Intelligent Decision Technologies 17 (2023) 73–125
DOI 10.3233/IDT-230092
IOS Press


# Artificial Intelligence and User Experience in reciprocity: Contributions and state of the art

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**Abstract.** Among the primary aims of Artificial Intelligence (AI) is the enhancement of User Experience (UX) by providing deep understanding, profound empathy, tailored assistance, useful recommendations, and natural communication with human interactants while they are achieving their goals through computer use. To this end, AI is used in varying techniques to automate sophisticated functions in UX and thereby changing what UX is apprehended by the users. This is achieved through the development of intelligent interactive systems such as virtual assistants, recommender systems, and intelligent tutoring systems. The changes are well received, as technological achievements but create new challenges of trust, explainability and usability to humans, which in turn need to be amended by further advancements of AI in reciprocity. AI can be utilised to enhance the UX of a system while the quality of the UX can influence the effectiveness of AI. The state of the art in AI for UX is constantly evolving, with a growing focus on designing transparent, explainable, and fair AI systems that prioritise user control and autonomy, protect user data privacy and security, and promote diversity and inclusivity in the design process. Staying up to date with the latest advancements and best practices in this field is crucial. This paper conducts a critical analysis of published academic works and research studies related to AI and UX, exploring their interrelationship and the cause-effect cycle between the two. Ultimately, best practices for achieving a successful interrelationship of AI in UX are identified and listed based on established methods or techniques that have been proven to be effective in previous research reviewed.

Keywords: Artificial Intelligence, AI, user experience, UX, human-ai interaction, intelligent user interfaces, human-centered artificial intelligence, user modelling, web search, recommender systems, intelligent help systems, virtual assistants, intelligent tutoring systems, e-learning

## 1. Introduction

Artificial Intelligence (AI) has been a driving force behind significant technological advancements that leverage big data, real-time computer communication via the Internet and the Internet of Things, and the vast accumulation of user input through sources like social media, search engines, and handheld devices [1–7]. Artificial Intelligence (AI) has numerous applications across different domains including healthcare, banking and finance, retail and product recommendations, education, energy, media and entertainment and many other domains [8–12].

These developments have caused a shift in the way people interact with computers, resulting in a transformation of the user experience as it was perceived in standard Human-Computer Interaction [13,14]. One important change is that computers that use AI are qualified to make decisions and produce feedback based on incomplete information. This is a form of reasoning that deals with uncertain or ambiguous information, where the conclusions or decisions reached may not be completely accurate or certain. AI-based reasoning encompasses various techniques like machine learning [15–19], deep learning [20,21], fuzzy logic [22], cognitive reasoning [23] and others.

One of the advantages of AI-based reasoning is that it can be used to handle complex situations where precise information is not available or is difficult to obtain. However, one of the disadvantages is that the conclusions or decisions reached using AI rely on incomplete or uncertain information, which can lead to unreliable conclusions or decisions. Additionally, AI-based applications may not always provide predictable output, which differs from traditional computing methods. AI-based reasoning has been in development for some time and is not entirely novel. The employment of AI for the enhancement of the User Experience (UX) of interactive software has been a long-standing goal of computer scientists for many decades prior to the latest advancements.

User Experience (UX) refers to the overall experience that a user has when interacting with a product, system, or service [24–26]. This includes everything from how easy it is to navigate a website to the emotions a user feels when using a particular application. UX designers work to create products that are easy to use and enjoyable for users, considering user behaviour, preferences, and needs. In view of the above, UX design is an important aspect of product design that involves understanding user needs and preferences and creating products that are easy to use, enjoyable, and engaging.

Artificial Intelligence has made significant contributions to User Experience design, resulting in progress in the development of intelligent interactive systems. These systems, such as virtual assistants, recommender systems, intelligent help systems, and intelligent tutoring systems, have the potential to enhance user experience by providing natural language processing, personalised recommendations, real-time assistance, and adaptive interfaces. Additionally, AI allows designers to automate repetitive tasks, enabling them to concentrate on more intricate design challenges. However, AI changes the UX of software applications in a way that it achieves enhancements but poses new challenges due to its intelligent features which may not always be well received and understood by humans.

The relationship between Artificial Intelligence and User Experience can be viewed as a cause-effect reciprocity, where AI can impact the UX of a system, and the quality of the UX can also affect the effectiveness and acceptability of AI. In other words, AI can be used to enhance the UX of a system, but the quality and nature of the resulting AI-based UX can also affect the accuracy, trustworthiness, usability and efficiency of the AI. In many cases, usability as it was perceived in standard Human-Computer Interaction [27–29] is violated by AI-based systems. The interdependence of AI and UX highlights the importance of designing AI systems with a focus on UX, and vice versa, to ensure that these systems are effective, efficient, and user-friendly. In many cases, the limitations, and challenges of AI-based UX design are addressed by new implementations of more sophisticated AI reasoning, resulting in a development cycle.

The state of the art in AI in User Experience is constantly evolving, with new research and advancement efforts aimed at improving the effectiveness and usability of AI systems. There is a growing emphasis on designing AI systems that are transparent, explainable, and fair, to address concerns about bias, discrimination, and lack of trust in these systems. Natural Language Processing (NLP) and Machine Learning (ML) techniques are being used to create more human-like interactions with AI systems. A new target is to improve the accuracy and relevance of recommendations and predictions. In addition, there is a growing focus on designing AI systems that prioritise user control and autonomy, protecting user data privacy and security, and promoting diversity and inclusivity in the design process. As AI continues to evolve and impact User Experience design, it is important to stay up to date with the latest advancements and best practices in this field while knowing important research of the past. Indeed, Norman and Nielsen cautioned computer scientists, developers, and industries that the developer community's ignorance of the extensive history and findings of HCI research leads them to feel empowered to release untested and unproven creative efforts on the unsuspecting public [30].

In this context, the paper critically analyses published academic works and research studies related to AI and UX to examine their reciprocity and cause-effect cycle by presenting a review of the author's past research along with other researchers' work in the field to identify significant findings, methodologies, and theories. Moreover, the study highlights gaps in knowledge and areas for future research, which are discussed in detail. By reviewing AI in UX, this study offers insights into the current state of knowledge, identifies best practices, and leads to the development of new research questions and hypotheses. The author emphasises the importance of past successful research and highlights the need for AI stakeholders to be aware of the extensive history and findings of HCI research to prevent the release of untested and unproven creative efforts on the public.

The remainder of this paper is organised as follows. Section 2 describes the cycle of contributions and limitations of Artificial Intelligence in User Experience and vice versa. In the subsequent Sections 3 and 4, descriptions of AI in UX are presented and discussed in the light of contributions in the sub-fields of interactive systems of web search, recommender systems, intelligent help systems and virtual assistants and intelligent tutoring systems. In particular, Section 3 outlines the utilisation of Artificial Intelligence reasoning to enhance User Experience and Section 4 presents and examines the impact of AI-based reasoning on User Experience. Section 5 of the article identifies the challenges and difficulties associated with integrating AI into UX and suggests possible solutions for expanding the use of AI in this field, drawing upon relevant research literature. Section 6 draws on the author's extensive previous research in the field of UX in AI to identify best practices that have resulted in the development of effective and personalised AI-based interactive systems. Lastly, Section 7 describes and discusses the conclusions and potential areas for further research.

## 2. The cycle of Artificial Intelligence and User Experience

The objective of UX is to generate favorable user experiences, which may involve designing software products that are user-friendly, visually attractive, and easy to navigate. A positive user experience can enhance user engagement and facilitate the achievement of users' objectives. UX designers often use various tools such as wireframing, prototyping, and user testing. Wireframes are basic visual representations that aid designers in creating product layouts, whereas prototyping involves developing a preliminary version of the product to experiment with different functionalities and user interactions. User testing involves monitoring users as they interact with the product, gathering feedback, and making improvements based on that feedback. With the increasing complexity and reliance on Internet connectivity of software applications, new technologies and methods have been introduced to improve the user experience. This is evident in cases where software operations necessitate Internet connections, such as e-commerce platforms, e-learning tools, e-health applications, email services, social media platforms, and web search engines, as well as in instances where they serve as supplementary features of standalone systems like customised information systems. In modern systems, Artificial Intelligence, Machine Learning, and Deep Learning are utilised at both the local and Internet levels to provide users with personalised and integrated interactions. These advanced technologies are employed in the development of sophisticated interactive software applications in the context of AI-enhanced software engineering [31–36] as demonstrated in Fig. 1.

As a result, modern User Experience design must consider all levels of reasoning within an information system itself as well as the Internet, which holds vast masses of data, to provide a seamless and personalised experience for the end-user. While the resulting AI-based UX aims to reduce the cognitive burden on users, the UX design process becomes considerably more complex for UX engineers. In addition, the functioning of Artificial Intelligence in the system can cause new User Experience challenges, as users may not be accustomed to its operation. Therefore, to further improve the User Experience, more Artificial Intelligence reasoning may be employed in response to these challenges.

The interaction between Artificial Intelligence and User Experience can be seen as a two-way relationship, where each can affect the other. AI can be used to enhance the UX of a system and the quality of the UX can impact the effectiveness of AI. This mutual influence emphasises the need for AI systems to prioritise UX design and for UX designers to consider the impact of AI on the user experience. By doing

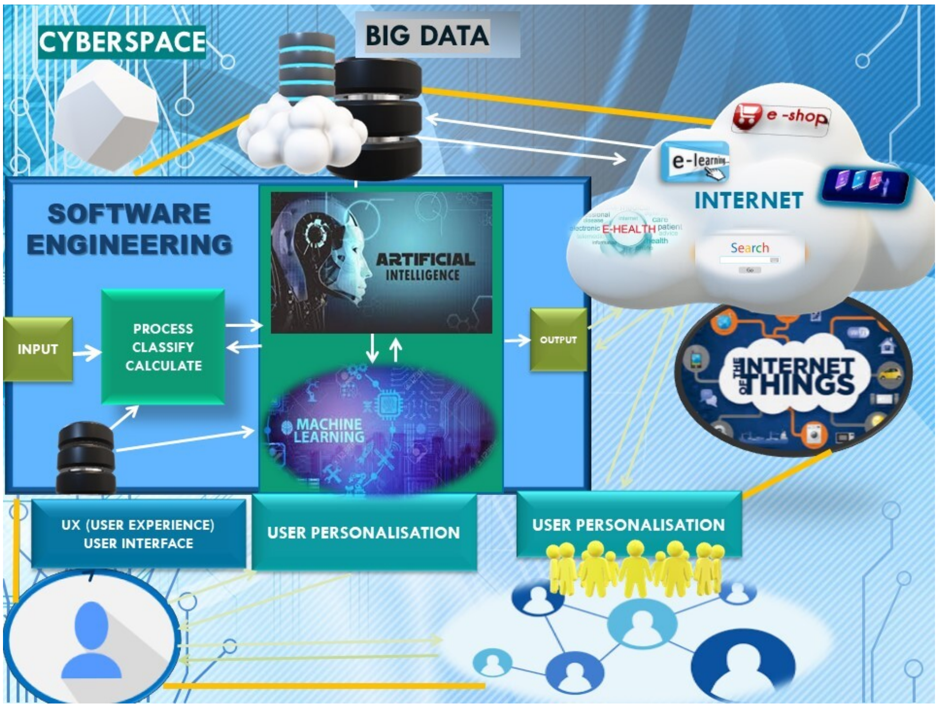


Fig. 1. Artificial Intelligence in interactive software applications.

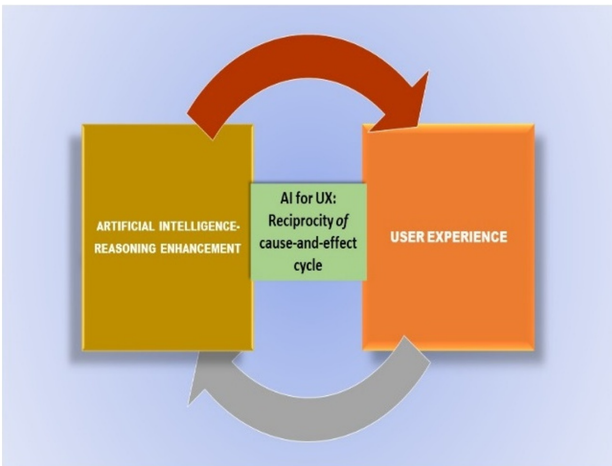


Fig. 2. AI in UX: Reciprocity of cause-and-effect.

so, the resulting systems will be more efficient and user friendly and will be created in a cause-effect cycle in reciprocity, as illustrated in Fig. 2.

In view of the above, a new field has emerged, that of Human-AI interaction [37,38] based on the evolution of knowledge-based Human-Computer Interaction [39,40]. This new field refers to the ways in which humans and artificial intelligence (AI) systems interact and communicate with each other. As AI becomes more prevalent in our daily lives, it is increasingly important to design interfaces and interactions that enable seamless and effective communication between humans and AI. The effects in UX of AI constitute impressive advancements but they also suffer from problems which need to be addressed.

For example, Artificial intelligence (AI) technology has been increasingly used in the implementation of advanced Clinical Decision Support Systems (CDSS) with major potential usefulness of AI-empowered CDSS (AI-CDSS) in clinical decision-making scenaria but post-adoption user perception and experience remain understudied [41]. As another example, when it comes to fully autonomous driving, passengers relinquish control of the steering to a highly automated system. However, the behaviour of autonomous driving may cause confusion and result in a negative user experience. As a consequence, the acceptance and comprehension of the users are critical factors that determine the success or failure of this new technology [42]. Furthermore, there has been a notable improvement in the quality of artificial intelligence applications for natural language generated systems. According to a recent study, participants found the process enjoyable and useful, and were able to imagine potential uses for future systems. However, although machine suggestions were given, they did not necessarily result in better written outputs. As a result, the researchers propose innovative natural language models and design options that could enhance support for creative writing [43]. This leads to the initiation of new AI employment cycles, which address the existing problems of user experience with AI.

## 3. Artificial Intelligence and user modelling in service of User Experience

AI technology can assist User Experience design in several ways. AI for UX (User Experience) refers to the use of artificial intelligence (AI) technologies to improve the user experience of digital products and services. By incorporating AI into UX design, designers can create products that are more engaging, effective, and accessible for users.

AI can be used to personalise the user experience by analysing user data and predicting user behaviour and preferences, allowing the product to adapt to the needs of each individual user. Moreover, AI can assist in gathering user research data, such as sentiment analysis or feedback analysis, to comprehend user needs and improve UX design. For instance, websites and apps can use AI to recommend content, products, or services based on the user's past behaviour or search history.

*User modelling* is used for personalisation while programs are being executed. User modelling is the process of creating representations or profiles of users based on their behaviour, preferences, goals, and other relevant characteristics. These user models are used in various applications, including personalised recommendations, adaptive interfaces, and intelligent tutoring systems, to tailor the user experience to the needs and interests of individual users. For example, in [44] user modeling is performed by detecting music similarity perception based on objective feature subset selection for music recommendation, in [45] two kinds of user model, student and instructor models and their interaction are created in an authoring tool for intelligent tutoring systems, while techniques for the prediction of data interaction in user modelling are presented and discussed in [46]. User modelling involves collecting and analysing data about users through various sources, including user feedback, user actions, and user profiles. Machine learning algorithms, cognitive reasoning, fuzzy sets or other statistical techniques are then used to identify patterns and gain insights in the data, which are used to create user models.

Individual users possess unique characteristics such as interests, preferences, educational background, expertise, personality traits, and emotions, which can be communicated to interactive applications via various input and output channels like keyboard, camera, microphone, mouse, and mobile or handheld devices. The processing of user inputs requires the use of artificial intelligence techniques. In this regard, user modelling can be utilised to create representations of individual user beliefs, which take into account their inputs from specific standalone applications, as well as inputs from other web-based applications through the internet. These inputs contribute to the formulation and accumulation of hypotheses about individual users and communities of users across one or more applications. These hypotheses can then be leveraged to personalise and enhance the user experience as illustrated in Fig. 3.

