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REVIEW

Personalized smart immersive XR environments: a systematic literature review

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Abstract
In this paper, we investigate the current state and development of personalized smart immersive extended reality environments (PSI-XR). PSI-XR has gained increasing traction across various fields such as education, entertainment, and healthcare, offering customized immersive experiences that address users' personalized needs. This study performs a systematic literature review by collecting and analyzing related journal and conference papers in the domain. Following a comprehensive search across three databases, which yielded 1276 papers, a refined selection of 94 publications was made to conduct an in-depth analysis of cutting-edge research in the field of PSI-XR. This review focused on examining application domains, relevant technologies, and smart techniques, including artificial intelligence, with particular emphasis on advancements in personalization. The study provides insights into prospective advancements while also identifying the opportunities and challenges in this evolving field. This review is beneficial for both researchers and developers interested in exploring the state-of-the-art personalized perspective in a smart immersive extended reality environment.

Keywords Extended reality · Personalized · Human-centered · Immersive XR · Virtual reality · Augmented reality · Mixed reality

1 Introduction

Extended reality (XR) has been increasingly adopted across various domains, demonstrating its expanding applications and transformative potential in both academic and industrial fields. XR is a broad concept that encompasses technologies like virtual reality (VR), augmented reality (AR), and mixed reality (MR), providing different degrees of a virtual environment with immersive experiences that allow users to explore and interact. According to Milgram and Kishino [1], the "virtuality continuum" can be used to define the different degrees of virtual environments, ranging from real environments to fully virtual environments, which is also called VR. VR isolates users from the physical world to engage entirely in virtual spaces, providing a fully immersive digital world. MR lies between the two extremes, blending the physical and digital worlds, allowing real and digital objects to coexist and interact seamlessly in real time. AR also lies between these two extremes, overlaying digital elements onto the real world, enhancing the physical environment with additional information or interactive features.

XR has become increasingly important in modern society [2], which has a wide range of applications, spanning fields such as education [3], healthcare [4], and entertainment [5], with significant potential already demonstrated. For instance, AR enhances chemistry experiments for students by overlaying digital guidelines onto physical laboratory setups, providing real-time instructions and visual aids that improve understanding and overall education quality [6]. Additionally, both MR and VR are revolutionizing entertainment and traveling, providing immersive gaming experiences to players and giving a novel interactive exploration of cultural heritage applications that recreate historical sites.

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Immersion is one of the crucial characteristics of VR systems [7, 8] and is equally important in personalized smart immersive extended reality environments (PSI-XR), which can be understood as the objective level of sensory fidelity provided by XR environments [9]. As XR technology becomes more widespread, XR immersive systems are also becoming a research hotspot. These systems combine the features of VR, AR, and MR to offer users an immersive interactive experience, enabling them to engage in realistic behaviors and reactions within virtual environments, which are similar to those in the real world. In recent years, the rapid development of devices such as head-mounted displays (HMDs) and AR glasses, for example, the Varjo-XR4 and XREAL One, has significantly advanced the evolution of immersive XR. These devices not only approach human eye resolution, greatly enhancing the sense of immersion for users, but also integrate various interaction techniques to enrich user interactions within virtual spaces. The advancements in these devices lay the foundation for building immersive systems. Meanwhile, smart techniques enable XR systems to capture, analyze, and adapt dynamically to user behavior and data, contributing to the smart XR environment.

In the background of advancements in various technologies and smart techniques, the design principles of human-centered approach and personalization have become important for further improving users' experience, which enhances the adaptability and interactivity of XR systems, improving user engagement and satisfaction within immersive XR. Therefore, exploring how to integrate and achieve personalization and human-centered principles into XR using various techniques and technologies is of great significance for optimizing user XR experience.

The definition of personalization in different fields is provided by Fan and Poole [10]. In cognitive science, personalization is concluded as "a system that makes explicit assumptions about users' goals, interests, preferences and knowledge based on an observation of his or her behavior or a set of rules relating behavior to cognitive elements" [10]. In the computer science field, personalization often refers to presenting customers with services that are relevant to their current locations, activities, and surrounding environments [11] or "a toolbox of technologies and application features used in the design of an end-user experience" [12]. Even though some works emphasize that only meeting the user's preference is personalization, Kramer et al. [12] argued that personalization is the approach to improve the end-user experience. This paper aims to explore the relevant application areas in PSI-XR and summarize the technology and human-centered techniques used to achieve PSI-XR.

PSI-XR is an advanced evolution of XR technologies, including VR, AR, and MR. Different from traditional XR, which only provides immersion in virtual or mixed realities, PSI-XR takes it a step further by leveraging smart techniques to create a human-centered environment, enabling users to achieve personalization and further enhancing their immersive experience.

It is worth mentioning that when we describe a concerned technique as *smart*, we refer to the definition of *smart* within the context of information technology by Bures et al. [13]. In this paper, for PSI-XR, we summarized the definition of *smart* as follows: Smartness enables the system to act with self-adaptation and self-optimization while also coordinating effectively with and responding to the environment, with a particular focus on its users. We assume that it could be built with or without artificial intelligence (AI). Hence, we do not limit ourselves to only AI-based smart techniques employed in the personalization process of XR environments.

Also, we aim to identify relevant work in PSI-XR to explore how personalization can be achieved. Finally, through this review, we hope to identify the challenges faced by current PSI-XR and summarize potential opportunities for future development.

To meet the overall aim of our review, the following research questions (RQs) have been identified:

- **RQ1**: What are the main application areas of personalized smart immersive XR environments?
- **RQ2**: What technologies and techniques have been used for personalized smart immersive XR environments?
- **RQ3**: How have human-centered techniques achieved personalization in smart immersive XR environments?
- **RQ4:** How have AI vs. non-AI techniques enabled the development of personalized smart immersive XR environments?
- **RQ5**: What are the opportunities and challenges of achieving personalized smart immersive XR environments?

The rest of the paper is structured as follows. Section 2 presents the related work regarding immersive XR, human-centered approaches, and personalization in different fields from previous reviews and surveys. Section 3 outlines our systematic literature review (SLR) methodology in detail, together with the approach for data collection, filtering, and evaluation. Section 4 presents the basic information of the selected papers and the response to our RQ1, RQ2, RQ3, and RQ4 in terms of application areas, relevant technologies and techniques, the achievement of personalization, and the analysis from an AI perspective. Subsequently, challenges and opportunities are discussed in Sect. 5 (RQ5) in light of the reviewed material, followed by the conclusion in Sect. 6.

2 Related work

This section presents the previous work conducted in different fields, reviewing the related research regarding smart techniques, immersive XR environments, human-centered approaches, and personalization. We have organized the following sections from the perspective of various prominent fields that have conducted reviews or surveys dealing with one or more aspects of immersive XR environments.

In the context of interfaces, Partarakis and Zabulis [14] review the work contributing to digital interface interaction and information processing. They argue that understanding the context, content, and users' semantic knowledge enables systems to provide more meaningful and personalized interactions, which is beneficial for various fields related to interfaces. AI helps human-centered XR systems understand user behavior and enhance users' experience based on context and preferences. According to their findings, interfaces will increasingly leverage AI to offer smart human-centered experiences, adapting in real time to user preferences, behaviors, and changing needs. They also emphasize the need for interdisciplinary collaboration involving design, psychology, technology, and ethics. Natural and intuitive interaction methods, such as voice recognition, gesture control, and gaze tracking, help reduce cognitive load and enhance the user experience. This work discusses only from the perspective of the human-centered interface, without other possible areas in XR.

In the healthcare context, Mazzolenis et al. [15] review the role of AI and VR in enhancing cognitive pain therapy for chronic pain management. They conclude that AI significantly enhances the personalization of treatment plans, and AI-driven avatars providing mental health support are expected to become a significant trend. Medenica et al. [16] conduct a literature review on the application of AI in neuropsychological rehabilitation for brain injury patients, specifically exploring the application in neuropsychological rehabilitation with personalized monitoring for patients with traumatic brain injury (TBI). This study emphasizes that AI provides personalized interventions during the rehabilitation process according to users' state, which improves assessment accuracy and optimizes rehabilitation strategies. However, users' state evaluations according to their situation are equally beneficial for worker training and student learning guidance, not just in the rehabilitation field.

In education, Qushem et al. [17] review personalized or precision education (PE) in integrating multimodal techniques, contributing to customizing individuals' learning experiences based on their preferences. Recent implementations and applications of systems are examined, including learning management systems, mobile applications, classroom techniques, etc. Finally, they provide four recommendations from the perspectives of practice and policy. However, they only consider the implementation of personalization in education at the application level and did not explore how the underlying techniques of these applications contribute to personalization in detail, nor which techniques are employed in achieving it. Also, they do not consider achieving personalization within the immersive experience provided by the XR Environments.

To explore personalization in education, Zhang et al. [18] conduct a literature review on integrating serious games and VR in education, demonstrating their role in history education. They find that VR and serious games enhance personalized and intelligent learning experiences and increase students' learning enthusiasm and academic performance. However, their work is limited to the context of history education, which does not fully reflect the impact of VR and serious games on the entire education field and other application cases.

Marougkas et al. [19] conclude that personalized approaches in VR are an effective strategy to help students improve learning efficiency. Personalized learning involves considering students' interests, abilities, learning styles, preferences, learning needs, and prior knowledge of the subject, resulting in an outcome-driven educational process. Four ways for achieving personalization are summarized: real-time object manipulation, intuitive navigation, personalized feedback systems, and guidance assistance. This work highlights how game strategies can be used for educational purposes to create personalized experiences, including controller tutorials, gamified scenarios, and reward systems. de Giorgio et al. [20] review the state-of-the-art XR technologies in manufacturing education and training. They examine the significant role XR plays in maintenance operations and safety protocols, exploring how XR can improve the quality of training while reducing costs. However, this work does not address how personalization can be used to enhance the XR educational experience.

As outlined in our RQs, compared with the related work above, the scope of our review covers various fields, not just limited to a specific field, such as education. Additionally, our review considers what smart techniques are utilized in XR and how they combine to contribute to the personalized XR experience, which provides insight from the perspective of smart techniques. It provides a detailed analysis of personalization in immersive smart XR environments and outlines the challenges and opportunities for future research.

3 Method

Our work follows the standard SLR procedure [21] to ensure transparency and completeness in the review process. Our strategy is developed based on clearly defined RQs, systematically identifying the related published work while following the explicit inclusion (IC) and exclusion (EC) criteria. This study aims to identify and critically assess relevant research in a personalized, smart, immersive XR environment in various fields and to collect and analyze data within this work.

A brief overview of the SLR method in this study is shown in Fig. 1. In the following, we outline our data collection strategy, including formulating the search string and the search process across the three datasets. Then, we present our IC/EC criteria and the data filtering process conducted by all authors in accordance with these predetermined criteria. Lastly, we present a summary of the data yielded after two rigorous rounds of review.

3.1 Data collection

Data collection followed the definition of our review aim. The search string was designed based on the five RQs we proposed, and the paper retrieval was conducted in the Association for Computing Machinery (ACM) Digital Library, the Institute of Electrical and Electronics Engineers (IEEE) Xplore, and Scopus libraries. Similarly, IC/EC criteria were established according to our review aim, including five RQs and the SLR standard procedure. Subsequently, all authors participated in the data filtering and evaluation process, applying the designed IC/EC criteria to include papers in our review that meet the requirements of our review aim.

3.1.1 Search string

Based on the aim of our review and the five RQs mentioned above, the search string was designed as follows:

(“*virtual reality*” **OR** “*augmented reality*” **OR** “*mixed reality*” OR “*extended reality*” **OR** *VR* OR *AR* **OR** *MR* **OR** *XR* **OR** “*3D scene*” **OR** “*3D environ**”) **AND** (*immers**) **AND** (*smart* **OR** *intellig** **OR** *AI* **OR** “*artificial intellig**” **OR** *ML* **OR** *DL* **OR** “*machine learning*” **OR** “*deep learning*” **OR** “*generative AI*” **OR** “*agent-based*”) **AND** (*personali** **OR** *human-cent** **OR** *custom** **OR** *user-cent** **OR** *adapt** **OR** “*context-aware**” **OR** “*empath**” **OR** “*affective**” **OR** “*user-aware**”)

To further analyze the search string we designed, it can be seen as composed of four different components, as shown in Table 1, with each unit representing a different search objective:

- The first substring attempts to capture the XR and connected three-dimensional (3D) environments, which is the basic search in our RQs and the fundamental area of our research. To capture this effectively, the search string included virtual reality, augmented reality, mixed reality, and their abbreviations *AR*, *VR*, *MR*, “*3D environ**”, as well as “*3D scene*”, etc.
- To filter XR and connected 3D environments that provide an immersive experience, the second substring included the term “*immers**.”
- Smart methods in their various forms were incorporated by adding the search terms such as “*smart*,” “*artificial intellig**,” “*AI*,” etc., to meet this search requirement.
- Since personalization of XR environments using different techniques is at the core of this SLR, the final substring included terms like “*personali**,” “*human-cent**,” “*custom**,” etc., to target personalized and human-centered experience.

3.1.2 Search procedure

The digital libraries for our search were identified parallel to determine the search string. To this end, the ACM Digital Library, the IEEE Xplore, and Scopus libraries were searched. We preferred digital libraries over confining the search to a specific publishing venue to obtain exhaustive results. Furthermore, we enabled the inclusion of publications in journals, conferences, and workshops, and both short and full papers could be filtered.

Scopus is an extensive database that includes as many papers as possible and avoids omitting any relevant papers. At the same time, the IEEE Xplore and the ACM Digital Library are well-known databases in our field. Therefore, they were included in our search despite duplications in the search results with Scopus. This way, we aimed to ensure no relevant published papers were missed.

The search yielded many hits for Scopus and other databases, while the search string was applied to three data fields: title, abstract, and keywords when querying the databases. The search results in different databases are shown in Table 2. Scopus, being the most comprehensive database, yielded the highest number of results, with 1057 articles. A total of 172 papers were obtained in the IEEE Xplore database search, and only 47 papers were obtained in the ACM Digital Library.

