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A Knowledge-Based Pilot Study on Assessing the Music Influence

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Abstract: A knowledge-driven approach is proposed for assessing the music influence on university students. The proposed method of modeling and conducting the interactive pilot study can be useful to convey other surveys, interviews, and experiments created in various phases of the user interface (UI) design processes, as part of a general human-computer interaction (HCI) methodology. Benefiting from existing semantic Web and linked data standards, best practices, and tools, a microservice-oriented system is developed as a testbed platform able to generate playlists in a smart way according to users' music preferences. This novel approach could bring also benefits for user interface adaptation by using semantic Web techniques. Statistical analysis based on the ANOVA method and post-experiment survey data led to the conclusion that music listened has a significant impact on students' cognitive abilities in various contexts. All obtained results were semantically enhanced by using different conceptual models in order to create a knowledge graph providing support for automated reasoning. Also, a knowledge-based persona Web smart editor was implemented in order to include music preferences for certain categories of the potential users operating a specific interactive system.

1 Introduction

In order to properly envision a user interaction to a certain—conventional, Web, mobile—complex application, various software engineering approaches are used. The article proposes a knowledge-driven method in modeling HCI (Human–Computer Interaction) surveys, interviews and experiments—such as user research, usability evaluation, field study, controlled experiment, etc. These processes are performed in different phases: A-priori (discovery, alpha, beta) and/or a-posteriori (during the actual deployment) of a given interactive application. The paper also illustrates the pragmatic use of *schema.org* conceptualizations [1] in HCI context, especially for annotation of music digital artefacts (i.e., playlists) and for specifying useful metadata with respect to HCI engineering processes.

By using well-known semantic Web standards [2]—such as expressing data as triples denoted by Web addresses (RDF—Resource Description Framework), remotely querying these triples (via SPARQL standard

language), conceiving knowledge models represented by meta-data vocabularies, taxonomies, thesauri, ontologies (OWL—Web Ontology Language), performing automated reasoning with help from specific logics, our aim is to describe a methodology able to specify, annotate and publish all useful assets and datasets associated to a given HCI experiment: research questions, contextual research (problem domain), participants, performed tasks, results, and others. This method is inspired by Negru et al. [3] which describe a knowledge-based system able of making decisions towards personalizing UIs based on user needs and preferences. A larger context has as foundation the concept-driven interaction design research [4].

As a real example, a pilot study was conducted to analyze the influence of listening to music on the efficiency of cognitive processes of students from technical specializations—in this case, Computer Science. Given that many students nowadays are used to listening to music while performing cognitive activities (learning, acquiring knowledge, solving tests and questions, interpreting texts and visual information) in the academic context, the present study is based on an experiment that highlights how these cognitive capacities are enhanced by simultaneous listening to music. Several kinds of studies related to this issue have been conducted in the literature, but our aim is to assess—with the help of the present-day semantic Web initiatives—how students' cognitive abilities are affected in two distinct situations: Listening to their favorite music genre and listening to a totally unpleasant music genre.

The obtained results were integrated into a persona Web editor able to create and manage classes of potential users of an interactive system in the phases of design practice and/or design exploration. This tool also makes use of current semantic Web standards in order to manage and suggest personas to be used in designing user interfaces.

The paper is structured as follows. Next section discusses several related approaches concerning the use of knowledge in the HCI areas, plus investigating how music has influence on users in various contexts.

The following section details the proposed methodology used for performing experiments—in order to study how students' cognitive abilities are affected by the preferred/unwanted background music. This section outlines our most significant contributions:

- The conceptualization of preliminary data gathered in the pre-experiment survey in order to group the involved participants according to their music genre preferences and demographics.
- Generating playlists, in an intelligent and novel manner, by using our microservice-oriented Web system adopting the functional (FaaS—Functions As A Service) serverless paradigm [4,5]; this prototype, deployed on a popular cloud computing platform, was developed to manage knowledge about user preferences of music genres. This approach could bring also benefits for user interface adaptation by using semantic Web techniques.
- Performing the statistical analysis of the data gathered from the conducted experiment and from the post-experiment survey, in order to offer insights and discuss the expected outcome.

The article continues with a presentation of an interactive Web application conceived to create personas in a smart way, including suggestions regarding the music preferences for each category of potential users. The purposes regarding the tool design and development are focused on two main directions: (1) Creating and managing knowledge about personas—modelling, editing, validation, annotation; and (2) Learning and understanding persona design methods—exploration, search, filtering, explanation. The tool has mainly an educational purpose and is currently used to specify personas for various HCI projects by post-graduate students enrolled in our "Human–Computer Interaction" discipline (MSc studies), stimulating design research activities and digital creativity. A case study on rule-based recommendations for performing certain tasks (in our experiment, suggesting to meet a person having a similar music taste) is also included.

Last section presents the conclusions and various future directions of research.

2 Related Work

2.1 Using Semantic Web Technologies in the HCI Context

There are relatively few proposals of using current semantic Web technologies for designing interactive systems or representing certain aspects of interest: UI components, interaction methods, personas, tasks, user behavior (e.g., gestures, emotions), context of use, processes (quality evaluation, user testing, usability experiments), and others [1,6,7].