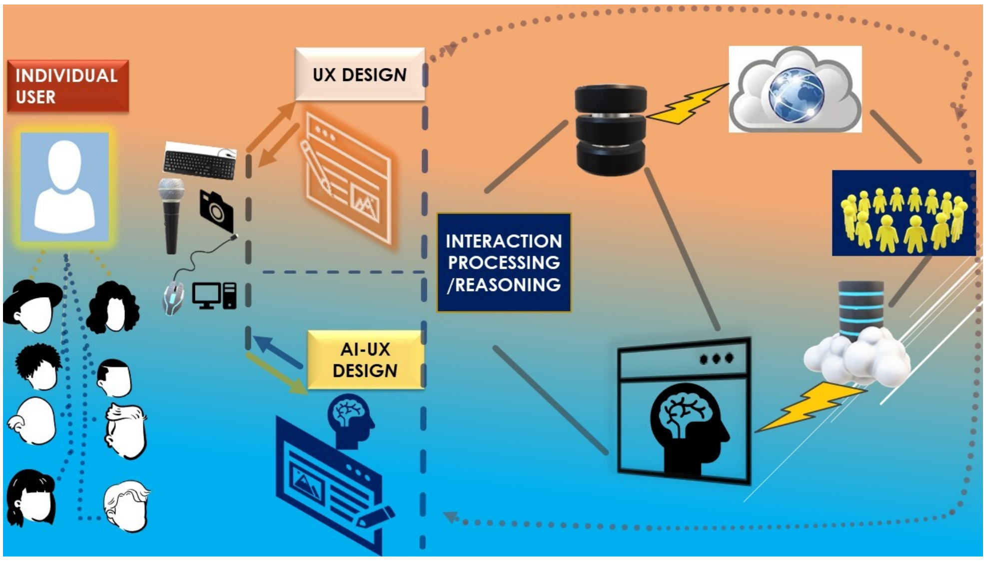


Fig. 3. AI-based reasoning and personalisation in UX.

The user models convey processed information and inferences about users, depending on the specific needs of the application. For example, a user model for a recommender system may include information on the user's past behaviour, product ratings, and preferences. In contrast, a user model for an intelligent tutoring system may include information on the user's knowledge level, learning style, and performance.

User models can be categorised along four dimensions, namely degree of *specialisation*, *modifiability*, *acquisition* and *temporal extent* [47]. The degree of specialisation refers to whether the user model concerns individual users or a community of users. Modifiability refers to whether the user model is static and does not change once determined or dynamic, in which case it may change after its initial determination. Acquisition refers to whether the user model is identified implicitly by the users' actions or whether it is constructed based on explicit information that the users give about themselves. Temporal extent refers to whether the user model is based on short-term information concerning one interaction session, in which case it is a short-term user model or whether it is based on long-term information that has been collected about users along many sessions, in which case it is a long-term user model.

*Individual user models* are created through the collection and analysis of data specific to a particular user, such as their search history, purchase behaviour, or interactions with a particular system or service. Then the collected individual data is processed so that the system may draw inferences concerning the individual user's needs. For example, individual user modelling has been employed for learn-and-play personalised reasoning from point-and-click to virtual reality mobile educational games to provide individualised tutoring and game recommendation according to the student-players' preferences in the context of edutainment [48].

*User models based on communities of users* refer to the creation of user models based on shared characteristics or behaviours among groups of users. Instead of focusing on individual users, user models based on communities of users aim to identify patterns and trends among groups of users who share common interests, preferences, or behaviours. These user models are created through the analysis of data from social media platforms, online forums, and other online communities. User models based on communities of users have a wide range of applications. For example, they have been used for dynamically extracting and exploiting information about customers in interactive TV-commerce [49] or for customer data clustering in an e-shopping application for assisting on-line customers in buying products [50].

*Short-term and long-term user modelling* are two complementary approaches to user modelling that focus on the temporal extent of capturing and analysing data related to user behaviour and preferences.

Short-term user models focus on current users' sessions by pursuing to capture and analyse data related to a user's immediate interactions with a digital system or service. This includes data such as the user's current context, current goals, current plans, current behaviour, and current preferences within the limits of an interaction session. Short-term user models are often used in real-time personalisation, such as in e-commerce websites that provide personalised recommendations based on a user's current session or in adaptive interfaces that adjust to the user's current task. The main advantage of short-term user models is that they can provide immediate and relevant recommendations or personalised experiences to the user.

On the other hand, long-term user models are based on historical data and user behaviour over an extended period of time. Long-term user models capture data such as the user's preferences, interests, demographics, and past interactions with a digital system or service. These models can be used to provide more personalised and effective user experiences over time, such as personalised content recommendations or customised interface layouts. The main advantage of long-term user models is that they can capture the user's preferences and behaviour over time, allowing for more accurate and personalised recommendations and experiences. However, they may require more data and computational resources to generate insights, and they may not be as effective in real-time scenarios as short-term user models.

*Cognitive-based user modelling* is a type of user modelling that focuses on understanding how users think, reason, and process information to create more effective and personalised user experiences. This approach to user modelling is based on the idea that a user's cognitive processes, such as attention, memory, and decision-making, are critical factors that influence their interactions with digital systems and services. These data sources provide insights into how users perceive, process, and interact with digital content and interfaces, which can then be used to create more personalised and effective user experiences. For example, cognitive theories have been used to model cognitive aspects, personality and performance issues of users in a Collaborative Learning Environment [51] or for creating cognitive-based adaptive scenarios in educational games [52].

*Machine learning algorithms* are used to identify patterns in user behaviour, such as the types of content they engage with or the topics they discuss. For example, they have been used to provide online recommendations or to create targeted advertising campaigns that appeal to specific groups of users or for crowdsourcing recognised image objects in mobile devices [53].

*Data mining techniques* are used to extract valuable insights and patterns from large sets of user data collected through various methods such as surveys, user testing, analytics, and other techniques. The goal of data mining in UX is to help designers and developers make informed decisions about product design, features, and usability. These can be applied to many domains. For example, data mining is used to extract useful information out of large data in e-government to help civil servants perform their work tasks [54].

*Fuzzy logic* is a mathematical framework for dealing with uncertainty and imprecision. Fuzzy logic is based on the idea of fuzzy sets, which are sets with boundaries that are not clearly defined. In UX it may be used for several applications. For example, the set of "forgetful users" is a fuzzy set because there is no clear boundary between forgetful user and not forgetful user in an intelligent assistive system for users with dementia problems [55]. In another example, fuzzy logic decisions have been used in conjunction with web services for a personalised Geographical Information System (GIS), that provides individualised recommendations on route selections depending on the users' geographical place, interests and preferences [56].

*The actual design process* of UX is also an important use of AI so that the UX becomes more appealing to the user. UX designers can anticipate situations that will occur frequently, impact a large number of users, and require a user to execute the same sequential set of actions to complete a task [57]. The availability of user data on the Internet can be exploited by AI, which can provide predictive analytics to predict user behaviour or outcomes, helping designers make informed decisions about UX design.

*Natural Language Processing* (NLP) can also be used to improve the conversational experience between users and AI-empowered products, such as chatbots and virtual assistants. NLP is a branch of AI that enables machines to understand and interpret human language to create a more natural and intuitive interaction. For example, [58] describes a mapping mechanism of natural language sentences onto an SPN state machine for understanding purposes. In another example, [59] describes a procedure of modelling natural language sentences into SPN Graphs, while [60] describes a Natural Language Understanding -based method for a first level automatic categorisation of AI-based security documents.

*Sentiment analysis* is a subfield of natural language processing (NLP) that involves analysing text to determine the sentiment or emotional tone of the language used. This can involve identifying positive or negative language, as well as more specific emotions such as anger, fear, or joy. Sentiment analysis is a method that has been used for revealing insight into unstructured content by automatically analysing people's opinions, emotions, and attitudes towards a specific event, individual, or topic based on user-generated data, as described in a review of sentiment analysis based on sequential transfer learning [61]. For example, sentiment analysis has been employed in a computational model for mining consumer perceptions in social media [62].

*Image, Sound, Voice and Video Analysis Technology* is also a kind of AI technology that is used to recognise and classify images, sounds and videos for improving UX. It can make interfaces more visually appealing and engaging and can be useful for applications such as product recommendations and visual search. For example, image analysis has been used in a concept-based image acquisition system which embodies the ability to extract a certain subset of images that are representatives of a user defined query concept [63]. As another example, markerless based human motion capture describes the activity of analysing and expressing human motion using image processing and computer vision techniques and aims at revealing information about the affective state, cognitive activity, personality, intention and psychological state of a person [64]. In another example, digital image libraries are organised according to a user-defined concept which is extracted from a set of images that the user submits to the system as its representative instances [65]. AI can also help improve accessibility for users with disabilities by providing alternative ways of interacting with digital products or services through natural language processing, image recognition, voice synthesising. For example, a voice assistant could offer audio feedback to visually impaired users [66], or in another example an intelligent mobile multimedia application supports the elderly users [67].

*Affective computing* is also another important area where AI has been used to improve UX. Affective computing consists of two sub-areas, emotion recognition and emotion generation.

*Emotion recognition* is the process of using artificial intelligence (AI) algorithms to identify and interpret human emotions based on their facial expressions, speech patterns, physiological signals and context. Emotion recognition by computers can be achieved through different methods. For example, facial expression recognition involves using computer vision algorithms to analyse the facial features of a person and identify emotional expressions, such as happiness, sadness, anger, and surprise [68]. Such analysis can be extended for emotion recognition of groups, such as a whole class of students [69]. Similarly, speech analysis can be used to identify emotions based on the tone, pitch, and other features of a person's voice [70]. Multi-modal affect recognition can combine many sources of evidence from multiple modalities, such as the keyboard, the microphone, the camera and other sources [71–73]. Emotion generation is the process of using artificial intelligence (AI) algorithms to create computer feedback that conveys empathy to the users. Affective computing has a wide range of potential applications, such as enhancing human-computer interaction, and providing more personalised experiences in fields like marketing, entertainment and e-learning [74].

All of the above, constitute different aspects and approaches for the improvement of UX through the use of AI and Machine Learning. The following subsections describe how AI technology is used for the benefit of User Experience in some important interactive application domains, such as Web searching, Recommender Systems, Intelligent help systems and virtual assistants and Intelligent Tutoring Systems.

### 3.1. AI techniques for the UX of web searching

AI can be used to enhance the user experience (UX) of web searching by improving the relevance and personalisation of search results. By analysing user behaviour and preferences, search engines can better understand what types of content and information the user is looking for and provide more accurate and useful results.

There are various kinds of AI techniques used in web searching. Many of them are used for personalisation involving user modelling. Personalisation techniques are used to customise search results based on the user's location, search history, and preferences. This approach involves analysing user data to create a personalised search experience. This includes data such as the user's search queries, click-through rates, time spent on search results pages, and search histories. AI can also be used to personalise search results based on factors such as location. For example, a search for "restaurants" in Athens, Greece may yield different results than a search for the same term in the Greek town of Chicago, U.S.A, as the AI can take into account the user's location and provide results based on local restaurants. User modelling in web searching refers to the process of recording and analysing user behaviour and preferences when searching for information on the web. There are several techniques used in user modelling for web searching.

Some common types of AI used in web search engines are the following:

- *Content-based retrieval* is a technique used in web search to retrieve information based on the similarity of content. It involves analysing the content of a web page, such as the text, images, videos, and audio, to determine its relevance to a user's query and provide relevant search results. For example, content-based retrieval has been used in an intelligent mobile application to retrieve music pieces from digital music libraries [75]. Another example involves using agents for feature extraction in the context of content-based image retrieval for medical applications [76].
- *Collaborative filtering* uses data from other users with similar search behaviour to recommend search results. For example, a model that represents a user's needs and its search context is based on content and collaborative personalisation, implicit and explicit feedback, and contextual search [77].
- *Hybrid filtering in web* search is a method of combining two or more different types of filtering techniques to improve the accuracy and relevance of search results. This approach can be used to address some of the limitations of individual filtering techniques and provide a more comprehensive search experience. For example, a hybrid filtering mechanism is proposed to eliminate irrelevant or less relevant results for personalised mobile search, which combines content-based filtering and collaborative filtering; the former filters the results according to the mobile user's feature model generated from the user's query history, and the latter filters the results using the user's social network, which is constructed from the user's communication history [78].
- *Machine Learning*: Machine learning allows search engines to learn from user behaviour, such as clicks and dwell time and adapt search results based on individual preferences. For example, if a user consistently clicks on results from certain websites, the search engine may prioritise those results in future searches. Machine Learning is used to improve the accuracy of search results. This technique is also used to identify patterns and relationships in large datasets. An example of this kind of approach is the use of machine learning algorithms based on experts' knowledge to classify web pages into three predefined classes according to the degree of content adjustment to the search engine optimisation (SEO) recommendations [79].
- *Deep Learning*: Deep learning is a subfield of machine learning that involves training artificial neural networks to learn from large datasets. The goal of deep learning is to enable computers to learn and recognise patterns, classify information, and make decisions in a way that is similar to how the human brain operates. Deep learning is used in web searching to improve the accuracy of image and voice-based search. Neural networks in web search are used in web search engines, ranking algorithms

citation analysis [80]. For example, in [81] a deep learning model of Convolutional Neural Network (CNN) is used in big web search log data mining to learn the semantic representation of a document to improve the efficiency and effectiveness of information retrieval.

- *Natural Language Processing* (NLP): NLP is used in web searching to understand the user's queries in natural language and match them with relevant web pages. NLP techniques include text segmentation, entity recognition, and sentiment analysis. For example, [82] presents a method for translating web search queries into natural language questions. The authors propose a system that uses natural language processing (NLP) techniques to transform a web search query into a question that can be answered using a knowledge base.
- *Semantic Search*: Semantic search uses machine learning and NLP techniques to understand the meaning behind user queries and deliver more accurate search results. This approach involves analysing the relationship between words and phrases and identifying entities in the text. Semantic search and semantic web are two related concepts in the field of information retrieval and web technologies. Instead of relying solely on keywords, semantic search algorithms attempt to understand the meaning of the query and the content being searched, and to provide more relevant results based on that understanding. Semantic search can be seen as an application of the principles of the semantic web to the problem of search. By using semantic technologies such as ontologies, taxonomies, and natural language processing, semantic search can provide more intelligent and accurate search results that better match the user's intent. Semantic web technology and semantic search are emerging areas of research that have the potential to transform the way we interact with information on the internet. According to [83], semantic web technology enables the creation of machine-readable data that can be easily interpreted by computers, leading to more intelligent and effective search results. In [84] the authors further explain how query technologies can be developed to enable semantic search in the context of the semantic sensor web, where sensors generate large amounts of data that require sophisticated search and analysis tools. Finally, in [85], the authors provide a diachronic study of publications comparing the terms "semantic web" and "web of data" over time and identifying the evolution of these concepts. Together, these works highlight the potential of semantic web technology and semantic search to improve information retrieval and analysis on the web.
- *Knowledge Graphs*: Knowledge graphs are used to organise and connect information in a way that makes it easier to find and understand. These graphs are used to identify entities, relationships, and concepts related to the user's query. For example, in [86] methods are proposed for extracting triples from Wikipedia's HTML tables using a reference knowledge graph.

### *3.2. AI techniques for the UX of recommender systems*

Recommender Systems provide information in a way that it is most appropriate and valuable to its users and prevent them from being overwhelmed by huge amounts of information that, in the absence of recommender systems, they should browse or examine [87]. Recommender systems are a type of information filtering system that aim to predict the preferences or interests of a user, and recommend items or products that the user may be interested in. They are commonly used in e-commerce, social media, online advertising, and other applications where personalised recommendations can enhance the user experience and increase engagement [88].

Artificial intelligence (AI) has been widely used to enhance the user experience (UX) of recommender systems to provide personalised recommendations to users based on their interests, preferences, and behaviour.

