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Article

ACUX Recommender: A Mobile Recommendation System for Multi-Profile Cultural Visitors Based on Visiting Preferences Classification

Markos Konstantakis *, Yannis Christodoulou, John Aliprantis and George Caridakis

Department of Cultural Technology and Communication, Aegean University, 81100 Mytilene, Greece
* Correspondence: mkonstadakis@aegean.gr

Abstract: In recent years, Recommendation Systems (RSs) have gained popularity in different scientific fields through the creation of (mostly mobile) applications that deliver personalized services. A mobile recommendation system (MRS) that classifies in situ visitors according to different visiting profiles could act as a mediator between their visiting preferences and cultural content. Drawing on the above, in this paper, we propose ACUX Recommender (ACUX-R), an MRS, for recommending personalized cultural POIs to visitors based on their visiting preferences. ACUX-R experimentally employs the ACUX typology for assigning profiles to cultural visitors. ACUX-R was evaluated through a user study and a questionnaire. The evaluation conducted showed that the proposed ACUX-R satisfies cultural visitors and is capable of capturing their nonverbal visiting preferences and needs.

Keywords: personalization; cultural heritage; mobile tourist guide; profile classification; user interface; cultural destinations; personalized suggestions

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1. Introduction

During the last decades, the abundance of online data resources has encouraged the rapid spread of information, but it is also responsible for *information overload* (https://www.interaction-design.org/literature/article/information-overload-why-it-matters-and-how-to-combat-it, accessed on 10 September 2022). A Recommendation System (RS) is an advanced search tool that alleviates this overload by suggesting content that is likely to meet the preferences and needs of potential users [1,2]. RSs have gained popularity in different fields through the creation of mostly mobile applications for delivering personalized information services to the end user. In this context, research efforts have been made in the Cultural Heritage (CH) domain to identify different profiles of cultural visitors, classify them into distinct types, and exploit such classifications in order to provide personalized suggestions of potential cultural POIs (points of interest) through RSs [3–6].

In an era where the typical cultural visitor holds smartphones and uses digital technologies to facilitate their trips, they expect to receive personalized suggestions when and where they should need them. In this ubiquitous computing environment, a mobile recommendation system (MRS) can act as a *mediator* between their visiting preferences and the available cultural content, with the objective of providing useful recommendations of potential POIs [7,8]. But in order to exploit such knowledge about visitors, relevant information must be provided to the recommender. Thus, when beginning to develop an MRS, the main question would be, "*What information is required and how to elicit it?*"

A critical fact to take into account when considering what information is required as input on behalf of the cultural visitor (often termed in the bibliography as *user feedback*) is that, especially at an early phase of a visit, they may not be consciously aware of their desires and thus not be in a position to state them explicitly [9,10]. An MRS intends to make the visitor more conscious of their desires during a visit by *classifying* them according to different *visiting profiles* using a variety of criteria. For example, Walsh [11] and Özel [12] classify cultural visitors based on criteria such as personal motivation, travel behavior characteristics, or demographics. McKercher [13] classifies visitors based on *cultural centrality* (high/low), i.e., the importance of cultural motives when choosing a destination and the *depth of user experience* (deep/shallow) intended when visiting cultural content. Missaoui [3] uses a combination of contextual information (such as location and time) with content from the visitors' social media interactions in order to provide personalized suggestions. Nevertheless, there is a common agreement that the effectiveness and reliability of the classification of cultural visitors in an MRS should be based on their *visiting preferences* as the primary classification criterion [14–18].

