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Towards a general user model to develop intelligent user interfaces

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Abstract
The way end-users interact with a system plays a crucial role in the high acceptance of software. Related to this, the concept of Intelligent User Interfaces has emerged as a solution to learn from user interactions with the system and adapt interfaces to the user's characteristics and preferences. However, existing approaches to designing intelligent user interfaces are limited by their user models, which are not capable of representing each and every user characteristic valid for any context. This work aims to address this limitation by presenting a user model that can abstractly represent a wide set of user characteristics in any context of interaction. The model is based on a synthesis of previous works that have proposed specific user models. After the analysis of these works, a more sophisticated user model has been defined, including some required characteristics not existing in previous works. This model has been validated with 62 real end-users who have expressed the users' characteristics that they consider as relevant to adapt the interaction. The results show that most of these characteristics can be represented by the proposed user model. This user model is the first step towards creating intelligent user interfaces that can adapt interactions to users with similar characteristics and preferences in similar contexts.

Keywords User model · Intelligent user interface · Conceptual model · User characteristic · User context

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1 Introduction

Developing systems that can adapt their Graphical User Interfaces (GUI) to different users has been a long-standing goal in Software Engineering. Intelligent User Interfaces (IUIs) emerged to achieve this objective. There are many definitions for IUIs, one of them provided by Brdnik et al. [1] defines IUIs as a subfield of Human–Computer-Interaction (HCI) with the goal of improving the interaction and the user experience with the system. To achieve this goal, the system must learn from the user and adapt the interfaces to his/her preferences. To achieve this, implementing an artificial intelligence algorithm that considers different characteristics to adapt the interface to the user is necessary. These characteristics could be user characteristics (such as personal traits, demographic information, user context, or user emotions), or characteristics associated with the system's purpose. For example, when the system detects that the user is alone in the room, it can enable voice commands to interact with him/her. Another example could be in an online clothing store, the system can display products that are better suited to the user's age, based on their demographic information.

Designing Intelligent User Interfaces presents several challenges as highlighted by the works of Volkel et al. [2] and Abrahão et al. [3]. These challenges include limitations in the existing user models, relying on the software's coevolution, and technical difficulties derived from the used technology (such as detecting false positives/negatives or training the software that classifies users). Another challenge consists of achieving positive user engagement. User engagement has several definitions based on the context of the system, but most definitions agree that user engagement is an attentional and emotional involvement while a user interacts with a system [4]. Doherty et al. [5] state that user engagement is a significant challenge to reach when developing HCI systems. This is because these systems must evoke positive emotions and feelings in users during their interaction; otherwise, users may opt for an alternative system that provides the positive emotions and feelings they seek. To demonstrate these challenges, Al Seraj et al. [6] provide a survey of existing user modelling systems, including both rule-based and data-driven approaches. Zanker et al. [7] explore a machine learning approach to user modelling, showing how this approach can be used to provide better recommendations. Among the different challenges, this paper focuses specifically on the challenge of defining a user model that can abstractly represent users' characteristics in any context**.** The choice of this challenge is because existing user models are often developed for specific contexts or applications, which limits their generalizability and usability in other contexts. For example, they are defined for specific groups of subjects (the elderly, blind people, etc.) or specific application contexts (music, teaching, etc.). For example, Frison et al. [8] implemented a driving system with the purpose of adapting the vehicle to the user and improving his/her user experience. Another example of this problem is presented in the work of Williford et al. [9], where the authors implemented a system to recognize the user's rectilinear strokes in order to draw free-hand perspective figures in real-time. These works demonstrate the limitations of user models that are only applicable in specific contexts. Therefore, the objective of this work is to develop a user model that can be used in a wider range of applications.

As a first step towards fixing the existing limitations, the main contribution of this article is to propose a first version of a more sophisticated user model that can be used in different contexts and capture all the necessary characteristics required to customize the GUI to the user, improving the user experience. This proposal has been designed by analysing 31 previous user models in various contexts and synthesizing a new user model that encompasses them all. Some required classes not existing in previous works have been included in the proposed user model. The article details the literature review process, explains the reasoning behind of the design of the user model's classes, provides an illustrative example of using the model, and reports the results of a pilot validation study with 62 participants. The results of the validation showed that the most important users' characteristics for subjects are already represented in our user model. However, there were some classes that were not as important for the subjects as expected. A discussion to provide insight into these results is also part of this article.

The user model proposed in this article is a first step to deal with conceptual models to support IUIs. As future work, we plan to include this user model in a Model-Driven Development method in such a way that both user characteristics and GUI widgets are abstractly represented. Our goal is to incorporate the proposed user model into existing interaction models to represent GUIs, such as IFML [10] or UsiXML [11]. We plan to define algorithms of GUI adaptation based on the widgets expressed in interaction models, along with the user characteristics saved in the user model.

This work is structured as follows. In Sect. 2, we review previous literature on user models for IUIs. Section 3 presents the proposed user model. Section 4 describes a practical example of using the user model. Section 5 outlines the results of a user study aimed at evaluating user conformity with the proposed user model. Finally, Sect. 6 concludes the work and outlines potential future research directions.

2 Related works

The goal of user modelling is to provide a better user experience by tailoring the interface to the individual user. This can include providing personalized recommendations, adapting the interface to the user's needs and preferences, and anticipating the user's goals and intentions. There have been many previous works that have focused on modelling user characteristics. Table 1 summarizes these related works, the context of application, the user characteristics used, whether the work has been validated and their limitations.

Regarding the context of Virtual user models (VUM), the work of Kaklanis et al. [12] presents a framework for the automatic simulation of accessibility using VUM. A virtual user model describes different fictitious users, focused on elderly individuals and people with disabilities, in order to simulate how these users interact with the system. To achieve this, the framework is based on a set of user models and is divided into 6 blocks: 1) the Abstract User Model, which is a high-level description of the potential of the different user models defined; 2) the Generic Virtual User Model, which describes a set of users with specific disabilities; 3) An Instance of a Generic Virtual User Model, which describes an instance of the Generic Virtual User Model; 4) Primitive Tasks, which defines and classifies each primitive human action related to a disability; 5) the Task Model, which defines the action that is being systematically performed by a virtual prototype; and 6) Simulation Models which describe the simulation scenarios proposed in the simulation process. Primitive tasks serve as the connection point between the defined blocks. For the application of the general virtual user model, the authors chose the *UsiXML* language because it allows the correct description of the different user tasks. The main advantage of this framework is that it is generic enough to implement tests based on *UsiXML*. Another advantage is that no knowledge of model development is required to implement the different models and blocks. To validate this framework, the authors propose two scenarios where the user

Table 1 Summary of related works

Authors	App. context	User characteristics	Validated	Limitation
Kaklanis et al. [12]	Virtual User Models (VUM)	Disabilities, Age, Gender, device	Yes	The proposed user models are focused on a specific user group
Filippeschi et al. [13]		Disabilities, Age, Gender	Yes	
Haag et al. [14]	Persona Method	Age, Gender, Interest, Study Level, Job	No	This method does not allow us to adapt the GUI dynamically
Nielsen et al. [15]		Age, Gender, Goals, Knowledge	Yes	
Schäfer et al. [16]		Age, Gender, job, hobbies, skills	Yes	
Jung et al. [17]		Age, Gender, Nationality, Interests, Job, study Level	No	
Wang et al. [18]	OCEAN Method	Emotional status	Yes	This method oversimplifies the user characteristics
Millecamp et al. [19]		Emotional status	Yes	
Andaloussi et al. [20]		Emotional status	Yes	
Cong et al. [21]		Emotional status	Yes	
Shen et al. [22]	Recommendation System	Emotion, gender, Age, Actual position (No nationality), Interests	Yes	The proposed user models are focused on providing music recommendations
Miao et al. [23]		User's interests,	No	
Song et al. [24]		Emotion, Age, gender, Actual position, Nationality	Yes	
Zangerle et al. [25]		Nationality, Interests	Yes	
Farahani et al. [26]		User's interests	No	
Palchumov et al. [27]	Voice Command Systems	Language, Nationality, Knowledge, Goals, Interests, Context, preferences	No	The proposed user models do not consider the user context
Alrumayh et al. [28]		Language, Nationality, device	Yes	
Zhu et al. [29]		Language, Nationality, Age, Gender, context, emotions	Yes	
Barifah et al. [30]	Web Personalization	Emotions, skills, Age, gender, job, working profile, level study	Yes	The proposed user models are focused on collecting characteristics about application context, without considering user characteristics
Jahanthi et al. [31]		Skills, interests, preferences	Yes	
Trifa et al. [32]		Knowledge, Skills, application context, device, Interest, preferences	Yes	

Table 1 (continued)

Authors	App. context	User characteristics	Validated	Limitation
Medjen et al. [33]	User's engagement in web	User's emotions	Yes	The proposed user models are focused on collecting emotional user's characteristics without considering others charcateristcis to define the user engagement
Basar et al. [34]		User's emotions	Yes	
Castiblanco et al. [35]		User's emotions	Yes	
Castiblanco et al. [36]		User's emotions	Yes	

uses a telephone and a stapler. They use elderly people with a reduced range of motion to validate these scenarios. The results show a high level of acceptance for the different scenarios proposed by the users, indicating that the different user models proposed help users to complete these tasks. Filippeschi et al. [13] define a system that combines various modules, including a Kinect sensor and a graphical user interface with touch or voice controls to learn about the behaviour of elderly people. This system is based on several modules for motion tracking, object recognition, and activity recognition. To classify users, the system calculates an internal score, where users with higher skills receive higher scores and those with lower skills receive lower scores. The authors validate this system with real users and determine that it can assist elderly people in the performance of their daily tasks. The main limitation of these works is that they are focused on a very specific group of users, which reduces their correctness and efficiency when they are applied to other users.