There are different types of AI techniques used in recommender systems, depending on the specific approach used to build the system. Some of the common types of AI techniques used in recommender systems are the following:

- *Collaborative filtering*: Collaborative filtering (CF) is a well-known recommendation method that estimates missing ratings by employing a set of similar users to the active user [89]. Collaborative filtering can be further divided into two sub-types: user-based collaborative filtering and item-based collaborative filtering.
  - *User-based collaborative filtering* is a widespread technique as many researchers consider important in the memory-based collaborative filtering recommender system (RS) to accurately calculate the similarities between users and finally finding interesting recommendations for active users [90].
  - *Item-based collaborative filtering* utilises the similarity values of items for predicting the target item [91]. The basic assumption of item-based CF is that user prefers similar items that he or she liked in the past [92].
- *Content-based filtering*: This approach recommends items to users based on the user's preferences and characteristics of the items. Content-based filtering uses attributes of the items to recommend similar items to the user. For example, in [93] the proposed content-based recommendation algorithm quantifies the suitability of a job seeker for a job position in a more flexible way, using a structured form of the job and the candidate's profile, produced from a content analysis of the unstructured form of the job description and the candidate's CV.
- *Hybrid recommender systems*: This approach combines collaborative filtering, which uses data on user behaviour to recommend content, with content-based filtering, which uses characteristics of the content itself to make recommendations. For example, in [94], a two-level cascade scheme is presented where a hybrid of one-class classification and collaborative filtering is used to decompose the recommendation problem, with the first level selecting desirable items for each user using a one-class classification scheme trained only with positive examples, and the second level applying collaborative filtering to assign rating degrees to the selected items.
- *Machine-learning based recommender systems*: This approach employs machine learning algorithms as the main underlying reasoning mechanism. For example, in [95] an artificial immune algorithm has been used in a system for music recommendation. In [96] the recommender system uses "musical genre classification" and "personality diagnosis" as inputs to make recommendations, by employing machine learning to classify musical genres and diagnose personality traits.
- *Deep learning-based recommender systems*: This approach uses neural networks and deep learning techniques to model complex relationships between users and items to make personalised recommendations. For example, an approach of biomarker-based deep learning is used for personalised nutrition recommendations [97].
- *Fuzzy-based recommender systems*: The presence of several works focuses on managing items' attributes with fuzzy techniques, strengthening the development of uncertainty aware content-based recommender systems [98].
- *Context-aware recommendation*: This approach takes into account additional contextual information, such as the time of day, user location, or weather conditions, to make more relevant recommendations. For example, in [99] environmental and social considerations are incorporated into the portfolio optimisation process and in [100] a tourism recommendation system is context-aware and is also based on a fuzzy ontology.
- *Constraint-based recommender systems*: These systems constitute a type of recommendation system that uses a set of constraints or rules to generate personalised recommendations for users. These systems are often used in situations where there are specific requirements or constraints that must be considered in the recommendation process, such as limited availability of products or services, specific user preferences or characteristics, or other business or operational considerations. For example, in [101] a constraint-based approach has been used in a job recommender system.

- *Knowledge-based recommender systems*. These systems rely on explicit knowledge about a user's preferences, needs, and characteristics, as well as knowledge about the product or service being recommended. This knowledge is usually represented as rules or logic statements that are developed by human experts in the domain. Knowledge-based recommendation systems typically do not rely on machine learning algorithms to generate recommendations. For example, in [102] a knowledge-based TV-shopping application is described that provides recommendations based on users' current input and historical profile from past interactions.
- *NLP, voice synthesisers, and animations in recommender systems*. These approaches can enhance the user experience and improve the effectiveness of the recommendations by providing more personalised, natural, and engaging interactions. For example, in [103] the incorporation of animated lifelike agents into adaptive recommender systems has been used to help users buy products in an e-shop in a more effective way.
- *Matrix factorisation*: This is a type of collaborative filtering that uses matrix factorisation to extract latent factors that explain the user-item interaction. The technique involves decomposing a matrix of user-item interactions into lower-dimensional matrices, and then using those matrices to predict missing entries and recommend new items. For example, in [104], the authors propose a lightweight matrix factorisation algorithm that reduces the number of parameters required for training, while maintaining the accuracy of the recommendations.
- *Association rule mining*: This technique involves finding patterns in large datasets to make recommendations. Association rule mining helps to find out the association between different attributes of the system. For example, if users of an e-bookshop who buy a book A also tend to buy a book B, then the system might recommend book B to users who have purchased book A by saying something like Users who bought the book A were also interested in buying book B. An example of an approach uses association rule mining to uncover hidden associations among metadata values and to represent them in the form of association rules. These rules are then used to present users with real-time recommendations when authoring metadata [105].
- *Reinforcement learning*: Reinforcement learning (RL) is a machine learning approach that learns by interacting with an environment to achieve a specific goal. The authors in [106] point out that unlike traditional recommendation methods, including collaborative filtering and content-based filtering, RL is able to handle the sequential, dynamic user-system interaction and to take into account the long-term user engagement and that although the idea of using RL for recommendation is not new, it used to have scalability problems in the past.
- *Graph-based recommendation*: This approach uses graph algorithms to model relationships between users, items, and other entities in the system. The graph structure can be used to generate personalised recommendations and to identify communities of users with similar preferences. For example, [107] presents a comprehensive framework for smoothing embeddings in sequential recommendation models. The approach involves constructing a hybrid item graph that combines sequential item relations based on user-item interactions with semantic item relations based on item attributes.

### *3.3. AI techniques for the UX of intelligent help systems and virtual assistants*

AI has played a significant role in enhancing the user experience of intelligent help systems and virtual assistants. Recently a lot of virtual assistants or intelligent personal assistants have been developed by leading software companies to enhance the user experience in many ways. The term "virtual assistant" is often used similarly with "intelligent personal assistant" to refer to AI programs designed to assist users. However, "virtual assistant" is a more general term that can refer to any type of AI assistant, while "intelligent personal assistant" specifically refers to AI assistants that are designed to interact with users in a personalised way, often through voice commands or natural language processing.

Natural Language capabilities in virtual assistants have progressed enormously during the past decade. However, the notion of having assistants with capabilities to communicate in natural language started many decades ago with the program named "ELIZA" which performed natural language processing (NLP) and was developed in the mid-1960s by Joseph Weizenbaum at MIT [108]. ELIZA was one of the first attempts to create a chatbot or conversational agent using pattern recognition and simple language processing techniques. ELIZA works by identifying keywords and phrases in the user's input and then generating a response based on a set of pre-programmed rules or scripts. The program is designed to mimic the behaviour of a psychotherapist, and as such, it often responds to questions with open-ended questions of its own, encouraging the user to continue talking and exploring their thoughts and feelings. While ELIZA's approach to natural language processing is now considered limited, it remains an important landmark in the history of AI and NLP and has influenced subsequent research in these fields.

The latest Intelligent Personal Assistants (IPA), such as Amazon Alexa [109], Microsoft Cortana [110], Google Assistant [111], or Apple Siri [112], allow people to search for various subjects, schedule a meeting, or to make a call from their car or house hands-free, no longer needing to hold any mobile devices [113] and they communicate in natural language with users. There is also ChatGPT, a large language model trained by OpenAI designed to answer a wide range of questions and engage in natural language conversations with users [114]. In [115] recent research and specific and complex Intelliget Personal Assistants (IPA) are presented and the authors highlight that the IPA must fit the users' profiles and learn their context (family and social) taking into account their emotional estates to resolve any potential request and that the IPA should be able to recognise users' goals, act proactively, and interact with other applications to accomplish them.

Virtual assistants are similar to intelligent help systems in that they are both AI-empowered programs designed to provide assistance to users. Both types of systems can answer questions, provide information, and offer guidance in a variety of areas. However, virtual assistants often have more advanced features, such as voice recognition technology and natural language processing, which allow them to interact with users in a more conversational and personalised way. Additionally, virtual assistants can often control smart home devices, make phone calls, engage in conversations, and perform other tasks beyond just providing information or guidance. AI-empowered intelligent help systems and virtual assistants can help users quickly and easily find answers to their questions or get assistance with complex tasks. Moreover, virtual assistants are AI programs designed to answer questions, provide information, and assist users in various ways. These systems can also proactively offer suggestions or assistance based on user behaviour, such as identifying common issues or errors and providing solutions.

Since the inception of intelligent help systems, they have been broadly categorised as either passive or active help systems [116].

- *Passive help systems* require that the user requests help explicitly from the system. For example, UC is a passive help system for Unix users that can answer to users' questions about Unix commands, using Natural Language [117].
- *Active help systems* should guide and advise a user like a knowledgeable colleague or assistant. For example, AI has been used to generate hypotheses about users while they are interacting with the Unix operating system so that it may provide spontaneous assistance [118,119].

There are several types of AI that can be used to improve the user experience of intelligent help systems and virtual assistants. The following are some AI techniques that have been successful in intelligent help systems and virtual assistants:

- *Goal recognition*: Goal Recognition refers to the ability to recognise the intent of an acting agent through a sequence of observed actions in an environment. While research on this problem gathered momentum as an offshoot of plan recognition, recent research has established it as a major subject of research on its own, leading to numerous new approaches that both expand the expressivity of domains in which to perform goal recognition and substantial advances to the state-of-the-art on established domain types [120].

- *Plan recognition*: Plan recognition in intelligent help systems and virtual assistants refers to the ability of these AI systems to infer the user's plans or goals based on their actions and behaviour. Plan Recognition is a closely related problem to goal recognition, where the premise of the observer is to recognise how the acting agent intends to reach its goal [121]. This involves analysing and interpreting the user's interactions with the system, such as their voice commands, search queries, and other input, to identify their intentions and anticipate their future actions. Plan recognition is a critical component of intelligent help systems and virtual assistants as it enables the system to provide more personalised and context-aware responses and recommendations, improving the overall user experience. Various techniques and algorithms are employed to implement plan recognition in intelligent help systems and virtual assistants. For example, a theoretical treatment of plan recognition is presented in [122] where the use of an interval-based logic of time to describe actions, atomic plans, non-atomic plans, action execution, and simple plan recognition is described. In another example, plan-based techniques for automated concept recovery are presented in [123]. The authors of [124] note that a recogniser is deemed superior to prior works if it can recognize plans faster or in more intricate settings, although this often results in a trade-off between speed and richness or computation time.
- *Plan generation*: Plan generation in intelligent help systems and virtual assistants refers to the ability of these AI systems to generate plans or sequences of actions that help the user achieve their goals or complete their tasks. This requires analysing the user's input and context to determine the appropriate course of action and generating a plan that is most likely to achieve the desired outcome. Plan generation is a necessary component of intelligent help systems and virtual assistants as it enables the system to provide more proactive and effective assistance to the user. Various techniques and algorithms, such as rule-based systems, decision trees, and reinforcement learning, are employed to implement plan generation in these systems. For example, in [125], to achieve the design target of responding accurately to complex users' queries that involve the interconnection of multiple commands with various options, the system requires a detailed representation of dynamic knowledge about command behaviour and a planning mechanism that can integrate the knowledge into a cohesive solution.
- *Error diagnosis* in intelligent help systems and virtual assistants concerns the ability of these AI systems to identify, diagnose and help in the rectification of human errors that the user may have made in the context of the problem domain. Rasmussen points out that human errors are not events for which objective data can be collected, instead they should be considered occurrences of man-task mismatches which can only be characterised by a multifaceted description [126]. An empowered AI-system performs error diagnosis by monitoring and analysing the user's input as well as contextual information and concerning the domain of use to determine if there are any errors or inconsistencies, and in case there are, identifying the root cause of the problem, so as to provide advice on the rectification of errors, which the user may have or have not been aware of. For example, in the domain of a compiler architecture for domain-specific type error diagnosis of programming languages, the authors define error contexts as a way to control the order in which solving and blaming proceeds [127]. Error diagnosis is an important AI-based operation in intelligent help systems and virtual assistants as it enables the system to identify a problem and offer helpful guidance to the user in resolving the diagnosed problem. As an AI method, error diagnosis involves using AI algorithms and techniques to analyse data and identify patterns that can help detect errors or anomalies in a system. This can be applied in various domains, such as healthcare, finance, and education, to improve the efficiency and accuracy of processes. Various techniques and algorithms, such as rule-based systems, cognitive theories, decision trees, and machine learning, are employed to implement error diagnosis in these

systems. For example, in [128] pronunciation error detection and diagnosis is achieved through cross-lingual transfer learning of non-native acoustic modeling.

- *Knowledge Representation and Reasoning*: This AI technique involves representing knowledge in a way that can be easily processed and reasoned about by the system. By using knowledge graphs, ontologies, and other techniques, intelligent help systems and virtual assistants can store and retrieve information in a way that allows for more efficient and effective assistance. For example, in [129] an intelligent help system sets the design target to advise users on alternative plans that would achieve the same goal more efficiently and along the way, a representation of plans, subplans, goals, actions, properties and time intervals is developed to recognise plans and then to advise the user.
- *Natural Language Processing* (NLP): This AI technology allows intelligent help systems and virtual assistants to understand and respond to natural language input from users. NLP can be used to create chatbots that can help users with their queries and problems as has been the case in intelligent help systems [130] and in more recent virtual assistants [131]. Chin [132] argues that intelligent help systems should not merely react to user input but actively offer information, correct misconceptions, and reject unethical requests, and to do so, they must function as intelligent agents utilizing Natural Language Processing and Plan suggestion situations.
- *Machine Learning* (ML): This type of AI can help intelligent help systems and virtual assistants learn from user interactions and improve their responses over time. ML algorithms can be used to personalise the user experience and provide more relevant help and recommendations. Supervised learning algorithms can be trained on labeled data to classify instances as normal or faulty, while unsupervised learning algorithms can be used to identify anomalies or outliers in the data. For example, Microsoft Cortana [110] uses machine learning to personalise user experiences, understand user queries, and provide relevant information and recommendations.
- *Neural Networks*: Neural networks can be used to learn the relationship between the observed actions and the underlying goals or intentions from a set of training examples. Once trained, neural networks can be used to infer the most likely goals or intentions based on the observed actions. Neural networks can also be used to diagnose errors or faults in complex systems, such as manufacturing processes or healthcare systems. By analysing sensor data and other inputs, neural networks can learn to predict when errors or faults are likely to occur.
  * *Convolutional Neural Networks* (CNNs) are a type of neural network which have a feature extraction part where the specified kernels are convoluted on the data [133]. CNNs consist of several layers of interconnected nodes, each of which performs a specific type of operation on the input data. One important advantage of CNNs is their ability to learn features automatically from raw input data, without requiring explicit feature engineering by humans. CNNs have been used effectively in a wide range of applications, including image and video recognition, natural language processing, which may all be used in Virtual Assistants and Intelligent Help Systems among other interactive application domains.
  * *Recurrent Neural Networks* (RNNs) are a type of neural network that extend a Feedforward Neural Network (FNN) model, which learned an appropriate set of features while it was learning how to predict the next word in a sentence. The extension allows RNNs to handle arbitrary context lengths [134]. One important advantage of RNNs is their ability to handle input sequences of varying length. This renders them a powerful method in applications such as speech recognition, where the length of the audio input may vary from one sample to the next. For example, Google Assistant [111] uses neural networks to improve its speech recognition and Natural Language Understanding capabilities. It uses a combination of CNNs, RNNs, and sequence-to-sequence models to interpret user queries and provide natural language responses.

    * *DNNs stands for Deep Neural Networks*, which are a type of artificial neural network that is designed to model complex relationships between inputs and outputs. A DNN is a collection of neurons organised in a sequence of multiple layers, where neurons receive as input the neuron activations from the previous layer, and perform a simple computation (e.g. a weighted sum of the input followed by a nonlinear activation) [135]. The depth of the network refers to the number of layers it has, which can range from a few to hundreds or even thousands of layers. DNNs are used in a wide range of applications, including image recognition, speech recognition, natural language processing, and autonomous vehicles, to name a few. DNNs have the ability to learn complex features from large datasets and thus they constitute a powerful method for solving many real-world problems. For example, Apple Siri [112] uses deep neural networks (DNNs) to recognise speech and understand user queries. It also uses recurrent neural networks (RNNs) to generate natural language responses.
- *Cognitive theories* are important for understanding how people learn, solve problems, and make decisions, and can be applied to the design of intelligent help systems and virtual assistants. These cognitive theories can inform the design of intelligent help systems and virtual assistants by guiding the selection of appropriate instructional strategies, the organisation and presentation of information, and the design of user interactions. For example, in [136] a cognitive theory has been employed to achieve automatic error diagnosis for users interacting with an operating system and offer spontaneous assistance.
- *Rule-based Systems*: Rule-based systems can be used to represent a set of rules that define the relationship between the observed actions and the underlying goals or intentions. By applying these rules to the observed actions, rule-based systems can infer the most likely goals or intentions. Rule-based systems that use a knowledge base and a set of inference rules can also be used to diagnose errors or faults. Moreover, they can be used to represent a set of rules that define the relationship between the initial state, the desired goal state, and the sequence of actions that should be performed to achieve the goal. By applying these rules to the initial state, rule-based systems can generate a plan for achieving the desired goal. For example, [137] describes a rule-based assistant system for managing the clothing cycle and in [138] an ontology and rule-based intelligent patient management assistant is described.
- *Fuzzy logic*: Fuzzy logic is a mathematical approach to deal with uncertain or imprecise data that are common in intelligent help systems and virtual assistants. It allows for degrees of membership in a set, rather than a strict binary membership. For example, [139] describes an intelligent fuzzy-based emergency alert generation to assist persons with episodic memory decline problems.
- *Hierarchical Task Networks* (HTNs): HTNs can be used to represent a plan as a hierarchy of subgoals and decompose the plan into a set of smaller, more manageable tasks. By recursively decomposing the plan into subgoals, HTNs can generate a plan that achieves the desired goal. For example, in [140] it is pointed out that integrating task and motion planning through the use of multiple mobile robots has become a popular approach to solve complex problems requiring cooperative efforts, as advancements in mobile robotics, autonomous systems, and artificial intelligence continue to rise.
- *Reinforcement Learning*: Reinforcement learning is a branch of machine learning concerned with using experience gained through interacting with the world and evaluative feedback to improve a system's ability to make behavioural decisions [141]. For example, [142] shows how Reinforcement Learning is helping to solve Internet-of-Underwater-Things problems.
- *Speech Recognition*: This AI technology can be used to enable voice-based interactions with intelligent help systems and virtual assistants. This can be especially useful for users who have difficulty typing or navigating a graphical user interface. For example, the voice recognition and natural language understanding (NLU) capabilities of Amazon Alexa [109] are powered by machine learning algorithms, which enable it to interpret user commands and respond with appropriate actions.