To answer the second part of the question, a variety of user feedback elicitation techniques are used to obtain the desired information from the visitor [19]. These techniques may be *explicit* (i.e., requiring some action) or *implicit*. *Explicit* techniques can be further distinguished into direct (e.g., collecting information through questionnaires, ratings, or free-text comments) or indirect, i.e., engaging the visitor in activities that do not appear directly relevant to profiling (e.g., gamification). In *implicit* techniques, on the other hand, visiting preferences are automatically deduced primarily by monitoring the visitor's online activity (e.g., "checking-in" places, social network activity, or browsing history). According to Antoniou [19] and Kanoje [2], in reality, some *combination* of both techniques is highly recommended since, in this way, both the (more static) characteristics and the (more dynamic) behavioral information of the cultural visitor are retrieved and combined in a way that can eventually lead to recommendations that are closer to the visitors' *current* desires and needs. However, such an approach requires a relatively high level of visitor engagement in order to be efficient, and thus actual effectiveness cannot be guaranteed [20,21].

Drawing on the above, in this paper, we propose ACUX Recommender (ACUX-R), an MRS, for personalized recommendation of cultural POIs to visitors based on their visiting preferences. The classification of visitors implemented in ACUX-R presents the following features:

- ACUX-R experimentally employs the ACUX typology [22] for assigning profiles to cultural visitors. The ACUX typology is the outcome of *harmonization* of existing typologies of cultural visitors that base their classification on visiting preferences. As such, ACUX-R determines the visitor's profile according to their cultural preferences rather than features of the cultural content per se (e.g., popularity or cultural significance) or other non-content-related criteria such as the visitor's time availability, income level, or family obligations.
- The classification of cultural visitors implemented in ACUX-R is *multi-label*; the deduced profile of a cultural visitor may constitute some combination of the eight ACUX profiles.
- The assigned ACUX-R profile is also adjustable; ACUX-R enables users to adjust their profile at any given time, and the recommendation of POIs is automatically updated accordingly.

The rest of the paper is structured as follows. Section 2 reviews related work. Section 3 describes the proposed system. Section 4 presents the evaluation of the system. Finally, conclusions and future research points are drawn in Section 5.

2. Related Work

Various RSs have been developed for the CH domain with the objective of assisting cultural visitors in planning their trips. As mentioned above, a critical factor for effective recommendation is to elicit the correct information about the user. In this context, a variety of approaches for collecting user information have been developed and proposed in the relevant literature. These include *content*, *collaborative*, *knowledge*, *demographic*, and *hybrid* approaches [23]. Meanwhile, Burke [24] argues that content-based and knowledge-based recommendation approaches are more frequently applied in the CH domain.

Indeed, ample RSs have been developed for the CH domain, applying content-based and/or knowledge-based approaches for collecting user information. Neidhardt [21,25] presents PixMeAway, a content-based RS that provides personalized recommendations of POIs to visitors. PixMeAway combines profiles from Golberg's [26] and Gibson's [18] visitor typologies in order to present a new typology, referred to as the *seven-factor model*. First, the visitor is prompted to choose among a set of pictures of POIs that they consider appealing when thinking of vacation. Next, the pictures are mapped to the aforementioned model, and a score is calculated for each factor according to the visitor's selections in order to determine their profile. Finally, a set of POIs is recommended to the visitor based on the deduced profile.

Grün [15] introduces Go2Vienna, a knowledge-based RS that provides recommendations of POIs within the city of Vienna. Go2Vienna also classifies visitors according to the *seven-factor model*. First, the cDOTT ontology (core Domain Ontology of Travel and Tourism) is employed for measuring the similarity between visiting preferences. Then, using the Pearson correlation coefficient, the similarity between the profiles of the seven-factor model and the visiting preferences is calculated in order to determine the visitor profile and recommend an initial set of POIs. Furthermore, if the visitor is not satisfied with the recommendations, they can rate the suggested POIs by stating positive/negative feedback, which is used to refine their profiles and deliver an updated set of POIs.

PicTouRe [27] is a newer content-based version of PixmeAway which also adopts the *seven-factor model* for classifying cultural visitors. PicTouRe allows visitors to upload three to seven pictures of their choice and sort them in order of preference. Then, the system determines the visitors' profile by mapping the uploaded pictures with the seven-factor model, where each factor receives a score according to the picture's ordering. Furthermore, PicTouRe allows visitors to refine their profile using sliders that increase/decrease the percentage of each of the seven factors.