3.2 Inclusion/exclusion criteria

To ensure that the selected papers were relevant to our overall aim and RQs, the papers were evaluated using the following IC/EC criteria.

A publication was included for further analysis if:

- *IC1*: it proposes a *concept* or *idea* that contributes to the personalized experience using smart techniques in an immersive XR environment.
- *IC2*: it proposes a *method* or *framework* based on the implementation that contributes to the personalized experience using smart techniques in an immersive XR environment.

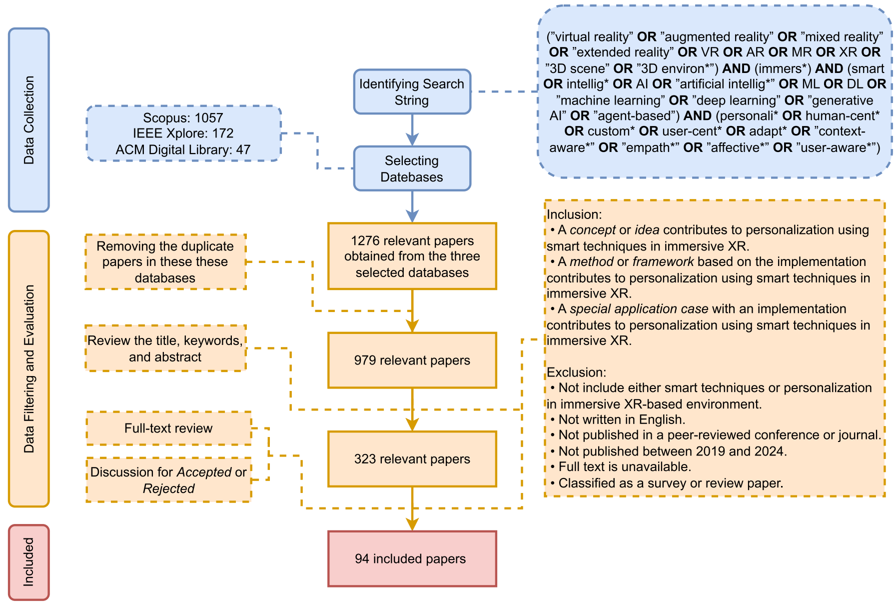

Fig. 1 Our SLR method includes data collection, data filtering, and evaluation process

Table 1 Based on the goals of our review, there are four related components that the search string targets: XR environment, immersive experience, smart techniques, and personalized experience

Target	Sub-string composition
XR environments	(“*virtual reality*” **OR** “*augmented reality*” **OR** “*mixed reality*” **OR** “*extended reality*” **OR** *VR* OR *AR* **OR** *MR* **OR** *XR* **OR** “*3D scene*” **OR** “*3D environ**”)
Immersive experience	(*immers**)
Smart techniques	(*smart* **OR** *intellig** **OR** *AI* **OR** “*artificial intellig**” **OR** *ML* **OR** *DL* **OR** “*machine learning*” **OR** “*deep learning*” **OR** “*generative AI*” **OR** “*agent-based*”)
Human-centered experience	(*personali** **OR** *human-cent** **OR** *custom** **OR** *user-cent** **OR** *adapt** **OR** “*context-aware**” **OR** “*empath**” **OR** “*affective**” **OR** “*user-aware**”)

- *IC3*: it combines a *special application case* with an implementation to achieve a personalized experience using smart techniques in an immersive XR environment.

A publication is excluded for further analysis if:

- *EC1*: it does not include smart techniques or human-centered/personalization in an immersive XR environment.
- *EC2*: it is not written in English.
- *EC3*: it is not published in a peer-reviewed conference or journal.
- *EC4*: it is not published between 2019 and 2024.
- *EC5*: it is not available for the full text.
- *EC6*: it is a survey or review paper that is excluded from any synthesis but discussed in the related work.

3.3 Data filtering and evaluation

Since there were duplicate papers in the search results from the three databases, the duplicate papers were discarded immediately. After that, there were two rounds of data filtering and evaluation.

In these two rounds, all papers were divided into three groups: *Accepted*, *Rejected*, and *Uncertain*. After the second round, only the papers in the *Accepted* group were ultimately included in the result analysis and discussion.

In the first-round review, the title, keywords, and abstract were considered to assess the paper's relevance to our review topic. This categorization was based on how closely the content of the title, keywords, and abstract aligned with the goal of our review, whether the paper could answer any RQs mentioned, and whether it met the requirements of the IC/EC criteria above. All papers were categorized by the first author in the first round of reviews. The first author has a background in digital twins for large-scale urban scenarios, providing needed insights for evaluating papers relevant to the topic of this SLR. Papers that could not be determined to be *Accepted* or *Rejected* in this round were classified as *Uncertain*, while papers assigned in the *Rejected* category were discarded directly.

Table 2 The number of papers retrieved from Scopus, IEEE Xplore, and the ACM Digital Library, based on the search string applied to author keywords, abstract, and document title fields. Each "|" between fields represents the 'OR' operator

Data fields	Database	Number of publications
Abstract |Author Keywords |Document Title	Scopus	1057
	IEEE Xplore	172
	ACM	47

In the second round, all papers from the *Accepted* and *Uncertain* categories in the first round were included for further re-evaluation and category. In this round, the full text of the papers was considered to facilitate classification. The classification criteria remained the same as in the first round, based on whether the paper met the requirement of our review goal by answering our RQs and the above IC/EC criteria. The authors have backgrounds in VR user studies, AI, and computer graphics, contributing with their domain knowledge in the second-round review selections. The papers were distributed among the authors, who then reassigned the papers to the appropriate categories. After all authors completed their review of the assigned papers, the papers were categorized into three groups—*Accepted*, *Rejected*, or *Uncertain*. For articles in the *Uncertain* category, discussions were organized among all authors about the relevance of each paper. After that, all articles in the *Uncertain* group were reclassified into either the *Accepted* or *Rejected* group. Thus, this step categorized all papers into the *Accepted* or *Rejected* group.

Finally, all papers in the *Rejected* group were discarded, while those in the *Accepted* group were included in the selected articles for further analysis of results and discussion. As mentioned, 1276 papers were obtained from the three databases based on our search string, with 297 duplicate papers. Thus, 979 papers proceeded to the first round after removing duplicate papers. After the first round of review, the number of papers was reduced to 323, and only 94 papers remained after the second round of review. These 94 papers were included in the review to analyze and answer our RQs.

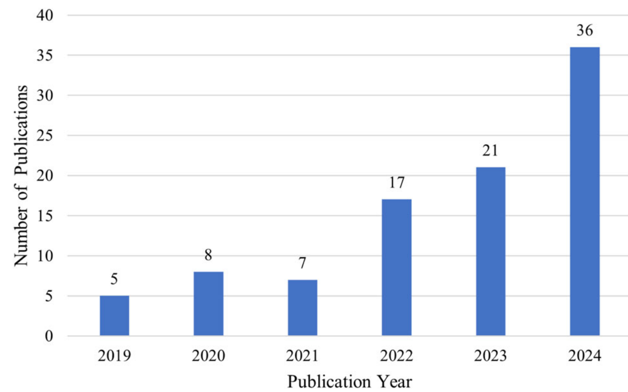

Fig. 2 Yearly distribution of the 94 selected papers from 2019 to 2024, with years on the x-axis while the number of publications on the y-axis

4 Results

This section systematically addresses RQ1, RQ2, RQ3, and RQ4 in this review. Firstly, it begins by analyzing the publication information to provide an overview of our selected papers. Following that, the main application areas of PSI-XR (RQ1) are discussed. Subsequently, RQ2 is answered from the perspectives of technologies and techniques, respectively. The discussion then transitions to the achievement of personalization in PSI-XR (RQ3), building upon the technologies and techniques previously discussed. Finally, further analysis of AI-based and non-AI techniques contributing to PSI-XR (RQ4) is concluded and presented.

4.1 Publication information

A brief picture of the review results is given in this section. The 94 selected papers were categorized in terms of publication year and country to show some basic information of our selected papers.

Publication year: As shown in Fig. 2, the number of papers published in PSI-XR has rapidly been on the rise since 2022. The papers published in 2023 and 2024 far exceed the total four years from 2019 to 2022. This indicates that research related to PSI-XR has steadily increased over the past six years.

Country distribution: The selected papers are authored by researchers from 30 countries and regions. In this work, we applied the rule proposed in [22] to identify and assign scores to the countries or regions these papers originated from. Each paper is worth one score. If all the authors of a paper are from the same country or region, that country or region receives the full score. If the authors are from different countries or regions, this score is divided among those countries or regions according to the formula "M/N," where N is the total number of authors, and M denotes the number of authors from that country or region. After calculating the score for every country or region, the top ten list (including ties for tenth place) is as follows: the USA, Germany, China, Taiwan, Australia, India, Italy, Greece, Portugal, South Korea, and the UK.

A market report [23] highlights several countries as key players in the VR industry. Notably, most countries in our top ten list, such as the USA, China, Germany, and Italy, are also prominently featured in the market report. This overlap underscores the synergy between academic research and market dynamics. It demonstrates that countries leading in VR-related research are often the same ones driving innovation and adoption in the commercial market. This alignment not only validates the importance of our academic analysis but also situates it within the broader context of global development and market expansion.

4.2 Main applications

To answer RQ1, we have identified and summarized the following main application areas that employ PSI-XR in the collected papers.

E-commerce & business: E-commerce has emerged as a popular application to benefit from XR environments. The applications of the work of Gironacci [24], Khatri et al. [25], and Pfeiffer et al. [26] allow customers to shop online using the XR environments with personalized recommendations. Additionally, by classifying customers' personality domains, Khatri et al. [25] contributed to customer behavior research during a purchase in a virtual retail store.

The main application area of the work of Manfredi et al. [27], Luidolt and Zhou [28], Tong et al. [29], Kumar et al. [30], Kumaar et al. [31], Zhuang [32], and Wong et al. [33] is online shopping in the XR environment. Manfredi et al. [27] propose a personalized avatar generation method for shopping clothes, while Luidolt and Zhou [28] propose a method that maps a two-dimensional (2D) image of clothes to a user's 3D personalized avatar. Kumar et al. [30] focus on tailored property purchase virtual experience, while Kumaar et al. [31] contribute to online shopping for virtually try-on products. In the virtual online furniture shopping field, Tong et al. [29] allow users to customize their furniture of interest to meet their personalized requirements. Zhuang [32] utilizes AI to create an interactive and secure shopping environment, ensuring privacy while offering personalized shopping recommendations. Do et al. [34] propose an intelligent mobile AR application for personalized furniture in online furniture shopping and digital commerce. Doungtap et al. [35] propose a shopping assistance automatic suggestion model integrated into VR environments in order to improve the online shopping experience.

For the domain of traveling, Veliz et al. [36] propose a method that supports trip visualization. Hotels and travel attractions are recommended to users based on their preferences. This allowed users to get a preview from the XR environment. Also, Constantinou et al. [37] propose a content-based (CB) filtering method to recommend sites and services to tourists, which can be applied in the travel industry.

For virtual meetings, Fuchs et al. [38] propose a novel virtual meeting room that provides the dynamic change of a virtual environment based on users' voices and discussion content, adjusting to suit the emotions of multiple users. Also, to balance the interaction and information displayed in an XR environment in a virtual meeting environment, Casoria et al. [39] propose a method to update the layout of current information for communication according to users' behaviors.

In engineering consultation, Wu et al. [40] and Trappey et al. [41] propose a chatbot to answer technical questions for different customers related to their specific industrial requirements. Zhao et al. [42] propose a method that contributes to XR live sessions and allows users to customize their avatars, including facial expression, sound, text, texture, and animation state, delivering a vivid performance.

Entertainment & art design: PSI-XR has the potential to significantly enhance both the entertainment and artistic design areas. For XR personalized game experience, de Lima et al. [43] propose a method to adjust the horror intensity based on the user's behavior in VR. Similarly, Ojha et al. [44] propose a method to adapt the game content to players' individual fears and preferences, which enhances the immersion and excitement of horror games.

Gesture nesting is a common problem when multiple gestures are performed simultaneously, resulting in gesture conflicts or misidentification. Gao [45] proposes a gesture recognition method, which solves the gesture nesting problem and improves the system's robustness, making it suitable for interactive games. In live sports spectating, Lo et al. [46] provide users with game-related information based on their preferences and the current game process.

For art design in 3D scenes, Valenza et al. [47] capture users' neuromonitoring data, functional magnetic resonance imaging (fMRI), and transferred this brain signal to 3D scenes for further art design. Music performance is the main application area in [48], which provides users with personalized gestures for music design. Additionally, Sanatani [49] proposes a method to predict users' emotions in the designed virtual space used in room space and architecture design. He et al. [50] propose a method to transfer users' text input into 3D content to support VR art design. Constantinides et al. [51] propose a system that allows users to interact with digital artworks via voice, posing questions, and receiving personalized responses. Forero et al. [52] propose a case study about transforming historical sites and scenic spots into a virtual space, which has great potential to be applied in virtual trips.

Education: PSI-XR has been increasingly integrated into education to enhance the personalized student learning experience. Veliz et al. [42], Zhao et al. [36], Coltey et al. [53], Yun et al. [54], Girhe et al. [55], and Ahmed et al. [56] provide personalized learning paths for users to suit their learning abilities. Tseng et al. [57] propose an XR smart campus education platform supported by case-based reasoning (CBR). This system provides students with adaptive learning content based on their requirements and characteristics. Similarly, Yu [58] introduces a personalized XR learning system where difficulty, environment scenarios, and tutoring interactions are adaptively adjusted according to the individual users. Additionally, Liu and Zhang [59] propose an analytical model of English learning ability. The personalization of the learning experience for students is facilitated by acquiring the learner's characteristics and learning level. Zhao [60] proposes a system to help students majoring in physical education improve their training quality by providing personalized movement guidance. Cinar et al. [61] present a VR application to enhance the learning experience of Python for electronic and electrical engineering students. Divanji et al. [62] propose *TogetherTales RPG*, a platform designed for children (of age four to six) aiming to foster prosocial skill development through interactive and collaborative role-playing. Gao et al. [63] develop DataliVR, a VR application to enhance the data literacy skills of university students using gamification within a given context for a personalized learning experience.