We considered also various papers describing certain knowledge models able to express, among others:

User-centered design process—an approach for designing usable products and systems, which encompasses a collection of techniques, procedures, and methods focused on the user. The proposal considers the use of HTML5 microdata (i.e., the *schema.org* model) and an ontological specification to denoted such processes [3].

Persona—a pragmatic solution to express the main categories of potential users for a given interactive application (demographic profile, preferences, needs and goals, frustrations and requirements) [8]. Several public conceptualizations are available such as an ontology (*PersonaOnto*) and a HTML5 template capturing data about a certain proposed persona [4].

Human needs—a family of ontologies for representing human needs is proposed in order to represent, enrich and query the results of a needs assessment study in a local citizen community [5].

Body movements—especially, gestures, and postures—performed by users in the context of interacting to certain devices (for example, Kinect) [6].

User emotions and affective states—a number of 20 ontologies are compared in order to assess the expressivity of denoting user behaviors driven by emotions, moods, and sentiments [9].

Concerning *user interface adaptation*, a high-level architectural proposal is discussed in Partarakis et al. [10] with respect to how semantic Web initiatives could be used to provide support for designing adaptable Web-based interfaces.

Regarding learning environments, a knowledge/rule-based e-learning ecosystem is described by Ouf et al. [7]. Unfortunately, the user preferences and motivations are not considered.

Several other research solutions concerning the adoption of semantic models to be used in various HCI systems and contexts are described in Hussein et al. [11].

None of these studies reflects the music influence on involved users.

2.2 Music and Cognitive Activities

A variety of studies have been conducted in the literature, with respect to the relation between music and cognitive activities [12–14], including the effects of background music on human subjects from various fields like education [15–17], or concerning different cognitive tasks [18–20].

We also reviewed the existing literature regarding the effects of background music on human subjects from various areas.

In the educational field, an interesting result was obtained by Taylor et al. [16] who researched the effect of Mozart's music on the performance of students having to solve trigonometry problems. The students who took the tests while listening to Mozart's music achieved significantly better results than those who took the test without background music. Concerning the "bullying" phenomenon, background music has a significant effect—under certain conditions, bullying may increase even with music played at a low volume [17].

An interesting study [15] analyzed how listening to music during learning activities helps reduce stress and anxiety for students. The results obtained from scientific research have shown that listening to music

during learning activities does not contribute to lowering anxiety levels. Moreover, the authors suggest that listening to music during learning could actually be a disturbing factor.

Another research focused on the effects of background music on cognitive tasks in four different environmental conditions: noise, silence, music with lyrics, music without lyrics. The study was unable to show notable results in terms of music influence for the proposed tasks [21].

In terms of task performances, a concern is whether background music affects human work concentration (subjects having background music versus no ambient music) [22]. The results showed that changes in performance depend less on the type of music and rather on preferences of workers to listen or not to music. The effects of music listened to in offices were investigated by performing empirical studies to highlight musical habits, the effects of music on work appreciation, and the impression of employees on their own activities. Based on a variety of music styles, the study concludes that there are no significant influences on performance-related tasks [18]. Also, music can have both positive and negative effects on different employees in different situations. According to the study, office music can be considered as having the role of blurring the boundaries between private space and public space and also it has the role of bringing personal habits into the official work space to improve personal comfort in public spaces [23].

The effects of background music have been examined by Sengupta et al. [19] to investigate how the users' performance regarding text editing tasks changes. The results showed that the presence of background music caused an increase in the rate of typing errors, but at the same time there was a significant relaxation process for users, which caused a 23% lower force in keyboard operation.

Music can also have effects on behavior when analyzing human interaction over the phone. In a call center, customers are less aggressive in days when background music is instrumental and become more aggressive when background music contains lyrics [21].

Unfortunately, all mentioned studies and experimental endeavors do not benefit from a conceptual (formal) model defined with the help of current semantic Web standards. Our proposed knowledge-based approach could be a proper solution to rigorously specify the main aspects with respect to various HCI experiments.

3 Proposed Method

3.1 A Knowledge-Based Experiment of Assessing the Role of Music in Performing Specific Tasks

Our approach is to assess how students' cognitive abilities are affected by background music in two distinct situations: listening to their favorite music and listening to a totally unpleasant style of music. We choose to adopt a method of investigation based on knowledge modelling techniques specific to actual semantic Web directions of research.

By following the methodological proposals presented in Jawaheer et al. [24,25], the main steps of the conducted non-invasive study are: (1) Selecting a random sample of voluntary participants. (2) Performing a pre-experiment to obtain useful demographics, plus favorite/undesirable music styles. (3) Grouping respondents according to the classification criteria: preferred music style versus unwanted music style. (4) Performing the experiment, by giving two tests conducted when the participants had their favorite music in the background, and the other set of tests was administered with undesirable background music. (5) Analyzing and discussing the results.

3.2 Conducting the Pre-Experiment

The study was conducted on a random sample of 40 university students—22 female students and 18 male students, aged between 21 and 25, enrolled in the final year of undergraduate studies on

Computer Science at the Faculty of Economy and Business Administration. All respondents signed a consensus statement agreeing to participate in this experiment and agreeing to have their data taken and analyzed by the authors of the study, including filming.

Each student was given a pre-experiment on-line survey to obtain useful demographics (gender, age, rural/urban origin) and favorite/undesirable music styles, including preferred songs and/or artists, in order to create suitable playlists and to avoid the cold start of recommended items of interest (in this case, musical compositions).

