instrument. Preceding qualitative user studies showed that this visualization is highly intuitive and generally informative for experts and novices alike [10].

3.3 Structure Visualization

The structure of a music piece can be referred to as a high-level temporal scheme in which the music is segmented in meaningful sections for explanatory purposes. As a sense of structure can be conveyed by different compositional resources, different visual rep-

Table 1: **The personality factors and examples of corresponding adjectives, according to the Five Factor Model (FFM) [11].**

Factor	Adjectives
Extraversion (E)	active, assertive, energetic, enthusiastic, outgoing, talkative
Agreeableness (A)	appreciative, forgiving, generous, kind, sympathetic, trusting
Conscientiousness (C)	efficient, organized, planful, reliable, responsible, thorough
Neuroticism (N)	anxious, self-pitying, tense, touchy, unstable, worrying
Openness (O)	artistic, curious, imaginative, insightful, original, wide interest

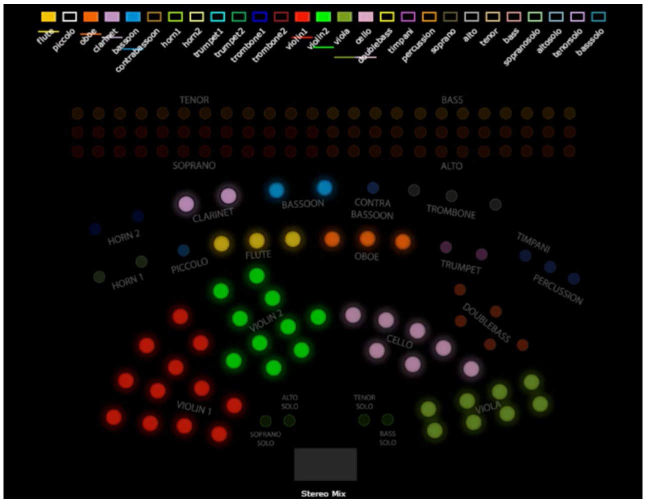

Figure 2: The *Orchestra Layout* visualization. The common layout of the orchestra in the concert hall is shown. Performers are grouped according to instrument groups and currently playing ones are highlighted.

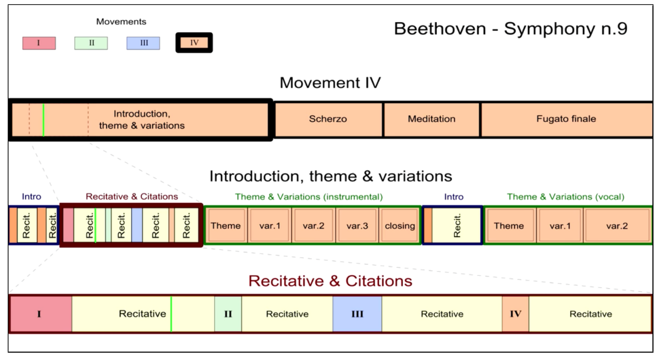

Figure 3: The *Structure Visualization* showing different structural elements at different levels of detail.

resentations can be designed accordingly. Sections can be distinguished by means of thematic material, tonality, orchestration, or character, to cite a few. More often it is a combination of factors that contributes to structure, and several different structures can be reasonable for a given music work. For this visualization, a musicologist decided a set of abstraction levels and time scales, ranging from the movement scale to short thematic materials. Structure and segmentation were explained by two different means: (i) textual labels using standard musical/analytical terminology with varied degrees of sophistication and (ii) coloring schemes for relating segments within and across structures at different levels. Similarly to the other visualizations, the audio-to-score alignment allows to locate the current performance time in the different structural layers, providing the user with a visual guide to the composition. A screenshot of the Structure Visualization, as used in the reported system, is depicted in Figure 3. As interactive functionality in the offline scenario the user can use any of the structural levels as indexes to navigate the piece. More details on the approach can be found in [4].

4. PERSONALITY-BASED PREFERENCES FOR MUSIC VISUALIZATION

As shown in earlier studies, users are diverse in their preferences for music visualizations [12, 18]. To account for this fact and in turn build a personalized system for displaying the visualizations described in Section 3, we conducted a user study to relate personality traits to visualization preferences and derive corresponding rules which serve to personalize the organization of visualizations. With *preference* we mean the pragmatic quality (PQ) scores, as defined by [6]. The PQ score is an aggregated value of answers to a set of questions on how much a visualization is considered technical, complicated, impractical, cumbersome, unpredictable, confusing, and unruly. We explored the diversity of users in terms of their *personality*, which was measured with the 44 questions from the Big Five Inventory (BFI) [8].