Other works that deal with modelling user characteristics are based on the Persona method. This method consists of creating representations of fictitious users, which are classified into several groups of users. The work of Haag et al. [14] states that the Persona method uses the natural appeal of other people and can help to define a user model, thereby improving the design of applications. Other works are focused on enhancing the Persona method by adding characteristics such as job [15] or medical information [16] to classify users. Additionally, some studies employ reverse engineering techniques to tailor user models to specific applications [17]. However, the main drawback of the Persona method is that it is not suitable for learning the evolution of user characteristics at runtime. For example, a user's characteristics and preferences may change over time, requiring regular updates to the user model. As a result, it is crucial to keep the user model up-to-date to reflect current user characteristics and preferences.

Other works in user modelling focus on personal traits. In this research line, one approach is the OCEAN method**,** also known as Five-Factor model, which is based on five taxonomies to define personality traits. These taxonomies are Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [18]. Some works focus on using the OCEAN taxonomies to improve the results provided by Internet browsers [19] or incorporating these taxonomies into an AEH (Adaptive Educational Hypermedia) system [20]. Furthermore, the work of Cong et al. [21] defines several behaviours that indicate how the user interface should be adapted to fit the user's personality. However, the main limitation of this method is that it oversimplifies the user, since many important user characteristics (such as age, gender, or nationality) cannot be represented in these taxonomies.

Regarding the context of recommendation systems, some studies are focused on a user model to classify users to recommend the best option. Based on this idea, we find the PEIA (Personality and Emotion Integrated Attentive) framework [22], which defines a user model to improve music recommendations by considering the users' likes, preferences and emotions. All these values are compared with social data to classify the users and provide recommendations. The objective of the PEIA framework is to improve the music recommendation experience by offering more relevant characteristics, which results in a better user experience. Another music recommendation framework is HRRS [23], which is based on a learning system that adapts to the user's interactions in the current session to offer music recommendations. The work developed by Song et al. [24] aims to develop a user model to provide recommendations based on empirical studies to analyse the relationship between human behaviour and music. Finally, it is worth mentioning the work carried out by Zangerle et al. [25]. This introduces a user model that considers demographic characteristics, such as nationality or language, to offer music recommendations. Farahani et al. [26] suggest a machine learning algorithm that tracks the user's interest changes in recommender systems. For this purpose, they propose a user model that represents the different attributes that describe user interest and its changes or dynamism. However, the main limitation of these works is that the user models are primarily focused on providing music recommendations, making them only valid for this type of system.

Regarding the context of voice command systems, we find the work of Palchumov et al. [27], which developed an intelligent assistant with the aim of identifying user desires and preferences based on semantic models of the user and the subject domain. The software has a user model that keeps in mind three types of speech acts, desires, and user goals. Based on this information, the software provides recommendations for each group of users. VORI [28] is a framework aimed at improving the interactivity of user interfaces through voice commands. Zhu et al. [29] conduct two different experiments that compare the emotional expressiveness of users who interact with a chatbot and those who do not interact, but visualize the interaction. They find that the vocabulary used by the system is a crucial factor to consider, since using a vocabulary that the user does not understand can result in poor ratings and a lack of expected responses. However, the main limitation of these works is that they are designed without considering the user context, which means that the system cannot detect itself when the user can only interact through voice.

Regarding the context of web personalization, some studies are based on determining how user characteristics affect search results with the aim to improve recommendations and adaptability of personalized web searches. In this line, we find the work of Barifah et al. [30], which aims to shed light on the causes of failed searches and identify associated emotions. To do this, they conducted a study to evaluate factors such as age, gender, level of education, discipline, current emotional state, and user knowledge concerning digital libraries. They concluded that the low usability and limited coverage of digital libraries often lead to incorrect search results, causing frustration for users who cannot find the information they are seeking. Jahanthi et al. [31] present a framework to facilitate personalized web searches. To do this, they propose an internal score, called a Group Interest Score (GIS), and select the results according to this value. They state that the results improve as the user profile converges; in other words, a new user profile has worse personalization than a converged user because the system has learned new parameters from the user. They conclude that using this framework, personalized web searches improve by 30–40% compared to other browsers. Trifa et al. [32] propose RPMAS (Referential Personalized Multi-Agent System). This system has an adaptive architecture based on agents to improve personalization in web services. RPMAS presents an architecture based on three layers: the observation Layer (where the system collects the information about the user and his/her behaviour), the Modelling layer and Data processing layer (where the information extracted in previous layers is analysed, the system classifies the users and determines how the interface should be adapted), and the Prediction recommendation and Evaluation Layer (where the different adaptations of GUI are presented to the user). To validate the approach, the authors conducted an empirical experiment with real users. In this experiment, they propose two different scenarios, one implemented with RPMAS and another one implemented with AUC (Area Under the Curve). They compare the grade of Graphical User Interfaces (GUI) adaptation using RMPAS and AUC. The results show that users prefer the adaptation offered by RMPAS. The main drawback of these works is that they are focused on collecting characteristics about the system context while few user characteristics are kept in mind.

Regarding the user engagement, some studies are focused on determining that user emotions may increase the engagement of the systems. We find the work of Medjen et al. [33] where the authors study different emotional aspects of users and how user interface customisations affect user interface engagement. To do so, they created a system capable of adapting user interfaces according to users' emotions. In the same line, we find HyLECA (Hybrid Long-term Engaging Controller Conversational Agents)[34], which introduces an architecture to improve the responses offered by chatbots by considering the specific user information, such as name, age, language. This framework is based on two modules. In the first module (retrieval module), data are processed and classified according to an internal ranking. Then, the second module (generation) generates a range of possible responses and returns the response candidate with more score. The objective of HyLECA is to improve the system response and interaction to increase the user engagement in task-oriented chatbots. In the work of Castiblanco et al. [35], the authors analyse the methods and metrics most used to measure the user experience in different works. The approach consists of a framework where the metrics and methods are presented and evaluated. The authors state that many works include the methods and metrics based on psychological characteristics of users, as personal traits, to increase the user experience. The work of Castiblanco et al. [36] conducts a study to analyse a non-traditional method based on electroencephalography when a user interacts with a human–computer interaction (HCI) application. The main limitation of these works is that these studies and frameworks are focused on user emotions to improve the user interface's engagement, not considering other methods based on the user's characteristics.

All the approaches described in this section present user models to identify the users' characteristics in various contexts, with a focus on distinct characteristics. However, there is not a general and more sophisticated user model to represent all user characteristics for IUIs in any context. Existing approaches are highly specialized in specific domains. This work aims to combine existing approaches to propose a general user model suitable for any context and any user characteristic. Our proposal integrates both dynamic and static user characteristics as a first step to build IUIs that can learn from users' interactions and users' profiles to adapt their design to the users' characteristics.

3 User model

The main contribution of this paper is the definition of a user model capable of representing the necessary user characteristics for the purpose of supporting the development of IUIs for any context. Our user model is based on existing user models and seeks to gather all relevant user characteristics into a single user model. Additionally, the proposed model includes some other characteristics that we consider important when designing IUIs based on our experience. The user characteristics represented in the user model will be used in future research to learn from users' interactions and adapt interfaces to other users with similar characteristics. Next, we describe the systematic process followed to look for existing user models and how we built our proposal of a general user model.

The search for user models in the literature was based on a Targeted Literature Research (TLM) method, which checks the Title OR Abstract OR Keywords with the following search string: ("user model" AND "user characteristics") OR ("intelligent interface" AND "user characteristics") OR ("user model" AND "Classify users") OR ("user model" AND "intelligent interface"). The inclusion criteria were: (IC1) the user model includes a precise description of its classes, and (IC2) the classes that make up the user model represent user characteristics that can be learned automatically through the interaction. The exclusion criteria were: (EC1) the user model has no direct application in the design of user interfaces;

(EC2) the user characteristics expressed in the user model do not allow the classification of users; (EC3) the user characteristics do not allow learning from the users' interaction. Before applying the inclusion criteria and reading the abstracts and titles, there were 200 works available. After applying the inclusion criteria, the number was reduced to 62 works. Next, we read the whole papers, and we applied again the inclusion and exclusion criteria to these 62 works. Finally, we reduced the group of papers to 29, which are used to define our proposal of user model. The search was conducted in June 2023 using Scopus, ACM Digital Library, and IEEExplore Digital Library.