– *Computer Vision*: This type of AI can be used to enable visual interactions with intelligent help systems and virtual assistants. For example, users could be interacting with a camera that performs image analysis on the face of the user to identify emotions of users while interacting and detect some displeasure on the part of the user which may need attendance. Another example in [143] describes research on detection of road potholes using computer vision and machine learning approaches to assist the visually challenged.

### *3.4. AI techniques for the UX of intelligent tutoring systems*

The User Experience (UX) in Intelligent Tutoring Systems (ITS) refers to how users perceive and interact with the system, including its interface, content, and features in the context of learning a particular domain being taught by the ITS. A well-designed ITS should provide an engaging and effective learning experience that meets the user's individual needs and preferences.

AI has been used to improve the user experience of intelligent tutoring systems (ITS) by providing personalised and adaptive learning experiences for individual learners. These systems use AI algorithms to analyse user data and behaviour to identify learning strengths and weaknesses and to provide personalised instruction and feedback. This can be done by recording and assessing the user's progress, identifying areas of users' weaknesses, and providing targeted feedback and additional resources to help them improve.

AI can also be used to analyse user data to identify patterns and insights that can help improve the effectiveness of the tutoring system in many aspects. For example, AI can be used to analyse student engagement, the effectiveness of different teaching strategies, and the impact of different resources on learning outcomes.

To improve UX in ITS, AI can be used to personalise learning content and adapt the system's feedback to the user's performance. AI can also analyse the user's behaviour and adjust the system's interface and content to enhance user engagement and motivation. For example, an ITS can use affective computing to understand the user's input and provide feedback with empathy, which can help the user feel more engaged and connected to the system.

There are different types of AI that can be used to improve the UX of intelligent tutoring systems. Some important approaches are the following:

– *Adaptive hypermedia* (AH) is a field of research that combines artificial intelligence (AI) and human-computer interaction (HCI) to develop systems that can dynamically adapt to the needs and preferences of individual users. AH systems use a combination of user modelling, content modelling, and adaptive navigation to provide personalised information and services to users. More specifically, adaptive hypermedia is an AI method that uses cognitive modelling, machine learning algorithms and other AI techniques to analyse data on users' behaviour and draw inferences about their respective level of knowledge, preferences, and interests, and then adapt the content and navigation of a website or application to meet their needs. For example in [144] fuzzy logic has been used for student modelling so that adaptive navigation techniques are applied to automatically adapt the pace of tutoring to individual strengths and weaknesses of students. In another instance, adaptive hypermedia are used to adapt tutoring of algebra-related domains to the individual needs of students [145].
– *Student modelling* is the process of creating and maintaining a model of a student's knowledge, skills, preferences, and other relevant attributes. The goal of student modelling is to provide personalised support and feedback to students, based on their individual needs and abilities in the domain being taught. It involves the use of artificial intelligence techniques to create and maintain the model. Some of the AI methods used in student modelling include machine learning algorithms, rule-based systems, cognitive theories and fuzzy logic. For example, in [146] an Artificial Immune System-Based student modelling approach is described to adapt tutoring to learning styles that fit the students' needs. At

another instance, student modelling is used to identify areas where learners have weaknesses so that the intelligent tutoring systems (ITS) may provide appropriate instruction to help them improve their performance in the domain of English as a second language [147]. A more comprehensive review of student modelling approaches and functions is presented in [148].

- *Learning Analytics*. A new research discipline, termed Learning Analytics, is emerging and examines the collection and intelligent analysis of learner and instructor data with the goal to extract information that can render electronic and/or mobile educational systems more personalised, engaging, dynamically responsive and pedagogically efficient [149].
- *Error diagnosis* is an important function of Intelligent Tutoring Systems that uses AI techniques to diagnose problematic parts of the students' behaviour or beliefs that lead to errors in assessment tests and reveal misconceptions. The deep error diagnosis frequently requires conflict resolution as erroneous behaviour may be due to many conflicting hypotheses about possible students' misconceptions. As an example, in an English tutor, a process of real-time evaluation of conflicting hypotheses about students' mistakes is used to perform a deep error diagnosis. This approach aims to identify the underlying students' weaknesses that may be causing the errors [150].
- *Knowledge Representation* is an important component of Intelligent Tutoring Systems that allows the representation of a domain being taught to be used by several AI inference mechanisms to find out the progress or weaknesses of students. For example, in [151], Fuzzy Cognitive Maps are used for the Domain Knowledge Representation of an Adaptive e-Learning System.
- *Fuzzy logic*. This is a type of AI that has been used in many aspects of Intelligent Tutoring Systems. For example, fuzzy logic has been used to determine the knowledge level of students of programming courses in an e-learning environment [152] and on another instance it has been used for student-player modelling in an educational adventure game [153].
- *Machine learning*: This is a type of AI that involves the use of algorithms and statistical models to analyse data and make predictions or decisions without being explicitly programmed. Machine learning can be used in intelligent tutoring systems to personalise the learning experience for each student by analysing their learning data, preferences, and behaviour. For example, [154] decribes a machine learning-based framework for the initialisation of student models in Web-based Intelligent Tutoring Systems of various domains, such as mathematics and language learning.
- *Deep Learning*: Deep learning is a subset of machine learning that uses neural networks to simulate the workings of the human brain. Deep learning can be used in Intelligent Tutoring Systems at many levels and for varying functionalities. For example, in [155] neural networks have been employed to perform visual-facial emotion recognition so that the tutoring system may analyse the face of a student through a camera and understand how the student feels about the lesson so that it may respond in an appropriate manner.
- *Cognitive theories*: This is a type of AI that is designed to simulate human thought processes, including perception, reasoning, and learning. Cognitive computing can be used in intelligent tutoring systems to provide more sophisticated feedback and guidance to students, based on their individual learning styles and cognitive abilities. For example in [156], student modelling is performed using cognitive theories to identify cognitive, personality and performance issues in a collaborative learning environment for software engineering. In another instance, the individualisation of a cognitive model of students' memory is performed in an Intelligent Tutoring System, so that the system may personalise the presentation and sequencing of revisions of teaching material depending on when the student is likely to have forgotten the material taught in preceding sections of the ITS [157].
- *Decision Theories*: Decision theories are a set of frameworks and models used to make rational and informed decisions in the face of uncertainty. These theories aim to identify the best course of action among a set of alternatives, taking into account the potential outcomes and their probabilities.

An example of an intelligent medical tutor that uses decision theories is described in [158]. This tutor offers adaptive tutoring on atheromatosis to users with varying levels of medical knowledge and computer skills, based on their interests and backgrounds. This adaptivity is achieved through user modelling, which draws on stereotypical knowledge of potential users, including patients, their relatives, doctors, and medical students. The system uses a hybrid inference mechanism that combines decision-making techniques with rule-based reasoning of double stereotypes.

– *Affective computing*: This type of AI focuses on recognising human emotions and generating responses that contain emotion-like feedback from the part of the computer. One way that affective computing can be used in ITS is through the use of emotion recognition technologies. These technologies can detect and interpret facial expressions, vocal tone, and other parts of the users' behaviour to determine a student's emotional state. An illustration of this process is the use of a voice recognition system and analysis of keyboard actions to perform emotion recognition of students in an Intelligent Tutoring System (ITS) [159]. The system takes into consideration the recognized emotions and utilizes a cognitive theory of affect to generate emotion-based responses that are appropriate for the learner's current affective state. These emotions are conveyed to the learner through an animated agent, which mimics human empathy by adjusting the tone and pitch of its voice while providing recommendations for specific learning materials or modifying the level of instruction difficulty. In a different scenario, described in [160], the cognitive theory of affect is utilized to identify the emotions of students instead of generating emotional responses. This approach is implemented within an Intelligent Tutoring System designed as an educational game. Three animated agents are employed to simulate the roles of a classmate, tutoring coach, and examiner, and they provide appropriate responses based on the recognized emotions of the student.
– *Mobile and smartphone senses*: Mobile and smartphone devices provide a wealth of sensors that can accumulate users' responses which, in turn, can be exploited for analysing users' behaviour in the context of an intelligent tutoring system. Mobile devices can provide profound reasoning [161] concerning users through smartphone senses [162]. One such example is the sentiment mapping through smartphone multi-sensory crowdsourcing described in [163].
– *Engagement and immersive technologies*: Engagement and immersiveness of learners in computer-based tutoring constitute important features that are sought by learning applications to maximise the educational effectiveness [164]. To achieve these there has been a growing emphasis on recognising human emotions in interactive computer-based learning applications, while using multi-modal user interfaces, natural language as well as virtual reality environment in conjunction with AI techniques.
– *Educational games and edutainment*: The technology of game playing has been blended with AI techniques and together they constitute important parts of educational software in the context of Intelligent Tutoring Systems to provide engaging challenges to students so that they stay active and alert while learning. These educational activities are used to educate and entertain and often titled as edutainment technology. For example, in [165] a software version of the well known game "Guess who" is developed to teach students parts of the English language as a second language. In [166], a 3D game is developed for the purposes of education and fuzzy-based reasoning mechanism is used to ensure that students receive a dynamically adjusted difficulty level of the game itself so that they may enjoy the game and attend the teaching material [167] without encountering difficulties or being bored with the game itself. In another instance, an educational adventure game encompasses adaptive scenaria to accommodate the individual learning needs of each student [168].
– *Collaborative Learning*: The social context of class involving students with classmates and allowing collaboration is important in the area of Intelligent Tutoring Systems to enhance learning experiences. For example, in [169] an intelligent recommender system for trainers and trainees has been incorporated in a collaborative learning environment in order to recommend to students and teachers teams of

students that appear to have complementary qualities for the purposes of educational collaboration in project assignments.

- *Social Networks*: Social networks may extend collaborative learning in the platforms of social media. For example, [170] describes an Intelligent Tutoring System over a social network for mathematics learning.
- *Natural language processing* (NLP): This is a type of AI that enables computers to understand, interpret, and generate human language. NLP can be used in intelligent tutoring systems to provide students with feedback on their written or spoken responses, and to help them practice their language skills in a more natural way. In this approach, AI-empowered tutoring systems can use natural language processing (NLP) and machine learning algorithms to understand user input and provide more human-like responses and feedback by achieving a more natural and interactive learning experience. For example, in [171] the focus is on the combination of various deep learning approaches to automatically help students to accelerate the learning process by automatic feedback, but also to support teachers by pre-evaluating free text and suggesting corresponding scores or grades.
- *Computer vision*: This is a type of AI that enables computers to analyse and interpret visual information from the world around them. Computer vision can be used in intelligent tutoring systems to track students' eye movements and facial expressions during learning activities, and to use this information to personalise the learning experience. For example, in [172] visual-facial data is collected and analysed for the purposes of group affect recognition in a the context of a class of students.
- *Authoring tools for Intelligent Tutoring Systems*: Authoring tools can provide user-friendly environments to human teachers so that they may deliver Intelligent Tutoring Systems to be used by their students in the domain of their teaching expertise. Technically they use AI-based techniques that have to be parameterised so that the teachers can author the content and the way they wish their students to be taught by the Intelligent Tutoring Systems. For example, in [173], an authoring tool for mobile intelligent tutoring systems is presented while in [174] a user model the instructor, termed instructor model, is created to help instructors with managing the difficulty level and the content of their teaching material to fit their teaching needs and their students' learning strengths and weaknesses.

## 4. User Experience enhancements through Artificial Intelligence-based interactions

The UX (User Experience) of AI (Artificial Intelligence) refers to how people interact with and experience AI systems in many application areas. The use of AI in UX design can bring many advantages, including automatic and real-time personalisation, improved efficiency, repetitive task automation, better decision-making, smarter data analysis, predictive analytics, improved product recommendations, multi-channel optimisation across multiple channels, such as mobile, web, and voice, creating a seamless and consistent experience for users, improved user engagement, better user retention, efficient Natural language processing, faster prototyping and testing.

The following subsections describe how the User Experience has been enhanced by AI in some important interactive application domains, such as Web searching, Recommender Systems, Intelligent help systems and virtual assistants and Intelligent Tutoring Systems.

### *4.1. Enhancements of UX of AI in web searching*

Artificial intelligence (AI) has greatly enhanced the user experience (UX) of web search. AI algorithms are able to understand user queries in a more detailed way and provide more accurate and relevant search results in a way that users become more satisfied with their interaction with web search engines.

More specifically, the UX of AI in web searching offers several advantages to users, including personalisation, contextual understanding, improved accuracy, speed and efficiency, natural language processing, and multilingual support. AI algorithms can analyse users' search history and behaviour to provide personalised search results that are tailored to their preferences, long term interests and needs, saving time and improving the relevance of search results. AI algorithms can also take into account the context of a search query, including location and time of day, to provide more relevant and useful search results. In terms of the actual interaction, AI algorithms can use natural language processing and machine learning techniques to better understand the intent behind a user's search queries, making it easier for users to find the information they need without having to use specific keywords or phrases. Moreover, AI-empowered search engines can support multiple languages, making it easier for users to find information in their preferred language. All of the above, delivers more accurate results.

In terms of the operation of AI-based search engines, they are able to process vast amounts of data quickly and efficiently, allowing users to find the information they need more quickly and easily.

In general, the UX of AI in web searching can help users to find what they are looking for more quickly and easily, which leads to a better user experience. Additionally, AI can analyse user feedback and behaviour to continuously improve the search experience, ensuring that users receive the most relevant and useful information possible.

### *4.2. Enhancements of UX of AI in recommender systems*

Artificial intelligence (AI) has revolutionised the user experience (UX) of recommender systems. By analysing user behaviour and preferences, AI algorithms can provide personalised recommendations that are tailored to each user's unique interests and needs. This not only improves the overall UX of the system, but also helps users to discover new content and products that they may not have found on their own. AI-empowered recommender systems can also adapt to changes in user behaviour and preferences over time, ensuring that the recommendations remain relevant and useful. In addition, AI can analyse large amounts of data and make connections that humans may not have noticed, leading to more accurate and diverse recommendations. Consequently, AI has greatly improved the UX of recommender systems, making them more effective and user-friendly.

More specifically, UX of AI in recommender systems can provide several advantages to users, such as persolnalisation, improved accuracy, increased efficiency, a variety of relevant recommendations, seamless and user-friendly experience and can accommodate expandability to very large sets of data and users. In some cases, users may have not been able to discover content that is being suggested by recommender systems due to the very large volume of information that exists in the internet or elsewhere. Recommender systems provide considerable cognitive alleviation and guidance and thus they have improved the user experience significantly.

### *4.3. Enhancements of UX of AI in intelligent help systems and virtual assistants*

The user experience (UX) of intelligent help systems and virtual assistants has been greatly enhanced by artificial intelligence (AI). With the help of AI, virtual assistants can perform a range of tasks, from scheduling appointments to ordering groceries, making them an increasingly popular and convenient tool for daily life. Natural language processing, machine learning and other AI algorithms enable these systems to understand user inquiries and provide accurate and useful responses. This allows users to receive immediate assistance and complete tasks more efficiently, which leads to a better UX. AI-empowered virtual assistants can also learn from user behaviour and adapt to their preferences over time, providing more personalised and relevant assistance. Furthermore, AI's ability to process vast amounts of data enables virtual assistants to offer insights and recommendations that users may not have considered otherwise. In view of the above important enhancements, it can be said that AI has revolutionised the UX of intelligent help systems and virtual assistants, creating more user-friendly and efficient interactions.