More precisely, the study was implemented as a web-based survey; subjects were recruited through Amazon Mechanical Turk and were paid 1.50 USD for their engagement with the study, which lasted on average 17 minutes. The study was active for a period of 5 days in April 2015. We did not acquire any personal data that could lead to the disclosure of the subjects' identities. We employed a between-subject design, where each subject was assigned only one of the three visualizations. The subjects first filled in the BFI-44 personality questionnaire [8]. Subsequently, participants were shown a demonstration video of the assigned visualization and asked to fill in the pragmatic quality questions according to [6], reported in Table 3. The chosen piece was Beethoven's 9th symphony and the video showed the first 2 minutes of the 4th movement. We decided to use parts of a single piece only, in order to avoid introducing more variables in the user study. After removing fake respondents based on control questions, we were left with 185 valid subjects. Descriptive statistics are reported in Table 2.

Table 2: Descriptive statistics of the user study.

Subjects	185
Age μ (σ)	34 (14.8) years
Males (Females)	78 (107)
Subjects in Score Follower	57
Subjects in Orchestra Layout	64
Subjects in Structure Visualization	64

On the data acquired in the user study, we preformed regression

Table 3: **Scoring questions related to the pragmatic quality (PQ) [6] of the visualizations.**

Question	Response Range
The visualization is ...	Technical (1) ... Human (7)
The visualization is ...	Complicated (1) ... Simple (7)
The visualization is ...	Impractical (1) ... Practical (7)
The visualization is ...	Cumbersome (1) ... Direct (7)
The visualization is ...	Unpredictable (1) ... Predictable (7)
The visualization is ...	Confusing (1) ... Clear (7)
The visualization is ...	Unruly (1) ... Manageable (7)

analysis. The dependent variables, i.e., those that we want to predict, are the user ratings to the questions reported in Table 3. The independent variables, i.e., those on which we will build our personalized visualization system on, are the personality traits inferred from the BFI-44 questionnaire. We identified a large number of significant correlations (according to the Pearson product-moment correlation coefficient [17]) at $p < 0.05$. In Table 4, we report the significant correlations with absolute correlation value higher than 0.3. Based on the outcomes of the regression analysis, we conclude that the selected independent variables account for a lot of variance and are good candidates to base a personalized music visualization system on.

5. PERSONALIZED SYSTEM FOR MUSIC VISUALIZATION

5.1 Personality-based User Clusters

In order to build a user-friendly system that is personalized based on the results of the study reported in the previous section, we decided to recommend to each user the visualization that has the highest average rating among the users with similar personality traits. However, there obviously exists a trade-off between the user's willingness to fill in the fully fledged BFI-44 questionnaire and the accuracy of visualization recommendations. Since the system is not only a research prototype, but is currently being implemented into a mobile application by our business partner in the PHENICX project, we decided to select only two initial questions, according to which users are categorized and their preferences assessed. To this end, we identified the BFI questions that account for most of the variance in the sample of users from the study. The cross-correlations between (a subset of) the personality items (marked with `BFI-1` to `BFI-44`) and pragmatic quality scores `PQ` are shown in Figure 4. The candidate questions that correlate well with the PQ scores are `BFI-7` (0.32), `BFI-13` (0.25), and `BFI-18` (-0.26). Since `BFI-7` and `BFI-18` exhibit the lowest absolute cross-correlation (-0.22), we chose these two. The corresponding `BFI-7` and `BFI-18` statements, for which the users have to answer on an agreement scale, are "I see myself as someone who is helpful and unselfish with others." and "I see myself as someone who tends to be disorganized.", respectively.

Based on the users' answers to the two questions, we cluster them into four groups, using the median value along each variable (`BFI-7` and `BFI-18`) as splitting point. The users who score lower than the respective median values on both of the questions are assigned to the `lo-lo` cluster. Those who score higher than the median on `BFI-7`, but lower than the median on `BFI-19` are assigned to the `hi-lo` cluster. Those who score lower than the median on `BFI-7` and higher than the median on `BFI-19` are clustered into the `lo-hi` cluster. Finally, those who score higher than the median on both questions are grouped into the `hi-hi` cluster.