One important aspect we want to emphasize is the privacy and anonymity of user data. These aspects are crucial due to the characteristics depicted in the user model in Fig. 1. To ensure this anonymity, the methodology employs an ID to identify each user, ensuring that the system does not store personal user data such as names. Regarding the user's salary and age, the system offers various ranges that users can choose from, ensuring that the specific value is not disclosed. For example, the system may provide age ranges like [0–10], [11–20], [21–30] and so on. Other private information such as gender, education level, nationality, language, or disabilities are encoded with an internal system code, preventing specific information from being obtained. For instance, the system may represent male gender as 1 and female as 0, making it impossible to discern the actual value of this characteristic without decoding.

Figure 1 graphically shows the proposed user model, which is composed of several key-value classes designed to support the classification of users according to their characteristics. Table 2 summarizes each class of the proposed user model, referencing the sources in the literature that support the necessity of these user characteristics and their motivations. In addition to the classes obtained from the literature, we have extended the user model with three new classes that are essential to capture important characteristics in order to adapt interfaces based on our experience: skills, device, and hobbies. Next subsections describe the details of the proposed user model and the selected works.

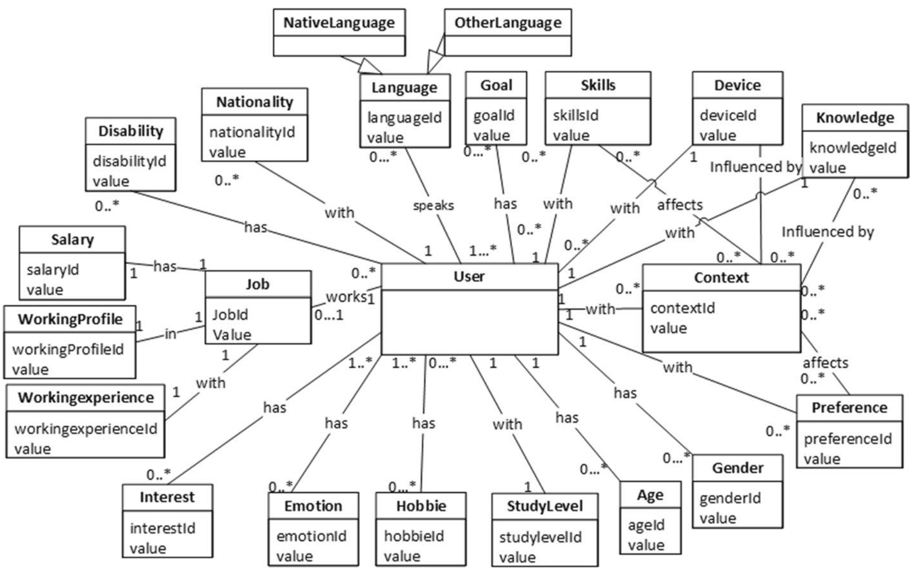

Fig. 1 Proposed user model

Table 2 Summary of the classes that make up our proposal for a general user model along with the motivation

Class	Work	Motivation
Knowledge	Vázquez-Ingelmo et al. [37],Abri et al. [38]	To adapt the GUI according to the user's level of knowledge
Study Level	Chen et al. [39], Aljedaani et al. [40]	To adapt the GUI according to the user's study level
Skills	New contribution of this work	To adapt the GUI to the level of accuracy expected by the user
Nationality	Zangerle et al. [25], Bauer et al. [41]	To adapt intrinsic characteristics that the system considers
Language	Chandra et al. [42], Zhou et al. [43]	To adapt the GUI so that user can understand
Gender	Aufderhaar et al. [44]	To adapt the GUI recommendations to gender
Age	Chen et al. [39], Jimison et al. [45]	To adapt the way in which the user communicates with the system
Job	Salminen et al. [46],Millecamp et al. [47]	To adapt the GUI recommendations to the current user's occupation
Salary	Jin et al. [48], Lanche et al. [49]	To adapt GUI shopping recommendations to the user's budget
Work Experience	Islam et al. [50]	To adapt GUI work recommendations to the user's job history
Working Profile		To adapt GUI work recommendations to the actual or desired working profile of the user
Context	Kompan et al. [51], Abidi et al. [52]	To adapt the GUI to the user according to his/her current situation
Preferences	Zhou et al. [53], Cami et al. [54]	To adapt the GUI to the user in a way previously specified by him/her
Emotions	Singh et al. [55], Miller et al. [56], Medjen et al.[57], Kropotov et al. [58]	To adapt the GUI to the user's expectations
Disabilities	Romero-Mariño et al. [59], Zouhaier et al. [60]	To adapt the GUI to allow correct interaction
Interest	Dumitrescu et al. [61], Guesmi et al. [62]	To adapt the GUI information to provide valuable information for the user
Goals	Vázquez-Ingelmo et al. [63],Abri et al. [38]	To adapt the GUI with visible options to those that meet these objectives
Device	New contribution of this work	To adapt the GUI to the device used by the user
Hobbies	New contribution of this work	To adapt the GUI to offer the most interesting information to the user

3.1 Knowledge, study level and skills

The work of Ingelmo-Vázquez et al. [37] presents a user model that includes "knowledge" as a class. This characteristic allows you to learn about the knowledge that the user has on the content offered by the system. This way the content of the GUI can be customised according to this knowledge. Similarly, the work by Abri et al. [38] highlights the importance of dynamic user characteristics, including knowledge, that constantly change. So, systems must be updated to such changes to ensure understandability. Based on these works, we include "Knowledge**"** as a class in our user model. This class aims to learn from the user's interaction and present content in a domain that the user can understand. For example, in an educational application, if a user is an expert, the system can provide more technical information to the user compared to the case of a novice user. In the latter, the system can use direct links to help with the interaction.

The work of Chen et al. [39] shows that the level of study affects users in e-commerce applications. According to the study, users with a university degree buy more via e-commerce, and these purchases are of more expensive and more specific products compared to those of users without a university degree. Supporting this idea, Aljedaani et al. [40] state that users with higher levels of education are more familiar with technology, resulting in faster and more precise interactions. Based on these studies, we decided to include "Study Level**"** as a class in the user model, because the study level allows the system to improve user classification according to their academic achievements. Additionally, we propose including the class "Skills**"** as a characteristic to classify users to these characteristics extracted from previous works, because users with more skills have faster and more precise interactions. The importance of user skills lies in their ability to utilize the features and functionalities of a system or technology effectively and efficiently. For example, a skilled user can use shortcuts such as the control button with $\pm$ to change the page zoom or the buttons "end", "Av.page" or "Re.page" to scroll pages. These shortcuts lead to faster and more precise user actions, and do not need visual help. However, a user with low skills does not make use of shortcuts and may need some visual help to understand the correct operation.

3.2 Nationality and language

The work of Zangerle et al. [25] describes how users' nationalities affect music listening or subscription behaviour in music applications. The results of that work indicate that users from the same country and surrounding countries share common characteristics. These characteristics may affect to the number of users who use the application, the musical genre they listen to, and the probability of them subscribing to the system. The work of Baurer et al. [41] highlights the importance of considering the user's country when making musical recommendations to users. They conclude that users' countries are important because they influence a series of social and cultural behaviours that distinguish them from users in other countries. Both studies conclude that neighbouring countries often share similar characteristics. Based on these works, the proposed user model includes "Nationality**"** as a class to support the adaptation of the GUI to the user based on their cultural or social preferences.

The work of Chandra et al. [42] describes the significance of the language in user interaction with the system. They conclude that users are more comfortable when interacting with a system in their native language, while the interaction becomes more difficult when the system does not support it. Zhou et al. [43] propose a user model to improve searches. They conclude that users prefer to search for information in their native language, but they also have other languages they use to search. Based on these findings, we decided to include "Language" in the user model, but differentiating between the native language, called "Native language", and other languages known by the user, called "Other languages". In both cases, the system stores a value that represents the language, with each user having a native language and potentially other languages. This division aims to help the system determine the correct language to display the content so the user can understand it easily.

3.3 Gender and age

The work of Aufderhaar et al. [44] presents findings from different studies that demonstrate the impact of a user's gender on their experience. These studies suggest that women tend to be more critical with the design, while men tend to be more critical with the usability. As a result, we included the "Gender" class in our proposed user model.