Pythia [28], City Trip Planner [29], and MyMytilene [30] follow a knowledge-based approach to collect user information, combining contextual information with visiting preferences as classification criteria.

TRIPMENTOR [31,32] is a bilingual (Greek/English) content-based MRS for Android and iOS devices, suggesting personalized routes for cultural visitors in Athens based on their visiting preferences. TRIPMENTOR is enriched with small gamification mechanisms that aim to enhance user engagement through social interaction and dynamically update the list of recommended POIs.

Regarding the collaborative approach, Herzog [33] proposes TourRec, a collaborative MRS for Android devices that recommends personalized routes to individual visitors or groups. First, TourRec determines the popularity of POIs by measuring the number of visits per POI and by matching geo-tagged photos (obtained from Flickr) with the POI's coordinates. Then, the visitor's profile is determined by combining the POI popularity, visiting preferences, and travel constraints (i.e., time limitations or the need to start/end at specific POIs). Finally, the system recommends routes of POIs that match the deduced profile. Figueredo [34] presents Find Natal, a collaborative MRS for both Android and iOS devices that recommend POIs to cultural visitors using social media photos and previous users' ratings and comments as user input information.

Moreover, various hybrid approaches have been proposed. Missaoui [3] presents LOOKER, a hybrid MRS for Android devices that delivers personalized POI recommendations to visitors, using a content-based filtering module that filters content (i.e., reviews in social posts) that the visitor has generated on social media. Then, using language models, the filtered content is converted into visiting preferences and is combined with contextual information to determine the visitor's profile. Based on the deduced profile, personalized recommendations of POIs are shown on a map or in a list, along with reviews of previous visitors. Logesh [35] introduces PCAHTRS, a personalized context-aware hybrid RS that uses contextual information, previous user reviews, and POI similarity in order to recommend POIs to cultural visitors. Finally, Meehan [36] presents VISIT, a hybrid RS that uses a combination of collaborative, content-based, and demographic approaches for classifying visitors in order to recommend POIs.

The literature review showed that, unlike ACUX-R, the great majority of RSs developed for the CH domain do not classify their users into distinct visitor profiles. Rather, the user provides the required information (usually visiting preferences, demographics, or/and contextual information), and the RSs directly suggest POIs based on that information. On the other hand, RSs that do perform user classification as an intermediate step for providing recommendations most of them classify visitors into multiple profiles (multi-label classification) and also allow them to manually fine-tune their assigned profile (as is the case with ACUX-R).

3. ACUX Recommender

3.1. ACUX-R Architecture

ACUX-R has been developed following a typical three-tier architecture, using Google's Android Studio and Flutter Software Development Kit (SDK) (see Figure 1):

- PRESENTATION tier, the GUI of ACUX-R, where the end-user (i.e., the cultural visitor) interacts with the application. The Presentation tier is responsible for collecting from the user all the information required for their classification (into one or more visitor profiles) and for displaying the generated recommendations to them. For that purpose, ACUX-R provides an icon-based interface for swift and intuitive information input/output.
- DATA tier, where all the application information is stored and managed in a Firestore Google Database (as it is compatible with Flutter SDK). This information can be distinguished into three categories:
  - ○ Content data, i.e., information about the available POIs (such as name, description, location, GPS data, or images).
  - ○ User data, i.e., information regarding the user's visiting preferences and assigned profile, together with other personal information (e.g., account details).
  - ○ Classification data: i.e., the knowledge required for classifying (i) the visitors and (ii) the POIs available, according to visiting preferences.
- LOGIC tier, which encapsulates the logic required to perform the tasks of user classification and subsequent recommendation of POIs. Implemented in Dart (https://dart.dev/, accessed on 8 September 2022), the LOGIC tier receives and processes information from the DATA tier using API calls and returns the recommendation outcome to the PRESENTATION tier.