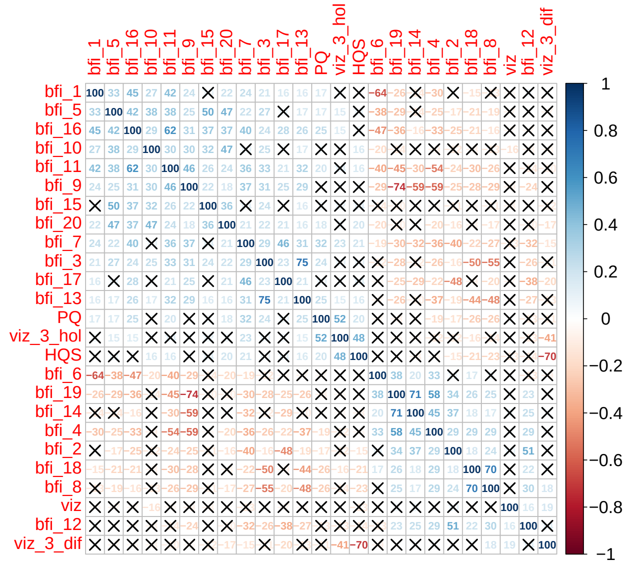

Figure 4: Cross-correlations between a subset of the personality items (marked with `BFI-1` to `BFI-44`) and pragmatic quality `PQ`. The correlation values are scaled to [-100, 100].

The sizes of the clusters, i.e., the number of users in each cluster, are 62, 53, 52, and 18 for the clusters `lo-lo`, `hi-lo`, `lo-hi`, and `hi-hi`, respectively. The distribution of users and sizes of the clusters are illustrated in Figure 5.

Looking at the distribution of ratings (pragmatic quality scores) for each visualization (cf. Figure 6) over the personality clusters, it becomes evident that preferences towards one or the other visualization indeed highly depend on personality traits. From the PQ scores shown in Figure 6, we infer a ranking of visualizations for each user cluster, which is shown in Table 5.

5.2 User Interface

Upon the first start of the system, the user is asked the `BFI-7` and `BFI-18` questions. Based on their answers, they are shown a page, where the three visualizations are presented in such a way that the top-ranked is placed in the central position occupying most of the space on screen. The other two are rendered smaller at the bottom of the interface; the second ranked being positioned on the left, the third ranked on the right (cf. Figure 7). Nevertheless, the user can also easily switch from the recommended visualization to any of the other two.

6. EVALUATION

In order to evaluate the proposed system, we conducted another user study via Amazon Mechanical Turk. The 79 recruited participants were paid 0.35 USD for a task that lasted 3 minutes on average. They were first asked the two personality questions `BFI-7` and `BFI-18`. Subsequently, participants were shown the snapshots of the three visualizations in a row next to each other (cf. Figure 8). The order was randomly assigned for each participant. The participants were instructed to watch each visualization for at least 20 seconds, which was checked by the system. Finally, the users were asked to rank the visualizations according to their preferences. The number of subjects in the clusters `lo-lo`, `lo-hi`, `hi-lo`, and `hi-hi` was 26, 16, 22, and 15, respectively.

Table 4: Correlations between the personality traits and the observed user ratings for the visualizations. Only significant correlations with an absolute value higher than 0.3 are reported.

Visualization	Personality Trait	Rating Question	Correlation	p-value
Score Follower	Conscientiousness	cumbersome-direct	0.30	0.02184
Score Follower	Extraversion	pragmatic quality (overall)	0.36	0.00633
Score Follower	Agreeableness	lame-exciting	0.31	0.01727
Score Follower	Agreeableness	pragmatic quality (overall)	0.32	0.01637
Structure Visualization	Extraversion	technical-human	0.30	0.01540
Structure Visualization	Agreeableness	technical-human	0.33	0.00729
Structure Visualization	Agreeableness	impractical-practical	0.45	0.00019
Structure Visualization	Agreeableness	cumbersome-direct	0.38	0.00207
Structure Visualization	Agreeableness	confusing-clear	0.42	0.00052
Structure Visualization	Agreeableness	unruly-manageable	0.42	0.00065

Table 5: Ranking of the visualizations, according to the personality clusters.