Very recent examples of commercial virtual assistants include Alexa, Siri, Google Assistant, Cortana and ChatGPT. These are all AI-empowered virtual assistants or intelligent personal assistants that are designed to assist users with a variety of tasks and enhance UX. While they all share some similarities, there are also some differences between them, including, language capabilities, device capability and smart home control. More specifically, ChatGPT, Google Assistant, and Siri are all language models that can generate text and engage in conversation with users. For this purpose, they use natural language processing to varying degrees, while Alexa and Cortana primarily rely on voice command. Concerning devices, Alexa, Google Assistant, and Siri are primarily associated with specific devices (such as Amazon Echo, Google Home, and Apple devices, respectively), while ChatGPT and Cortana are available across a wider range of platforms. Finally, Alexa, Google Assistant, and Siri can all be used to control smart home devices, such as lights and thermostats, while ChatGPT and Cortana do not have this capability. The above examples have ameliorated the user experience in their respective domains.

Advantages of AI to user experience of virtual assistants and intelligent help systems include personalisation to users' preferences, beliefs and needs. Moreover, they provide proactive assistance, which helps to prevent issues before they occur and improve the overall user experience but can also provide corrective feedback in potential users' errors when they occur. Indeed, Intelligent help systems and virtual assistants powered by AI can quickly and efficiently identify and diagnose problems and can provide real-time feedback to users, helping them to improve their performance or resolve issues more quickly which can reduce user frustration. In other cases, they provide contextual and personalised suggestions for users' plan completion so that errors may be avoided, and the users achieve their goals faster and more efficiently. Intelligent help systems and virtual assistants can provide assistance to users with disabilities, such as those who are visually impaired or have limited mobility, which can improve their experience with the software. Moreover, the user interactions are often accommodated by natural language processors that can provide a chatty and more user-friendly experience while they can support multiple languages, which can enhance the user experience for non-native speakers.

Considering the significant enhancements discussed, it can be concluded that AI has transformed the UX of intelligent help systems and virtual assistants, by providing a wide range of benefits to users, including improved consistency, real-time feedback, proactive assistance, and enhanced search functionality, among others. These benefits can help to improve user satisfaction, increase engagement with the platform, and reduce the workload of human users and human support staff.

### *4.4. Enhancements of UX of AI in intelligent tutoring systems*

The UX (user experience) of AI (artificial intelligence) in intelligent tutoring systems offers several advantages that enhance the overall learning experience. Firstly, intelligent tutoring systems powered by AI can provide personalisation that tailors the learning experience to the individual needs, preferences, and learning styles of each user. This can be educationally beneficial while alleviating the cognitive load of students' learning. Additionally, AI-empowered tutoring systems can provide personalised pacing that adapts to the pace of each user's learning, providing more time and support for difficult concepts while moving more quickly through easier material. This can optimise learning outcomes and ensure that users are not overwhelmed or bored.

Moreover, AI-empowered tutoring systems can provide personalised tests, challenges, and exercises based on the strengths and weaknesses of the user, further optimising learning outcomes and providing an efficient learning experience. Real-time corrective feedback is another advantage of AI-empowered tutoring systems, allowing users to correct mistakes and improve their performance. This feature can help to increase user confidence and motivation and improve learning outcomes. Intelligent tutoring systems powered by AI can also provide real-time support and assistance to users, such as chatbots and virtual assistants, that can answer questions, provide feedback, and guide users through learning activities. This can also help to increase learning outcomes and provide a more effective and efficient learning experience.

The adaptivity of intelligent tutoring systems powered by AI is also noteworthy as they can adjust to the user's learning style, preferences, and performance, providing personalised learning experiences, targeted feedback, and guidance to help users achieve their learning goals. Additionally, AI algorithms can analyse learner data, such as facial expressions, voice tone, and text input, to identify the learner's emotional state and respond with appropriate feedback. By supplying emotional support, ITS can help to reduce frustration and anxiety, and enhance the overall learning experience.

In terms of interaction and presentation of tutoring content, AI-empowered tutoring systems can provide interactive and engaging learning experiences that incorporate multimedia, simulations, and gamification techniques. They can also incorporate multimodal interaction techniques, such as speech recognition, natural language processing, and gesture recognition, to provide a more intuitive and natural learning experience. This can help to increase engagement and motivation and provide a more immersive learning experience.

In the social context of a class where students participate, intelligent tutoring systems powered by AI can facilitate collaboration and social learning through features such as discussion forums, peer review, and group projects. This can help to increase engagement and motivation and provide a more interactive and rewarding learning experience.

All the above features can be adapted to users with diverse needs. Indeed, intelligent tutoring systems powered by AI can provide accessible learning experiences for users with diverse needs, including users with disabilities or language barriers. This can help to increase the reach and effectiveness of the system and provide a more inclusive learning experience.

Intelligent tutoring systems can resolve problems of operation that frequently may cause problems to users. For example, Intelligent tutoring systems powered by AI can be designed to scale to accommodate large numbers of users, making them ideal for use in educational settings and online learning platforms. This can help to increase the reach and impact of the system and provide a more efficient and cost-effective learning experience. Moreover, they can automatically enhance their own operation by incorporating new data and feedback to be used for continuous learning and for improving the accuracy and effectiveness of the system. This can help to provide a more effective and efficient learning experience and improve the quality of the system over time.

As human teachers play an important role in the educational process, there are also authoring tools to support to human instructors. These tools can help to streamline the authoring process by automating the creation of instructional materials, assessments, and feedback. AI authoring tools can analyse existing educational content and suggest improvements or generate new content based on identified learning gaps. This can help to reduce the time and resources required for individualised content creation, while also improving the quality and effectiveness of the instructional materials.

As a concluding remark, the UX of AI in intelligent tutoring systems offers a range of advantages that can help to improve engagement, motivation, and learning outcomes for users, whether they are students, or human instructors. By incorporating AI technologies and techniques into intelligent tutoring systems, educators and instructional designers can create more effective and engaging learning experiences that meet the needs and preferences of a diverse range of learners.

## 5. Challenges of Artificial Intelligence in User Experience and reciprocal AI solutions

AI has contributed impressive enhancements to the UX. However, there are also several demanding challenges and potential problems that necessitate further attention and resolution.

### *5.1. Challenges and problems of Artificial Intelligence in User Experience*

AI-based reasoning for user experiences involves the utilisation of artificial intelligence algorithms to process and analyse user data related to key factors of human behaviour and personality such as emotions, goals, beliefs, and knowledge, in order to provide personalised and effective experiences. However, the outcome of AI-based reasoning yields hypotheses about users' internal cognitive and epistemic states, which are not necessarily facts. In some instances, AI-based reasoning needs to generate hypotheses about both the user's present state of mind and their desired state, which may differ. This generates a potential triangular connection between the AI's assumptions concerning the user's existing, intended, and factual state of mind for each essential element, including emotions, goals, knowledge, and beliefs. This results in a separate triangle for each key factor, as demonstrated in Fig. 4.

Ideally, each triangle would be reduced to a single point, representing the alignment of the AI's hypotheses with both the user's real and intended states of mind. Moreover, in an ideal situation, assumptions and hypotheses would exist for all the factors that represent various aspects of the user's state of mind and there would be a cohesive connection between all of them. However, this is not often the case. As discussed above, users' interaction with AI may result in failures due to either incorrectness of the hypotheses generated by AI or incompleteness in the representation of the users' state of mind.

In addition to the failures that can occur due to incorrect generated hypotheses or incomplete AI representations of the user's state of mind, there are several other potential failures in user-AI interaction. Communication failures can also arise when AI fails to effectively communicate with users, leading to misunderstandings or misinterpretations of user inputs or requests. Privacy and security failures can occur when AI fails to protect users' sensitive information or data breaches occur. Additionally, ethical failures can occur when AI engages in behaviour that is unethical or discriminatory. The nature of these failures can vary depending on the specific context and application of AI.

Several challenges arise when integrating AI into UX design, which must be taken into careful consideration. In the subsequent paragraphs, we discuss challenges, problems, and failures concerning human expectations of AI, problematic levels of trust, the black box problem, explainability, levels of knowledge, levels of depth and breadth of AI implementation, and personalisation in terms of basic characteristics.

Among these challenges is determining the appropriate level of anthropomorphic characteristics that an AI system should possess. This is a challenge because it involves finding a balance between creating AI systems that are relatable and user-friendly, and those that maintain a clear distinction between humans and machines. AI systems that are too human-like may lead to ethical concerns, such as the potential for users to form emotional attachments to the AI or the creation of false expectations about the AI's abilities. On the other hand, AI systems that lack human-like characteristics may be difficult for users to interact with or may not be able to effectively perform tasks that require social or emotional intelligence. Thus, finding the appropriate level of anthropomorphic characteristics for an AI system is a complex challenge that requires careful consideration of both technical and ethical aspects.

One of the most important challenges that AI systems face today is achieving an appropriate level of accuracy in their outputs, which is necessary to gain human trust. If an AI system's output is not accurate, it can lead to a loss of confidence in the technology, and people may not rely on it for important decisions. However, accuracy alone is not enough to establish trust in an AI system. Another challenge that must be addressed is the potential for bias and ensuring fairness in the system's operation. Bias can occur when the data used to train an AI system is not diverse or representative enough, leading to unequal treatment or outcomes for certain groups. Thus, it is vital to eliminate bias and ensure fairness in AI systems to build trust and confidence in their outputs.

One of the challenges for AI systems is providing user control and usability, in addition to accuracy and fairness. While user control is essential to ensure that the AI system functions according to user

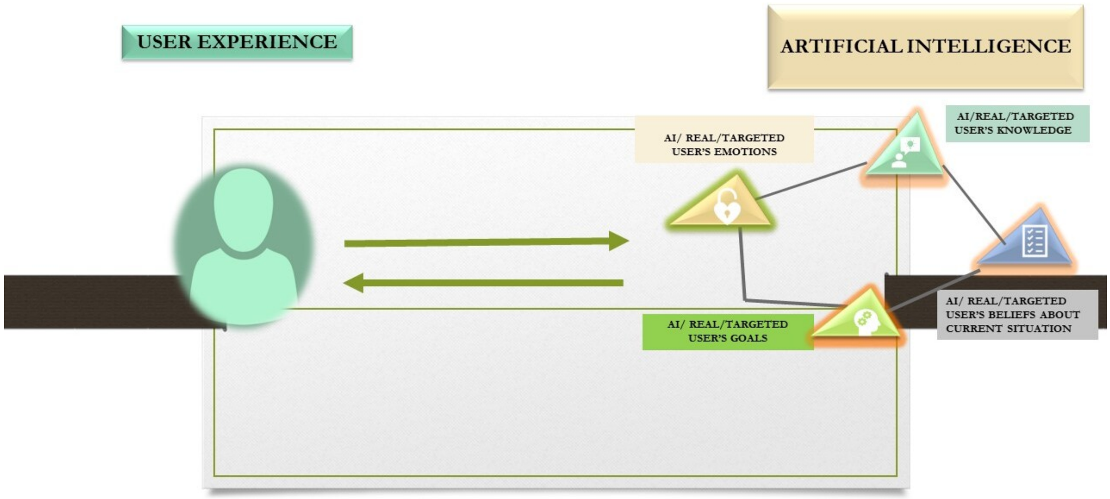


Fig. 4. The user experience of AI-based reasoning as it relates to various user factors.

preferences and needs, providing it can be challenging due to the complexity and opacity of some systems. Therefore, ensuring that AI systems are user-friendly and transparent is very important for building trust and encouraging adoption. Addressing the problem of usability related to user control is a significant challenge that needs to be addressed in the development and deployment of AI systems.

Furthermore, it is essential to balance the degree of user control and autonomy in the AI system to ensure that users feel in control while ensuring that the AI system operates correctly. For example, the AI system may provide decision support for human decisions or extend to autonomous decision-making, which is sensitive, particularly when ethical issues or human lives are at stake. The privacy and security of data are also major concerns, with designers needing to consider the privacy and security of raw data, preprocessed data, and AI inferences based on processed data. As AI-empowered systems develop their reasoning mechanisms and collect and process personal data, ethical considerations constitute a significant challenge that must be addressed to ensure responsible and ethical AI use.

In the following paragraphs, the paper identifies and describes important elements concerning human beliefs and needs in relation to AI reasoning, responses and limitations, that constitute a conceptual map of the challenges that are encountered in AI in UX.

– Human expectations and unexpectedness of AI
  * Expectation of the unexpected
    * *Unpredictability of AI behaviour in all possible situations by AI programmers and consequently AI users*. While human programmers can design and train AI systems, they cannot always predict how the system will behave under all possible situations, let alone human users of AI. This is why it is essential to test AI systems thoroughly before deploying them in real-world applications and to monitor their behaviour to ensure that they are operating as intended. Having mechanisms to identify and rectify errors or unanticipated and undesirable behaviours in AI systems is crucial.
    * *Unpredictability of AI behaviour due to fallibility*. The effectiveness of AI is not guaranteed, as it is highly dependent on the quality of the training data it receives, and it is prone to biases and errors. In cases where AI is trained on data that is biased, it can perpetuate these biases, leading to the creation of discriminatory outcomes. Furthermore, the predictions and hypotheses generated by AI may not always be accurate or reliable, which can result in incorrect conclusions or decisions.

  * *Unpredictability of AI behaviour due to complexity and interconnections of AI*. In the field of AI, it is often expected that unexpected outcomes or results may occur, especially in the development and implementation of complex systems. AI systems can exhibit unpredictable behaviour due to their complexity and the interactions between various components. As AI systems become more complex and interconnected, it becomes increasingly difficult to predict their behaviour accurately.
  * *Unpredictability of AI behaviour due to unknown limitations or biases of training data*. Moreover, AI can only respond to what it has been trained on, and it may not be able to adapt to situations that are too far outside its training data. AI algorithms are designed to learn from data and make predictions or decisions based on that data. They use statistical techniques to identify patterns in the data and make inferences based on those patterns. However, the behaviour of an AI system is ultimately determined by the data it has been trained on, and it may produce unexpected or undesired results if it encounters situations that were not present in the training data.
  * *Unpredictability of AI behaviour to unexpected situations*. AI is not capable of creative problem-solving in the way that humans can, so it may not be able to respond to unexpected situations in the same way that humans can.
* Uncertain expectations
  * *Overestimation of AI capabilities*: There may be exaggerated claims about what AI can do, leading to unrealistic expectations. For instance, some people may think that AI can solve any problem, regardless of its complexity or uncertainty.
  * *Misunderstanding of AI's capabilities*: There may be a misunderstanding of what AI can and cannot do. Some people may assume that AI can replace human intelligence and judgment completely, which is not the case. AI is a tool that can assist humans in making decisions, but it cannot replace human judgment entirely.
  * *Fear of job displacement*: There may be concerns that AI will replace human workers and lead to widespread job displacement. While AI can automate many tasks, it cannot replace humans entirely.
* False expectations
  * *Omnipotence of AI*. AI is not panacea and cannot solve all problems. While it can help human users analyse data, recognise patterns and make predictions, it cannot solve complex social, economic, and political issues. It is essential to have a holistic approach and use AI as a tool to assist humans in solving these problems.
  * *Omniscience of AI*. AI does not possess complete knowledge or understanding of all, as it is limited by the quality and quantity of the data it is trained on. Despite being designed to learn from data and make decisions based on that data, AI algorithms are incapable of true understanding or consciousness. Although AI has demonstrated remarkable abilities in areas such as image recognition, natural language processing, and game playing, it has many limitations and cannot substitute human intelligence and judgment in every domain.
  * *Infallibility of AI*: AI is not infallible. On the contrary, AI is fallible, as its performance heavily relies on the quality of the data it is trained on, and it is susceptible to errors and biases. Additionally, its predictions and hypotheses are not necessarily accurate and true, which can lead to incorrect conclusions or decisions.
  * *Replacement of Human Intelligence*: AI cannot replace human intelligence completely. While AI can perform certain tasks better than humans, such as analysing vast amounts of data, it cannot replicate human creativity, intuition, and empathy. AI lacks the emotional intelligence and holistic understanding that humans possess, which is essential in many fields such as healthcare, education, and social services.