The work of Chet et al. [39] highlights the relevance of age as a parameter when shopping online. They find that individuals between the ages of 20–30 have a higher likelihood of making purchases online, while those over the age of 51 have the lowest likelihood. Jimison et al. [45] propose a dynamic user model to deliver customised health advice. They consider age as a key factor since health advice must be adapted to the age of the user. Older users may not understand the same message as younger users, or they may have difficulties interacting with the system. Based on these studies, we included "Age" as a class in the user model. For example, elderly people are more likely to make purchases using a credit card, so this option must be preferentially placed in the GUI.

3.4 Work

The work of Salminen et al. [46] compares different user's characteristics related to their jobs which can help the system adapt to the user's purpose and recommendations based on their budget. The works of Millecamp et al. [47] and Jin et al. [48] include job characteristics in their user models as this allows the system to classify users into specific musical groups and offer more precise recommendations. Similarly, Lamche et al. [49] include job, working sector and salary as important characteristics to offer more precise recommendations when a user performs a search for information related to their work. Similarly, Islam et al. [50] include salary as an important user characteristic in the context of online e-commerce, because they consider that the user's salary may determine the budget that the user has to spend in the e-commerce. Based on these works, we decided to include job characteristics such as "Job", "Salary", and "Working profile" in our user model. Knowing these characteristics allows the system to adapt to different job profiles and know the user's spending potential. Apart from these characteristics extracted from previous works, we propose including the "Work Experience" class as a characteristic to classify users depending on their salary (in the case of an e-commerce system), depending on their skills in work (in the case of a job search system) and to allow the system to learn about user skills in the context of her/his working profile. If a user has a high level of work experience, she/he will commit fewer errors and will complete the tasks faster than a user without work experience in the system's context. For example, while a junior and a senior programmer belong to the same job profile, they may have different salaries and thus different spending potential.

3.5 User context, emotional status, device, preferences, and disabilities

The work of Kompan et al. [51] describes how the user's context can provide information related to user preferences. The context helps in determining the user's behaviour and, consequently, her/his preferences. In the same way, Abidi et al. [52] state that the user's context is important to adapt the interaction. For example, voice interaction is more appropriate when the user is exercising. These authors also highlight that the device being used is a characteristic to consider, since physical elements, such as screen size, can affect how the user interacts. For example, in an augmented reality system, elements will be displayed smaller on a mobile device than on a tablet. Based on these findings, we propose including the classes "User Context**"** and "Device**"** in the user model.

The work of Singh et al. [55] and Miller et al. [56] demonstrates that user interactions are also influenced by emotions. Poor user experiences can lead to a rejection of the system due to negative emotions. Singh et al. also highlight the impact of colour choices on users' emotions, as the combination of colours can affect user emotions. The work of Castiblanco et al. [35] and Medjen et al. [57] address user emotions using biometric data, such as facial expressions, heart rate and skin conductance. In these works, the authors state that the number of papers focused on this topic has been increasing in recent years. Also, the authors demonstrate that recognizing and adapting the user interface to user emotional status helps increase the use's engagement when the user interacts with the system. Based on these findings, we decided to include "User Emotional Status**"** as a class in the user model to help the system to know the user's current emotional state. Also, based on the work of Kropotov [58], personal traits are defined as psychological concepts related to a user, which may be described as patterns connected with emotions, motivations, etc. Consequently, we also consider the user's personal traits in the User Emotional Status class.

The work of Zhou et al. [53] and Cami et al. [54] proposes algorithms that provide recommendations based on user preferences. They conclude that user preferences allow the system to classify users according to preferences and offer personalized recommendations to each group. Based on these works, we decided to include "User Preferences**"** in the user model.

Finally, in order to have a complete view of the context, it is crucial to consider disabilities. The work of Romero-Mariño et al. [59] describes the importance of including disabilities in the user's profile to effectively deal with the adaptation process. Specifically, they recommend including these disabilities in the "Persona" profile. Similarly, the work of Zouhaier et al. [60] emphasizes that users' disabilities must be considered in interface design. For example, colour choices may cause confusion for colour-blind users. Based on these works, we decided to add "Disabilities**"** in our user model to address issues such as tired eyes, myopia, astigmatism, or colour blindness. For example, if the system is aware that the user has tired eyes, it can display the information in a larger font size or eliminate non-essential options.

3.6 Interest, goals, and hobbies

The work of Dumitrescu et al. [61] and Guesmi et al. [62] proposes a user model that includes user interests. User interests change over time; what may not be interesting today may become interesting in the future. These proposals assess interests by analysing the most recent searches. For example, when the system shows the results of a query, it is necessary to differentiate terms that have been previously searched for, since they are the terms of interest for the user. Based on these studies, we decided to add "User Interest" to the user model, as it helps to identify the best option to display.

The works of Vázquez-Ingelmo et al. [63] and Abri et al. [38] describe the importance of considering users' goals when offering better recommendations. For example, when the user conducts a query to carry out a demographic study, the system should identify this goal and adapt the results to an ordered list of cities according to their population. So, we decided to include "User Goals" as a class in the user model as this characteristic helps the system to classify users based on their goals. In addition, we propose including the class "Hobbies" in the user model since hobbies are part of user interests, for example searching for a video online during the user's leisure time. These hobbies may indicate what response the user expects when she/he interacts with the system.

4 Example of use

In this section, as an illustrative example of the user model, we define two scenarios that provide an insight into how user characteristics affect the GUI.

4.1 E-commerce

The first scenario describes the adaptation of the GUI of a marketplace with a diverse product catalogue to accommodate the needs of two different users, based on their characteristics represented in the user model. In this example, both users are looking to buy a new T-shirt. The characteristics of each user in this scenario are outlined in Table 3.

User 1 is a 50-year-old Spanish man with limited knowledge about fashion and low internet skills. His interests and hobbies include sports and photography. This user has a low-income -salary level and is currently feeling tired, stressed and alone at home. Additionally, he has myopia, accesses the marketplace through a computer device, and prefers to view the search results in the form of a list, indicating which results he has previously consulted.

User 2 is 27-year-old Irish woman who possesses extensive knowledge in the domain of fashion and high internet skills. Her interests and hobbies are reading books and writing in her fashion blog. This user has a high-income salary level and is currently feeling tired and peaceful, and she is accompanied at home. She does not have any disabilities, she accesses the marketplace through a tablet device, and prefers to visualize the search results as a grid, ordered by rating.

Figure 2 depicts the default configuration of the GUI, which represents the GUI without any adaptations. In this configuration, the elements are displayed as a list, providing the user with an image of the product, its name, brand, price, rating, and a button to add the product to the cart. By default, the GUI supports both voice and text commands to perform searches.

Figure 3 a illustrates the adaptation of the GUI for User 1. In this adaptation, the results are displayed as a list with a picture of the product, its price, and prioritizing previously searched items. Due to the user's visual disability, the product titles are displayed in a larger font size compared to the default setting. The texts are shown in Spanish and the prices in euros to align with the user's characteristics. Moreover, since the user is specifically looking for T-shirts and he is a man, the system exclusively displays products from

Table 3 User characteristics for each user in the marketplace example

Characteristic	User 1	User 2
Knowledge	Low knowledge about fashion	High knowledge about fashion
Study Level	School certificate	Master's degree
Skills	Low internet skills	High internet skills
Nationality	Spanish	Irish
Native Language	Spanish	English
Other Languages	Chinese, English	Danish, Spanish
Gender	Male	Female
Age	50 years old	27 years old
Job	Building worker	Software engineer
Salary	Low level	High level
Work Experience	30 years	3 years
Working Profile	Construction	IT
Context	Alone at home	Accompanied at home
Preferences	Show products as a list, and search for a previously ordered product	Show products as a grid, ordered by ratings
Emotions	Stressed and angry	Tired, peaceful
Disabilities	Myopia	None
Interest	Photography	Reading books
Device	Personal Computer	Tablet
Hobbies	Doing Sport and playing video games	Writing her fashion blog and going out with friends

the men's section. The system also recognizes that the user is alone and activates the voice command option to facilitate interaction. To alleviate the user's stress, only results that the user has previously ordered are shown.

Figure 3 b illustrates the adaptation of the GUI for User 2. In this adaptation, the results are displayed in an ordered grid based on ratings. Each result includes a product image, price, and rating. Since the user speaks English, the system displays all the information in English and shows product prices in pounds to align with the user's characteristics. Moreover, the system recognizes that User 2 intends to buy a T-shirt for herself, so only products from the women's section are displayed. Additionally, since User 2 is interacting with a Tablet device, the system activates gesture recognition to enhance the user's interaction experience. Furthermore, considering that User 2 is feeling peaceful, the system displays more results ordered by rating, compared to User 1. This ensures a wider range of highly rated products to match with User 2's preferences.