Figure 1. The ACUX-R 3-tier architecture.

3.2. Recommendation Algorithm

The ACUX-R algorithm consists of three stages. In the first stage, the Classification stage (Section 3.2.1), the visitor is classified under one or more ACUX profiles according to their visiting preferences. In the second stage, the Adjustment stage (Section 3.2.2), the user is allowed to manually adjust their assigned profile(s), if desired, overriding the outcome of the Classification stage. In the third and final stage, the Recommendation stage (Section 3.2.3), the set of recommended POIs is calculated according to the user's final visiting profile, and the recommended POIs are presented as pins on a map and/or in the form of a list. Table 1 presents an overview of the ACUX-R algorithm.

Table 1. The ACUX-R recommendation algorithm.

Classification stage	User SELECTs icons (minimum 5) **FOREACH** selected icon ASSIGN corresponding profile to user (multi-assign) **FOREACH** profile assigned (at least once) CALCULATE score (Equation (1)) DISPLAY ACUX-R profile (as a set of scores)
Adjustment stage	**IF** user **NOT** satisfied with ACUX-R profile User UPDATEs ACUX-R profile (manually) DISPLAY final ACUX-R profile
Recommendation stage	DETERMINE recommended POIs (Equation (2)) DISPLAY recommended POIs

3.2.1. Classification Stage

The Classification stage is the initial stage of the recommendation algorithm, where the user's visiting profile is determined based on their visiting preferences. The user selects and provides as input information a set of icons (five or more) representing their visiting preferences. For example, the icons depicted in Figure 2 (from left to right: sculptures, galleries, arts and crafts, concert halls, and graffiti) represent the Art Seeker profile.

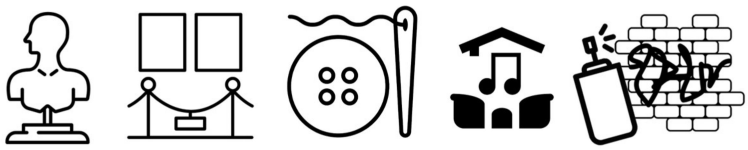

Figure 2. Icons visually representing the Art Seeker profile.

According to the specification of the ACUX typology [22], the various visiting preferences that form the ACUX profiles are not necessarily matched with a single profile. As such, the icons created in ACUX-R to represent those visiting preferences (forty in total) may correspond to multiple ACUX profiles. For example, the icon galleries, which represents the preference of visitors to visit galleries, is assigned to both the Archaeologist and the Art Seeker.

Next, based on the user's selected icons, a score is calculated for each ACUX profile as follows:

$$\begin{gathered}\text{foreach i}\\ \mathbf{SCORE_i = s_{i/}s \times 100}\end{gathered} \tag{1}$$

where i is the ACUX profile identifier, $\mathbf{s_i}$ is the number of selected icons per ACUX profile, **s** is the total number of selected icons ($\mathbf{s} \geq 5$), and $\mathbf{SCORE_i}$ is the score per ACUX profile, which is a number between 1 and 100.

For example, let's assume that Visitor1 selects the icons: museums, theatres, graffiti, lakes, distilleries, farms, and temples. According to the ACUX typology [22], museums are assigned both to the Archaeologist and the Art Seeker profiles, theatres and graffiti to the Art Seeker profile, lakes and farms to the Naturalist profile, distilleries to the Gourmand profile, and temples to both the Religious Seeker and the Archaeologist profile. As a result, Visitor1 is classified under the following profiles: Archaeologist with a score of 29 (2 out of 7 icons), Naturalist also with a score of 29 (2 out of 7 icons), Art Seeker with a score of 43 (3 out of 7 icons), Gourmand with a score of 14 (1 out of 7 icons), and Religious Seeker also with a score of 14 (1 out of 7 icons).