VaezAfshar et al. [64] integrate AI-driven gamification to enhance heritage education, creating an engaging and immersive virtual environment, providing personalized historical learning content. Similarly, Troussas et al. [65] propose a educational VR system for cultural heritage, ensuring a personalized and immersive experience for different users, such as novice or expert users. Salehi et al. [66] implement a child interview training system in VR to train interview skills, especially when communicating with children. Wang et al. [67] introduce a ChatGPT to the VR-based experiential learning for learning feedback. Ourahmoune et al. [68] design a system for clinical training of breast palpation in VR. Tolba et al. [69] propose an interactive AR system for learning phonetics using AI, providing learners the feedback immediately.

Sports & training: In sports and training, PSI-XR is increasingly being leveraged to enhance athletic performance and training efficacy according to users' personalization. Lee et al. [70] propose a treatment and exercise system that detects and evaluates users' movement posture and gives the user suitable motion feedback, which is used in exercise guidance. Similarly, Kang et al. [71], Lopes et al. [72], Afyouni et al. [73], Mazhar et al. [74], Li et al. [75], Izountar et al. [76], and Pelosi et al. [77] present approaches for automatically adjusting the difficulty level of XR exercises or serious games to match patients' abilities, usefulness in personalized exercise systems or rehabilitation processes. For instance, Afyouni et al. [73] develop a virtual assistant to guide patients to finish different gestures for rehabilitation purposes, adapting to users' abilities and expectations of joint movements.

In the field of training systems, Casoria et al. [78] and Tsiatsos et al. [79] propose a professional sports player training system that tracks players' performance to provide players with personalized training by adjusting the intensity of XR training. Similarly, Chan et al. [80] propose an air traffic control tower training system. Trainees are categorized into different levels for different training content based on their individual profiles and training records. For worker training, Doolani et al. [81], Peterson et al. [82], and Zhang et al. [83] propose the XR training system that monitors the current training difficulty level and task performance of users. Trainees are provided with different training difficulties and feedback based on the user's actions to help them reach a higher level. Additionally, Tao et al. [84] and Lor et al. [85] propose an AI-based method to assess users' confidence in their decisions within the training process to dynamically adjust and personalize learning experiences. Then a personalized guide or training plan is created based on confidence analysis. Castets et al. [86] create a framework for real-time inferences of the user's state during the problem-solving process in training systems, including emotional and physiological conditions. Liu et al. [87] present AI battling buddy which is an integrated baseball batting training system to provide an immersive and realistic training experience in VR. Lucas-Pérez et al [88] personalize the training experience with adaptive VR that responds to an individual's physiological states based on multimodal data. Han et al. [89] investigate users' emotional response to game timer change as a dynamic difficulty adjustment mechanism for immersive VR exergaming.

Healthcare: In the healthcare domain, PSI-XR is used to tailor patient treatments and interventions. For autistic child patients, Xu [90] proposes a framework to design an individual treatment plan according to their physical and psychological characteristics. Similarly, Belmaqrout et al. [91] propose a personalized treatment architecture for autistic patients, where different VR contents are adjusted based on user profiles and measurements from a chatbot. Also, Alimanova et al. [92] propose a treatment method for children with autism spectrum disorder. A virtual agent is designed to ask different questions based on users' emotions to enhance the participant's communication skills.

In the context of treating affective disorders such as depression, Valenza et al. [47] capture users' neuromonitoring data (fMRI) and transfer it to 3D scenes to support therapeutic interventions. Similarly, Hardy et al. [93] use an AI model to process and classify the user's behavior in a VR environment. Based on their emotional requirements, some behavioral improvement feedback and a personalized treatment experience are generated. To address the anxiety and depression in some patients stemming from unmet psychological needs in childhood, Ghaznavi et al. [94] propose a method to construct a VR childhood avatar on behalf of patients for use in psychotherapy. This aims to provide therapeutic benefits by addressing unresolved psychological needs. Zhang et al. [95] provide immersive, generative AI-enhanced therapeutic virtual experiences to help parents process grief, particularly after the loss of a child. Trappey et al. [96] design a VR system to provide empathy-driven counseling through a chatbot, targeting college students who face various stresses such as academic pressure, personal relationships, and career concerns. Zhang and Cao [97] employ ambient intelligence (AMI) to monitor patients' daily behaviors and identify early symptoms in the home environment for Alzheimer's disease using simplified and personalized VR. Lei and Li [98] utilize MR and haptic feedback to enhance hand dexterity among geriatric patients with movement disorders, providing a personalized rehabilitation experience.

Virtual avatar creation: In virtual avatar creation, advancements in personalized 3D facial avatar generation enable more personalized and dynamic representations of users. In the field of personalized 3D facial avatar generation, Yang and Zhang [99] propose an end-to-end deep learning (DL) method to reconstruct users' 3D faces using one image. Furthermore, Molano et al. [100] propose a method to generate an animation of users' facial avatars with different emotions (happiness, sadness, anger) with a standard static facial avatar model.

To enhance user satisfaction with their avatars for personalization, Reddy et al. [101] present a method to select features from users' feedback to generate new avatars iteratively, thereby aligning with users' preferences. Additionally, Ghaznavi et al. [94] propose a method to construct a user's child avatar with only one single childhood photo. The facial and body features of avatars are adjusted based on the user's preference to customize a child avatar. Talapuru et al. [102] focus on improving user immersion by creating personalized, realistic human avatars from 2D images.

Other Applications: Yang et al. [103] investigate the application of AI generated content to allow users to customize their personalized virtual spaces, enhancing the metaverse experience. Hou et al. [104] developed the "Digitized You in My Eye" spatial communication prototype to combine the potential of AI and 5 G communication in VR environments while addressing the bottlenecks, managing personalized XR experiences based on user behaviors and preferences. Sun et al. [105] present a prototype system called "Neighbor-Environment Observer", which employs non-invasive sensors to support users in managing interruptions outside the virtual world, aiming to provide users with an immersive virtual experience.

Various identified applications are summarized in Table 3. Due to the separation of entertainment and art design into two distinct categories in Table 3, an additional category is presented in the table.

4.3 Technologies for immersive XR environments

PSI-XR includes immersive techniques such as VR, AR, and MR, which are supported by several technologies. Each type of XR differs in hardware requirements and interaction modes. Here, to answer RQ2, we categorize the selected papers according to various technologies that enable the use of XR.

HMDs: HMDs are widely utilized in VR and MR environments. Devices such as the HTC Vive, Oculus Quest, Oculus Rift, Microsoft HoloLens 2, and Varjo XR3 headset are applied across various domains. It is worth mentioning that Quest devices are video-see-through MR headsets instead of purely VR, which are still widely used in VR applications. Among the selected papers, the HTC Vive remains the most commonly used HMD, extensively employed in fields such as e-commerce and business [24, 106], healthcare [73, 75, 92], and education [42, 53]. In addition to HTC Vive, other HMDs, such as the Oculus Quest 2, Meta Quest Pro, and Varjo XR3 headset, are also increasingly adopted in diverse domains. For instance, the Varjo XR3 headset has been used in educational applications [63], while the Meta Quest Pro and Oculus Quest 2 are highlighted for their roles in training [77, 88, 89] and education [56, 61, 66]. HMDs provide users with an exceptionally immersive virtual experience, enabling them to fully engage with virtual environments and interact with virtual objects. This immersive capability proves particularly valuable in virtual training scenarios, where active user interaction enhances immersion and learning outcomes [78, 80]. The widespread adoption of devices such as the Oculus Quest 2 in unspecialized applications and general education underscores their versatility and accessibility [35, 103].

Smart phones: Smartphones have become one of the most widely used devices in XR environments, especially in AR and VR. Smartphones' low cost and widespread adoption make them a preferred device in various fields. For instance, Android phones were frequently applied in XR training [81], e-commerce, and the business area [36], while iOS devices were also widely used in e-commerce and business [29]. In education, smartphones provide students with portable learning tools, enhancing the learning experience through AR applications [57]. [97] use a combination of visual smartphone and audio sensors, for example, smartphone, to capture human data for Alzheimer's disease in VR healthcare system.

Screen: In this context, 'screen' refers to traditional 2D display devices such as computer monitors. The screen is another crucial display in XR, especially in education [58, 59], and healthcare [76, 90]. The accessibility and high penetration of screens make them an ideal choice for low-cost XR solutions. Though screen devices do not offer a fully immersive experience like HMDs, users can still experience

Table 3 Main application areas of personalized smart immersive XR environments (RQ1)

Main applications	References
E-commerce and business	[24–42, 106]
Entertainment	[43–46, 51, 52]
Art design	[47–50]
Education	[36, 42, 53–69]
Sports and training	[70–89]
Healthcare	[47, 90–98]
Virtual avatar creation	[94, 99–102]
Others	[103–105]

a fairly realistic virtual environment and interact with keyboards, mice, and other input devices.

AR and polarized 3D glasses: AR glasses are applied in training [84], e-commerce, and business [28], with devices such as Magic Leap One and Microsoft HoloLens 2 leveraging the advantages of both virtual and real worlds. These devices overlay virtual information onto the real environment, providing enhanced visual experience in industrial training and business presentations. Similarly, even though it does not offer the full immersive experience compared with HMDs, polarized 3D glasses [26] are used in e-commerce and business, providing stereo vision to enhance user engagement and interaction in virtual shopping scenarios.

Smart mirrors: In the selected papers, only one publication [70] mentions the application of smart mirrors used for exercise motion correction. Smart mirror contributes to an immersive AR environment, allowing users to see a virtual reflection of their movements and compare them with their standard movements. This real-time feedback from the smart mirror AR system has great fitness and health management potential, helping users correct their movements through visual feedback.

The categorization of identified XR technologies is summarized in Table 4.

4.4 Techniques for personalized smart XR environment

To further answer RQ2, we identified the following techniques in the reviewed literature in PSI-XR. We do not distinguish techniques with or without AI in this section, as a detailed analysis is provided in Sect. 4.6.

Eye tracking and eye blinking detection: Eye tracking and eye blinking detection are used in XR environments to track users' psychology, attention, and interests to improve the personalization of the experience. Pfeiffer et al. [26] and Khatri et al. [25] use eye-tracking techniques to record users' attention distribution during online shopping to further analyze their psychological state and desired products. Lo et al. [46] propose a method to avoid direct (manual) event triggering; users' eye motion is used as one of the reference information to track their attention and interest distribution. Liebers et al. [112] propose a method to automatically recognize different users; users' eye motion during the login process is used as one of the factors to help differentiate between users. In [39], eye tracking is utilized to detect whether the potential interlocutor is looking at the users to analyze his/her intention to contact the user. If so, the layout of environmental information and interactive objects on the screen will be optimized for the following communication. Users' blinking state captured by the blink detection algorithm is used as one of the factors in [42] to analyze the user's emotional state and adjust avatars in the virtual environment. Additionally,, Tao et al. [84, 85] utilize users' eye gaze as one of the elements to estimate users' states or emotions in the XR training environment. Eye tracking is integrated with the user interaction in the work of Lucas-Pérez et al. [88] to personalize the complexity of tasks in training system.

In summary, eye tracking plays a crucial role in analyzing user attention distribution, psychological states, and emotions, enabling the analysis of users' preferences and requirements. Eye-blinking detection techniques can also support emotional analysis and the creation of virtual avatars. They significantly contribute to improving the personalization of smart immersive XR environments.

Face and facial expression detection: Face and facial expression detection are vital in enhancing user experience in XR environments, enabling the system to capture emotional states and personalize interactions accordingly. In [76] and [92], users' facial and expression information is detected to determine their state during serious games or treatment. Supported by facial tracking techniques, Zhao et al. [42] and Yang and Zhang [99] track dynamic facial information or facial features of users to generate virtual, dynamic facial avatars.

Also, Lopes et al. [72] detect users' lip movements and facial expressions to infer their current state in serious games. Eyebrow movement and facial action unit data are used by Han et al. [89] to adjust the difficulty level in virtual games.

Table 4 Categorization of publications based on the immersive equipment and XR types in the selected papers (RQ2)

XR type	References
AR	**HMDs**
	Microsoft HoloLens 2: [39]
	No specific brand: [29, 46, 99, 107, 108]
	AR glasses
	Magic Leap One Creator Edition: [84]
	No specific brand: [28, 30]
	Smart phone: [29, 31, 37, 55, 57, 69, 81]
	Smart mirror: [70]
VR	**HMDs**
	Oculus Quest: [48, 54, 74, 94, 109]
	Oculus Quest 2 / Meta Quest 2: [38, 61, 66, 77, 80, 92, 103]
	Oculus Rift: [78, 110]
	Oculus Rift DK2: [45]
	HTC Vive: [24, 53, 73, 105, 106, 111]
	HTC Vive Pro: [25, 112]
	Isuru Play VR: [49]
	Varjo XR3: [63]
	Meta Quest Pro: [89]
	No specific brand: [33, 41, 42, 47, 54, 56, 60, 67, 71, 72, 75, 99, 107, 113]
	Screen: [27, 37, 40–43, 58, 59, 68, 76, 90, 99, 107]
	Polarized 3D glasses: [26]
	Smart phone: [36, 94, 97]
MR	**HMDs**
	Microsoft Hololens 2: [86, 114]
	No specific brand: [83, 99, 107]

Additionally, in the interaction method proposed by Casoria et al. [39], the potential interlocutor's facial position is detected and analyzed whether he/she has an attempt to communicate with the user. With this the appropriate information about the environment and interaction objects are displayed on the virtual screen without disrupting the interaction process.

By analyzing users' emotional states and enabling personalized interactions, face and facial expression detection improve the immersion and personalization of the smart XR environment. It enhances user engagement in serious games and therapeutic scenarios while improving information delivery and display in interactions between multiple users, thereby boosting the immersive, personalized experience.