3.2.1 Formalization

There are various proposals regarding how user preferences could be formally modelled in order to be properly used in the context of recommender systems.

The preliminary data can be formalized as tuples Ds, $s \in S$, where D is the set of gathered preferences and demographics for a given participant, and S represents the set of subjects (all participants in the experiment; in this case, students).

Each Ds has the following structure: $<pgs(m), pcs, g, a, o>$, where $pgs : M \rightarrow R$ denotes the preference of the subject (student) s for a music genre m—an element of the taxonomy of all considered music genres ($m \in M$). R signifies the set of expected ratings—for example, using a scale from 1 ("I totally dislike") to 10 ("I totally like") or other (symbolic) conventions. The pcs construct represents the list of preferred music compositions (usually, songs) or artists (musicians such as singers, pop stars, rock bands, coral ensembles, symphonic orchestras, etc.) stated by the subject s, and has a similar definition to pgs.

The last three items—g, a, and o—indicate demographic information: gender, age, and origin, respectively.

Using the description logics formalism [26], a preference could be considered as a functional property having as a domain the set M and as a range R, where M is a (sub)class from a conceptual model (i.e., a taxonomy or an ontology) related to music genres and other things of—for instance, MusicMoz[1] (see below) or Music Ontology[2], and R denotes the class *Rating* defined by the *schema.org* specification. A similar approach is used to specify user demographics.

As we shall describe below, these models are useful to easily group the subjects according to the most (un)liked music genres.

3.2.2 A RDF-Based Conceptualization of User Music Preferences

Gathered data from this survey are semantically annotated with *schema.org* semantic constructs [27] and modelled as RDF[3] triples: $< subject, predicate, object >$, typically denoted by Web addresses—URIs (Uniform Resource Identifiers) or IRIs (Internationalized Resource Identifiers).

The following example, adopting the standardized Turtle[4] format of the RDF abstract model, asserts that a given subject (*subject33*) is a female person who loves pop and dislikes jazz music genres. Also, she has as a preferred song a techno piece by Moby (Richard Melville Hall). Techno genre represents a subclass of the electronic dance music. In order to make further assumptions and automated reasoning, each concept is uniquely denoted by Wikidata's URLs. The "*ex*" prefix denotes our own vocabulary regarding the knowledge about the conducted experiments and schema corresponds to the schema.org conceptual model.

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[1] *MusicMoz*—https://musicmoz.org/

[2] *Music Ontology Specification*—http://musicontology.com/specification/

[3] *Resource Description Framework*, a standard model for data interchange on the Web—https://www.w3.org/RDF/

[4] *RDF 1.1 Turtle: Terse RDF Triple Language*—https://www.w3.org/TR/turtle/

```
# Expressing metadata about a participant
:subject33 a schema:Person ;
 schema:gender <http://schema.org/Female> ; # the subject is a female person
 schema:description "Anonymous participant #33"@en ;
  ex:prefMusicGenre [ # this participant dislikes jazz (concept denoted by a Wikidata identifier)
   schema:genre <https://www.wikidata.org/wiki/Q8341> ; schema:ratingValue 0 ] ;
  ex:prefMusicGenre [ # …but loves pop music
   schema:genre <https://www.wikidata.org/wiki/Q37073> ; schema:ratingValue 10 ] ;
  ex:prefComposition [ # a preferred music composition (a song)
   a schema:MusicComposition ;
   schema:genre <https://www.wikidata.org/wiki/Q170611>
   schema:name "Feeling So Real"@en ; schema:composer <https://www.wikidata.org/wiki/Q14045> ] ;
  # opinion on personal efficiency (is music making work more efficient?)
  ex:musicEfficiency [ schema:ratingValue 6 ] .
```

We also asked participants to state their preferences and opinions on several topics such as:

Listening to music by using various types of speakers: standalone speakers, laptop speakers, or headphones. Unsurprisingly, the majority of subjects prefer to use headphones. We also learn that only 27% of subjects choose to listen to music at a high volume.

Listening to music in the academic context (for example, when studying lecture notes or working on homework)—results: 15.4% never, 65.4% sometimes, 19.2% often.

Opinion on personal efficiency with respect to listened music (i.e., if music makes work more efficient) on a scale of 0 to 10, where 0 denotes "I don't know" or "I don't want to respond to this question". In our case, the arithmetic mean value was 5.92, the median value was 7, and the mode (most frequent value in the dataset) was 8.

Preferring foreign or national music: 53.8% foreign, 42.3% any, and only 3.9% countrywide music. This denotes a higher grade of musical cosmopolitanism among younger generation.

With respect to urban/rural origin, 54% of subjects are from urban areas and 36% from rural regions.

3.3 Conducting the Pilot Study

3.3.1 Distributing Subjects According to Music Preferences

Respondents were divided into three distinct groups (see Tab. 1) according to the classification criterion: the preferred music style versus the unwanted music style. To distribute respondents according to musical genres, an adaptation of the taxonomy provided by MusicMoz was made, inspired by Ferwerda et al. [25].