4.2 Autonomous car

The second scenario describes the adaptation of the GUI for an intelligent car equipped with a tablet device for two different users based on the characteristics represented in the user model. These examples provide valuable insights into how user characteristics impact the GUI adaptation. In this particular example, the users aim to use the navigation component to find the shortest route to their respective homes. Table 4 provides an overview of the characteristics of each user in this scenario.

Fig. 2 Example of the Predetermined GUI adaptation

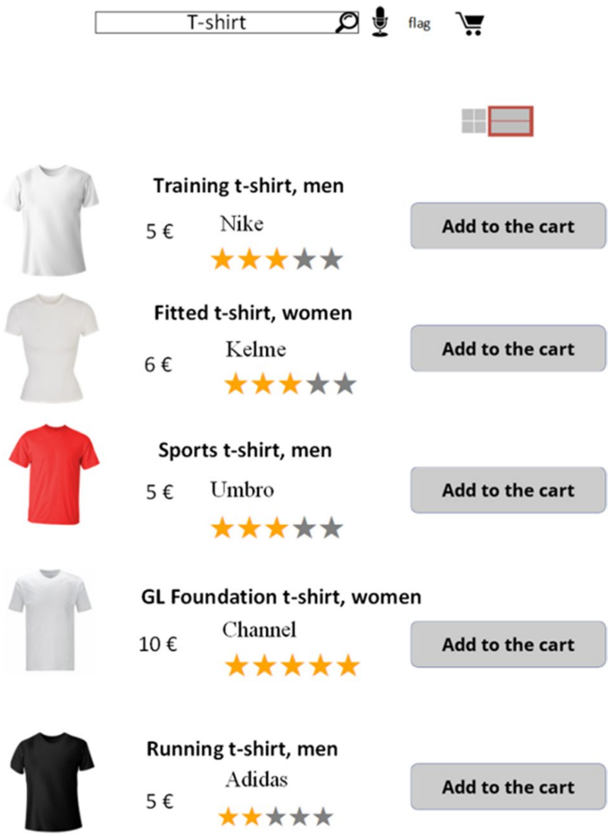

Fig. 3 **a(left)** example of GUI adaptation for User 1. **b(right)** example of GUI adaptation for User 2

Table 4 User characteristics for each user in the intelligent car scenario

Characteristic	User 1	User 2
Knowledge	Low knowledge of intelligent cars	High knowledge of intelligent cars
Study Level	Master's degree	PhD
Skills	Mid-level driving skills	High level driving skills
Nationality	Spanish	Italian
Native Language	Spanish	Italian
Other Languages	English, French	English, Danish
Gender	Male	Female
Age	30	45
Job	Data analyst	Researcher
Salary	Medium level	High level
Work Experience	2 years	18 years
Working Profile	IT	Computer Science
Context	Driver, alone in the car, driving	Passenger
Preferences	Interact with touch commands and large icons. He wants to see the weather forecast for the next 5 h	Interact with voice commands
Emotions	Tired	Relaxed
Disabilities	Myopia	Motor disabilities
Interest	Drawing	Sports
Device	Tablet	Tablet
Hobbies	Playing video games and listening to music	Doing sport, reading about cars, and listening to music

User 1 is a 30-year-old Spanish man with limited knowledge regarding intelligent cars and medium level skills in driving intelligent cars. His interests and hobbies are playing video games and listening to music. This user has a medium-income salary level and is currently tired and driving alone. Additionally, User 1 has myopia and prefers interacting with the system through gesture commands and large icons. He aims to visualize the weather forecast for the next 5 h while driving.

User 2 is a 45-year-old Italian woman with advanced knowledge and skills about intelligent cars and driving. Her interests and hobbies include doing sport and listening to music. This user has a high-income salary level and is a front-seat passenger, feeling relaxed during the interaction. Since this user has motor disabilities, she prefers to interact with the system through voice commands.

Figure 4 depicts the default configuration of the GUI without any adaptations. This configuration is divided into three sections. Section 1, positioned at the bottom, shows a menu that contains various configuration icons. Section 2 is divided into two parts. The first part (2.1) is located on the left side and includes battery indicators, options for opening the trunk and hood, and displays the current speed along with the maximum speed limit of the road. The second part (2.2) contains the navigation map. Section 3 is also divided into two sparts. The upper part provides information such as the location, climate, weather forecast, time, and the available connections of the car. In this case, only Bluetooth is activated. The lower part in Sect. 3 shows information about the song that the user is listening to, or the phone call that the user is answering.

Fig. 4 Example of the Predetermined GUI adaptation

Fig. 5 Example of GUI adaptation for User 1

Figure 5 illustrates the adaptation of the GUI for User 1. Considering the user characteristics previously described, the system shows all texts and alerts in Spanish and configures the user's location to Spain to facilitate inserting the desired destination (the same name of the place can be found in two or more countries, so the system may eliminate these unwanted results). Due to the current context and the preferences of the user, the system displays a large icon without text and an additional component showing the weather and location information. The system adapts the size of the icons and includes the weather forecast for the next 5 h. Due to the user's fatigue, the system turns down the volume of voice commands. Additionally, since the user likes listening to music, the system plays the user's favourite playlist.

Figure 6 illustrates the adaptation of the GUI to User 2. Considering the user characteristics of this user, the system displays both the icon and the name (for example "Auto" in Fig. 6). As the user speaks Italian, the system presents voice commands and texts in Italian and configures the user's location to Italy to facilitate the input of the location where the user wants to go. Since this user is a passenger in the car, the system hides unnecessary menu icons, activates voice commands for interaction with the user (because user 2 has motor disabilities), and introduces a new part displaying information about the car's proximity sensors, current speed, maximum speed limit, and safety belt information. Finally, considering the preferences of user 2 concerning playing music, the system incorporates a part showing the song name and playlist.

5 Validation of the user model

The purpose of this experiment is to examine which user characteristics are deemed most important by users for adaptation in each context. This analysis aims to determine whether certain characteristics are more or less relevant from the perspective of end users.

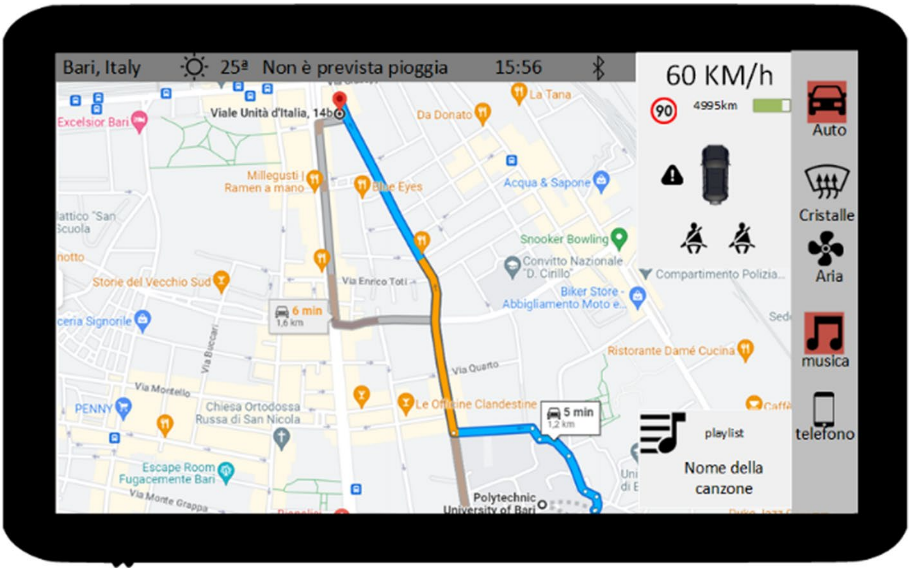

Fig. 6 Example of GUI adaptation for User 2

5.1 Research questions and hypothesis formulation

Through this experiment, our objective is to verify whether these characteristics match the characteristics expected by real users. Next, we describe the research question that corresponds to this objective.

RQ1: *Which users' characteristics are relevant for end users in order to adapt GUIs?* The metric used to measure this research question is the percentage of votes received for each characteristic of the user model. A questionnaire with 15 scenarios is used to collect the votes. Each characteristic is presented in multiple scenarios, and end-users are asked to vote for the characteristics that they consider relevant for GUI adaptation in each scenario. By addressing this research question, we want to assess whether the characteristics expressed in our proposed user model are perceived as useful for adaptation from the perspective of end-users. We also aim to analyse whether end users would add any user characteristics that we have not considered in our user model.

5.2 Participants

In the experiment 62 users (51 males and 11 females) participated. These participants were between 20 and 49 years old, with an average age of 22 years old. All the participants were students at the Universitat de València (UV, Spain) who have previously taken software engineering courses. They all had previous knowledge in software engineering and GUI design, and they had high-level internet skills.