Head position detection: Head position detection is used in PSI-XR, allowing systems to track users' focus and areas of interest. By using head detection techniques, Khatri et al. [25] and de Lima et al. [43] use head position data as one of the inputs to analyze the areas of interest and focus of users to obtain their psychological states in virtual online shopping and the horror game separately. Similarly, Lo et al. [46] use head position data as one of the elements to analyze users' interests without direct (manual) trigger events from users.

Also, users' head position data are used as one of the inputs in [112] to automatically recognize different users without knowing who the user is during the login process. Additionally, Casoria et al. [39] propose a method to detect the potential person who will interact with users based on their facial and head positions, then provide a comfortable layout with suitable information.

Head position detection enables PSI-XR to capture users' focus and interests in applications such as virtual shopping and gaming. Tracking head movements facilitates seamless login processes, identifies potential interaction partners, and optimizes the interaction process. This technique enhances the user experience by enabling more intuitive, efficient personalization within immersive environments.

Human body pose tracking: Human body pose tracking is widely utilized in XR applications to monitor users' movements and assess their performance, offering valuable feedback for various activities. Users' body pose is tracked and used as one of the inputs to determine users' motion accuracy and abilities in the work of Zhao [70], Lee et al. [79], Lopes et al. [72], Pelosi et al. [60], and Tsiatsos et al. [77]. For instance, human body pose is detected during users' exercise to compare with the standard motion [70] or is captured and analyzed during the medical treatment [72].

Additionally, Manfredi et al. [27] propose a method to map the customer's body movements onto its 3D avatar in real time. During this process, the motion tracking system tracks users' body motion in the proposed virtual image consulting dressing room (VICO-DR).

Human body pose tracking enables the accurate analysis of user movements for medical treatment and rehabilitation. By capturing and mapping body poses, it supports the creation of realistic 3D avatars, facilitating applications like virtual dressing consultations. The precise motion is able to be captured and analyzed to achieve personalization in PSI-XR.

Natural language processing (NLP): With the support of NLP, PSI-XR facilitates intuitive interactions, enabling users to communicate with virtual agents and be assessed according to oral answers. The rapid advancements in large language models (LLMs) and Generative AI (GenAI) have further enhanced this integration, which significantly improves natural language understanding and response generation.

Fuchs et al. [38] utilize ChatGPT [115], LLMs, to analyze users' voices from their discussion, extracting emotions and dynamically adjusting the lighting in the virtual meeting room to create a calming atmosphere. Meanwhile, based on the understanding of users' conversations, different images are generated and displayed on a virtual wall with some possible ideas, which are created by GenAI. In this case, NLP allows the virtual space to interact with users intelligently, providing an immersive experience. Yu [58] develops an intelligent chatbot agent based on transformer neural networks to analyze students' responses, assessing their learning performance and mastery of skills. Based on this analysis, the VR learning system provides adaptive difficulty levels and interactive assistance tailored to their learning progress, enabling a personalized learning experience. Kumaar et al. [31] utilize GenAI to develop a chatbot that provides communication to users about personalized virtual product try-ons, personalized recommendations, and real-time guidance in online virtual shopping experiences. Constantinides et al. [51] utilized GenAI to understand natural language to allow the exhibition system to provide a personalized experience by responding to visitors. Wong et al. [33] utilize GenAI to allow the virtual shopping assistant to respond to customers, which enables it to analyze and handle users' inquiries, offering personalized suggestions. Salehi et al. [66] integrate ChatGPT to avoid sexual and physical abuse. In addition to employing ChatGPT, Gao et al. [63] integrate Oculus's Voice Software Development Kit (SDK) for text-to-speech conversion and employed OpenAI's Whisper model for speech-to-text conversion.

Trappey et al. [41] develop a system for a large-scale customized chatbot for industrial transformers. For that, they collected 1,272 2 frequently asked questions (FAQs) from the knowledge base of a power transformer manufacturer for question matching and answer retrieval. At the same time, 1.2 million Wikipedia engineering pages were used to train a word embedding model for natural language understanding of question intent. Retrieval-based NLP is employed to handle complex engineering queries and provide answers from the developed knowledge base, offering clear and detailed design consultation support and manufacturing of complex power transformers. Similarly, to allow users to ask technical questions to the engineering consultation chatbot, Wu et al. [40] utilize a conversational question answering (Q&A) system to extract users' content of questions in the form of text used as the input of the consultation chatbot. Wang et al. [67] develop a feedback system for the hands-on tasks in VR learning environment by utilizing NLP. Trappey et al. [96] utilize NLP based on machine learning (ML) to recognize and analyze users' oral speaking with response in the empathy-centric counseling VR chatbot system.

To analyze users' emotions in the virtual environment, Alimanova et al. [92] develop a speech recognition algorithm to detect and analyze users' oral speaking in autism treatment, while Belmaqrout et al. [91] propose a framework that applies Chatbot to extract users' talking conversations and transfer them to text, which helps understand the user's emotional state. Additionally, Chan et al. [80] propose learning systems that utilize speech and voice processing algorithms to transcribe trainees' oral answers to text answers. By doing this, the learning system gives trainees feedback for improvement. Tolba et al. [69] and Yun et al. [54] use speech and voice processing algorithms to analyze learners' pronunciation. Similarly, Peterson et al. [82] propose a teaching system that applies NLP techniques to monitor and respond to users, constructing a responsive environment. It allows learners to navigate simulated scenarios and modify the learning context based on their needs, offering further enhancements to interactive, experiential learning.

NLP enables PSI-XR to analyze users' conversations and extract their emotions, which is particularly useful in autism therapy. It also facilitates personalized and interactive learning experiences by analyzing student responses to assess learning progress and adapt the learning content accordingly. Additionally, it is employed in engineering consultations, responding to common technical queries from clients. The rapid advancements in LLMs, such as ChatGPT, and GenAI have significantly enhanced natural language understanding and the generation of complex, context-aware responses, further facilitating the achievement of personalization in PSI-XR.

Gesture recognition: Gesture recognition is a key interaction technique in XR environments, allowing users to control and interact with virtual objects through specific hand movements or gestures. Gesture recognition algorithms help users activate specific functions in VR in [107, 109]. Each specific gesture corresponds to specific functions triggered when the gesture is recognized. For example, if the designed gesture is detected, users can adjust the size of their virtual hand [109] while different gestures correspond to the basic functions of a mouse (left-click, right-click, etc.). [107, 114] designed a hand haptic feedback system in VR, including a hand tracking module and a hand haptic module. The hand tracking module tracks the user's gestures and motion in VR. It determines whether the interaction between the user's hand and the virtual object occurs or not, which in turn triggers the haptic feedback module.

Similarly, Afyouni et al. [74], Mazhar et al. [73] utilize gesture recognition algorithms to develop serious games of healthcare. The user's gestures are detected by the gesture recognition algorithm, and the detected gesture movements are projected into the virtual serious game [74], which corresponds to the related actions in the game, such as grasping the club. Also, Afyouni et al. [73] employ the gesture recognition algorithm to detect whether the gestures made by users in the serious game are correct or not, guiding patients to make the correct gesture for their hand rehabilitation. Also, Rhodes et al. [48] propose a customized music gesture method using electromyography (EMG) data. Different gestures correspond to different notes, so users can use gestures to create music in VR. Gao [45] proposes a method based on a naive Bayes algorithm to recognize different gestures. In particular, the proposed method considers the problem of gesture nesting, which improves the accuracy of the system's response under multiple continuous gestures.

Gesture recognition enables PSI-XR to provide a natural and intuitive interaction with virtual environments by capturing and analyzing users' hand movements. Gesture recognition techniques are employed to activate specific functions, trigger haptic feedback, and provide support in serious games and medical rehabilitation. Combined with EMG data and Naive Bayes, gesture recognition has improved in both accuracy and responsiveness, providing robust support for the development of PSI-XR.

Physiological signal detection techniques: As one of the biometric techniques [116], physiological techniques allow PSI-XR to monitor users' physiological states and help further analyze their emotional conditions from a physiological view. Lopes et al. [93], Hardy et al. [72] use wearable sensors to acquire the user's heartbeat data as one of the physiological feature signals to help track users' emotional states. Specifically, heart rate (HR) [93] and heart rate variation (HRV) [72] obtained from devices in the Internet of Things (IoT) information collection systems, such as wristbands, are used as inputs for the analysis of employees' emotions and patients' emotional changes, respectively. Similarly, Tsiatsos et al. [79] propose a framework that uses galvanic skin response (GSR), HR, and HRV to monitor sports players' stress levels and abilities in training. Tsiatsos et al. [79] propose a framework that used blood volume pulse (BVP), body three-axis acceleration, body temperature, body electrodermal activity, and pupil diameter to estimate users' states in the AR training environment. Iwane et al. [117] utilize electroencephalogram (EEG) to recognize whether the user has a sense of control over the avatar in virtual interaction process.

Using biometric devices in VR can better recognize complex, custom gestures with more detail than traditional optical sensors [48]. The Myo armband [118] is used in the method proposed by Rhodes et al. [48] to collect eight channels of 8-bit EMG data. The EMG data, along with the orientation data obtained from the inertial measurement unit (IMU), are used as input for ML to train and recognize specific gestures, particularly in instrumental music performance.

Valenza et al. [47] propose a wearable monitoring system to capture the users' brain activity. When user think of different scenes in their mind, there are different brain signals related to the brain activity. Users' neuromonitoring data, fMRI, are captured and used to generate the sense description in users' thoughts.

Physiological signal detection techniques help monitor users' physiological states and emotional changes, enabling deeper user analysis. Wearable devices are widely used to capture various physiological signals, including GSR, HR, EMG, and HRV. These signals are applied in scenarios like emotion tracking, stress assessment, and gesture recognition. Furthermore, neuro-monitoring, such as capturing brain signals via fMRI, opens new possibilities for personalized emotional analysis and immersive experiences. These physiological techniques significantly enhance personalization in PSI-XR.

Haptic feedback techniques: Haptic feedback techniques are employed in PSI-XR to enhance user immersion by providing tactile sensations, allowing users to physically feel virtual objects from the tactile feedback. Rewkowski and Lin [111] design a safety system with a virtual companion (a virtual dog) and a physical dog robot. When the user reaches the safety boundary of the area, haptic feedback and natural motion constraints are given to users through locomotion and pulling a leash from the robot dog. Zhang et al. [114] design haptic gloves to give users haptic feedback when interacting with virtual objects. The haptic controllers' gloves adjust the collision pattern and intensity of force to provide accurate and real haptic feedback according to the semantic information about the rigidity of the object touched by users. In the serious game proposed by Mazhar et al. [74], the forearm-mounted miniature disc motors are activated by a 0.5-second vibrational signal from an Arduino to provide user haptic feedback of their motion when users employ tools for environmental interaction or the grab event. Ahmed et al. [56]

create a virtual clinic for medical students to interact with lifelike patients, with the support of haptic feedback, fostering deeper engagement and skill acquisition.

Haptic feedback techniques enhance user immersion by delivering realistic tactile sensations, which enrich the sense of realism during virtual object interactions, such as grasping actions. Precise tactile responses are able to be provided based on user actions and virtual object properties. Additionally, haptic feedback has been integrated into safety systems, combining virtual companions and robots. This greatly enhances the interactive experience within PSI-XR.

Agent-based approaches: Agent-based approaches enable autonomous agents to continuously perceive their environment, adapt to changes, and take independent actions to achieve their objectives [120], which support to construct a PSI-XR. Ojha et al. [44] use an agent-based model to monitor player behavior and modify the environment accordingly. A smart agent in the VR horror game dynamically adjusts the game's pace and horror elements based on real-time fear detection. Similarly, de Lima et al. [43] propose an agent-based "Horror Director" that tracks the player's fear to dynamically adjust the game content. In the virtual air traffic control training system, Chan et al. [80] features a pilot agent that responds dynamically to trainees' voice commands, comparing transcribed speech with expected responses to provide real-time feedback and personalizing training content. Yu [58] involves an AI-driven agent that monitors students' behaviors and progress in the VR-based learning system. The agent continuously updates difficulty levels and tutoring interactions based on students' performance and skill acquisition, ensuring a personalized learning experience. Casoria et al. [78] utilize a reinforcement learning (RL)-based agent to dynamically adjust game difficulty based on players' personalized training needs. The proposed intelligent agent is used to monitor player performance and optimize training tasks accordingly.

Hou et al. [104] implement an agent-based approach through the DYME manager to create AI-driven NPC agents with diverse personalities and life backgrounds, responding to user actions and contributing to an immersive, adaptive game-based learning environment. Yun et al. [54] utilize an intelligent agent to work collaboratively to track user behavior, analyze facial expressions, and adapt emotional responses in real time. The AI-driven agent dynamically adjusts virtual environments and interactions, ensuring a personalized and emotionally responsive XR experience. Similarly, Lucas-Pérez et al. [88] integrate an AI-driven agent to monitor learning activities in virtual training. The intelligent tutoring agent assesses user performance and dynamically adjusts training scenarios based on individual progress. Supported by the AI-based agent, the system personalizes task difficulty, feedback mechanisms, and real-time adaptive guidance, optimizing the learning experience for each user. Artizzu et al. [119] propose an intelligent conversational agent as an adaptive assistant for end-user development in XR, allowing users to create and modify virtual environments without programming expertise.

The agents applied in PSI-XR operate without direct human intervention, dynamically determining their actions according to the real-time environment. Intelligent agents tailor experiences by analyzing user behavior and preferences to ensure adaptive content delivery to users, providing a personalized XR experience.

Context awareness: Context-aware computing allows systems to sense, process, and react to environmental changes intelligently by analyzing contextual data to construct a PSI-XR. Lo et al. [46] introduces a context-aware AR interface for sports spectating, dynamically adjusting displayed information according to the game states and users' individual preferences, ensuring a more engaging and personalized AR sports experience. Tseng et al. [57] apply context-awareness in smart campus learning, leveraging IoT, AR, and AI to deliver adaptive educational content based on students' current location and past activities. Doungtap et al. [35] apply context-aware principles in the AI-driven recommendation system for VR shopping. The system analyzes user behavior, interaction history, and preferences to refine product recommendations, ensuring a personalized shopping experience. Supported by context-aware computing, Troussas et al. [65] dynamically adapt information in a VR cultural heritage system. For example, when users approach a sculpture for the first time, a short introduction is given to ensure maximum engagement and understanding of the artwork with appropriate contextual information.