Table 1: Groups of respondents according to their music style preferences

	Preferred genre	Unwanted genre
Group 1	Classical + Easy listening	Blues
Group 2	Rock	Folk
Group 3	Pop + Dance	World

Thus, the groups of musical genres that were considered are: blues, classical (including opera, ballet, etc.), dance (including electronica, techno), easy listening (including new age, movie music, ambient), folk, hip-hop/rap, jazz, pop (including europop, synthpop), country, soul & R'n'B (including funk and disco), rock (alternative, classic rock, progressive, post-rock, etc.), world (ethnic).

By following [28], we analyze the pre-experiment gathered data and found that female subjects prefer classical music and male participants like rock. Pop is also preferred by women, and is correlated to dance, but not to rock. Usually, classical music is correlated to the easy listening genre. Rock music—somehow strange—is not correlated to blues (both genres share a common root), but is correlated to preferences for hip-hop/rap music. Subjects from urban areas have hip-hop/rap, pop, and classical as most liked music genres, and dislike folk, world, and soul & R'n'B. Respondents having a rural origin prefer dance, easy listening, and pop music, but manifest aversion to rock, soul & R'n'B, and hip-hop/rap genres.

3.3.2 Recommending Music Playlists

A knowledge-based Web system was designed as a serverless platform[5] and developed by using microservices in order to recommend suitable playlists with favorite/unpleasant music genres. The general software architecture is presented in Fig. 1. Having multiple benefits—such as maintainability, scalability, complexity reduction and others [28,29], the microservice architectural pattern [29] was considered the best solution to accomplish our goals. All microservices, aligned to the serverless functional paradigm (FaaS) [30], were deployed on the AWS Lambda cloud platform[6].
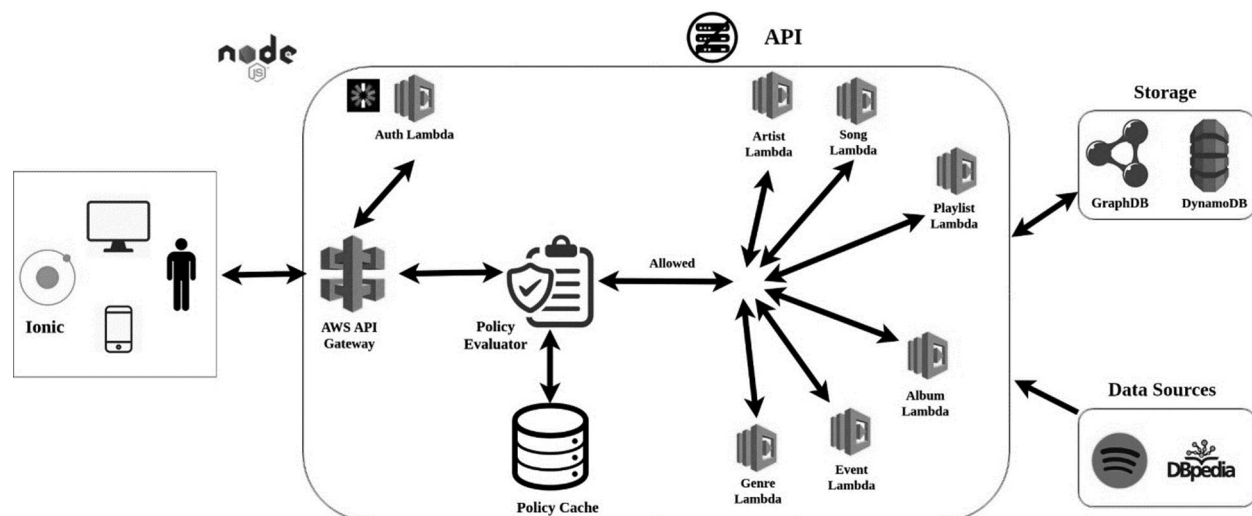

Figure 1: Overall architecture of the knowledge-based playlist recommendation system

To recommend tracks (songs) of interest to be included in a playlist, several aspects were taken into account: (1) Music genre, including related (sub)genres—those preferred by users and/or automatically discovered by software (see discussion below). (2) Avoiding repetitions (e.g., already chosen tracks) and monotony—for this, various constraints were formulated: selecting only less that 5-minute long tracks, using similar artists to preferred ones, generating playlists no longer than a given duration (i.e., the duration of the experiment itself), etc. (3) Popularity—choosing actual popular songs from each considered genre.

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[5] Roberts, M., *Serverless Architectures* (2018)—https://martinfowler.com/articles/serverless.html

[6] *AWS (Amazon Web Services) Lambda*—https://aws.amazon.com/documentation/lambda/

The Wikipedia's machine processable knowledge provided by DBpedia [31] and Wikidata [32] was used to find and recommend resources of interest, including music entities (e.g., musicians and compositions) and relationships between these entities. This solution could be considered as an alternative to well-known methods from the music information retrieval field [33].