3.2.2. Adjustment Stage

At the Adjustment stage, the visitor can override the results of the Classification stage and adjust their generated ACUX-R profile manually, given that they are not completely satisfied with the profiling outcome. This is a non-obligatory stage and has been implemented by providing in the GUI a set of slider controls, which enable the user to increase or decrease the generated score for each ACUX profile.

Following the same example, let us assume that Visitor1 is satisfied with the score of the Religious Seeker, Art Seeker, and Naturalist profiles but wishes to adjust the score for the Gourmand and Archaeologist profiles in order to receive more recommendations for restaurants and breweries and fewer for archaeological destinations. Consequently, Visitor1 sets the Archaeologist score to 15 and the Gourmand score to 30.

3.2.3. Recommendation Stage

The Recommendation stage is the final stage of the ACUX algorithm, where the recommended POIs are specified based on the scores assigned in the previous stages. For each ACUX profile assigned to the user (i.e., for each ACUX profile with a non-zero score), one or more POIs are recommended as follows:

$$\begin{gathered}\text{foreach i whose SCORE}_\text{i} > 0\\ \mathbf{DISP_i = ROUNDUP(SCORE_i/}100 \times \mathbf{p_i, 0)}\end{gathered} \tag{2}$$

where $\mathbf{p_i}$ is the total number of POIs per ACUX profile, i is the ACUX profile identifier, $\mathbf{DISP_i}$ is the number of recommended POIs per ACUX profile, and $\mathbf{SCORE_i}$ is the generated score per ACUX profile. The total number of recommended POIs is the sum of $\mathbf{DISP_i}$.

Finally, drawing on the same example, the recommended POIs are presented to the user as pins on a map and also in the form of a list sorted according to the score of the Archaeologist, Art Seeker, Religious Seeker, Naturalist, and Gourmand profiles.

4. Evaluation

To assess the usefulness of ACUX-R in practice, we conducted a user study and an online questionnaire survey. Fifty participants of various ages, educational backgrounds, and current professions were chosen to participate in the user study, including academic staff and students from Aegean University, Android, and iOS developers, and also members of the local community (Mytilene, Lesvos). In general, the participants were regular smartphone users who enjoyed traveling and who had already visited the city of Athens or were planning to do so in the near future. Their ages ranged between 20 and 55 years.

First, the participants were asked to submit their background information, including demographic data and level of familiarity with cultural-tourism MRSs and mobile applications in general. As a next step, participants were briefly informed about ACUX-R and instructed to download and install it on their mobile devices, following online instructions (http://ii.ct.aegean.gr/acux-evaluation/, accessed on 5 September 2022). Participants were advised to work in groups or individually. Finally, a discussion was held based on the following topics:

- Level of satisfaction with the features offered by the ACUX-R
- Level of satisfaction with the recommendations provided
- GUI usability
- Quality of provided POI information
- Suggestions for improvements.

As a next step, we conducted an online questionnaire survey. Thirty-five participants installed and used ACUX-R and then filled in a questionnaire (https://tinyurl.com/yayw3853, accessed on 9 September 2022) (Appendix A), which is a part of the User Experience Questionnaire (UEQ) data analysis tool [37,38]. Both classical usability aspects (efficiency, perspicuity, dependability) and user experience aspects (originality, stimulation) were measured. Each item of the UEQ consisted of a pair of terms with opposite meanings (e.g., not understandable to understandable, inefficient to efficient). Each item was rated on a 7-point Likert scale. Thus, answers ranged from −3 (fully agree with a negative term) to

+3 (fully agree with a positive term). This analysis yielded the final questionnaire with 26 items, arranged in six scales:

- Attractiveness: Do users like ACUX-R? Is it attractive, enjoyable, or pleasing?
- Perspicuity: Is it easy to get familiar with the ACUX-R? Is it easy to learn? Is ACUX-R easy to understand and unambiguous?
- Efficiency: Can users solve their tasks without unnecessary effort? Is the interaction with ACUX-R fast and efficient
- Dependability: Do users feel in control of the interaction? Can they predict the system's behavior? Do users feel confident when working with ACUX-R?
- Stimulation: Is it exciting and motivating to use ACUX-R? Does it capture the user's attention?
- Novelty: Is ACUX-R innovative and creative?