Context-aware computing enhances personalization in PSI-XR by dynamically adapting content based on user behavior, preferences, and real-time context. It is applied in various areas, such as AR sports spectating and VR cultural heritage, where systems adjust information delivery and interactions to optimize user experience.

Empathic computing: Empathic computing enables real-time emotional recognition, which allows the system to dynamically adapt users' requirements, enhancing user engagement and personalization. Combined with DeepFace model [121], Izountar et al. [76] analyze user's emotions during the virtual game, dynamically adjusting the game difficulty to match the user's ability, which enhances the personalized experience. Similarly, Rokhsaritalemi et al. [108] use the DeepFace model to analyze users' emotions, providing customized virtual content according to their emotions. Castets et al. [86] propose an MR-based empathic computing framework that uses physiological signals and pupil measurement data to infer user emotions and adaptively adjusts the virtual environment to optimize the user interaction experience. Combined with IoT techniques, Hardy et al. [93] propose an empathic computing framework based on AI, which is able to analyze users' emotional and physiological states. The emotional results are used to generate personalized feedback, adaptive treatment plans, and real-time emotional health management, enhancing individual well-being and optimizing user experiences in various applications. de Lima et al. [43] assess users' level of fear by analyzing their behavioral and physiological data in XR horror games. By analyzing their emotional state, the system adjusts the game pace and horror elements in real time to enhance immersion and optimize the personalized horror experience.

[113] analyze users' speech features to recognize emotions from both the semantic content (meaning of the speech) and the acoustic properties (tone, pitch, and pace of the speech). Similarly, Forero et al. [52] use both semantic and acoustic analysis to predict users' emotional states, enabling nuanced emotional representations in the virtual experience. Fuchs et al. [38] design an emotion-aware virtual meeting room that is able to analyze the user's voice using NLP to understand their emotional state. The system dynamically adjusts the room ambiance (e.g., light color) and the images displayed on the virtual wall according to the user's emotions to create a personalized and emotionally adaptive virtual environment. Combined with facial and speech recognition algorithms, Alimanova et al. [92] propose a medical system to detect the user's emotions and dynamically adjust the question content based on the emotional state. This adaptive approach enhances the social and communication skills of individuals with autism spectrum disorder, offering a personalized and immersive virtual treatment experience tailored to their needs. Trappey et al. [96] design an empathy-driven counseling system to identify the emotional state of college students with the problem of stress, providing personalized responses.

Empathic computing is widely used in immersive XR environments, for example, virtual games, treatment, and training, to support a personalized experience. By analyzing users' speech content, facial expressions, and other cues to interpret their emotional state in real time, empathic computing enables the dynamic adaptation of the virtual environment and system feedback, creating a personalized user experience.

IoT: A typical IoT environment is composed of communication interfaces, sensors, advanced algorithms, and cloud interfaces [122]. It can be understood as a complex network of uniquely addressable and identifiable devices. These "things" within IoT connect to servers to exchange data and derive valuable insights, which enables the efficient delivery of tailored services. Tseng et al. [57] propose an AR-based smart campus platform that leverages IoT to interconnect smart devices across the campus. By integrating AR and IoT techniques, the platform enables the creation of context-aware AR applications, allowing teachers to design IoT-enhanced AR learning content tailored to specific points of interest. This approach enhances the learning experience by combining virtual objects with real-world environments across the whole campus. Hardy et al. [93] highlight the role of IoT in collecting data to support an AI-driven system that analyzes and classifies user behavior within VR environments. By leveraging IoT-enabled information, the system provides tailored feedback and treatment experiences designed to address patients' emotional needs, which provides a personalized VR experience. Similarly, Tsiatsos et al. [79] propose a framework that utilizes IoT to connect various devices for monitoring and analyzing bio-signals in sports, which enables identifying optimal training periods in sports and physical activities while monitoring recovery and potential over-training. Lopes et al. [72] emphasize the use of IoT to gather data from various devices, such as the patient's actions in the game, body posture, lip expressions, HR, HRV, and breathing patterns. These signals gathered by IoT enable real-time analysis and dynamic adjustment of the game's parameters and difficulty, allowing ML to personalize and optimize rehabilitation exercises for patients.

IoT enables PSI-XR to collect various data from different devices, such as sensors that track bio-signals, users' actions, and environmental factors. By connecting devices and processing data seamlessly, IoT enhances the responsiveness and efficiency of PSI-XR, providing users with personalized experiences in various fields, such as healthcare and education.

Others: In addition to the previously mentioned techniques, various other techniques are applied in XR environments to enhance user experience in personalization. Ghaznavi et al. [94] use an industrial tool Avatar SDK [123] to provide some customization functions for personal avatar design, which support the treatment of chronic anxiety and depression. Tong et al. [29] use image segmentation techniques in AR to recognize and change the color and texture of furniture, which may suit users' preferences. These techniques also support the construction of PSI-XR, facilitating the realization of personalized experiences.

All the techniques mentioned above, which are employed in smart and personalized XR environments, are summarized in Table 5.

4.5 Achieving personalization

This section discusses how the above-mentioned techniques are applied to achieve personalized user experience in PSI-XR (RQ3). First, some methods predict users' requirements with corresponding services, including recommending personalized products and content supported by AI-based recommendation systems. The difficulty level of XR games is adjusted to match users' abilities. Secondly, some meth-

Table 5 Techniques contributing to personalized smart immersive XR environments (RQ2)

Technique	References
Eye tracking	[25, 26, 39, 46, 84–86, 112]
Eye blinking detection	[42]
Face and facial expression detection	[39, 42, 72, 76, 89, 92, 99]
Head position detection	[25, 39, 43, 46, 112]
Human body pose tracking	[27, 60, 70, 72, 77, 79]
NLP	[31, 33, 38, 40, 41, 51, 54, 58, 63, 66, 67, 69, 80, 82, 91, 92, 96]
Gesture recognition	[45, 48, 73, 74, 107, 109, 114]
Physiological signal detection techniques	[39, 47, 48, 72, 79, 86, 93, 117]
Haptic feedback techniques	[56, 74, 111, 114]
Agent-based approaches	[43, 44, 54, 58, 78, 80, 88, 104, 119]
Context awareness	[35, 46, 57, 65]
Empathic computing	[38, 43, 52, 76, 86, 92, 93, 96, 108, 113]
IoT	[57, 72, 79, 93]
Others	[29, 94]

ods combine psychological theories with smart techniques to perceive users' psychological states and emotions in XR for users' personalization. Also, the virtual avatar of users serves as their "face" in the virtual world. Thus, granting users the ability to customize their avatars is an important way to achieve personalization. Additionally, some implicit human-centered functions are proposed in various methods to simplify users' operations and improve the immersive experience through optimized operation details. Finally, to address errors users make during XR exercise, some methods utilize human body tracking techniques to provide real-time correction for physical activities, delivering a highly personalized exercise experience. Following this, how personalization is achieved in PSI-XR is discussed based on the above-mentioned aspects.

Personalized content and performance: This section discusses two aspects related to personalized experience: content and performance. Personalization in the XR environment can be achieved by providing the user's desired content. For example, recommending products or applications to users that may be of interest to users' requirements significantly enhances their personalized experience.

Additionally, the XR experience tailored to the user's capabilities offers another approach to achieving personalization. Adaptive adjustment of the training/game difficulty based on the user's level, including physiological changes and training/game performance, dramatically improves the user's experience in the XR environments. Personalized training difficulty is not only the basis for a good experience but also essential for patients who are taking rehabilitation training.

Personalized content synthesis: Personalized content synthesis in XR environments leverages user data and adaptive algorithms to deliver customized experiences tailored to individual preferences and behaviors. Supported by the item-based recommendation system, Gironacci [24], Gironacci et al. [106] provide adaptive XR Apps from the application databases to users to meet their requirements based on their input and users' profiles to achieve a personalized experience. Similarly, Pfeiffer et al. [26] use support vector machines (SVM) to predict the eye gaze movement for every next second to predict what product customers are looking for. This allows shopping motives to be identified early to provide a personalized shopping experience in VR shopping. Kumaar et al. [31] leverage user data to refine recommendations and align with individual preferences, providing personalized try-on product recommendations in virtual online shopping. Similarly, Zhuang [32] personalizes the experience by continuously adapting to consumers' preferences, behaviors, and shopping patterns. Through intrusion detection, this work ensures users' privacy protection during the shopping process. Wong et al. [33] develop a virtual shopping assistant to respond to customers' questions and provide them with recommendations, which enhance a stronger sense of presence and contribute to a personalized experience. Do et al. [34] propose merging the virtual world with the real world for a more intelligent personalization by integrating space-aware room depth from Lidar. On the other hand, Doungtap et al. [35] use AI with NPCs for work voice-based interactions for customized product recommendations in VR. Hou et al. [104] integrate the user-specific management module to personalize XR experiences based on user behaviors and preferences. Game-based learning with generative AI to create NPCs with diverse personalities and life backgrounds. Artizzu et al. [119] utilize virtual agent tailors assistance based on user behavior, preferences, and contextual needs to adjust component suggestions and rule-based customization dynamically. The system ensures a personalized and user-friendly XR experience.

Luidolt and Zhou [28] propose a method to map the 2D images clothes to their avatars that customers are interested. By allowing users to visualize how garments fit on their avatars, this method gave users a clear picture of their appearance in the selected clothes and created a highly personalized virtual immersive shopping experience. Tong et al. [29] propose "AR furniture" that captures users' preferences by their eye gaze and allows users to envision their interested furniture in different colors and styles. For example, users are allowed to change the real furniture in different colors to meet their preferences with the support of AR glasses and semantic segmentation and image colorization. Regarding tourism, an intelligent component based on CBR is used in [36] to recommend hostels for tourists according to their preferences, which are captured from a questionnaire designed by marketing and tourism sector experts. Also, Constantinou et al. [37] propose a CB filtering method to recommend sites and services to tourists according to their historical information and their preferences, which is extracted by two questionnaires. Kumar et al. [30] use AI-based predictive algorithms to analyze and predict users' preferences to forecast property prices and trends, giving them a personalized AR real estate shopping experience.

In sports events, commentators and guides often display information on the screen that may interest the audience, such as the game time remaining or the current score of a star player. However, this information is presented to all viewers and may not align with what each individual wants to see, making it non-personalized. Lo et al. [46] propose a context-aware interface for personalized sports spectating using AR glasses, which utilizes a state inference model [124] to analyze the game state and detect users' eye gaze and head position. This aims to predict the appropriate game information and players' information that users may be interested in at the right moment. No direct and manual trigger events are needed from users to show this information, which ensures audiences are fully engaged while watching the game.

Tseng et al. [57] propose an AR-based smart campus platform supported by CBR, which includes four similarity functions for similarity-based case reasoning and knowledge discovery. Adaptive learning content can be provided to students based on their requirements and characteristics, while the case database and reasoning quality are improved according to either new cases or feedback. Similarly, in the training system proposed in [80], trainees are categorized into three levels for different training content. Personalized feedback from the AI-based domain expert is given to each trainee after the trainee responds with a voice command from the system. Additionally, Peterson et al. [82] estimate user learning progress based on the profile settings, such as curriculum vitae (CV) from social media platform (LinkedIn), biometrics, interface (UI) interaction, and users' answers in training. According to the analysis, personalized feedback is given to users to reinforce their sense of community while enhancing their experience.

Fuchs et al. [38] propose a method that provides a dynamic change in a personalized virtual meeting room. Text is extracted and analyzed from users' voices to obtain users' emotions and feelings in the virtual room. A calming effect is achieved by adjusting the color of the light (smoothing or warm color). Also, pictures on the wall are updated by AI based on users' conversations. Wu et al. [40], Trappey et al. [41] propose an enabled engineering consultation chatbot to answer the technique questions from customers. This allows customers to obtain tentative costs of their projects by asking technical questions related to their requirements. Alimanova et al. [92] propose a personalized treatment method for children with autism spectrum disorder. Facial recognition and voice recognition algorithms detect patients' emotions and answers. By doing this, a virtual agent is designed to ask different questions based on users' emotions to enhance the participant's communication skills. In contrast, Belmaqrout et al. [91] proposes an autistic treatment framework in which different VR contents are switched to patients based on their profiles and the conversation evaluation conducted by a chatbot. Girhe et al. [55] utilize ML to assess a child's strengths and weaknesses, curating personalized learning content for children with intelligence disabilities, which makes sure they are learning in their own peace. Divanji et al. [62] allow children to have a personalized avatar to interact with the virtual environment and collaborate with peers to solve challenges.

Trappey et al. [96] propose a VR chatbot system that is capable of identifying the emotional state of the user and providing personalized, empathetic responses. Wang et al. [67] provide feedback to the hand-on tasks submitted in the VR learning environment. Additionally, Gao et al. [63] utilize ChatGPT to provide personalized learning assistance while Yang et al. [103] leverage AI to generate intelligent content, enabling personalized creations. VaezAfshar et al. [64] apply AI-driven virtual characters in virtual heritage education to respond to users in real time. Troussas et al. [65] use the fuzzy-based model to personalize the virtual heritage experience by adjusting the difficulty and complexity of assistive messages to suit users with different levels of expertise.

He et al. [50] provide users with tailored immersive creation process in VR using text-to-image models and 3D modeling. The idea in users' text is transferred to 3D content to meet users' requirements for personalized VR design. Similarly, Constantinides et al. [51] utilize GenAI to provide a personalized response to visitors' questions in the art exhibition. The visitors are able to receive tailored information about the art, such as its creator, historical context, and significance. Salehi et al. [66] apply GenAI to adjust the interview context based on the input of the users. Zhang et al. [95] propose a method to support the personalization of grief experiences through the use of GenAI for custom virtual environments, allowing users to recreate significant places or memories associated with their lost loved ones.