Additionally, an internal ontology, based on concepts from DBpedia and *schema.org*, was envisioned to properly model knowledge about music genres and playlists. An excerpt of this ontological model is displayed in Fig. 2, where the "*dbo*" prefix specifies the DBpedia ontology and "*dbc*" denotes a concept defined via SKOS (Simple Knowledge Organizational System)[7], a standard for defining thesauri for machine processing.
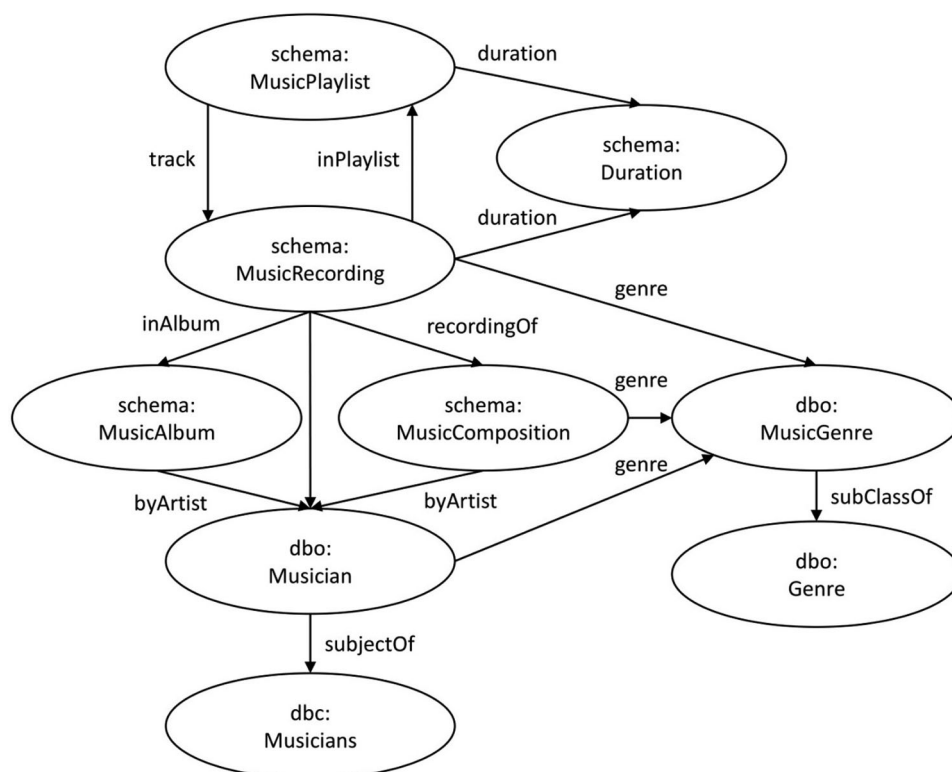

Figure 2: Main concepts involved in recommending a suitable playlist

Key classes defined to suit our aims are described below.

MusicPlaylist includes instances (tracks) from the *MusicRecording* class. *MusicRecording* is a subclass of *CreativeWork* and can have specified, among other things, a certain music genre defined by the *MusicGenre* class. *MusicComposition* is connected to *MusicRecording* via *recordingOf* property and can have links to one or more instances of the *Musician* class. *Musician* denotes the musically talented persons having skills like performing, conducting, singing, composing, and others. A musician can be associated to one or more musical genres—i.e., instances of *MusicGenre* class. *MusicGenre* class could be aligned to any conceptual model concerning music-related knowledge, such as *MusicMoz* taxonomy or *Music Ontology*.

Each entity is internally stored in a knowledge base—in this case, a semantic graph database management system: Ontotext GraphDB[8].

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[7] *SKOS Reference*—https://www.w3.org/TR/skos-reference/

[8] *GraphDB*, a graph database with RDF and SPARQL support—http://graphdb. ontotext.com/documentation/free/

The implemented Web application can also suggest entities (artists, events of interest, songs) and can offer playlist recommendations expressed in RDF and based on various criteria (search keywords, already added songs in the personal playlists, historical data). Generated playlists can be accessed via a SPARQL endpoint (service) that will provide a way of accessing data from the RDF data management system.

For example, by using the *musicSubgenre* relation, our application generates specific queries to obtain from DBpedia the sub-genres of a music genre (following the provided conceptualization, surf music and post-punk are related to rock music). Additional relations defined by the DBpedia ontology—such as *stylisticOrigin*, *musicFusionGenre*, and derivative—are also utilized to provide simple yet straightforward recommendations.

In order to play the recommended music and to discover the current popular songs/artists for each music style, a streaming popular service was used—in this case, Spotify accessed via the provided API (Application Programming Interface)[9]. Being based on microservices, our software platform is flexible enough to accommodate other streaming solutions.

For reusing purposes, the playlists can also be imported/exported by using XSPF (XML Shareable Playlist Format) or JSPF (JSON Shareable Playlist Format)[10].

3.4 Performing the Experiment

The experiment itself had no invasive character and the participants were told from the beginning that they can quit the experiment anytime they feel uncomfortable. All respondents went through the experiment until the end. The participants were given 2 sets of 20-question tests, and the time set for each set of tests was 20 minutes. The tests were different, but with the same degree of difficulty. The tests were administered using the BlackBoard Learn e-learning platform—an already familiar e-learning system among the students, according to [34].

Three types of questions were used: (1) Technical questions (from the current IT curricula of the target respondents). (2) Logical questions—similar to the standardized tests designed to assess human intelligence. (3) Questions of cognitive interpretation of an unfamiliar text containing new information—for example, medium-level descriptive articles about physics, biology, medicine, and others.

For each group of participants indicated in Tab. 1, the background music—preferred versus unwanted genre—was the same and was generated based on the generated playlists (a process described above). The music was broadcast via external speakers and the sound level varied between 30 and 35 decibels, the level being considered safe according to international regulations, specialized scientific studies [35], and from the perspective of national regulations imposed by the Ministry of Health.