Then, the mean values per scale for ACUX-R are compared with the existing mean values per scale for other products from a dataset provided by the UEQ data analysis tool, which contains data from 21,175 people from 468 studies concerning different products (business software, web pages, mobile apps, social networks). The overall results of the ACUX-R mean values per scale compared to the UEQ data set are depicted in Table 2 and Figure 3.

Table 2. ACUX-R mean values per scale compared to the UEQ dataset.

Scale	Mean	Comparison to UEQ Data Set
Attractiveness	1.96	Excellent
Perspicuity	1.81	Good
Efficiency	1.84	Good
Dependability	1.03	Below Average
Stimulation	1.19	Above Average
Novelty	1.03	Above Average

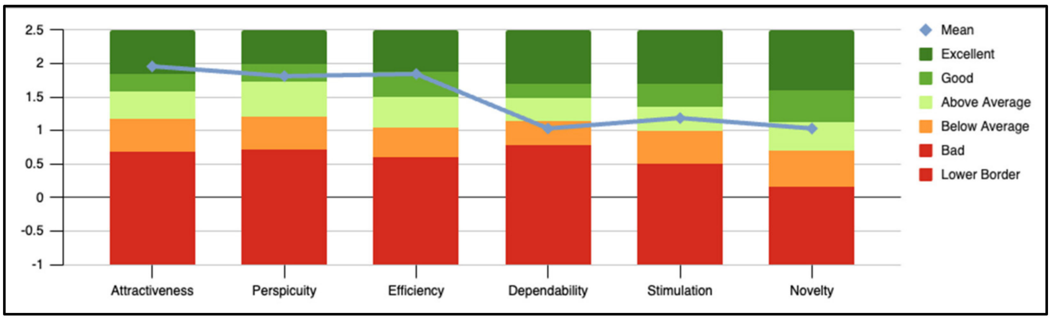

Figure 3. ACUX-R mean values per scale compared to the UEQ dataset.

In Table 3, the confidence interval per scale for the precision of the estimation of the scale mean is presented. The smaller the confidence interval, the higher the precision of the estimation and the reliability of the results.

Table 3. ACUX-R confidence intervals per scale.

Confidence Intervals					
Scale	**Mean**	**Std. Dev.**	**Confidence**	**Confidence Interval**	
Attractiveness	1.958	1.178	0.872	1.086	2.831
Perspicuity	1.813	1.201	0.890	0.923	2.702
Efficiency	1.844	1.260	0.934	0.910	2.777
Dependability	1.031	0.828	0.614	0.418	1.645
Stimulation	1.188	1.425	1.056	0.132	2.243
Novelty	1.031	1.333	0.987	0.044	2.018

In the user study conducted, ACUX-R was rated high in inspiration, excitement, interest, and enthusiasm. Most of the participants stated that they would like to get a diversified set of recommendations at the beginning when no further specific preferences are known to the system. Most of them stated that they chose recommendations based on the profile determined by ACUX-R, whereas only a few adjusted their profiles. Another issue discussed was that a future add-on of uploading images for profile classification could be overwhelming for most of the participants or lead to the absence of cultural features for a few of them. Moreover, most of the participants stated that even the best advice couldn't keep unexpected things from happening to cultural visitors while visiting a destination. For example, attractions may be temporarily closed due to inclement weather, and outdoor performances may be canceled. Finally, most participants appreciated the detailed information describing the ACUX profiles, which helped them understand why certain POIs had been recommended.