    * *Perfection in Natural Language Processing*: AI cannot understand human language perfectly. Although AI has made great progress in natural language processing, it still cannot understand human language perfectly. AI may not understand subtleties or humorous comments, and can be misled by human deception or irony.
  * *AI preconceptions*: AI preconceptions, if they exist in one's beliefs, can lead to biased or incorrect assumptions about AI's capabilities, limitations, and potential impact. Preconceptions may be based on limited or outdated information, cultural or personal biases, or unrealistic expectations.
  * *AI phobia*: Artificial intelligence phobia (AI-Phobia) is defined as the feeling of fear or anxiety toward adoption of artificial intelligence [175]. In the emerging AI era, "AI phobia" is similar to what used to be "computer phobia" in the past. Jay [176] defined computer phobia as a negative emotion or attitude towards computers that exhibits three primary characteristics: (1) avoidance of discussing computer-related topics, (2) displaying anxiety and fear towards computers, and (3) holding negative and extreme opinions of computers. Consequently, AI phobia is a fear and anxiety towards artificial intelligence that can cause individuals to feel uneasy or terrified about the idea of machines potentially taking over human decision-making processes or replacing human jobs, and this fear leads to negative expectations and prevents these users from using AI programs.
- Levels of Trust for Humans
  Trust is described by Körber [177] along six dimensions: 1. reliability, 2. predictability, 3. the user's propensity to trust, 4. the attitude towards the developers, 5. the user's familiarity with automated systems and 6. general trust in automation.
  However, the user's trust may reach some problematic levels that can affect the reliability of the whole interaction. In this research work, the identified problematic levels of trust or absence of it are the following:
  * *Distrust*: implies a lack of trust predicated on previous experience or knowledge.
  * *Mistrust*: implies a broader absence of confidence that does not necessarily stem from something specific.
  * *Overtrust*: means that a person's trust exceeds the system's capabilities.
- Black box problem and explainability
  Many AI methods such as deep learning are quite efficient but do not provide explanations as to how they have reached their conclusions. For example, in [178] it is argued that when applied to the healthcare domain, machine learning models fail to meet the needs for transparency that their clinician and patient end-users require and that opaque models (1) lack quality assurance, (2) fail to elicit trust, and (3) restrict physician-patient dialogue. According to Carabantes the most powerful artificial intelligence models based on machine learning are often the ones with the most opaque black-box architectures, despite the increasing demand for their use in various domains in computerized advanced industrial societies [179]. Thus, this gives rise to an important control problem for human society. The lack of transparency in the reasoning of opaque AI systems not only undermines users' trust but also obstructs communication between domain experts who use the AI systems and their clients who require justifications, as well as among domain experts who need arguments to collaborate effectively in a human team. This is because people are skilled arguers, using reasoning both to evaluate and to produce arguments in argumentative contexts [180]. The categories for black box problems faced by users can be classified in the following restrictions concerning human users:
  * Restricted verification and cross-examination of AI outcomes.
  * Restricted novel creation and extension capabilities based on AI outcomes.
  * Restricted capacity for human-AI collaboration.
  * Restricted capacity for integrating AI as a third party in human-human collaboration.

- Levels of depth in terms of human reasoning of AI in the systems
  According to Nilsson achieving real human-level artificial intelligence would necessarily imply that most of the tasks that humans perform [181]. According to the Bloom's Taxonomy there is hierarchy of thinking skills at 6 levels, namely, 1. Knowledge, 2. Comprehension 3. Application, 4. Analysis, 5. Synthesis, 6. Evaluation. The thinking skills of the three lower levels of the taxonomy – Knowledge, Comprehension, and Application – are referred to as lower-order thinking skills, and those of the higher levels – Analysis, Synthesis, and Evaluation, as higher-order thinking skills [182]. Butterworth and Thwaites argue that creativity and imagination are equally important to rational thinking in human development and that the overlap and interdependence between the two make it hard to differentiate them. Usually, the upgrade from low level thinking to higher level thinking has been the goal for human educators concerning human students. For example, in [183] the authors show a chemistry course that provides the opportunity for students to move beyond surface-level thinking to critical thinking as they use quantitative reasoning skills, analyse data, and draw connections between observations and explanations [184]. However, to what degree AI methods can attain these human thinking levels?
  * *Surface-level thinking*: This is the most basic level of thinking, where people rely on their initial impressions, assumptions, and stereotypes to make decisions. Surface-level thinking tends to be quick and effortless, but it can also be prone to errors and biases.
  * *Analytical thinking*: This level of thinking involves taking a step back and examining a problem or situation more closely. It involves breaking down complex information into smaller parts, identifying patterns, and using logic and reasoning to draw conclusions. Analytical thinking requires more effort than surface-level thinking, but it can also lead to more accurate and nuanced understanding.
  * *Critical thinking*: This is the deepest level of thinking, where people question assumptions, evaluate evidence, and consider multiple perspectives before making a decision or drawing a conclusion.
- Levels of knowledge
  According to [185] different types of knowledge in terms of what knowledge is needed to do a particular type of work or take a particular action and are categorised as surface knowledge, shallow knowledge and deep knowledge. Shallow knowledge is when you have information plus some understanding, meaning and sense-making. Deep Knowledge refers to an extensive, versatile, and flexible comprehension of a particular subject that enables advanced thinking and problem-solving at an expert level.
  * *Surface Knowledge*: Surface knowledge is predominantly but not exclusively information learning to improve recall, and few connections to other stored memories [186].
    Surface Knowledge can lead to various problems in the context of UX design.
    *Shallow Knowledge*: Shallow knowledge can be defined as having access to information along with a basic level of understanding, interpretation, and sense-making. Shallow Knowledge can also be problematic in the context of UX design.
  * *Deep Knowledge*
    Deep knowledge refers to an extensive, versatile, and flexible comprehension of a particular subject that enables advanced thinking and problem-solving at an expert level. Deep knowledge can improve UX design.
- Levels of personalisation and user modelling
  * *Acquistion*: The ways of acquisition of user models are implicit or explicit. However, the use of AI imposes a new challenge of acquisition of user models from explicit and implicit feedback of users as a response to AI programs (e.g. recommendations or advice).
  * *Degree of individualisation*: The degree of individualisation concerning whether an individual user has been modelled or a community of users is not easily specified as many clustering techniques tend to model communities of users and do not always aim at modelling the individual user.

  * *Modifiability*: Is the user model continuously updated while the program is being executed to include more aspects of users and their changes? Does it take into account users' feedback or their cognitive changes due to the influence of the AI system itself? For example, in a recommender system where a user is asked to rate a recommendation, is this considered in updates of the user model? Recently, more issues concerning the generated user models have emerged that would need automatic internal revision, such as self -bias. For example, people often take user ratings/reviews into consideration when shopping for products or services online. However, such user-generated data contains self-selection bias that could affect people's decisions and it is hard to resolve this issue completely by algorithms [187].
  * *Temporal Extent*: Are users remembered after logging out so that they may enjoy personalisation for longer periods?
- Levels of anthropomorphic characteristics
  * *Natural Language*: Natural language is a convenient means of communication among people, which enhances user experience. The absence of Natural Language Processing (NLP) may result in increased difficulty and human errors. On the other hand, the existence of NLP may raise expectations to a level that exceeds the system's capabilities, resulting in unrealistic human-like expectations.
  * *Simulation of Human Reasoning*: The incorporation of a simulation of human reasoning renders the user experience more human-like and convenient. It considers both the ways that people think as well as their cognitive limitations. For example, cognitive modeling can be used to design interfaces that are optimised for the way people think and process information, making them more intuitive and user-friendly. However, there are also challenges associated with the simulation of human reasoning in UX. For example, the expectations of users may become too high if the system is designed to simulate human reasoning to a high degree of accuracy. If the system falls short of these expectations, users may become frustrated, and the user experience may suffer.
  * *Emotion recognition/generation*: Incorporating emotion recognition and generation into user experience can enhance empathy, leading to a stronger connection between users and AI-empowered systems. However, it is important to consider the design implications of implementing emotion recognition, including how emotions are detected and which emotions are exhibited by the computer in response.
  * *Anthropomorphic agents*: Anthropomorhic agents who can speak or move in animations can enhance the user experience to become more human-like and familiar. However, the resemblance to humans may cause frustration if the agents' reasoning is not good enough to satisfy the users who may raise their expectations higher because of the anthropomorphic features of the agents.
- Degrees of User control
  By extending the categorisation of intelligent help systems to passive and active, to span all interactive systems that incorporate intelligence, there can be the following two categories of AI systems depending on who has the initiative of the interaction and thus user control:
  * *Passive AI-empowered interactive systems* require that the user requests explicitly the interaction from the AI-system. In this case the user has the initiative and control of the interaction. For example, in a recommender system, the user requests recommendations.
  * *Active AI-empowered interactive systems* refer to systems that intervene spontaneously in the appropriate context to offer knowledgeable AI feedback to users. In this case the system has the initiative and control of the first interaction. For example, a recommender system, may provide spontaneous recommendations. In this category of system, there has to be careful design concerning when and how the AI system will intervene so that it may be helpful without being intrusive. Certainly, it is needed for the system to have a high degree of certainty about the accuracy of its hypotheses concerning the assistance that it has to offer.

- Bias and Fairness
  AI systems can exhibit bias due to a variety of factors, including the algorithm used, the input data selected, and hidden correlations within the training data. According to Roselli and colleagues there are three primary categories of bias: those that stem from the translation of business objectives into the AI implementation, those that result from the distribution of samples used for training (including the impact of historical data), and those that exist within individual input samples [188]. Nelson gives examples from the medical field to demonstrate how Artificial intelligence (AI) operating without oversight could maintain prejudice: "Imagine an algorithm that selects nursing candidates for a multi-specialty practice – but it only selects white females. Consider a revolutionary test for skin cancer that does not work on African Americans" [189].
  Concerning fairness of AI, Shrestha and Das point out that although, the relevant discussion within the realm of ML and AI is a recent development, fairness problems and discrimination have roots within human society where the unfair treatment toward the minority is documented in the data that has been created over time and therefore, the inadvertent learning and perpetuation of implicit biases is a longstanding issue in ML/AI systems due to historical biases in the data we have accumulated, which can lead to discriminatory outcomes such as an advertisement algorithm showing more high-paying technical jobs to men than women [190].
  In addition to bias resulting from training data, AI systems may also be affected by unintended bias that can originate from the algorithms and the developers involved in their creation. According to Borenstein and Howard, the decisions made by developers during the design process not only carry ethical implications but also reveal the developers' ethical values. However, developers often view ethics as a responsibility belonging to someone else, such as lawyers or ethicists, rather than as an integral part of their own technological work. [191].
  Finally, it is possible for bias in AI systems to be intentionally introduced with malicious intent. This can occur when developers intentionally manipulate the training data or algorithms to produce biased results, either to promote their own agenda or to harm a particular group or individual. For example, recommender systems may suffer from being attacked by malicious raters, who inject profiles consisting of biased ratings since recommender systems are widely deployed to provide user purchasing suggestions [192].
- Usability
  The adoption of software by human users is primarily determined by its usability, as stated in ISO/IEC 25010 [193]. Usability refers to the extent to which a product or system can be used by specific users to achieve specific goals effectively, efficiently, and satisfactorily in a specified context of use. Usability of all interactive programs is affected by the existence of appropriate feedback and by the ability of the system to perform effective error prevention while users are interacting with the system in pursuit of their goals. However, a lot of important usability factors remain understudied and this is worsening while AI is expanding in the UX. For example, despite the importance of errors in the usability, a recent preliminary study on usability found that errors are among the least commonly considered usability attributes [194].
  Certain aspects of usability are particularly important for Human-AI Interaction. Norman pointed out that the ability to control our systems through interactions that bypass conventional mechanical switches, keyboards, and mice is a valuable addition; however, it also presents new challenges, potential for significant errors and confusion, despite its potential benefits [195]. Nielsen highlights the lack of standards and expectations for UI design on iPad apps which means that anything that can be shown and touched can be a UI on the device [196]. Similarly, to these apps, many assistive AI functionalities are evoked without sufficient notification to the user and thus may cause errors and confusion. For example, If the AI-empowered personal assistant is evoked accidentally by the user,

it may suggest something that the user did not intend to ask for or may not be interested in, which can also cause confusion, misunderstandings, and errors. In the context of usability in UX in AI, two important factors are feedback and error prevention:

∗ *Feedback*:
  ∗ *AI system feedback*: Users should receive feedback whenever they interact with the system, including feedback on any actions taken by AI systems to assist them without explicit request.
  ∗ *User Feedback*: Interactive AI programs can incorporate feedback mechanisms where users can rate the relevance of assistive results or provide explicit feedback on why certain results were not helpful. This feedback can then be utilised to improve the algorithm of the program over time. This mechanism can be applied to various AI-based interactive programs.

∗ *Error Prevention*: To prevent errors and misunderstandings, it is essential to provide feedback to users whenever the AI system takes an initiative to assist them without an explicit request. This feedback should aim to clarify the actions taken by the system and avoid any confusion between the user and the AI system.

– Privacy and security of data
Privacy and security issues are very important in the UX of AI as all personalisation techniques gather information about all possible aspects of users, to be used to tailor user experiences and fit the needs of individual users. However, the information that has been gathered could contain both factual data and conclusions drawn about users, potentially without their knowledge or agreement. This data could also be exploited, altered in a harmful manner, or unlawfully obtained by third parties with a history of engaging in fraudulent or cyber-criminal activities.

∗ *Privacy and security of raw data*: Privacy and security are important considerations when it comes to raw data accumulated for AI processing.
∗ *Privacy and security of preprocessed data*: Preprocessed data can still contain sensitive information, and it is crucial to ensure that it is protected against unauthorised access, misuse, and abuse.
∗ *Privacy and security of AI inferences based on processed data*: When an AI model infers new data, it may generate new information or insights that were not present in the original dataset. This new data may also contain sensitive information. that needs to be protected.

– Ethical Considerations
Ethics of AI studies the ethical principles, rules, guidelines, policies, and regulations that are related to AI. Ethical AI is an AI that performs and behaves ethically [197]. In general, AI ethics encompasses various ethical considerations that aim to ensure AI benefits people, remains impartial, safeguards privacy and security, and operates with transparency and accountability. Ethical considerations are extremely important in some cases in security contexts such as armed conflict, law enforcement, and disaster relief, decisions must often be made with incomplete information, while under the pressure of time and stress. To alleviate some of this pressure, AI systems can provide valuable decision-making support. As a result, such systems will become increasingly vital. Nonetheless, since human lives may be at risk in these situations, humans should retain ethical accountability for any decisions made, regardless of the AI system's involvement, whether it's as a decision-making or decision-support system [198].

### *5.2. Reciprocity of AI-challenges and AI-solutions*

As previously noted, the pursuit of solutions to challenges and problems often takes place within the realm of AI, resulting in a cycle of AI-challenge and AI-solution. This sub-section proposes AI-based solutions from the relevant literature for the challenges that were identified in the previous sub-section.

- *Human-Centered Artificial Intelligence*: (HCAI) is an approach to developing AI systems that prioritises the needs and values of humans. This approach involves designing AI systems that are focused on enhancing human well-being, rather than just optimising technical performance or efficiency. According to Shneiderman, linking the development of AI systems to guidelines that assure transparency and accountability will enhance innovation, public confidence, societal value, and commercial value [199]. The UX of AI should prioritise human-centered design, which means creating interfaces that are intuitive and easy to use. The AI system should be designed to fit seamlessly into the user's workflow and provide value without being intrusive.
- *Explainable AI* (XAI): XAI is an AI system that can provide human-understandable explanations of its decision-making process. In various practical domains, such as medical diagnosis, financial services, legal decision-making, scientific research, and social media analysis, the interpretability and openness of AI models are crucial not only for their end-users and stakeholders but also for the developers and investigators building the AI solutions. For example, researchers are working towards bridging the gap between explicit knowledge-based AI methods, such as Knowledge Graphs, and implicit knowledge-based AI methods, such as Deep Neural Networks, by combining their strengths through Explainable AI research [200]. Explainable Artificial Intelligence (XAI) can play a significant role by providing interpretable and transparent models, which can enhance users' trust in the system [214].
- *Responsible AI*: Ethical discussions are a vital foundation but raising the edifice of responsible AI requires design decisions to guide software engineering teams, business managers, industry leaders, and government policymakers [201]. Regarding responsible AI, one potential approach is to integrate ethical reasoning into the AI systems themselves during their development and incorporation. This means designing AI algorithms and systems with ethical considerations in mind, such as fairness, transparency, privacy, and accountability. By building ethical reasoning directly into AI systems, it becomes easier to ensure that they align with ethical principles and values, which can reduce the risk of unintended harm or negative impacts. This approach can also help promote trust and confidence in AI among users, stakeholders, and the broader public [202].
- *Prosocial AI*: Prosocial AI refers to the development and application of AI technologies with the goal of promoting human well-being and social welfare. This includes the design of AI systems that are transparent, explainable, and trustworthy, as well as those that support ethical decision-making and minimise the risk of negative consequences or unintended harm. By incorporating prosocial principles into the development and deployment of AI, it is possible to create systems that are aligned with human values and promote the greater good. For example, Paiva points out the prevailing view of human decision-making in AI design, which is based on the homo economicus principle, and proposes exploring the creation of AI agents that prioritise prosocial behaviour to cultivate cooperation and contribute to the social good in human settings [203].
- Combination of multiple AI techniques
  AI techniques have advanced to a high extent over the years and involve different approaches. It is considered that AI contains, as a subset, all machine learning algorithms, which in turn contain, as a subset, all deep learning techniques, including neural networks.
  * *Levels of depth of implementations of AI in the systems*
    Artificial Intelligence (AI) can be implemented at different levels of depth, ranging from simple rule-based systems to advanced neural networks. Here are the different levels of depth of AI implementations:
    * *Rule-based systems*: At the simplest level, AI can be implemented as a rule-based system. These are considered very good for explainability, as they can provide human-understandable explanations of the AI-system works.