5.3 Task and procedure

Firstly, the participants filled out a demographic questionnaire aimed at gathering information regarding their profiles. This questionnaire included questions about age, hobbies, and preferences when interacting with the applications. The collected descriptive data from the demographic questionnaire is summarized in Table 5.

Questions are shown in several scenarios, such as internet searches, online shopping, home automation, driving, games, medicine, music, or job-related activities. The user model characteristics were equally distributed across the different scenarios. The scenarios and demographic questions can be found in Appendix A. Table 6 presents the different scenarios of the questionnaire, including the corresponding characteristics that were assessed in each scenario. Each question is set in a specific scenario. The participants were asked to specify the characteristics they considered most relevant when adapting the interfaces. There were no limitations on the number of characteristics that could be voted for in each scenario. Each scenario presents at least six characteristics to select, which facilitates answering the questionnaire in a short time. Moreover, this number of responses allows us to maintain a balance in the frequency of appearance for each characteristic throughout the experiment. Apart from the six different options, each question includes the option "Other" (see Annex A). So, subjects that would like to select a different characteristic can do so. It is important to note that in this study, there are no right or wrong answers, since our goal is to identify which characteristics are more significant to users in specific contexts. Therefore, our focus is on studying the diverse responses to understand the preferences of this user group regarding different characteristics.

Table 5 Results of demographic questions

Value	N	Value	N
Gender		**Preferences**	
Female	11	Doing sports	47
Male	51	Listening to music	43
Studies		Drawing	5
Bachelor's degree	45	Reading	23
FP	7	Gaming	42
College	8	Collecting	9
Master	1	Playing an instrument	10
Ph.D	1	Others	7
Age		**Working Profile**	
MIN	18 y	Student	49
MAX	49 y	Freelance	2
MEAN	22 y	Computing	7
MODE	20 y	Others	4

5.4 Threats to validity

This subsection discusses the different threats to validity of this experiment, following the classification proposed by Wohlin et al. [64]. The threats are categorized into four groups: construct validity, internal validity, external validity, and conclusion validity. For each threat, we indicate whether our experiment is affected by it, whether we have mitigated its impact, or if we have managed to avoid it.

Construct validity These threats are related to correctly identifying the operational measures necessary to experiment and generalize the result of the experiment to the concept or theory behind it. This experiment may suffer the following construct validity threats: (1) *Interaction between scenario and context*, which appears when the selected contexts do not represent the importance of the user characteristics. This threat affects the experiment since some scenarios cannot be the most suitable to highlight the importance of specific users' characteristics. To mitigate this, we distributed the same characteristics among several scenarios. For example, we use a scenario related to work to analyse the users' characteristics related with it (job, work profile and work experience) (see scenario 9 in Appendix A). Another threat that affects the experiment is (2) *Hypothesis guessing* which appears when subjects may try to deduce the purpose of the experiment and this deduction may affect their answers. This threat affects our experiment because users may try to infer what user characteristics are expected in each scenario. To avoid this threat, we have hidden the research question from the users. Another threat that affects the experiment is (3) *Evaluation apprehension,* which arises when some users are afraid of being evaluated. This threat affects the experiment because there may be a few users who do not participate in the experiment for fear of failing in the evaluation process. To mitigate this threat, we looked for volunteer users who were motivated to increase their score in the class where the experiment was conducted. Another threat that affects the experiment is (4) *Experiment expectancies,* which means that the experimenters can bias the results by looking for specific expectations. This threat affects the experiment because the researchers that propose

Table 6 Representation of each option in the proposed scenarios

Scenario	Option 1	Option 2	Option 3	Option 4	Option 5	Option 6
1- Web search	Goals	Study level	Knowledge	Language	Interest	Work profile
2- Shopping	Salary	User's skills	Nationality	Goals	Interest	Device
3- Payment	Age	Interests	Language	Disabilities	Nationality	Skills
4- Smart home	Language	Preferences	Gender	Age	Disabilities	Skills
5- Autonomous car	Gender	Context	Nationality	Preferences	Emotions	Device
6- Health	Disabilities	Language	Age	Device	Context	Emotions
7- Voice assistant	Nationality	Language	Preferences	Interests	Emotions	Hobbies
8- Sports	Gender	Emotions	Hobbies	Skills	Interest	Device
9- Job search	Job	Study Level	Salary	Age	Work experience	Work profile
10- Virtual reality	Disabilities	Context	Interests	Preferences	Salary	Hobbies
11- Augmented reality	Disabilities	Device	Interests	Language	Age	Gender
12- Leisure	Work Experience	Interests	Goals	Job	Work profile	Knowledge
13- Searching code	Study Level	Work Experience	Work profile	Goals	Job	Knowledge
14- Series	Emotions	Disabilities	Hobbies	Interests	Knowledge	Salary
15- Working with robots	Emotions	Disabilities	Job	Context	Work experience	Work profile

the user model are the experimenters who evaluate it. Our design is affected by this threat, since all the experimenters are co-authors of the user model.

Internal validity These threats describe how the cause-effect relationship established in the experiment cannot be explained by other factors. This experiment may experience the following threats of this type: (1) *Testing,* which means that if this experiment is repeated, users may respond differently because they know how the test is conducted. We avoid this threat because users answer each scenario without seeing the results of the other subjects and without receiving feedback in any scenario. Another threat that appears is (2) *Mortality,* which means the probability of dying while the experiment is in progress. This threat may affect the experiment if a user considers the experiment very long and she/he abandons it. We avoided this threat since the experiment is so short (around 20 min) that no-one abandoned the experiment. Another threat that appears is (3) *Maturation,* which means the effect of reacting differently as time passes. This threat is avoided for the same reason as mortality. Another threat that affects the experiment is (4) *Instrumentation,* which means that the artifacts used in the experiment may affect the results. We experienced this threat because the instruments used in this experiment may not show the real importance of the characteristics represented. We mitigated this threat by validating the questionnaire using a pilot study with two subjects, who were not considered as participants in the experiment.

External validity These threats aim to generalize the results of the experiment or the theory behind the experiment. This experiment may experience the following threats of this type: (1) *Interaction of selection and treatment,* which consists of having a subject population which is not representative of the population we want to generalize. Our experiment is conducted on a very homogeneous group of users. So, we cannot guarantee that the results can be generalized to subjects who do not have a good background in computer science. To address this potential issue in the future, we intend to replicate the study with participants from diverse backgrounds. We have access to students attending various degrees, including medicine, law, and philosophy, among others. The analysis of results from these fields can provide different perspectives, potentially offering insights distinct from those in the current study. Another threat that appears is (2) *Problem dependency,* which means that the results are related to the problems used in the validation phase. We experience this threat because the results are related with the scenarios (problems) used in the questionnaire. To mitigate this threat, we used different scenarios for the same user characteristics (see Table 6). As future work, to mitigate this threat, we plan to use problems in other contexts such as smart homes, teaching applications, or real-time systems. The last threat that appears in our experiment is (3) *Limit of the scope of the experiment,* which means that the study has been carried out with a limited or narrow scope. We experience this threat since there are a lot of application contexts (health context, driving context, etc.) and all the contexts cannot be evaluated in this experiment. It is impossible to present a scenario for each context including all user characteristics a similar number of times. To mitigate this threat, we may repeat the experiment in the future adding more contexts.

Conclusion validity These threats aim to demonstrate that the procedure carried out to perform the experiment can be repeated with the same results and extract the same conclusions. This experiment may experience the following threats of this type: (1) *Low statistical power,* which means that the number of subjects is not enough to reveal a true pattern in the data. The goal of our validation is to analyse whether individuals with a strong background in computer science find the characteristics of our user model relevant for adapting interfaces. Other studies, like Brysbaert [65], have suggested that a sample size of 50 subjects is sufficient to draw conclusions. In our case, as there are no subjects with different profiles, a sample size of 62 is adequate to assess the participants' opinions regarding the importance of the characteristics represented in the user model. So, we mitigate the threat. Another threat is (2) *Random heterogeneity of subjects,* which means that heterogeneity always exists in an experimental group and these differences may hide factors that affect the results. To avoid this threat, we selected users with similar profiles; undergraduate students who have previously taken courses in software engineering and interface designs. Additionally, we include a demographic questionnaire to detect the differences between the subjects' profiles. Another threat is (3) *High homogeneity of subjects*, which means that most subjects share the same profile. This threat is a direct consequence of the previous threat mitigation plan. This involves that results can only be generalizable to subjects with a similar profile to the recruited participants: high knowledge of computer science and usability. The last threat consists in (4) *Reduced generalizability of results,* which implies that the conclusions can only be extended to subjects of a specific profile. Our validation faces this limitation, as the recruited subjects share a common profile. Consequently, we cannot generalize the results to subjects with profiles different from experts in computer science.