Students had their own workstation each and did not visually interact with other colleagues, having their own individual work space in the experiment—a snapshot taken during the experiment is presented in Fig. 3. At the end of the experiment, subjects were symbolically rewarded.

To properly process the knowledge about the HCI experiment, an RDF dataset was generated by using additional conceptual models—mainly, a set of concepts provided by *schema.org* (such as *Question*, *Answer*, *PeopleAudience*). The dataset itself was annotated by using various properties related to *Dataset* concept. Multiple datasets regarding our experiments could be organized into a data collection expressed by *DataCatalog* constructs. An alternative solution is to adopt the Evaluation and Report Language (EARL) format[11].

In addition, our own Usability Testing extensions [3] to *schema.org* model were adopted.

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[9] *Spotify Web API*—https://developer.spotify.com/documentation/web-api/

[10] *XML Shareable Playlist Format* and *JSON Shareable Playlist Format*, Xiph.Org Foundation—http://www.xspf.org/

[11] *Evaluation and Report Language (EARL)*—https://www.w3.org/WAI/standards-guidelines/earl/

Figure 3: Several participants to the experiment

For instance, the following facts are denoted: The experiment has *Group1* (a group of persons) as audience target (an instance of *Audience* class specified by *schema.org* ontology) for assessing behavior during performing an action—*e.g.*, denoted by *ListenAction* concept. For this particular case, the participants are listening to tracks belonging to classical and easy listening music while performing various tasks (instances of *ControlAction* class defined by *schema.org*).

One of the tracks included into the generated playlist specifies a variety of (meta-)data about the played melody. For example, the track is a well-known aria from *Adriana Lecouvreur*, an opera by Francesco Cilea, performed by Angela Gheorghiu. Following the LOD (Linked Open Data) principles [36], for each item of interest several external Web addresses pointing to other public datasets are provided in order to expand the knowledge about a given resource. Using this method, further processing can discover, in a smart manner, that Angela Gheorghiu is a Romanian opera soprano and appears on various professional organizations' Websites such as Carnegie Hall[12] and Discogs[13]. Using these Web identifiers, a software agent can automatically learn about biography, released albums and public appearances of a particular artist.

A task from the designed HCI experiment represents an instance of *ControlAction* class and should be rescheduled since it is failed. Estimated time to perform this task is 20 minutes—expressed in a machine-friendly standardized format.

From our point of view, this annotated data/knowledge is very useful to be further processed in order to prepare similar experiments or to schedule or propose assessment tests regarding the behavior of users involved in specific interactive tasks.

3.5 Results and Discussion

Following the experiment, the number of correct answers provided by the respondents was counted in both cases: favorite versus unwanted music. Considering that the same 40 students participated in the experiment in two different situations from the point of view of the listened music, we can say that the series of analyzed data are dichotomous. The number of questions each student answered correctly in the two tests is statistically frequent within the set of the analyzed data.

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[12] *Carnegie Hall Linked Data*—https://github.com/CarnegieHall/linked-data

[13] *Discogs*—https://www.discogs.com/artist/899551

4 Results, Analysis and Statistical Processing

4.1 Considered Hypotheses

From these perspectives of considered hypotheses, we were interested in finding descriptive statistics values at the following levels (globally, male gender, female gender):

Globally—the data obtained from all respondents for all questions.

H_0: For the group of all respondents, the average of correct answers is equal for both playlists of background music (preferred versus undesirable genres). H_1: For the group of all respondents, the average of correct answers differs significantly for the considered music genres.

The descriptive statistical values were calculated using the ANOVA method (see Tab. 2). In the case of subjects listening to unpleasant music, the average of correct answers was 9.1—variance: 5.12. The other case provided an average of 14.1 correct answers—variance: 9.63.

Table 2: ANOVA—global results

Source of variation	SS	df	MS	F	*p*-value	F crit
Between groups	500.00	1	500.00	67.80	3.31E-12	3.96
Within groups	575.20	78	7.37			
Total	1075.20	79				

At the male gender level—i.e., data obtained from male respondents for all questions.

H_0: For the male respondents' group, the average of correct answers is equal for the two playlists of music. H_1: For the male respondents' group, the average of correct answers differs significantly for each of the two playlists.

In this particular situation, the results are: For the 18 male subjects listening to unpleasant music, the average of correct answers was 8.89—variance: 3.87. In the case of favorite music, the average of correct answers was 14.22, with a variance of 8.89. These findings are presented in Tab. 3.

Table 3: ANOVA—male respondents

Source of variation	SS	Df	MS	F	*p*-value	F crit
Between groups	256.00	1	256.00	40.13	3.17E-07	4.13
Within groups	216.89	34	6.38			
Total	472.89	35				

At the female gender level—data obtained from female respondents for all questions.

H_0: For the female respondents' group, the average of the correct answers is equal for all music listened to. H_1: For the female respondents' group, the average of the correct answers differs significantly for the two musical backgrounds.

The obtained results are presented in Tab. 4. For the 22 female subjects listening to undesirable music, the average of correct answers was 9.27—variance: 6.30. Regarding the opinion on pleasant music, the average of correct answers was 14, with a variance of 10.67.