Personality Cluster	1st Rank	2nd Rank	3rd Rank
lo-lo	Orchestra Layout	Structure Visualization	Score Follower
lo-hi	Orchestra Layout	Structure Visualization	Score Follower
hi-lo	Structure Visualization	Orchestra Layout	Score Follower
hi-hi	Score Follower	Orchestra Layout	Structure Visualization

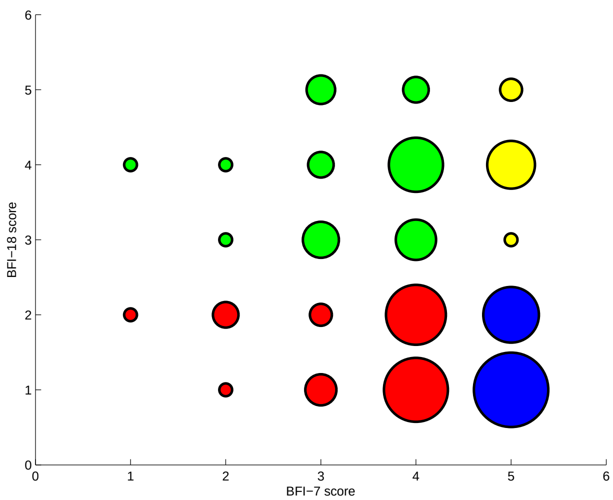

Figure 5: Number of users in the personality clusters. The size of the circle is proportional to the number of users with the same scores for the two questions `BFI-7` and `BFI-18`. The users in cluster `lo-lo` are colored in red, those in `hi-lo` in blue, those in `lo-hi` in green, and those in `hi-hi` in yellow.

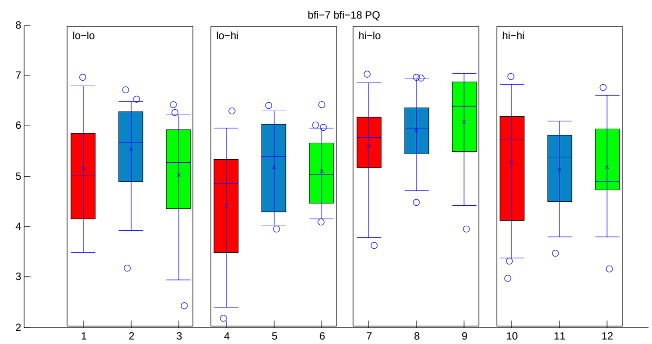

Figure 6: Distributions of the pragmatic quality (PQ) scores for the three visualizations and four user clusters. The first three boxplots (from left to right) correspond to `lo-lo`, the next three (fourth to sixth) to `lo-hi`, then `hi-lo`, and finally `hi-hi`. Within each triple, the first (leftmost, colored in red) boxplot corresponds to the Score Follower, the second (colored in blue) to the Orchestra Layout, and the third (colored in green) to the Structure Visualization.

To quantify the quality of the personalized rankings, we used the normalized discounted cumulative gain (NDCG) [7]. Originating from information retrieval research, the NDCG measures the usefulness of a certain order of documents retrieved for a given query and a given user. It is widely used both in academia [7] and industry.[3] In our case, NDCG measures the usefulness of the recommended visualizations based on their position in the ranked list. Since we always rank only three items, we employ a non-logarithmic version of NDCG, which is computed according to Equation 1, where $G(r)$ is the gain/usefulness of the visualization presented at rank r and $IDCG$ is the ideal DCG that is obtained with a perfect ranking, i.e., $G(1) = 3$, $G(2) = 2$, and $G(3) = 1$.

$$NDCG = \frac{DCG}{IDCG} = \frac{\sum_{r=1}^{3} G(r)/r}{4.33} \quad (1)$$

If the recommended visualizations are perfectly ranked, NDCG equals 1.0. In our case of ranking three items (visualizations), the worst possible NDCG is 0.69. We compared the mean NDCG of the recommended visualization rankings ($NDCG_{rec}$) to the mean NDCG of randomly ranked visualizations ($NDCG_{rand}$). The obtained values were $NDCG_{rec} = 0.87$ and $NDCG_{rand} = 0.82$. The independent t-test showed that the difference of the means was significant ($p = 0.03$). The significant difference means that our