6 Results

Figure 7 shows the results of the percentage of votes received for each characteristic of the user model. Users stated that User context (74.19%) is the most significant characteristic to adapt the interface, followed by Interests (60.93%) and Knowledge (60.48%). This choice may be based on the fact that all these three characteristics have a clearer impact on the

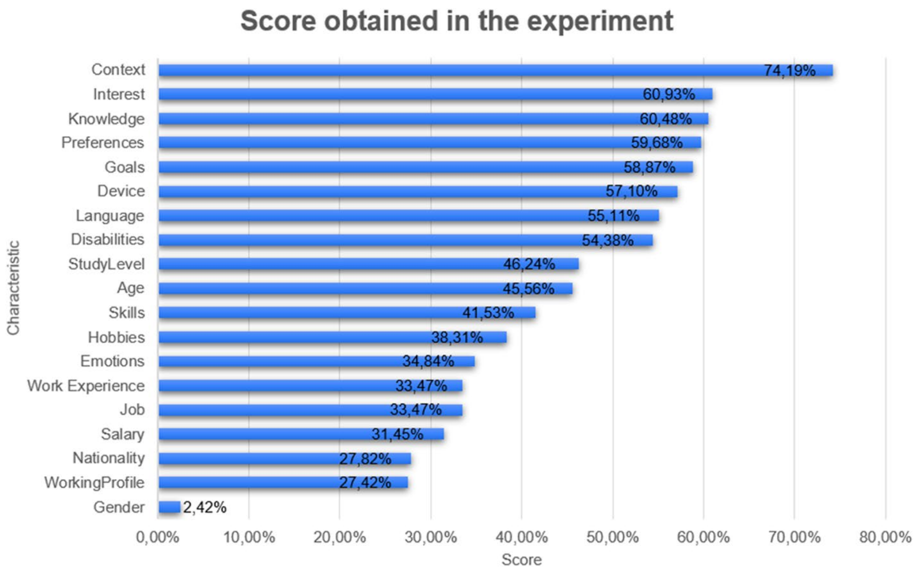

Fig. 7 Graphic of the results of validation with users

GUI. For example, context is important to know how the user must interact (using commands or voice) and knowledge is important to know whether options that require more experience must be activated. Other characteristics such as Preferences (59.68%) or Goals (58.87%) are more relevant in specific contexts, such as the intelligent car, smart homes, or e-commerce. On the other hand, subjects showed that Gender (2.42%), Working profile (27.42%), and Nationality (27.82%) are the least important characteristics. Note that subjects shared the same value for these three characteristics as they were mainly male students, with the same nationality and similar working profile (see Table 5). So, the homogeneity in these characteristics may decrease the perceived importance for the subjects.

Next, we are going to compare the results obtained in the experiment with the expected results according to previous works. This comparison is summarized in Table 7, which shows the scores obtained in the experiment for each characteristic (column "value"); the degree of importance according to the value (column "importance"); and whether the value agrees with the expectations considering previous works (column "expected?"). Then, we determine three groups of importance: low importance (when a user characteristic obtains a score between 0 and 29%), mid-level importance (when a user characteristic obtains a score between 31 and 59%), and high importance (when a user characteristic obtains a score between 61 and 100%). Some user characteristics obtained values aligned with our expectations and others did not. User characteristics such as working profile, emotions, hobbies, goals, preferences, and language received lower scores than expected. Age, gender, nationality, job, salary, work experience, knowledge, study level, skills, interest, device, context**,** and **disabilities** received scores that agree with our expectations. In conclusion, the findings from RQ1 indicate that **the user** characteristics proposed in our user model are considered relevant for adapting GUIs**.** Apart from the proposed characteristics, a pair of subjects suggested including Budget in the user model as a way to prioritize

Table 7 Comparison between obtained and expected results

User Characteristic	Value	Importance	Expected?
Gender	02.42%	Low	Yes
Age	45.56%	Mid	Yes
Nationality	27.82%	Low	No
Job	33.47%	Mid	Yes
Salary	31.45%	Mid	Yes
Work experience	33.47%	Mid	Yes
Working profile	27.42%	Low	No
Study Level	46.24%	Mid	Yes
Knowledge	60.48%	High	Yes
Skills	41.53%	Mid	Yes
Interests	60.93%	High	Yes
Hobbies	38.31%	Middle	No
Goals	58.87%	High	No
Device	57.10%	High	Yes
Emotions	34.84%	Mid	Yes
Disabilities	54.38%	High	Yes
Context	74.19%	High	Yes
Preferences	59.68%	High	No
Language	55.11%	High	Yes

elements in a purchase. All the experimental material with raw data and results is available in [66].

7 Discussion

This section discusses the results, comparing them with previous evaluations and the experimenters' expectations. In cases where our results differ from the expectations, we analyse possible justifications. Regarding the current user context, this particular characteristic has obtained a high score. Previous studies have also emphasized the importance of this characteristic for user adaptations [51, 52]. Therefore, we expected that the user context would receive the highest percentage of votes across the different scenarios, as indicated. Based on our findings, we can conclude that user context is indeed the most significant user characteristic for customising the GUI to the users.

Regarding job, work experience, work profile, and salary, these characteristics generally have a mid-level or low score, which aligns with expectations based on previous research. The only characteristic that received a lower score than expected is the work profile. Previous studies have indicated that job, work profile, salary, and work experience are considered user characteristics with a mid-low level of importance [46, 48]. However, it is worth noting that these previous works did not evaluate these characteristics with real users. Note that even in scenarios strongly related to jobs (such as scenario 9 in our validation, Appendix A), where the user aims to change jobs, these characteristics were not considered as the most relevant ones when designing IUIs. So, we can conclude that the user's job, work experience, work profile and salary are not highly significant factors to define the user profile.

Regarding skills and device**,** these have mid-level and high scores, respectively. While these characteristics have not been extracted from previous works, we believe they are important to detect device features and potential user mistakes based on their skills. Both the device and skills can influence the response time that a user can tolerate during an interaction. These expectations are supported by the results of the experiment. Skills received a mid-level value, possibly because all the subjects possessed a high skill level with technology, which may have led to the characteristic being considered less relevant. On the other hand, the device received a high value, indicating that the type of device was considered crucial for the design of IUIs. These results demonstrate a relationship between skills and the device in various contexts. For example, a user may make more mistakes if a device has a smaller touch screen or inadequate voice recognition, and the significance of these mistakes may vary, depending on the user's skills.

Regarding hobbies**,** this characteristic received a mid-level score. To the best of the authors' knowledge, there have been no previous evaluations involving real users that would allow for a direct comparison with our results. However, we consider hobbies to be an important user characteristic because they can provide insights into the type of responses a user may expect. For example, if a user enjoys country music, the system can prioritize, displaying songs of that genre in the initial lines of a list. Despite these expectations, our validation results did not fully support this hypothesis, as hobbies were classified as moderately important. In our experiment, scenarios 7, 8, 10, and 14 (Appendix A) specifically evaluated users' hobbies. The highest value was observed in the leisure context (scenario 14), where 55% of the users considered this characteristic important when determining the user profile in a leisure context. Thus, we can conclude that the importance of users' hobbies varies depending on the context.

Regarding goals and preferences, these received a high score in the experiment. Previous works have highlighted that users always have a goal, even if it is implicit [63]. Other previous works have emphasized the importance of user preferences to customize the resources offered to the users [53, 54]. Based on the previous works, we expected a high score in both characteristics. However, while we received high scores, our expectations were not satisfied since we expected a higher score (we expected over 70% for preferences and 65% for goals). In our experiment, the user's goals and preferences were evaluated in scenarios 2, 4, 5, 7 and 13 (online shopping, autonomous home, autonomous car, autonomous home and working context). In all of these scenarios, these user characteristics obtained the highest scores with 73%, 54%, 71%, 71% and 70%, respectively. From our findings, we have learnt, on the one hand, that user goals are particularly important in determining the user profile in the contexts of online shopping and working. For example, if a user's goal is to update their computer, the shopping system's recommendations will prioritize displaying computer sales. On the other hand, we have also learnt that user preferences play a significant role in determining the user profile in the contexts of autonomous car and autonomous homes. For example, in an autonomous home system, if a user spends a considerable amount of time in a specific room and he/she expresses a preference for it, the system will always display the configuration of that room.

Regarding user knowledge, this characteristic has received a high score in the experiment. Previous works have emphasized the importance of user knowledge as a key characteristic to consider in adaptive interfaces. The level of knowledge allows the system to configure the widgets and provide the most appropriate customisation for the user's profile [37]. Other works have also stated that user knowledge leads the user to consider the system more usable [67]. Thus, we expected that knowledge would yield a high value, which agrees with the actual results of our validation. In our experiment, we evaluated this characteristic in scenarios 1, 12, 13 and 14 (recommender systems, YouTube search context, academic search context and leisure context). It was found that knowledge scored the highest in the educational search context and the recommender systems. Based on these findings, we conclude that user knowledge is a fundamental characteristic to determine the user profile. For example, in an online library context, a high school user will look for low technical information to conduct an educational task while a PhD user will look for innovative, precise, and technical information to conduct the investigation.