Table 4: ANOVA—female respondents

Source of variation	SS	Df	MS	F	p-value	F crit
Between groups	245.82	1	245.82	28.97	3.05E-06	4.07
Within groups	356.36	42	8.48			
Total	602.18	43				

By analyzing the above data, it is observed that all three values of the p-value are less than $\alpha = 0.01$. Therefore, based on the ANOVA tests, we can conclude that all H_0 hypotheses are rejected for a 99% significance threshold.

Additionally, to verify the results obtained by the ANOVA type test, the *chi*-squared and *t*-test were performed, choosing $\alpha = 0.01$. The obtained results are presented in Tab. 5.

Table 5: *Chi*-squared and *t*-test results

Group	Chi-squared p-value	Chi-squared result	t-test p-value	t-test result
All subjects	0.0000274	p-value < α	4.9502E-14	p-value < α
Males	0.0012272	p-value < α	4.7497E-08	p-value < α
Females	0.0017220	p-value < α	1.9177E-07	p-value < α

We notice that the p-value $< \alpha$ condition is met for each of the three groups. Corroborated with the ANOVA test results, this condition allows us to reject the null hypothesis, paving the way for the alternative hypothesis.

The statistical interpretation of the experiment shows that the 40 students had better results when they perceive their favorite music in the background, compared to the situation when the unpleasant music was played in the background. Therefore, the music listened to has a significant influence on students' cognitive abilities.

4.2 Analyzing the Post-Experiment Survey Data

Additionally, after the experiment was concluded, all participants were asked to frankly give responses to several questions regarding the following aspects:

The difficulty of performed tasks, using a scale from 1 (not at all difficult) to 10 (very difficult)—for unwanted music, the average value was 3.65 (median = 4) versus preferred music, where the average was 3.2 (median = 3.5); in conclusion, from the participants' subjective point of view, *the tasks were perceived as being much more difficult if the background music was annoying*.

How music influenced the test on a scale from 0 (none) to 10 (maximum impact)—in the case of undesirable music, average = 5.5 (median = 5) and for enjoyable music, average = 6.85 (median = 7); therefore, participants considered that *the pleasant music had a greater influence*.

The emotion/mood/sentiment experienced during the test—subjects had the opportunity to freely express their feelings regarding the experiment; using the Tone Analyzer service provided by IBM Watson Developer Cloud services, we processed all terms (translated into English) denoting a positive/ negative sentiment—for example, "relaxed", "happiness", "peace" versus "nervous", "pressure",

"irritation", "stress". We found only 45% occurrences of positive terms in the case of listening to undesirable music, in contrast to 75% occurrences when participants listened to a playlist delivering pleasant music. Therefore, these user-oriented findings also confirm the statistical analysis detailed in previous section.

If the perceived grade of effectiveness depended on the music listened to during the experiment—for results, see the chart depicted in Fig. 4.
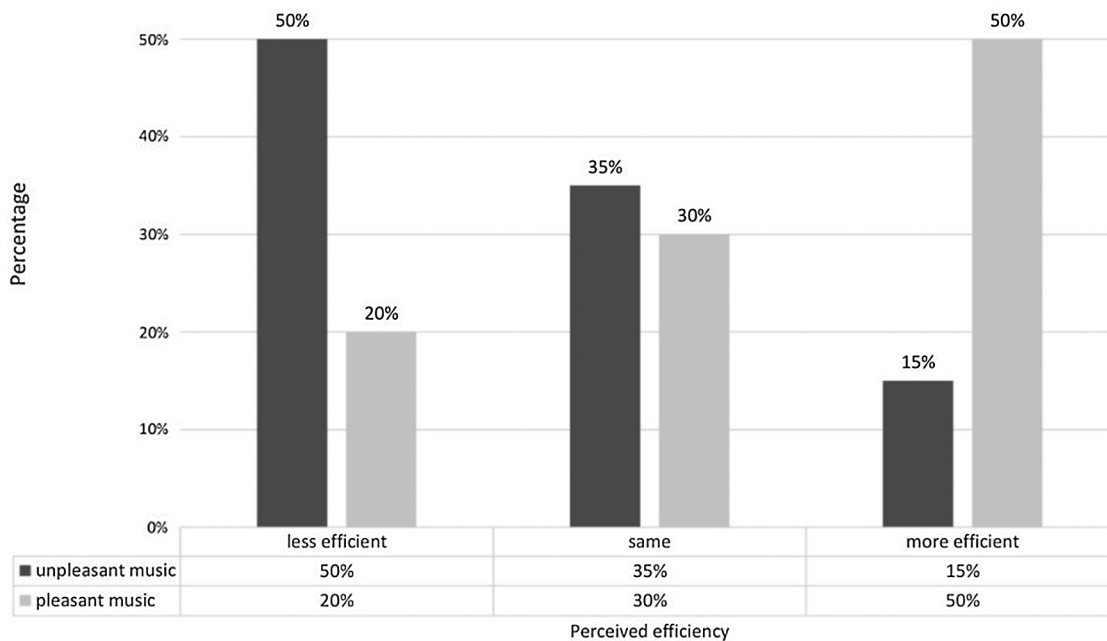

Perceived efficiency	less efficient	same	more efficient
■ unpleasant music	50%	35%	15%
■ pleasant music	20%	30%	50%

Figure 4: Grade of effectiveness by music

5 Discussion: Incorporating Music Preferences in Personas

By using the above findings, a knowledge-based Web editor was built in order to provide support for creating and experimenting with set of personas.