[3]http://www.ebaytechblog.com/2010/11/10/measuring-search-relevance/

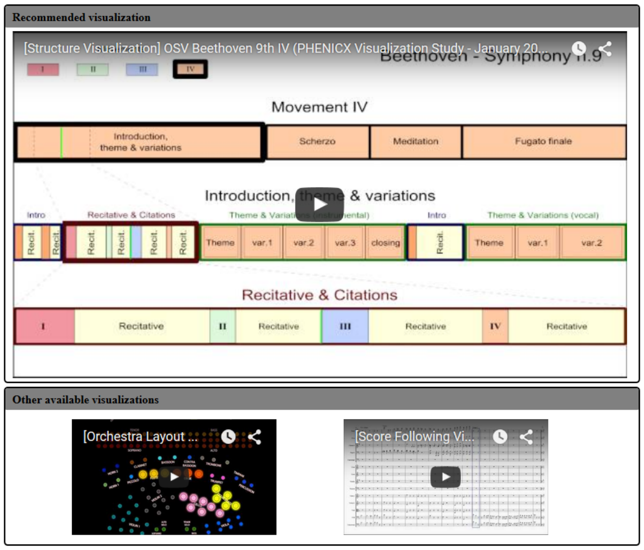

Figure 7: Rendering of the visualizations with the top-ranked one bigger and positioned predominantly. The second ranked is positioned at the bottom left and the third ranked at the bottom right. The screenshot depicts an example for a user from the `hi-lo` cluster.

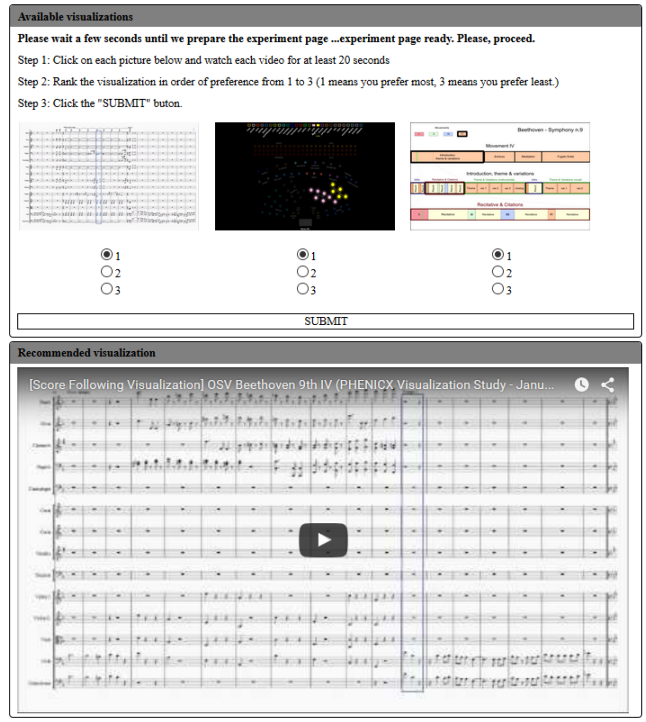

Figure 8: User interface of the evaluation user study. The users clicked on a snapshot image (upper part) and saw the video in the main part (lower part).

system's better average NDCG metric was not due to chance, but due to a systematically better organization/ranking of visualizations.

7. CONCLUSIONS AND FUTURE WORK

We presented a personalized system to organize three different visualizations (Score Follower, Orchestra Layout, and Structure Visualization) for classical music performances, which can be used both during a concert or in an offline setting (before or after the concert. We based the system's personalization on a conducted user study that investigated the relationship between personality traits and visualization preferences. Measuring visualization preference in terms of pragmatic quality scores, we found substantial correlations between preference and personality traits. Incorporating the findings of the study, we created a personality-based adaptive system to present the different visualizations in the way deemed most useful to the listener. To this end, users are grouped into four clusters according to personality scores and the order of the visualizations for a given user is adapted with respect to the ranking preferred by other users in the same cluster. Evaluation of the system was carried out by a second user study that showed a significantly higher normalized discounted cumulative gain (NDCG) for the personalized system in comparison to a system with randomized order of the visualizations.

As for future work, we plan to look into other performance-related music visualizations, e.g. [4], and investigate if they are suited for incorporation into our system. In addition, we plan to extend the degree of personalization of our system to factors other than personality, such as musical education, experience, and knowledge, musical preferences beyond classical music, or music sophistication [15].

8. ACKNOWLEDGMENTS

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