Personalized performance adjustment: A personalized experience can be achieved by adjusting the level of training, rehabilitation, or learning process. Liu and Zhang [59], Li and Chen [110] and Yun et al. [54] propose an analytical model of students' level to help them learn English, while Tolba et al. [69] provide immediate feedback based on students' pronunciation. Acquiring the learner's characteristics facilitates the personalization of the learning experience for the learner with suitable learning content. A tool called adaptive learning system (ALS) is applied in [53] in an immersive XR learning environment. The task difficulty is adjusted based on users' performance to meet their abilities, and corresponding tutorials are adjusted based on users' completion. Also, Yu [58] proposes a personalized XR learning system that is supposed to be used in different subjects. An AI-driven agent is designed to monitor each student's behaviors and progress. In contrast, the student model is updated according to the student's performance and skill acquisition, analyzed by NLP. Difficulty level, environment scenarios, and tutoring interactions are adaptively adjusted based on the student's model to provide them with the personalized experience. In the virtual medical learning system [56], adaptive personalized learning pathways and real-time performance feedback are provided to students according to their performance in their interaction with virtual lifelike patients. Students can interact with virtual representations of complex programming concepts through a virtual assistant and example generator in the work proposed by Cinar et al. [61] to learn Python. Han et al. [89] employ gamification with game time changer as a dynamic difficulty adjustment mechanism, wherein results indicated that this led to more neural responses concomitant with improved gaming performance. Kang et al. [71] proposed an intelligent combat training simulation system, which dynamically adjusts training scenarios and difficulty levels using AI, providing trainees with personalized feedback and suggestions for improving decision-making and tactical skills.

Mazhar et al. [74] construct a serious game using gesture detection and forearm-mounted miniature disc motors, which provide tactile sensations. According to users' performance, the game difficulty is automatically adjusted to suit patients' abilities to provide a personalized and immersive rehabilitation system. Similarly, Li et al. [75] propose a VR game for elderly people in which the difficulty is adjusted dynamically based on users' state. Gameplay conditions, posture detection, and other information related to users are captured and fed into the AI model. The most suitable parameters for users to match their abilities are returned from the prediction of AI. The game's difficulty is adjusted automatically to suit users' abilities based on the results of their emotion analysis. The similar gesture detection is applied in the work of Ourahmoune et al. [68] for clinical training of breast palpation. Personalized feedback is provided based on learners' performance. Pelosi et al. [77] integrate a RL algorithm that allows the game to modify the position of the objects based on the patient's performance. Xu [90] proposes a framework to analyze the user's physical and psychological characteristics using big data. Then, a treatment plan only for the user is designed to suit the patient's physical and mental characteristics. Based on an AI-based real-time analysis from their bio-data, including users' actions, body posture, lip expression, HR, HRV, and breathing pattern, Lopes et al. [72] propose a method that automatically adjusts the exercises' difficulty to suit patients' abilities during the execution of the rehabilitation procedures.

Casoria et al. [78] propose an XR soccer player training system that tracks players' performance to offer difficulty adjustment to users using RL. Accordingly, the difficulty is adjusted quickly, which supports an improved analysis as players are in higher demand. Similarly, Tsiatsos et al. [79] propose a framework that uses ML to classify users' biosignal features, including GSR, HR, and HRV, into anxiety levels in the sport. Users' abilities are followed by analyzing the stress to monitor recovery status and any potential overtraining. At the same time, the optimal training is identified. Doolani et al. [81] propose a working training XR system that keeps track of the current difficulty level and users' task performance. Supported by RL, different difficulty levels and feedback based on the user's actions are given to the users to maximize their task performance and assist the user in reaching higher levels. Zhang et al. [83] propose a virtual training system in the power industry, allowing real-time feedback and monitoring to adjust training dynamically. Hardy et al. [93] propose a framework that utilizes an AI model to process the data collected from the IoT and classify users' behavior in the VR environment. Finally, behavioral improvement feedback and the personalized treatment experience are generated based on their emotional requirements. de Lima et al. [43] analyze the horror intensity for users and the intensity of different horror elements according to users' behavior in VR. The game's pace and adaptive horror elements are adjusted in real time to maximize the horror experience for a personalized game experience. Similarly, Ojha et al. [44] use ML to analyze gameplay data and identify specific fear triggers for each player, which is used to adjust the horror elements in real-time, ensuring the game stays engaging by matching the level of fear to the player's personalized tolerance. Liu et al. [87] provide personalized feedback by comparing the user's baseball performance with professional athletes and provide training feedback and recommendations. Lucas-Pérez et al. [88] adjust the complexity and the nature of training tasks to balance the challenge and skill. Multimodal data help in obtaining various variables for assessing the physiological states.

Psychological and emotional analysis: Some studies propose methods to analyze users' psychological and emotional states in virtual environments, which contributes to a deeper understanding of users, facilitating personalization. Xu [90] proposes an AI-based framework to analyze the physical and psychological characteristics of patients with autism using big data. Then, a treatment plan is designed using AI to only belong to the patient according to their characteristics. Combining SVM and psychological tests, Khatri et al. [25] extract users' high-level motives from users' input and bio-information, for example, eye gaze and motion, in the VR online shopping activities. Their shopping requirements are analyzed and obtained from their motives, which contribute to providing a personalized XR shopping experience.

Tao et al. [84], Lor et al. [85] propose an AI-based method that detects how confident trainees are when they make a decision in VR training by analyzing their eye gaze, controller pose, and event-driven data. By doing this, not only whether the decisions made by the trainees are correct or not but also how confident they are about their decisions are recognized. A personalized guide or training plan is then conducted for the next training step.

During the rehabilitation program in [76], a set of images is captured and analyzed to extract users' emotions. Izountar et al. [76] analyze users' emotions using the affective computing algorithm and DeepFace model[121] by inputting images. The result of emotional analysis is used to adjust the game's difficulty to suit users' abilities. Similarly, supported by the DeepFace model, [108] dramatically adjust virtual content around users to suit their emotions during the virtual experience. [52, 113] create effective virtual environments based on users' oral speaking. Speech emotion recognition and sentiment analysis are used to analyze users' audiovisual content, offering a personalized experience that reflects the user's emotional state. Castets et al. [86] propose a framework to infer users' emotional and physiological conditions based on physiological and pupillometry data used in the XR problem-solving process. Using the data collected from the IoT, Hardy et al. [93] propose a framework that utilizes an AI model to process emotional and physical conditions. Different personalized applications are conducted by the emotional result, for example, the behavioral improvement feedback, the personalized treatment experience, and the worker's emotional healthcare.

de Lima et al. [43] analyze the player's fear in an XR horror game according to the user's behavior and bio-information. The game's pace and adaptive horror elements are adjusted in real-time based on their fear state to suit their emotion and improve their experience in the horror game. To construct a personalized virtual space, Sanatani [49] proposes a method to predict users' emotions in the designed virtual space with nine spatial parameters of architecture, supported by affective analysis of spatial enclosures [125]. Fuchs et al. [38] propose a virtual meeting room where the environment is changeable based on users' emotions. Users' emotions and feelings in the virtual room are extracted and analyzed from users' voices with the support of NLP. Finally, the atmosphere of the room (adjusted by light color) and the picture on the virtual wall are updated based on users' emotions to get a calming effect. In [92], facial and voice recognition algorithms are employed to detect participants' emotions and answers. Different questions based on their emotions are asked by a virtual agent to enhance the participant's communication skills with autism spectrum disorder.

Avatar and VR environment customization: Constructing a personalized avatar and customizing a personalized VR environment contributes to achieving personalization in PSI-XR. For the personalized emotional expression in XR, Zhao et al. [42] propose a method that allows users to customize their facial expressions. The sound, text, texture, and animation state of their avatars are changed by users for their current expressions of different emotions. Supported by the neural network, Yang and Zhang [99] propose the Fast 3D Facial Avatar Digitization (F3FAD) pipeline that allows users to re-design their avatar based on their 3D face model. Firstly, users' 3D facial models are reconstructed from one image. Then, facial attributes are abstracted and constructed to generate users' avatar faces by the Adaptive Instance Normalization (AdaIN) [126, 127]. In this process, users can decide what percentage of their original facial attributes are retained in their avatar to meet their preferences. Talapuru et al. [102] propose a method to generate personalized avatars, allowing them to reflect specific user actions and emotional expressions, enhancing immersion in the virtual experience.

Similarly, Basi Reddy et al. [101] optimize the avatar based on a few parameters representing facial features, body proportions, hairstyles, etc. Genetic algorithms are used to generate a diverse set of initial avatars. Users assess the avatars, and the high-score avatars are kept for the next generation to evolve the avatars based on user continued feedback. Given a standard user's facial avatar model (without emotions), Molano et al. [100] propose a method to generate an animation of users' facial avatars with different emotions, for instance, happiness, sadness, and anger. By doing this, users are allowed to express their personalized feelings in the XR experience. Manfredi et al. [27] propose the VICO-DR, which takes an input 2D image from an RGB (Red, Green, Blue) color camera of the customer side and reconstructs the 3D mesh and the corresponding skeleton for the user's avatar. To combine with the avatar, a digital clothes database is constructed to show how the dress looks in the avatar. Finally, the motion tracking system of VICO-DR maps the customer's movements onto the 3D avatar in real time for users' personalized shopping. Iwane et al. [117] utilize RL to analyze EEG data to adjust the motion mapping of avatars in real time to optimize the user's VR interaction experience.

Ghaznavi et al. [94] propose a method that allows users to customize their childhood avatar by adjusting different body features (hair color, size of the head, head position, shirt color, etc.) from their basic avatar models constructed from one image. Further, the virtual scene can be customized to simulate the users' childhood bedrooms for users' personalized requirements. Additionally, with the neuromonitoring data fMRI from users, Valenza et al. [47] propose a method to create a personalized immersive virtual environment. By extracting the scene description from users' brain signals, a 360-degree image is mapped onto a spherical surface using AI.

Providing assistance: To achieve personalization, some methods provide users with human-centered assistance that provides a comfortable environment, simplifies their interaction process, and keeps them safe.

As an assistant function to improve users' immersive feeling in the virtual meeting room, Fuchs et al. [38] propose a method to change the virtual environment according to users' discussion. Sun et al. [105] propose a system to assist the users in dealing with interruptions to their virtual immersive experience with non-invasive sensors.After obtaining users' emotions in the virtual room through their voice and conversation, as explained by NLP, the atmosphere of the virtual room is adjusted through the switch of the warmth and coolness of light. By doing this, the virtual environment is targeted to provide a calming effect to users, making them feel comfortable according to their personalized state. Liebers et al. [112] categorize different users' eyes and head motion data to recognize different users. The proposed ML model recognizes users without giving them personalized information the next time they log in, improving their immersion in the virtual environment. Rewkowski and Lin [111] propose a method to keep users safe when they walk near the safe boundary. A virtual companion (a virtual dog) and a physical robot (a dog robot) are created to remind users when they walk near the safe boundary. The dog robot provides haptic feedback and natural motion constraints by locomotion and leash pulling. Also, a warning bark from the virtual dog reminds the user through voice. This aims to provide a natural and immersive safety reminder in the XR environment. Casoria et al. [39] propose a method to detect the potential interaction person, automatically adjusting the information layout during communication. The smart management of the interface creates a personalized experience by balancing interaction and displaying information in an XR environment without users' manual operation.

Zhang et al. [114] propose a method to give users an immersive experience through tactile feedback in the interaction process. When users "touch" the virtual objects in VR, the hand-tracking model is used to detect users' hand motion, and the rigidity of objects is recognized by a DL model (Inception V3) [128, 129]. Finally, the designed haptic controllers' gloves generate different intensities of force to provide tactile feedback based on the collision pattern between users and the virtual object. Also, Mazhar et al. [74] propose a serious game where the forearm-mounted miniature disc motors are triggered to provide tactile sensations when users grab a tool or strike an object in the game. The tailored hand dexterity rehabilitation regimen in the work of [98] with the help of MR and AI gamifies the task of enhancing a patient's gripping mechanism. The problem of gesture nesting in VR seriously affects the user's operation experience and the efficiency and robustness of the system. Gao [45] proposes a gesture recognition method and a 3D interactive interface supported by collision detection, helping users' operation for continuous gesture flow in practical application scenarios. Visible feedback is also provided when interaction occurs to improve the realism. Karthick et al. [107] utilize the You Only Look Once (YOLOv8) model to recognize four gestures to achieve a virtual mouse's basic functions instead of a physical handheld controller, which enhances immersion and improves users' virtual experience.

Bhowmick et al. [109] propose a method to assist users in selecting small virtual objects by adjusting the size of users' virtual hands. Users are allowed to change their virtual hand to the size they want by making a fist gesture with a different rotation angle till the size is suitable enough to select the target. It aims to provide users with a comfortable and user-friendly selection process in VR and addresses the challenge of selecting tiny VR objects. Rhodes et al. [48] propose a method that allows users to design their music using customized gestures. Users can manipulate the velocity of different phonetic symbols with different timbres and sounds in 3D space using customized gestures based on visual data and EMG data, which brings the immersion and simplicity of music design in VR.