Persona method is one of the popular processes for analyzing user research data in user-centered design [4,37,38]. A persona represents user archetypes, giving a precise description of the user of an interactive system, and of what (s)he wishes to accomplish—i.e., user goals, needs, and preferences. Also, a persona offers reliable and realistic representations of the key audience segments for a given interactive system and could add empathetic focus to the design.

There are numerous studies on using persona method for multiple purposes and in many contexts, from common disciplines and domains of practice to "exotic" areas. Several interesting pragmatic usages include healthcare [39], assistive technologies for wireless applications [40], mobile medication selfcare [39], and many others.

Knowledge-driven procedures are usually not taken into consideration.

5.1 Our Proposal

By incorporating music preferences and adopting the *PersonasOnto* ontology, a modular Web editor was designed. This software prototype primary manages the concept of *Persona* denoted by a class having attached a list of properties expressing knowledge about: (1) *Identity* (name, plus photos), demographic information + personality, disability (if any), education background, frustrations (if any), etc. (2) *Goals*—

depending on each persona type (primary, secondary, additional), could be categorized into business goals, personal (life goals), experience goals, technical goals, etc. (3) *Technology level*—typical values: none, novice, intermediate, advanced, expert. (4) *Occupation*—an additional conceptual model, adapted from HRM Ontology[14], is used to represent most frequent professions. (5) *Group*—denotes a user entourage (e.g., a research team or a club for opera music aficionados).

We extended this knowledge model in order to accommodate the concepts regarding the music preferences (i.e., preferred/unwanted music genres, songs, artists).

Our developed Web application provides a Web form—using HTML5 semantic mark-ups and *schema. org* microdata denoting *PersonasOnto* constructs—to be filled in with requested information about a given persona specified for a given UI/UX design project.

All provided data is converted into RDF triples and stored by using a dedicated storage solution.

Various persona profiles can be created, edited, filtered, and visualized according to user needs. Also, support for defining specific team groups is provided, in order to facilitate a collaborative approach in designing personas for a given HCI project. In addition, persona recommendations are suggested according to selected criteria: Type, age, occupation, music preferences, demographic factors, etc.

A microservice architecture was adopted. All operations are exposed by a REST API in order to reuse the functionalities in various multi-platform scenarios. All knowledge-based processing is performed by using Apache Jena[15], a well-known open-source framework for building semantic Web applications.

Using these enriched datasets and the proposed semantic Web-based tool, one of the next steps is to give insights—for example, to suggest (proto-)personas [8]— in designing the interaction means with a platform concerning music recommendations for specific tasks.

5.2 Use Case

The following use case concerns a multi-device adaptive and customizable tool able to determine (e.g., learn) and recommend the ideal weekday and time for performing a set of desired actions—for example, initiating a teleconference—in a real context of use, including music preferences of a given user.

An example of a primary persona—defined by our tool and considered as a most significant user for the designed application—is a young PhD student, researcher at the University of Oxford. His music preferences consist of classical and opera genres. A photo and other realistic random data (e.g., name, location, date of birth) are automatically generated. Each information of interest is denoted by a specific concept, according to the formal models chosen to express the desired knowledge.

For each persona, several usage scenarios could be described by the designer in order to stimulate brainstorms during some phases of the adopted UI/UX methodology.

The algorithm—using automated reasoning techniques—of recommending a better schedule for performing a certain task (in this circumstance, calling an old friend sharing common music interests) takes into consideration the music preferences by using the conceptual models presented below. For example, using the rule-based reasoning support provided by Jena framework[16], a suggestion is made to initiate a videoconference between a group of persons by taking into account their mutual preferred music genre(s) and composition(s), plus an interval of spare time.

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[14] *Human Resources Management Ontology*—http://mayor2.dia.fi.upm.es/oeg-upm/index.php/en/ontologies/99-hrmontology/

[15] *Apache Jena*—https://jena.apache.org/

[16] *Apache Jena inference support*—https://jena.apache.org/documentation/inference/

6 Conclusions and Further Work

The paper presented an original approach in conducting HCI experiments in a systematic manner. Our aim was to perform a pilot study for assessing music's influence on students enrolled in Computing Studies. To accomplish this goal, various conceptualizations and best practices were adopted with the help of the existing (semantic) Web standards and technologies.

Our experimental findings confirmed the fact that music has a significant impact on the cognitive abilities of participants in the controlled experiment. By using these results, a persona editor was developed in order to suggest suitable personas for specific interactive applications. Using this knowledge-based tool, the paper describes a multi-device Web application focused on providing suitable intervals of time for performing various actions according to users' needs and preferences, including music ones.

All involved data and knowledge were modelled as RDF datasets conforming to the Linked Data principles [36] in order to facilitate the discoverability of additional music-related resources available on the Web. Therefore, a future direction of research is to consider the complex user behavior manifested during the experiment, especially in the context of COVID-19 pandemic situation.

The current study will be continued and deepened by analyzing the influence of music on cognitive capacities considering different age categories. It would also be interesting to explore whether the level of music intensity has an effect on differences in cognitive capabilities. Also, the experiment should be conducted on a broader palette of subjects, in order to study the influence of music on cognitive abilities for persons with a background in other areas such as arts, social sciences, engineering, and others.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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