Regarding the online survey, the Stimulation and Novelty scales scored above average, indicating that, in general, found ACUX-R motivating and creative. Moreover, positive ratings on the Perspicuity and Efficiency scales indicate that ACUX-R usability features met or exceeded high criteria. The Dependability rating was below average, indicating that several participants experienced security and confidence difficulties. Finally, the Attractiveness scale was rated excellent, implying that the icon-based approach results in a pleasant experience.

5. Conclusions and Future Research

In this paper, we proposed the ACUX Recommender (ACUX-R), an MRS for personalized recommendations of cultural POIs to visitors based on their visiting preferences. The ACUX-R experimentally employs the ACUX typology for assigning profiles to cultural visitors. To assess the usefulness of ACUX-R in practice, a user study and an online questionnaire survey were conducted.

The evaluation showed that ACUX-R satisfied cultural visitors as it successfully captured their nonverbal visiting preferences and needs. Most of the participants stated that they agreed with the recommended POIs provided, whereas some adjusted their profiles.

In the future, we are planning to enhance the icon-based representation of visiting preferences with more multimedia elements, such as audio or video. Another interesting feature would be to reutilize past recommendations by recording them in order to feed them to future visitors with similar profiles. Finally, social media, gamification, and AR tools will be utilized in order to boost the visitor's motivation to visit a cultural destination, further improving the usability and effectiveness of ACUX-R.

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Appendix A. UEQ Questionnaire

Please fill out the following questionnaire for the assessment of the ACUX-R. The questionnaire consists of pairs of contrasting attributes that may apply to the product. The circles between the attributes represent gradations between the opposites. You can express your agreement with the attributes by ticking the circle that most closely reflects your impression.

For example:

attractive	○	⊗	○	○	○	○	○	unattractive

This response would mean that you rate the application as more attractive than unattractive.

Please decide spontaneously. Don't think too long about your decision to make sure that you convey your original impression. Sometimes you may not be completely sure about your agreement with a particular attribute, or you may find that the attribute does not apply completely to the particular product. Nevertheless, please tick a circle in every line.

It is your personal opinion that counts. Please remember: there is no wrong or right answer!

Please assess the product now by ticking one circle per line.

	1	2	3	4	5	6	7		
annoying	○	○	○	○	○	○	○	enjoyable	1
not understandable	○	○	○	○	○	○	○	understandable	2
creative	○	○	○	○	○	○	○	dull	3
easy to learn	○	○	○	○	○	○	○	difficult to learn	4
valuable	○	○	○	○	○	○	○	inferior	5
boring	○	○	○	○	○	○	○	exciting	6
not interesting	○	○	○	○	○	○	○	interesting	7
unpredictable	○	○	○	○	○	○	○	predictable	8
fast	○	○	○	○	○	○	○	slow	9
inventive	○	○	○	○	○	○	○	conventional	10
obstructive	○	○	○	○	○	○	○	supportive	11
good	○	○	○	○	○	○	○	bad	12
complicated	○	○	○	○	○	○	○	easy	13
unlikable	○	○	○	○	○	○	○	pleasing	14
usual	○	○	○	○	○	○	○	leading edge	15
unpleasant	○	○	○	○	○	○	○	pleasant	16
secure	○	○	○	○	○	○	○	not secure	17
motivating	○	○	○	○	○	○	○	demotivating	18
meets expectations	○	○	○	○	○	○	○	does not meet expectations	19
inefficient	○	○	○	○	○	○	○	efficient	20
clear	○	○	○	○	○	○	○	confusing	21
impractical	○	○	○	○	○	○	○	practical	22
organized	○	○	○	○	○	○	○	cluttered	23
attractive	○	○	○	○	○	○	○	unattractive	24
friendly	○	○	○	○	○	○	○	unfriendly	25
conservative	○	○	○	○	○	○	○	innovative	26

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