  * *Machine Learning* (ML): Machine Learning is a more advanced level of AI that uses statistical algorithms to find patterns in data. It has a lot of advantages concerning the analysis of large datasets but it suffers at the explainability level.
  * *Deep Learning* (DL): Deep Learning is a subset of Machine Learning that uses neural networks with multiple layers to learn representations of data. It is able to produce highly accurate results and achieve deep reasoning, but it is considered as the most opaque approach of all, due to its complexity.
  * *Natural Language Processing* (NLP): Natural Language Processing is a specialised field of AI that deals with understanding and processing human language.
  * *Reinforcement Learning* (RL): Reinforcement Learning is a type of Machine Learning where an agent learns to make decisions based on feedback from its environment. RL algorithms are commonly used in robotics and game playing.
  * *Artificial General Intelligence* (AGI): Artificial General Intelligence is the theoretical concept of building a machine that can perform any intellectual task that a human can. AGI is currently the subject of ongoing research and development.

* *Synergies of AI methods* are used to overcome difficulties and provide solutions to large scale complex problems. Bourbakis points out that AI techniques have advanced to a satisfactory level of maturity as independent entities, and their application to small and uncomplicated problems has yielded impressive outcomes. Nonetheless, when it comes to large and intricate issues, these AI techniques alone are not always adequate in delivering satisfactory results [204]. Synergies of AI techniques refer to the cooperative interaction between different AI techniques to achieve better results than what would be possible with any individual technique alone. In many cases, of AI techniques can enhance considerably the accuracy of AI based systems. For example, synergies of AI may be the combination of natural language processing and computer vision techniques to build an AI system that can understand and interpret visual scenes. In this case, natural language processing is used to interpret the language used to describe the visual scene, while computer vision techniques are used to analyse the visual data. The combination of these techniques allows for a more comprehensive understanding of the scene, leading to more accurate and effective results, thus the focus is on combining AI techniques in a way that leads to better overall performance.
  *Fusion of AI methods*: Fusion of AI techniques refers to the combination of different AI techniques or algorithms to solve a particular [205]. One example of fusion of AI is the combination of image processing and machine learning techniques to build an automated quality control system in manufacturing. In this case, image processing is used to detect defects in manufactured parts, while machine learning is used to analyse the images and classify the defects. The combination of these techniques allows for a more accurate and efficient quality control system and the focus is on combining specific AI techniques to solve a specific problem.
* *Hybrid AI*: Hybrid AI is a problem-solving approach that integrates various AI approaches and technologies to address complex challenges. Hybrid AI can combine rule-based systems, Machine Learning, Deep Learning, and other techniques to create more effective and accurate solutions. For example, while rule-based systems were more popular in the past, recent progress in machine learning and deep learning has resulted in the emergence of more refined and adaptable artificial intelligence systems. Nevertheless, deep learning results in the black box problem whereas rule-based systems can still have utility in specific domains, such as decision support systems that require transparency and interpretability. Therefore, a hybrid approach could be adopted for this problem. In another instance, in [206], an approach to hybrid artificial intelligence problem solving aims to forecast physical parameter values in a complex and dynamic ocean environment in situations where system rules are unknown or fuzzy, showing that a combination of connectionist and symbolic techniques can outperform either used separately.

- Levels of breadth of implementations of AI in the systems
  Artificial Intelligence (AI) can be implemented at varying degrees of breadth, depending on the scope and scale of the application. Here are some examples of different degrees of breadth in AI implementations:
  * *Narrow or Task-Specific AI*: Narrow or Task-Specific AI is designed to perform a specific task or set of tasks. These AI systems are focused on solving a particular problem and have limited capabilities beyond their specific task. For example, an approach for automatic task-specific fingertip production and application is described in [207]. Examples include chatbots for customer service, speech recognition for virtual assistants, and image recognition for security systems.
  * *Strong AI or Artificial General Intelligence* (AGI): Artificial General Intelligence (AGI) also known as Strong AI is designed to perform any intellectual task that a human can do. Qualitatively speaking, though, there is broad agreement in the AGI community on some key features of general intelligence such as that General intelligence involves the ability to achieve a variety of goals, and carry out a variety of tasks, in a variety of different contexts and environments and that a generally intelligent system should be able to handle problems and situations quite different from those anticipated by its creators [208]. The development of "strong artificial intelligence" remains a challenging problem due to the difficulty of effectively organizing long-term memory in cognitive agents. Without the ability to use life experience and general knowledge to contextualise situations, it is challenging for these agents to solve complex problems [209]. Despite ongoing research, progress towards a solution has been slow [210]. The importance of context in artificial intelligence has been recognised for some time, with researchers pointing out that contextual information is important for creating effective artificial agents [211]. Nonetheless, the current state of the field suggests that much work remains to be done before we can achieve true artificial general intelligence.
- *Accuracy, Trust and Explanations*
  Trust, accuracy, and explanations are key factors in the design and deployment of AI systems. Studies have shown that users' trust in AI is closely linked to the accuracy of the system's outputs and the quality of explanations provided by the system [212,213]. Lack of trust in AI can lead to decreased reliance on automated systems, which can impact the system's effectiveness. Therefore, it is important to provide accurate and reliable AI models that are capable of providing clear and concise explanations to users, which can build trust in the system [212,214].
  Furthermore, the role of human-in-the-loop [215] is being recognized as a critical aspect to ensure that AI systems align with human values and comply with regulatory frameworks such as the European Union's General Data Protection Regulation (GDPR) [216]. The GDPR emphasises the importance of data protection, and it is the responsibility of organisations to ensure that their AI systems comply with the regulations. Trust and regulation are important factors in the development of human-in-the-loop AI, which involves a collaboration between humans and automated systems. Solutions for accuracy, trust and explanations include the following:
- *Uncertainty quantification*: AI systems can be designed to quantify the uncertainty associated with their predictions.
- *Human supervision*: AI systems can be designed to work in conjunction with humans, who can provide oversight and make decisions based on their own judgement.
- *Human-in-the-loop*: The importance of the human-in-the-loop approach is gaining recognition [215]. It is considered a critical aspect to ensure that AI systems align with human values and comply with regulatory frameworks, such as the European Union's General Data Protection Regulation (GDPR) [216]. The GDPR places a strong emphasis on data protection, and organizations are responsible for ensuring that their AI systems comply with the regulations. Trust and regulation are essential factors in the development of human-in-the-loop AI, which involves collaboration between humans and automated systems [212].

– *Levels of AI development iterations*: An iterative development process can enhance the accuracy and efficiency of AI systems. This involves making incremental improvements over time by gathering feedback, analysing performance metrics, and adjusting algorithms, training data, or infrastructure. By repeating this process over multiple cycles, AI systems can achieve significant performance gains, particularly in machine learning, natural language processing, and computer vision.

To summarise, it is very important to address UX issues in AI for successful adoption and a positive user experience. With the increasing prevalence of AI in our daily lives, addressing these issues is even more vital. As shown, potential solutions include the use of additional AI techniques in a reciprocal cycle. However, this also highlights the need for further enhancement of UX and the resolution of emerging problems that may arise from the complexity of the AI-based solutions. Table 1 presents a summary of various challenges and problems that have been previously identified and discussed, along with their corresponding solutions based on AI.

## 6. Best practices and lessons learned in UX and AI

The intersection of UX and AI requires best practices and research goals that prioritise the development of user-centered, intelligent, and effective systems. As demonstrated in the preceding sections, UX and AI are mutually reinforcing in reciprocity, with advances in one contributing to the improvement of the other, but also with challenges of one requiring further extensive research in the other. The current state-of-the-art UX design for AI-based systems, such as recommender systems, web search engines, virtual assistants, intelligent tutoring systems, and intelligent help systems, has impressively enhanced the user experience. Nevertheless, significant problems remain or have emerged, and solutions must be sought for AI systems that exhibit greater sophistication in reasoning, continuous learning, transparency, and ethical design practices while positioning the human and societal benefit in the centre of the effort. Therefore, it is imperative to incorporate best practices from previous research to facilitate the smooth evolution of UX in AI. In particular, this section outlines best practices in the intersection of AI and UX that are sourced from the author's extensive previous research. These practices have been shown to produce effective and personalised AI-based interactive systems, using methods, processes, and techniques that have demonstrated remarkable efficacy in achieving successful collaboration between AI and UX.

### *6.1. Integrating multiple AI methods to achieve major enhancements in the UX*

A critical best practice for enhancing UX through AI, is the integration of multiple complex AI techniques, so as to have the strengths of each one of them joined together and address the current challenges of AI in UX. However, this approach demands meticulous planning, very careful design and coordination of the requirements and the results, the acquisition of data, the appropriate selection of data sets that are used as well as conducting rigorous empirical studies and evaluation experiments to validate the methods used and ensure better accuracy of the hypotheses generated.

For example, Virvou in [217] has demonstrated the successful combination of Human Plausible Reasoning, which is a cognitive theory and has been used for error diagnosis, with a rule-based system performing goal recognition for response generation in a generate-and-test method in the context of an intelligent help system. This synergistic approach which combines three different techniques, a rule-based system for goal recognition, error detection in sequences of users' actions and human plausible reasoning, has achieved an efficient and user-friendly operation of giving advice to users. The goal recognition system is based on a set of predefined rules that help identify the user's goals based on their actions and inputs. Error detection is performed based on the evaluation of effects of users' actions in terms of the recognized goals. The human

Table 1
Challenges of AI in UX and AI solutions

| Challenges of Artificial Intelligence in User Experience | | | AI solutions |
|---|---|---|---|
| Expectations and unpredictablility | Expectations of the unexpected | Unpredictability of AI behaviour in all possible situations by AI programmers and consequently human users of AI. | 1. *Human-centered AI* (HCAI) to improve human well-being and design AI systems with users at the center of attention. |
| | | Unpredictability of AI behaviour due to fallibility of AI. | |
| | | Unpredictability of AI behaviour due to complexity and interconnections of AI. | |
| | | Unpredictability of AI behaviour due to unknown limitations or biases of training data. | 2. *Explainable AI* (XAI): XAI is an AI system that can provide human-understandable explanations of its decision-making process. |
| | | *Unpredictability of AI behaviour to unexpected situations*. AI is not capable of creative problem-solving in the way that humans can, so it may not be able to respond to unexpected situations in the same way that humans can. | |
| | Uncertain expectations | Overestimation of AI capabilities | 3. *Responsible AI*: Responsible AI requires that AI systems be transparent, which means users should be able to understand how the system works and how it makes decisions and recommendations. Responsible AI requires that AI systems be designed to avoid bias and discrimination and function in an ethical manner. |
| | | Misunderstanding of AI capabilities | |
| | | Fear of job replacement | |
| | False expectations | Omnipotence of AI | |
| | | Omniscience of AI | |
| | | Infallibility of AI | |
| | | Replacement of human intelligence | |
| | | Perfection of natural language processing | |
| | AI preconceptions | AI preconceptions can lead to biased and incorrect assumptions about artificial intelligence, including its capabilities, limitations, and potential impact on society. | |
| | AI phobia | AI phobia is a fear and anxiety towards artificial intelligence that can cause individuals to feel uneasy about the idea of machines potentially taking over human decision-making processes and this fear leads to negative expectations. | 4. *Synergies in AI* techniques refer to the cooperative interaction between different AI techniques to achieve better results than what would be possible with any individual technique alone. For example, accuracy can be enhanced with synergies of AI techniques. |
| Level of trust (causing problems) | Distrust | A lack of trust predicated on previous experience or knowledge. | |
| | Mistrust | A broader absence of confidence that does not necessarily stem from something specific. | |
| | Overtrust | When a person's trust exceeds the system's capabilities. | |
| Black box problem and explainability | The restricting *Dilemmas of Users' Acceptance without explanation* in AI Systems: | Restrictions due to the black box problem: | 5. *Fusion of AI Tecchiques* refers to the combination of different AI techniques or algorithms to solve a particular problem. |
| | "Accept it without explanation and persuasion or leave it" | Restricted verification and cross-examination of AI outcomes. | |
| | "Accept it with no further amelioration or leave it" | Restricted novel creation and extension capabilities based on AI outcomes. | |

Table 1, continued

| Challenges of Artificial Intelligence in User Experience | | | AI solutions |
|---|---|---|---|
| | "Accept it with no collaboration or leave it" | Restricted capacity for human-AI collaboration. | |
| | "Accept it with no sharing or leave it" | Restricted capacity for integrating AI as a third party in human-human collaboration. | |
| Levels of knowledge | *Surface knowledge* primarily involves memorisation of information to aid recall, with limited connections made to other stored memories. | Surface knowledge in UX design relies on assumptions stereotypes and in some cases, prepackaged "canned" knowledge with limited reasoning and understanding capabilities of user needs and can lead users to frustration and lower engagement and *a poor user experiences* (UX). | 6. *Hybrid AI* is a problem-solving approach that integrates various AI approaches and technologies to address complex challenges. Hybrid AI can combine rule-based systems, Machine Learning, Deep Learning, and other techniques to create more effective, accurate and explainable solutions. |
| | *Shallow Knowledge* Shallow knowledge can be defined as having access to information along with a basic level of understanding, interpretation, and sense-making. | Shallow knowledge can lead to restricted comprehension, analysis, and ability to make sense of users, ultimately resulting in *problematic user experiences* (UX). | |
| | *Deep Knowledge* Deep knowledge refers to an extensive, versatile, and flexible comprehension of a particular subject that enables advanced thinking and problem-solving at an expert level. | Deep knowledge can lead to comprehensive understanding of users, their needs, behaviours, preferences, and contexts of interaction and is an essential aspect of designing *successful user experiences* (UX). | 7. *Uncertainty quantification*: AI systems can be designed to quantify the uncertainty associated with their predictions. |
| Levels of anthropomorphic characteristics | Acquisition | Implicit or explicit acquisition needs to be extended in AI systems to include implicit or explicit users' feedback revealing more aspects of users to be modelled to *enhance user experience further*. | 8. *Human supervision*: AI systems can be designed to work in conjunction with humans, who can provide oversight and make decisions based on their own judgement. |
| | Degree of individualisation | Machine learning may address clusters of users rather than individuals. Individual user modelling is more accurate of a person's profile and needs to take over in an interactive system to *enhance user experience further*. | |
| | Modifiability | Modifibility refers how dynamic the user model is in real-time to reflect changes in user behaviour. It also considers whether feedback given by users is incorporated into updates of the user model. *These are important concerns for enhancements of UX*. | 9. AI techniques to improve data security and privacy |
| | Temporal extent | Is it possible for users to experience personalised features for an extended duration even after logging out? | 10. *Affective computing* Progress in affective computing will ensure the incorporation of empathy to AI systems |
| Levels of anthropomorphic characteristics | Natrual language | Natural language provides ease of use as it is the natural way of communication among humans. In the absence of NLP, the user experience may suffer from human errors and higher difficulty. However, the existence of NLP may lead to high human-like expectations that surpass the system's capabilities. | 11. *Natural Language Processing* Progress in NLP aims at a more natural way of communication between users and AI systems |