Exercise motion correction: Evaluating and correcting users' motion is another way to achieve personalized exercise in PSI-XR. In contrast to personalized performance adjustment, this section focuses on the precision of the user's motion, with the goal of assisting users in correcting their motions to support effective rehabilitation. Lee et al. [70] utilize RGB color with depth (RGB-D) data and the human pose detection algorithm to detect and evaluate the user's movement posture. The angle of the user's skeleton is compared with the prerecorded professional and standard skeleton to evaluate whether the user's motion is correct. For instance, if the joint angle difference between the expert motion data and the user's motion is within 10 degrees, the system recognizes it as a correct posture. Conversely, users are alerted and corrected if the angle difference is too large. Afyouni et

Table 6 Classification of the achievement of personalization with the use of AI in smart immersive XR environments (RQ3 and RQ4). GenAI in the table indicates generative AI, UnspecAI indicates the work that employs the unspecified type of AI, while WAI denotes works without the use of AI

Personalization	ML	DL	RL	GenAI	UnspecAI	WAI
Content synthesis	[24, 26, 28, 30, 36, 37, 40, 46, 55, 57, 96, 106]	[29, 32, 35, 82, 108]	N/A	[31, 33, 34, 38, 50, 51, 62, 63, 66, 67, 95, 103, 104]	[41, 64, 80, 91, 92, 119]	[65]
Performance adjustment	[43, 44, 56, 68, 71, 72, 79, 93]	[54, 58, 69, 72, 87, 110]	[77, 78, 81, 88, 90]	N/A	[53, 59, 61, 75, 83, 98]	[74, 89]
Psychological and emotional analysis	[25, 43, 49, 52, 84–86, 93, 113]	[76]	[90]	[38]	[92]	N/A
Avatar creation	[27, 101]	[99, 102]	[117]	N/A	[42]	[100]
VR environment customization	N/A	[47]	N/A	N/A	N/A	[94]
Human-centered assistance function	[39, 45, 48, 107]	[97, 112, 114]	N/A	[38]	N/A	[74, 105, 109, 111]
Exercise motion correction	[73]	[60]	N/A	N/A	N/A	[70]

al. [73] develop a serious game that includes a virtual assistant to guide patients to finish different gestures for rehabilitation. A 3D motion sensor (Kinect) with a gesture recognition algorithm is used to capture and evaluate patients' gesture motion. The automatic correction technique is incorporated in the guiding engine, which provides users with detailed feedback on joints that are not performing as expected and guides them in improving their current motion. It aims to provide an entertaining and personalized rehabilitation XR experience for patients. By capturing students' body motion, Zhao [60] provides real-time feedback on movement accuracy to achieve personalized corrective guidance.

Table 6 provides a summary of the selected papers, categorized by the type to achieve personalization and the use of AI that is discussed in the following section.

4.6 AI versus non-AI techniques

In the previous section, we identified the techniques used in PSI-XR in the reviewed literature. This section aims to identify the use of AI vs. non-AI methods (RQ4). In this study, AI is defined as the study of agents that receive percepts from the environment and perform actions, implementing a function that maps percept sequences to actions [130]. This broad definition emphasizes AI as an overarching field aiming to enable various agents to autonomously perceive their environment and make decisions to achieve specific goals. Within the scope of this section, our analytical discussion selectively incorporates research techniques and methodological strategies that explicitly conform to the delineated AI definition. Conversely, methodological approaches failing to meet this precise definition will be explicitly designated as non-AI methods.

As a subset of AI, ML is widely used in the selected papers. Notably, some papers claim that ML is used in their approaches but do not explicitly specify what type of ML technique is applied. Meanwhile, some papers explicitly indicate the specific ML type that is used, such as RL, DL, or GenAI. In our categorization, the ML category, as shown in Table 6 and Fig. 3, includes articles that claim to use ML but do not provide further clarification on the specific type of ML. Although DL, RL, and GenAI are subsets of ML, we did not include them in the ML category in the following discussion. Instead, the DL, RL, and GenAI categories are addressed separately, specifically covering articles that clearly state the use of these respective techniques.

Of the 94 papers included, 85 utilize AI methods, representing 92.6% of the total. As shown in Fig. 3, ML category includes the largest number of papers, with 34, accounting for nearly half. DL is used in 19 papers, while 6 papers utilize RL. It's worth mentioning that one paper [72] is included in both DL and ML categories because it employs two distinct networks. One specifically leverages DL technique and the other is only reported using ML technique. 13 papers employ GenAI models and 14 papers explicitly mentioned the use of AI without specifying the exact type. Additionally, 9 papers that do not employ AI in their work but contribute to personalization in smart immersive XR are categorized as non-AI techniques. The following discusses the existing work between AI and non-AI techniques, categorized in Table 6 with personalization.

ML: ML is the most commonly employed AI technique, covering almost all areas in the selected papers. It is the method of learning from data or experience [131] and automates analytical model building. Sanatani [84], Forero et al. [93], Tao et al. [49], Lor et al. [86], Castets et al. [113], Hardy et al. [52], and Forero et al. [85] utilize ML to assess user states by analyzing various inputs such as eye-tracking data in VR, physiological signals (BVP, three-axis acceleration, body temperature, electrodermal activity), users' behavior, or questionnaire responses, which provide an understanding of users' emotional, physiological, or learning states.

Several studies [24, 36, 37, 57, 106] use ML as the basis of the recommendation system, analyzing user questionnaire responses, users' input history, or users' features extracted during the VR learning process. Then, the ML-based recommendation system suggests content that users may be interested in, including hotel recommendations, tourist attractions, learning materials, and VR applications. Similarly, Kumar et al. [30] utilize ML to analyze and predict users' preferences in real estate, providing personalized experience in real estate purchase.

Gao [48], Rhodes et al. [107], and Karthick et al. [45] use ML to address gesture control issues in VR human-computer interaction. Rhodes et al. [48] employ ML to extract data from physiological signals for recognizing user gestures, while Gao [45] uses ML to resolve the nesting of gestures, enhancing the robustness of gesture interaction. Karthick et al. [107] utilize YOLOv8 to identify different gestures for different interaction functions.

Both Khatri et al. [25] and Pfeiffer et al. [26] use SVM to analyze user behavior in VR shopping. Khatri et al. [25] classify users into *Big Five* personalities [132, 133] based on their eye-tracking and motion data using SVM, while Pfeiffer et al. [26] use SVM to analyze eye-tracking data, predicting the user's possible focus in the next second. In both cases, SVM is employed to identify users' shopping motivations. Similarly, Ourahmoune et al. [68] utilize SVM to detect users' palpation gestures and provide feedback for adjustment. In the virtual clothes shopping method proposed by Luidolt and Zhou [28], the ML model DensePose [134] is employed to map every pixel in the 2D garment to the 3D human avatar to show the user's virtual try-on appearance.

ML is applied to optimize VR interface layouts in the works proposed by Casoria et al. [46] and Lo et al. [39]. It is used to analyze the progress of sports games to display relevant content [46], as well as to identify potential interactive objects, optimizing the layout of information within the user's field of view during interactions with others [39].

de Lima et al. [73], Ojha et al. [43], Lopes et al. [79], Afyouni et al. [72], and Tsiatsos et al. [44] also employed ML to adjust the difficulty of VR games, training systems, or rehabilitation serious games to match the patient's level. Users' reactions to game elements in VR, training scores, or physiological signals are analyzed to predict the most suitable parameters that are used to adjust the intensity of the VR application.

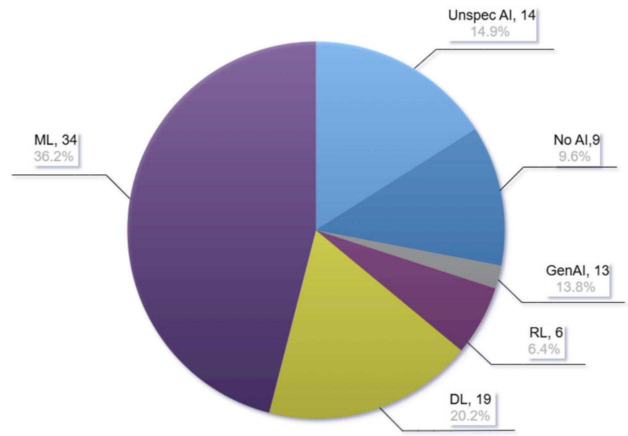

Fig. 3 Distribution of the use of AI in the reviewed papers with the number and percentage in different categories. Both DL and ML are employed in [72], resulting in the number of papers totaling up to 95

Common questions customers raise during technical consultations are usually found in the FAQ conversation dataset. To reduce the workload of consultations, Wu et al. [40] propose an ML-based chatbot to answer FAQs extracted from the technical FAQ database. Additionally, Manfredi et al. [27] use ML to reconstruct users' 3D mesh and the skeleton of avatars from a set of 2D images, which is used to combine with the virtual clothes dataset to show how the clothes look in the avatar. Basi Reddy et al. [101] employ ML to extract avatar facial features of interest to users for generating avatar that aligns with users' preferences.

Girhe et al. [55] propose a child with intellectual disabilities learning system that utilize ML to customize learning content based on user assessments, allowing them to learn at their own pace. Ahmed et al. [56] propose a ML-based virtual clinic learning system that provides students with personalized learning pathways and real-time performance feedback, helping users refine diagnostic and decision-making skills in medical. Trappey et al. [96] utilize ML to classify sentiments and understanding user issues, building a VR chatbot system. Kang et al. [71] utilize ML to develop an intelligent combat training simulation system, which enables the training system to simulate realistic combat environments tailored to the individual roles of the trainee, providing personalized feedback.

DL: As a subset of ML [135], DL represents learning methods from data, where computation and processing are carried out through multi-layer neural networks. The term "Deep" in DL refers to multiple hierarchical levels or stages through which data are processed to construct a data-driven model [136]. DL is utilized in various aspects to achieve personalization in different application areas. Yu [58], Izountar et al. [76], Li and Chen [110] use DL to adjust the difficulty of their learning and rehabilitation systems separately. Yu [58] proposes a learning system that employs a DL-based AI model to monitor each student's behaviors and progress, updating the student's model according to the student's performance and skill acquisition. The difficulty, environment scenarios, and tutoring interactions are adaptively adjusted. Similarly, in the rehabilitation system [76], patients' emotions are analyzed by a DL model, which adjusts the rehabilitation program's difficulty based on the emotional analysis result. Also, in the serious game proposed by Lopes et al. [72], a DL model is used to analyze the sentiment of the users' phrases with the assistance of language models. Rokhsaritalemi et al. [108] utilize a DL-based AI model, DeepFace model, to analyze and understand users' emotions in the virtual environment. DL models in addition to GPT-3, BERT, and T5 have been utilized in the work of Doungtap et al. [35] for customized product recommendations using voice-based interactions. Zhuang [32] use DL to detect intrusion, analyzing user behavior, and generating personalized shopping recommendations based on consumer data.

In the worker training VR system [82], a DL model is used to estimate user learning progress based on the data gathered from their profile settings from the social media platform, for example, LinkedIn, biometrics, and the UI interaction. DL is also used for semantic analysis in virtual objects. For instance, the DL model [128, 129] is used to recognize the rigidity of the virtual object the user interacts with. The rigidity information is then used to support the haptic controllers' gloves [114] to give real tactile feedback to users. Similarly, Tong et al. [29] use a DL-based semantic segmentation algorithm to separate users' interested furniture and allow users to envision their interested furniture in different colors and styles, which enhances user experience in AR-based indoor decoration.

Valenza et al. [47] capture users' neuromonitoring data, fMRI, which is used as input of a DL model to transfer to 3D scenes. Yang and Zhang [99] propose an end-to-end DL method F3FAD which is used to reconstruct a user' face in 3D by using one single image. After that, another DL-based algorithm [126, 127] is used to extract facial attributes, which allows users to design their avatar by maintaining a different percentage of his or her original facial attributes. Liebers et al. [112] propose a DL-based method to categorize users' eye gaze and head position data. The DL model recognizes users based on the above information without knowing who the user is in the proposed system login process. Yun et al. [54] use DL model and Tolba et al. [69] utilize long short-term memory (LSTM), an RNN algorithm to analyze a student's pronunciation and deliver instant corrective feedback. Talapuru et al. [102] use DL model to identify the differences between the foreground (users) and the background in an image or a sequence of images, which supports to construct the user's avatar. Zhao [60] utilizes a human body tracking algorithm which is based on DL to capture users' motion, providing personalized movement analysis. A combination of the use of CNN and RNN to analyze the change in user behavior captured using devices is proposed by Zhang and Cao [97]. Similarly, a hybrid AI composing CNN for image recognition and RL for adapting the training difficulty is employed in the work of Liu et al. [87].

RL: RL is a type of ML method that has the advantage of avoiding labeled data to direct the algorithm. The task of RL is to use observed rewards to learn an optimal (or nearly optimal) policy for the environment [130], which supports in achieving personalization in training and healthcare. Doolani et al. [81] propose an AR work training system that utilizes RL to track difficulty levels of tasks and users' performance. RL is employed to monitor and analyze users' operational proficiency. Varying task difficulties and feedback are provided by the RL model according to users' performance to maximize task performance and assist users in reaching higher levels. Additionally, Casoria et al. [78] propose an immersive VR system for analyzing and training professional soccer players' executive functions (EFs). The developed adaptive tracking game mode uses RL to analyze users' speed, the number of correct rounds, accuracy, and execution time and to adjust the training speed accordingly. RL model allows training increases in difficulty as the user progresses, with enhanced analysis as the player's demands of higher levels increase. Xu [90] introduces a framework for children with autism in VR where the user's avatar continuously interacts with the virtual environment, acquiring relevant information and making adjustments based on environmental changes. An RL-based reward and punishment mechanism continuously monitors users' states, adjusting their task difficulty and deciding whether to give rewards. RL is utilized to analyze users' EEG data in the proposed method of Iwane et al. [117] to determine whether the avatar's actions are perceived as erroneous. The error motion is adjusted by RL, providing users with immersive virtual interaction. Additionally, Lucas-Pérez et al. [88] utilize RL to adjust the complexity of training tasks in the training process. A RL-based method is used to dynamically adjust the placement of the next bubble in a VR bubble-catching rehabilitation game. This adaptation is guided by the patient's real-time performance, ensuring a personalized and responsive training experience [77].

GenAI: GenAI represents a transformative advancement within ML, enabling the creation of content that mimics human-like quality and creativity. Generative adversarial networks (GANs) have accomplished extraordinary results that were once thought nearly impossible for artificial systems, such as creating highly realistic fake images with real-world-like quality [137]. Beyond visual domains, LLMs, another key pillar of GenAI, are designed to predict the probability distribution of language expressions [130]. These models excel in producing coherent, contextually appropriate text, showcasing the versatility of GenAI across visual and textual tasks.

He et al. [50] utilized GenAI to capture users' design ideas from their text and transfer them into 3D content to support their VR design. Similarly, Constantinides et al. [51] utilized GenAI to provide personalized feedback in the art exhibition when visitors ask specific questions to meet their personalized curiosity.