Regarding user current emotional state, this characteristic received a mid-level score. Previous works have highlighted the importance of considering the user's current emotional state when designing IUIs [55]. However, we did not find previous works that specifically evaluate these statements with real users. We initially expected that this characteristic would receive a high score, but our validation yielded a mid-level score. This slight deviation may be due to the different contexts in which the question was asked. In a music context, for instance, 91% of the participants regarded emotional status as highly significant. Conversely, when we asked users whether they considered emotional status as an important user characteristic in the music context, only 52% expressed its importance in terms of customizing the graphical user interface (GUI). These results indicate that we have not effectively demonstrated the significance of the user's current emotional state in Scenario 8, which involved a music application context. It suggests that the importance of emotional state may vary depending on the context of use.

Regarding user gender, this characteristic received a low score in the experiment. Previous literature considers that user gender does not hold significant importance in determining the user profile, and other demographic characteristics such as age and nationality may be more relevant to classify users rather than gender [44]. Therefore, we expected a low score for gender, which agrees with the results of our validation. In our experiment, the user's gender was evaluated in scenarios 4, 5, 8, 11 (autonomous home, autonomous car contexts, music context and augmented reality context). In each context, the user's gender received the lowest score, with no votes recorded in the autonomous home and autonomous car contexts (scenarios 4 and 5). Consequently, we can conclude that the user's gender is not considered an important user characteristic to define the user profile in any of the examined contexts.

Regarding user nationality, this received a low score in the experiment. Previous works state that both characteristics are important to customize the GUI, as behaviours can vary from across different nationalities (i.e. the willingness to pay for a subscription) [41]. Therefore, we expected a mid-level value for this characteristic, which contradicts our findings. In this experiment, the user's nationality was evaluated in scenarios 2, 3, 5, 7 (shopping context, payment context, autonomous car contexts and autonomous home context). In each context, except for the autonomous home context (scenario 7), the user's nationality received the lowest score. However, in the autonomous home context, it garnered 65% of the votes. Consequently, we can conclude that the user's nationality may be significant in scenarios where the user needs to interact with an intelligent device such as Alexa but is less important in other contexts.

Regarding age and study level, both characteristics received a mid-level score in the experiment. Previous research highlights their relevance in designing IUIs. However, in experiments involving real users, these characteristics yielded a mid-level user acceptance [33, 38, 44]. Therefore, we expected a moderate score for both characteristics, which agrees with our results. In this experiment, the highest score for the user's age is in scenario 6, where it yields a mid-level value of 52%. This highest score for study level is 83% in scenario 9. This mean that, in general, the user's age and study level are important, but not crucial to determine the user profile.

Regarding interests and language, these received a high score in the experiment. Previous studies emphasize the importance of user interest as a crucial user characteristic to adapt GUIs, as it allows highlighting previously accessed information in subsequent searches[56]. Moreover, previous works state that users feel more comfortable and perceive higher usability in systems that use their native language [42, 43]. Therefore, we expected these characteristics to receive a high score in the experiment, which aligns with the results of the study. In this experiment, the user's interest characteristic received the highest number of votes in the shopping, home automation, music, and leisure contexts (scenarios 2, 7, 8, 12 and 14). Regarding the user's language, this has yielded a high score in the health and autonomous home contexts (scenarios 6 and 7) with 65% and 70% of votes, respectively. Based on these findings, we conclude that user interests play a fundamental role in determining the user profile, particularly in the leisure context, where it received 97% of the votes. User interests are also highly significant for customizing the GUI in the shopping, home automation and music contexts. However, this characteristic is not considered important to determine the user profile in the payment (30%) (scenario 3).

Regarding disabilities, this has yielded a high score in the experiment. Previous works [59, 60] consider this characteristic as an important user characteristic when designing IUIs. Furthermore, experiments conducted with real users have shown that systems with adapted GUIs enable users with disabilities to perform tasks more efficiently and quickly compared to systems without GUI adaptation. Users also reported that disability-adapted systems are more usable and provide a better user experience

[68, 69]. Therefore, we expected a high number of votes for this characteristic, and our expectations were satisfied in this experiment. In the experiment, user disabilities were evaluated in scenarios 3, 4, 6, 10, 11, 14 and 15 (payment platform, autonomous home, health, virtual reality, augmented reality, leisure, and smart company contexts). The results indicate that this characteristic received the highest number of votes in the context of health, virtual reality, and interaction with robots (scenarios 6, 10 and 15) with the 69% and 68% and 75% of the votes, respectively. However, disabilities received fewer votes than expected in the leisure and payment platform contexts (scenarios 3 and 14) with 29% and 33% of the votes, respectively. We can conclude that disabilities are important in all contexts, but they are particularly relevant in health and virtual reality contexts.

Furthermore, within our validation, we observed several relationships among classes of the user model. One of these relationships is between hobbies and device. Users whose hobby is playing video games considered the device to be more important in a video game context, while users whose hobby is listening to music considered the device more important than in other contexts. The results showed that 78% of users who have as a hobby listening to music, considered the device an important factor in this context. This result highlights the importance for this kind of users that usually has access and experience on many different devices, such as mobile phones, personal computers, or MP3 players, where each device is used in a specific context. For instance, when a user listens to music while exercising, they typically use a mobile phone with headphones. Another relationship was identified between disabilities and skill level. The results showed that 79% of users with disabilities or visual problems, considered user's skills as an important user characteristic in any context that deals with disabilities. This could be possible because a person with disabilities or visual problems can make more errors than users without disabilities, and these errors decrease the user's skill level as perceived by the system. Another possible reason may be that users with disabilities need more time to interact with the system, which in turn reduces the user's perceived skills according to the system.

Finally, we have identified some potential relationship among classes of the user model that we were unable to evaluate with our validation due to the high homogeneity of the subjects. This homogeneity is because most subjects are university-level students between the ages of 18 and 25 (88% of users fell within this age range). Moreover, most subjects have a similar work profile (IT work profile), similar work experience (ranging between 0.5 and 1.5 years of experience) and similar salaries. Finally, all the subjects are highly skill, have previous knowledge of designing user interfaces (as they have done several courses on implementing graphical user interfaces), and do not have any disability other than a visual impairment (46.77% of users has visual problems which are considered as a disability in this study). However, 75% of the users state that suffering any visual problem may affect the user's experience and interface's adaptation. One of the relationships that could not be evaluated due to the homogeneity of the subjects is between Age and Salary, where typically, older individuals earn higher salaries due to their accumulated work experience. Another relationship could exist between Age and Disabilities, as older individuals may be more prone to certain disabilities, such as visual problems. Moreover, users' disabilities can be mitigated depending on the device used to interact. For example, a user with reduced mobility may use a device that interacts using voice commands. Hobbies and Interest can also be related to Skills, since contexts which the user is more interested in may lead to better skills (making fewer errors and spending less time doing actions).

8 Conclusions and future work

In this paper, we have conducted a targeted literature review to study the existing user models. As a result of this search, we have gathered all the knowledge in a single user model. This new user model includes some classes not included in previous works, but which are considered as important when designing IUIs. To validate the user characteristics abstractly represented in our user model, we conducted an experiment with 62 subjects. In this experiment, the subjects were asked, in various scenarios, to select the most important user characteristics to adapt interfaces to their preferences. The results were measured in terms of the percentage of votes received for each user characteristic. The paper analyses the characteristics represented in the user model that are most relevant from the point of view of the end user to achieve IUIs. The paper also compares the obtained results with the previous works that evaluated the importance of each characteristic.

As future work, we plan to use machine learning techniques to classify users into similar profiles in such a way that users with the same profile can share the adaptations. The collection of quality data for training machine learning techniques is an essential process in the development of these adaptations. Building prototypes that implement or support collaboration between humans and systems will allow us to obtain data from various users in our user model as they perform collaborative tasks with the system. Prototyping will provide feedback that closely resembles the reliable operation of the system. This data will be used to train the machine learning algorithms, enabling them to learn about human behaviour before the system itself goes live. To achieve this, we will employ supervised machine learning techniques, such as Support Vector Machine (SVM) or Decision Tree Learning [70]. These techniques, which require labelling of training data, enable us to build predictive models that take human information and current context into account, allowing us to determine the best interaction mechanisms required to perform the task. The proposed user model will be used to automatically capture the end-user's characteristics and preferences during the use of the system in a transparent way for the end user. Additionally, we plan to replicate the validation with a more diverse group of subjects to see how variations in the user profile may affect the relevance of the classes in the user model.

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Declarations

Conflict of interest The authors declare that they have no conflict of interests.

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