Table 1, continued

| Challenges of Artificial Intelligence in User Experience | | | AI solutions |
|---|---|---|---|
| | Simulation of human reasoning | The process of simulating human reasoning, including cognitive theories, is tailored to the cognitive abilities of users while considering the limitations inherent in human cognition. In the absence of this process, user experience may become unfamiliar to users. | 12. *Progress towards strong AI* that aims to the ability to achieve a variety of goals, and carry out a variety of tasks, in a variety of different contexts and environments and that a generally intelligent system should be able to handle problems and situations quite different from those anticipated by its creators. |
| | Emotion recognition/ generation | By integrating emotion recognition and generation into user experience, designers can improve empathy and establish a stronger bond between users and AI-empowered systems, but it is important to consider the design implications of emotion recognition such as the accuracy of detection and which emotions the computer should exhibit. | |
| | Anthropomorphic agents | Animated agents that possess human-like abilities such as speech and movement can improve the user experience by making interactions more relatable and familiar.<br>Nevertheless, the similarity to humans may lead to dissatisfaction if the agents' cognitive abilities are insufficient to meet users' expectations, which may be elevated due to the anthropomorphic attributes of the agents. | 13. *Prosocial AI* By incorporating prosocial principles into the development and deployment of AI, it is possible to create systems that are aligned with human values and promote the greater good |
| Degrees of User control | *Passive* AI-empowered systems | Interactive systems that are AI-empowered in a passive manner necessitate the user to explicitly request interaction from the system, giving them the initiative and control over the interaction. | 14. *Ethical AI* is an AI that performs and behaves ethically |
| | *Active* AI-empowered systems | Active AI-empowered interactive systems are those that spontaneously intervene in the relevant context to provide informed AI feedback to users, with the system having the initiative and control of the initial interaction. These systems require careful design to ensure that the AI intervention is helpful without being intrusive and redundant. | 15. *AI development iterations* An iterative development process can enhance the accuracy and efficiency of AI systems. |
| Usability of AI | Feedback | *AI system feedback*: Users should receive feedback whenever they interact with the system, including feedback on any actions taken by AI systems to assist them without explicit request.<br>*User Feedback*: Interactive AI programs should incorporate feedback mechanisms where users can rate the relevance of assistive results or provide explicit feedback on why certain results were not helpful. This feedback can then be utilised to improve the algorithm of the program over time. | |

Table 1, continued

| Challenges of Artificial Intelligence in User Experience | | | AI solutions |
|---|---|---|---|
| | Error prevention | To prevent errors and misunderstandings, it is essential to provide feedback to users whenever the AI system takes an initiative to assist them without an explicit request. This feedback should aim to clarify the actions taken by the system and avoid any confusion between the user and the AI system. | |
| Privacy and security of data | On *raw data accumulated* | Privacy and security are important considerations when it comes to raw data accumulated for AI processing. | |
| | On *preprocessed data* | Preprocessed data can still contain sensitive information, and it is crucial to ensure that it is protected against unauthorised access, misuse, and abuse. | |
| | On *new data created by AI inferences* | When an AI model infers new data, it may generate new information or insights that were not present in the original dataset. This new data may also contain sensitive information. that needs to be protected. | |
| Bias and fairness | Bias due to the incorporation of particular organisational objectives into the AI implementation | The AI system is designed and programmed to achieve a particular business objective that can lead to bias. E.g. An AI system that is designed to screen job applicants for a company may be programmed to prioritise certain qualifications such as a particular college degree. | |
| | Bias due to uneven distribution or representation of samples used for training | The data that is used to train the AI system may not be representative of the real-world population that the system is supposed to operate on. This can result in the AI system making inaccurate or unfair predictions for certain groups. | |
| | Bias due to individual pieces of data that contain inherent biases or inaccuracies and are used for training | The individual pieces of data that are used to train the AI system may themselves be biased or contain errors, which can lead to bias in the AI system's predictions. | |
| | Bias due to developers' unintentional biases in beliefs | AI systems may also be affected by unintended bias that can originate from the algorithms and the developers involved in their creation. | |
| | Bias due to malicious manipulation of data | AI data may be misused and maliciously manipulated to contain bias. | |
| Ethical considerations | AI benefits people | Ethics of AI studies the ethical principles, rules, guidelines, policies, and regulations that are related to AI. | |
| | AI remains fair and impartial | | |
| | AI safeguards privacy and security | | |
| | AI operates with transparency and accountability | | |

plausible reasoning component allows the system to use the cognitive theory to diagnose the cause of errors and generate responses that are more natural and understandable for humans. The generate-and-test approach for advice generation allows the system to generate possible solutions and then test them against the rules of the goal recognition component and human plausible reasoning to determine their validity and plausibility respectively. By combining these different techniques, the synergistic approach can achieve greater accuracy and efficiency than using a single technique alone.

To address user errors in operating systems due to lack of experience, confusion about the system's functionality, or other reasons, the author proposes a two-phase system using automatic reasoning to identify the error's cause and provide relevant help and guidance. The two phases proposed are: error identification and error correction. In the error identification phase, the system uses a knowledge base and inference engine to analyse the user's actions and determine the likely cause of the error. This might involve identifying a mismatch between the user's intended action and the system's expected response or detecting a violation of a system constraint or rule. Once the error has been identified, the system moves to the error correction phase, where it provides the user with relevant help and guidance to correct the error. This might involve displaying a message explaining the cause of the error, generating and suggesting alternative actions the user could take, or providing step-by-step instructions for correcting the error. The system is designed to be adaptable and customisable, allowing it to be tailored to the specific needs and abilities of individual users. The system can also learn from previous interactions with users, allowing it to improve its accuracy and effectiveness over time.

The aforementioned approach which was developed in the context of command-language user interfaces has also been applied by Virvou and Stavrianou [218] in a different type of user interface, such as a Graphical User Interface (GUI) that has shown the generalisation of the approach. Building on this successful generalization, the GUI approach has been extended by Virvou and Kabassi to be combined with a decision-making theory in [219] to improve further the ranking of the hypotheses generated concerning user modelling. In a very different context, the cognitive theory of Human Plausible Reasoning has been combined with two other cognitive theories by Virvou, Katsionis and Manos and all three have been incorporated in the student-modelling approach of a virtual reality educational game to model, in a synergistic way, several aspects of students and achieve a more complete representation of students' internal cognitive, affective and epistemic state [220].

In another research work, Tsihrintzis, Virvou, Alepis and Stathopoulou have shown how to improve the accuracy and reliability of visual-facial emotion recognition through the use of complementary keyboard-stroke pattern in the context of an Intelligent Tutoring System [221]. This work combines neural networks for visual-facial analysis, with analysis on keyboard behaviour of users in terms of speed of writing, frequency of erasing, and accuracy of users' responses. In addition, in machine learning, a movie recommender system based on ensemble of transductive SVM classifiers is an example of how different AI techniques can be combined in a synergistic way to achieve a common goal, resulting in a more effective and powerful solution. In this system, different AI techniques are combined in a synergistic way to achieve the common goal of recommending movies to users. Specifically, the system uses an ensemble of transductive SVM classifiers, which is a combination of multiple SVM models trained on labeled and unlabeled data. This approach allows the system to handle a large amount of data and improve its accuracy over time [222]. Additionally, the system may also incorporate other AI techniques such as collaborative filtering, natural language processing, or deep learning to improve its recommendation accuracy and functionality.

The expansion and combination of well evaluated research approaches with other AI techniques may contribute results in UX with higher accuracy and this is considered a very good practice. For example, the research work by Tsihrintzis and Nikias describes the development of data-adaptive algorithms for signal detection in sub-Gaussian impulsive interference [223] and Tsihrintzis and colleagues in [224]. While this work does not specifically address the fusion of AI techniques for UX, it is possible that the algorithms presented in this work could be combined with AI techniques to improve the performance of signal processing systems in various applications, including UX design. Indeed, the algorithms could be used to filter out noise from user interactions with a device, while AI techniques such as deep learning could be used to recognise patterns in user behavior and adapt the system to the user's preferences. The foundational concepts and techniques presented in the above work could serve as a valuable starting point for researchers and practitioners seeking to develop high quality combined approaches to signal processing and UX design.

### 6.2. *Iterative deveopment and empirical studies of AI-empowered interactive systems*

The best practice of iterative development with empirical studies and evaluation experiments in each iteration is supported by various research projects in AI development for user experience. In particular, empirical studies and evaluation experiments require a significant amount of planning and coordination, involving multiple users and researchers and must be carefully designed and executed to ensure the highest possible accuracy and reliability of the hypotheses generated. For instance, researchers have emphasised the importance of breaking down the project into smaller, manageable pieces, and continuously evaluating each iteration to ensure it meets user needs and goals. This approach has been discussed in research articles of the author of the present paper with colleagues, such as work on the regulation and validation challenges in AI-empowered healthcare applications [225], or in another instance, on addressing the issue of undeclared work with CRISP-DM [226], on research concerning the software life cycle of an intelligent tutoring system [227], on clustering for user modelling using RUP [228] and in another instance, on a knowledge-based software life-cycle framework [229]. Additionally, the use of established software life cycle frameworks has been shown to provide a structured approach to iterative development and improve the quality of the final product of AI development for user experience. Evaluations in each iteration can involve user testing, data analysis, and feedback from stakeholders, which can help identify and address issues early on, leading to a more refined and effective end product.

Best practices for UX in AI also require the conduct of empirical studies to ensure that AI systems meet the needs, expectations, and limitations of stakeholders. Virvou and Tsiriga [230] emphasise that involving end-users, such as teachers and students, throughout the development of an intelligent tutoring system can help ensure that the system is user-friendly and accurately tailored to their needs. Moreover, it is important to conduct risk analysis for identifying and managing risks in the development of AI based UX, such as the work demonstrated in [231] for the UX of online educational software. This is a significant practice for conducting empirical studies and risk analysis for UX in AI.

Clear requirements specifications, as illustrated by the study on facial expression classification by Stathopoulou and Tsihrintzis [232], are also very important for the effective development of AI systems. In this work, the empirical study led to the accumulation of a database of images of users' emotions as expressed in their respective face images. An appropriate database of images is vital for the accuracy of personalisation. Cultural factors can heavily influence the expression of emotions in people's faces, with some cultures displaying more intense or different expressions than others. Thus, the training of neural networks for the recognition of emotions should be performed based on appropriate databases. Finally, combining multiple modalities, as demonstrated by Virvou and colleagues [233], such as audio-lingual and visual-facial, can enhance the accuracy of emotion recognition systems, after having conducted detailed empirical studies, concerning each modality, namely audio by collecting empirical evidence on users' voices, lingual by collecting empirical evidence on the use of words for sentiment analysis, and visual -facial as described previously. By following these best practices, UX designers and developers can develop effective and user-friendly AI systems that meet the needs and expectations of stakeholders.

### 6.3. *Thorough and multi-aspect evaluations of AI-empowered interactive systems*

Thorough and multi-aspect evaluations are very important as a best practice when assessing the effectiveness of artificial intelligence (AI) systems. Multi-aspect evaluation refers to the approach of considering multiple different aspects or dimensions of an AI system's performance, such as its effectiveness, usability, and user experience, especially when combined roles or combined methods of AI are involved. In [234], Virvou provides insights into the evaluation of the combined role of educating and entertaining of virtual reality games and animated agents in the context of edutainment, which can be extended to evaluations of UX of AI systems in other domains. Evaluating aspects such as usability, likeability, user experience, and educational effectiveness can also provide valuable information, as demonstrated in studies such as [235–237].

This is particularly important in cases where the aimed UX requirements possibly have conflicting effects on user experiences. For example, in educational games, the aim is to provide likeable and motivating learning experiences that will reduce the users' fatigue caused by the cognitive load of the users' learning a new subject. However, it has to be evaluated if the gaming environment is educationally effective, as this is the primary aim of the whole software [235]. Moreover, it has to be evaluated if the gaming environment does not lose its attractiveness for the users due to the possibly conflicting and fatiguing aspect of tutoring, or that the user does not become cognitively overwhelmed by having to play a complicated game on top of learning a difficult subject [236], or that the gaming features are not too hard for the user to handle [237].

Another aspect to be evaluated is whether the addition of anthropomorphic features in AI-based UX dies indeed ameliorate the user experience and the effectiveness of the AI-empowered interactive application as in [238] which describes research on the evaluation of the persona effect of an interface agent in a tutoring system. In cases, where the human-like interfaces are aimed to produce better user experiences with more effective outcomes detailed and carefully designed evaluations are necessary for demonstrating how well an AI system meets the needs and expectations of its users, and how it can be improved to enhance its performance in the aimed qualities of UX. One important approach is to compare AI systems' performance with human experts as in [136,239,240] or with non-AI versions to determine their effectiveness, as in [241,242]. This can provide valuable insights into the strengths and weaknesses of AI systems.

Another effective approach is to construct and simulate user-agents for multiple evaluation experiments, as demonstrated in [243]. This approach can provide a more comprehensive understanding of the performance of an AI system and how it interacts with users. Evaluating acceptance by both experts and non-experts is also important, as seen in [244]. Such evaluations can provide a more holistic understanding of the effectiveness of an AI system.

In view of the above, thorough and multi-aspect evaluation approaches are critical when assessing the effectiveness of AI systems. By considering different evaluation methods and aspects, we can gain a more comprehensive understanding of an AI system's performance and how it can be optimised for better results.

### *6.4. User modelling servers and authoring tools*

Best practices in user experience (UX) and artificial intelligence (AI) include the development of user modelling servers and authoring tools. As demonstrated in previous sections, the development of sophisticated UX in AI can be difficult, complex and costly. Therefore, the generalisation of techniques, which are incorporated in user modelling servers and authoring tools, constitutes a best practice to gain reusability, customisability and refinement in many circumstances. User modelling servers, such as the one described in [245], allow for the creation of personalised adaptive help systems that adjust to the users' needs and preferences. Authoring tools, such as the web-based tool described in [246], can be used to generate intelligent tutoring systems. Additionally, FSP Creator, a novel web service API creator for students' progress profile using fuzzy sets as described in [247], enables the creation of personalised profiles for learners. Another example of an authoring tool is INMA, a knowledge-based tool for music education described in [248]. These tools enable designers and developers to create more cost-effective complex AI-based interactive applications that enhance UX.

### *6.5. Responsible AI and personalisation*

Responsible AI is very important in ensuring that AI systems are developed and used ethically and that the benefits of AI are maximised while minimising its potential negative impacts. One aspect of responsible AI in UX is data privacy, which has to be ensured in personalisation. As personalised AI systems often collect and process personal data, data privacy should be at the forefront of design and development.

The General Data Protection Regulation (GDPR) provides a framework for protecting personal data, and compliance with this regulation is necessary for any AI system that processes personal data [249]. To ensure compliance, AI systems should be designed appropriately while still delivering the intended functionality. Additionally, consent should be obtained from users before collecting their personal data [250].

Smart educational games are an example of personalised AI systems that require careful consideration of data privacy [251]. To ensure GDPR compliance, designers of such games should develop systems that obtain informed consent from users before collecting their personal data. This can be achieved by providing clear and concise information about the data collected and how it will be used [252]. By following best practices in data privacy, AI designers and developers can ensure that their systems are ethical, secure, and trustworthy.

## 7. Conclusions and future research

In conclusion, the reciprocity between AI and UX is becoming increasingly important as AI-based systems become part of our daily lives routine spanning all aspects of professional, personal and social activites. In this paper, we have reviewed the current state of the art in AI and UX, including user modelling, web searching, recommender systems, intelligent help systems, virtual assistants, and intelligent tutoring systems, and identified best practices and research goals for future work.

We have found that user modelling is a key area for improving the UX of AI-based systems, and that individual and community-based models can both provide valuable insights. Additionally, personalisation and explainability are important factors for effective and relatable user experiences and AI-based interactive systems can benefit from the use of natural language processing, affective computing and adaptive feedback.

Future research should focus on the development of more sophisticated AI algorithms and models that can better incorporate human behaviour and preferences. Additionally, continued investigation into the ethical implications of AI-based systems will be necessary to ensure that they are deployed in a way that benefits users and society as a whole. One solution to ethical problems encountered in UX and AI, is the development of ethical AI models to be incorporated in the reasoning of AI.

In general, the field of AI and UX is a rapidly evolving and exciting area of research, with many promising opportunities for improving the usability and effectiveness of intelligent interactive systems and with a lot of challenges to be resolved by further development of AI.

## Acknowledgments

I wish to thank Professor George A. Tsihrintzis, Editor-in-Chief of this journal for kindly reviewing this paper and offering constructive comments.

This work has been co-financed by the European Regional Development Fund of the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under thecall RESEARCH-CREATE-INNOVATE (project “KnowYourVisitor”, project code: T2EDK-02654).

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