Fuchs et al. [38] extract the text from users' oral discussions using ChatGPT [115] in their virtual meeting. Then different images from the text description are generated by a GenAI model known as *Stable Diffusion* [138], which are subsequently displayed on the wall of the virtual meeting room. The generative image created based on the conversation content provides participants with a dynamic meeting environment that benefits the meeting discussion with some possible new ideas. In this case, both of the key strengths of GenAI, LLMs for language processing and image generation, are effectively utilized to create a personalized VR environment. Wang et al. [67] utilize ChatGPT [115] to provide automatic feedback for the students hands-on AIoT tasks.

Divanji et al. [62] allow children to cooperate with a virtual role created by ChatGPT, providing a virtual education experience. Hou et al. [104] utilize GenAI to create personalized content to meet users' personalized preferences. Kumaar et al. [31] develop a chatbot based on GenAI that offers customized recommendations and expert guidance in try-on online shopping, providing customers with a personalized virtual shopping experience. Wong et al. [33] develop a virtual shopping assistant based on LLMs which is able to have a conversation with customers. The personalized recommendation is given to users by analyzing their conversation requirements. For the personalized furniture selection, Do et al. [34] employ GenAI together with an intelligent recommendation system. GenAI and ChatGPT aided in the personalized virtual space generation in the work of Yang et al. [103]. The use of LLMs and chatbot provides personalization for data literacy education in the work of Gao et al. [63], while in the work of Salehi et al. [66], LLMs are applied for personalize scenarios of interview training. Zhang et al. [95] use GenAI to enhance the personalization and interactivity in VR grief therapy by creating personalized content based on users' verbal descriptions or visual inputs.

AI without type specified (Unspec AI): Some works do not mention the specified type but still use AI in developing immersive personalization. Coltey et al. [53] and Li et al. ID267 utilize AI to adaptively adjust the complexity and difficulty of the learning process and the serious game, respectively, suiting the user's abilities. Coltey et al. [53] apply an AI-based training system, ALS, to increase or reduce the task difficulty when users completed the current or not. In the serious game for elders in [75], gameplay conditions and user's posture are captured and fed into the AI model, which returns the most suitable parameters for users to match their abilities.

Both Trappey et al. [41] and Belmaqrout et al. [91] use an AI-based chatbot to connect with users. By collecting FAQs, Trappey et al. [41] propose a chatbot to offer clear and detailed design consultation support from the knowledge base for designing and manufacturing complex power transformers. Belmaqrout et al. [91] propose an AI-based chatbot to communicate with patients according to the patient profile and autism patient database. The chatbot switches the VR treatment content based on the measurement of the emotional situation of patients. Similarly, Chan et al. [80] propose an AI-based domain expert to compare the answers of the trainee and the correct solution. Then, the AI-based domain expert responds to trainees appropriately; otherwise, the trainee is informed of his/her error through the UI.

The AI-based facial recognition and voice recognition algorithms in a treatment method for children with autism spectrum is proposed in [92], followed by the AI-based analysis of participants' emotions and answers. Also, Zhao et al. [42] utilize AI to detect face position, facial emotion, and eye blinking states to analyze users' emotions and provide them with suitable expressions in VR. Liu and Zhang [59] employ AI to analyze students' English levels and their features in the XR learning system, providing suitable learning content to them based on their levels.

Artizzu et al. [119] utilize an AI-based conversational agent to customize the experience by understanding user intent through voice, gaze, and pointing. Zhang et al. [83] utilize AI to provide real-time feedback, adjusting the training process dynamically to suit the proficiency level of workers. Cinar et al. [61] utilize AI to provide students with complex programming concepts through a virtual assistant. VaezAfshar et al. [64] utilize AI to provide real-time responses to students in virtual heritage education, providing personalized conversation in their virtual experience. Whereas NLP enables the speech recognition module in hand dexterity therapy in the work of Lei and Li [98] for human-device communication, the AI algorithm used for assistive guiding is not mentioned.

Non-AI techniques: Some methods do not utilize AI but rely on traditional computing and sensor techniques to make intelligent decisions to enhance user experience. Although these approaches do not depend on AI, they provide effective and smart solutions within their respective domains.

Lee et al. [70] and Rewkowski and Lin [111] focus on improving user movement accuracy and safety without AI. Lee et al. [70] use RGB-D data and joint angle comparison to monitor user movements, precisely assess and correct posture, and ensure users' exercise correctness. This system achieves motion monitoring through direct data comparison rather than relying on intelligent analysis. Rewkowski and Lin [111] introduce a safety system combining virtual and physical feedback. Users are warned when approaching safety boundaries by providing two-way haptic feedback through a virtual dog and a physical robot dog. This method enhances user safety through tactile feedback and physical constraint mechanisms without relying on AI for data processing or behavior prediction.

Ghaznavi et al. [94] allow users to customize virtual avatars based on childhood photos, including appearance and environmental settings. Their system achieves personalization through graphical adjustments and user customization options rather than using AI for personalized suggestions or adjustments. Also, Molano et al. [100] use the *candide* model [139] to generate emotional animations for users' facial avatars with vivid virtual expressions, according to human face parameters without AI. Sun et al. [105] design a personalized module to modify the action probabilities, allowing the agent to adapt to the individual preferences of various users. Mazhar et al. [74] and Bhowmick et al. [109] improve user interaction accuracy and naturalness without relying on AI. Mazhar et al. [74] develop a game incorporating gesture recognition with haptic feedback, adjusting game difficulty based on user scores and adjustment mechanisms rather than dynamically adjusting game content with AI. Bhowmick et al. [109] propose a method to adapt virtual hand size through gestures to improve virtual object selection accuracy without AI. Combined with fuzzy logic, Troussas et al. [65] classify users into five proficiency levels (Fundamental, Basic, Intermediate, Advanced, Expert), delivering appropriate assistance based on the classification. Personalization is achieved in the work of Han et al. [89] through collected human data that do not require the use of AI for processing or personalization.

5 Discussion

In this section, we analyze and reflect on the insights gained from the RQ1, RQ2, RQ3, and RQ4 results. Additionally, we explore the opportunities and challenges for the ongoing development of PSI-XR (RQ5).

5.1 Current research status

Applications: PSI-XR has been widely applied across multiple fields. E-commerce and healthcare are the most prominent within the application areas. For instance, the PSI-XR provides a highly tailored shopping experience by offering products that align with users' preferences, shopping history, and real-time feedback. Similarly, XR environments are utilized in the healthcare sector for personalized treatments and rehabilitation, adjusting exercises or therapies based on the patient's condition and progress. Other significant areas also make use of the capabilities of PSI-XR.

Driven by the rapid development of technologies like HMDs, XR has brought new possibilities to various fields with high immersion and interactivity, enabling XR to be widely applied in different areas. Smart techniques, for example, NLP, gesture recognition, and eye-tracking, have infused XR with personalization, making it more intelligent and human-centered, which transform traditional XR environments into intelligent systems, PSI-XR, that adapt to users' needs or requirements in real-time.

Technology: PSI-XR primarily relies on the technological foundation constructed by hardware devices such as HMDs. With their high-precision motion tracking and high-resolution displays, HMDs have become the preferred devices for immersive environments. For example, HTC Vive is widely used in various scenarios. Currently, HMDs are continuously being upgraded and optimized, some advanced HMDs like the Meta Quest Pro and Varjo XR3 are also applied to contribute to PSI-XR. In particular, the Meta Quest Pro, with its native features like eye gaze recognition and facial expression recognition, is particularly well-suited for achieving personalization in PSI-XR. Meanwhile, these devices offer higher resolution and more precise motion tracking and enable more natural interactions and immersion, increasing the immersive quality of XR environments. In addition, HMDs, smart mirrors, and AR glasses are also being applied in different fields, providing opportunities to merge real and virtual spaces for applications like exercise guidance and virtual try-ons. These devices expand the scope of XR interaction, allowing users to engage with digital content in more diverse settings. Screens and smartphones also play important roles in XR applications. Though these devices may not provide the same level of full immersion as HMDs, their portability makes them more accessible for daily use at a lower cost. Smartphones, in particular, support convenient AR applications, allowing users to easily integrate XR into their daily lives, enhancing learning and work experience. Projector-driven XR systems transform physical spaces into virtual environments by projecting virtual content onto real-world surfaces. This approach enables shared immersive experiences, making it ideal for collaborative learning and group-based tasks.

Techniques: PSI-XR employs various techniques to gather users' bio-information, actions, and behaviors, which benefit understanding users' interests and requirements. For example, eye tracking and head position detection enable systems to recognize users' interests and focus by tracking the user's gaze direction and head movements. Face and facial expression detection help systems assess the user's emotional state. They all detect users' points of interest based on their behavior and bio-information, which enables PSI-XR to understand users' interests and requirements. Physiological signal detection techniques (such as HR or GSR monitoring) gather users' physiological data to help analyze their state. This allows PSI-XR to adjust the intensity according to users' stress from the physiological metrics, optimizing the experience, especially in serious games or training scenarios. Some techniques ensure smooth and responsive interactions for users, enhancing their experience. Body posture tracking enables XR environments to precisely detect user motions and behavioral responses, while the gesture recognition technique allows users to interact with virtual objects naturally. Other techniques, like haptic feedback, provide tactile sensations during interaction, enhancing immersion in PSI-XR. A combination of various smart techniques allows PSI-XR to sense and track changes in the user's state from different perspectives, ensuring dynamic and highly personalized responses to user behavior, emotions, and physiological changes.

Personalization: PSI-XR achieves personalization in multiple strategies to meet users' requirements during their XR experience. For example, offering users personalized content that is interesting to users can improve their immersion and experience [24, 29, 106]. Personalized performance adjustment suits the abilities of patients or trainees, which benefits the rehabilitation or learning process. The achievement of personalization ensures that the activities provided in PSI-XR are enjoyable and suitable to users individually, meeting their situations and preferences. Psychological and emotional analysis [25, 49, 76] according to users' behaviors or expressions supports in understanding users' requirements or interests, allowing PSI-XR to be a personalized environment that improves users' XR experience based on users' psychological state.

AI vs. non-AI: PSI-XR employs AI to analyze and understand users, providing personalized experience, which is crucial for personalization. Some work employs AI to capture users' motion [45, 48, 107] and expression [76, 92] and analyze their oral conversation [36, 37, 57]. Some work utilizes AI to adjust the difficulty of performance [43, 78, 81] and recommend content to users [25, 26]. AI allows PSI-XR to understand users' behavior by analyzing their actions or concerns and determining their requirements and preferences. On the other hand, AI supports adjusting the task or environment to suit users' emotions and abilities, especially in rehabilitation systems. Various AI are utilized in the reviewed work, while ML is the most employed AI. They all play a similar role in personalized achievement based on the special application context. Some papers utilize GenAI to create personalized virtual content to users, understanding their personalized requirements by communication. We believe that the adoption of GenAI will greatly facilitate personalization in the XR environment, and it will be widely employed in various fields to guide users in learning/training and help users create customized content/avatars and psychological treatment-based conversations. While AI holds significant potential in PSI-XR, non-AI techniques are also worth exploring. Some methods [94, 100] enhance user experience through traditional computing and well-designed systems, and their simplicity and efficiency remain important in certain scenarios.

5.2 Opportunities and challenges

Based on the discussion about application areas, technologies, techniques, AI vs. non-AI methods, and the achievement of personalization, we have identified the following opportunities and challenges in different applications dealing with PSI-XR:

Data limitation in XR: Data insufficiency could be a significant challenge for personalized recommendations in some XR applications requiring advanced devices. As shown in Table 4, there are many works developed based on HMDs or 3D glasses in AR, VR, and MR, while the public does not widely adopt these devices. This results in an insufficient number of users in the related application, leading to data limitation in these types of XR applications.

Some work attempts to circumvent data limitations in this field. In the case of VR application recommendation, the compromise has been suggested to infer users' potential preferences for VR applications, for instance, based on their past movie preferences [24, 106]. However, the connection between potential preferences in the VR application and other industries' applications must be further explored.

Some work applies questionnaires to assess user preferences for recommendations as a solution around the data limitation issue, for instance, in the work of Veliz et al. [36] and Constantinou et al. [37]. This has effectively captured user preferences to some extent. We believe that further exploration of users' preferences in terms of other industries' data or questionnaire design, especially in the context of data limitation.

Due to the high cost of data acquisition in 3D reconstruction for real objects and environments, some recommended content can only be displayed to users in 360-degree videos rather than a virtual environment that users can explore and interact freely, for instance, in hotel/tour recommendation [36, 37]. Supported by DL, some 3D reconstruction algorithms have emerged in recent years, such as the neural radiance field (NeRF) [140] and 3D Gaussian splatting [141]. However, they usually require expensive computational resources, making it still challenging to develop a universal and low-cost method. Further exploration in developing a low-cost, widely accessible, and high-quality 3D reconstruction method would benefit hotel/tour managers' usability and convenience of 3D reconstruction, making large amounts of 3D data available.

Task difficulty adjustment: The premise of adaptive task difficulty adjustment is that the user's actual level is accurately assessed. A frequently used method is to increase the difficulty when the user completes a task; if they fail to complete it, the difficulty is reduced [53]. Alternatively, the user's score in training/serious games is used to judge to appropriate difficulty level [74]. Similarly, some studies use AI to identify the relationship between users' input data, physiological data, and the final training score [72, 93]. However, these methods could benefit from the information on which part of the task users struggle more with. We believe that providing special content related to what users are struggling with could benefit the personalization in rehabilitation or worker training.

To this end, some studies [43, 84] introduce self-assessment feedback of user abilities. For instance, Tao et al. [84] propose an AI model to evaluate users' confidence levels, to assess their confidence when making a decision, rather than simply evaluating their abilities based on correctness. We believe that further exploring the connection between users' level of the task and different data obtained from various smart techniques to define users' level could be an opportunity to improve personalization in PSI-XR.

In our review, Khatri et al. [25] attempt to use psychological theories to extract users' needs and personalities from their inputs and bio-information, providing personalized experience. Additionally, determining how much to increase the game difficulty to appropriately help trainees push their level boundary is a large challenge for adaptive difficulty adjustment, even though we accurately grasp the actual level of patients/trainees. We believe that establishing a collaboration between PSI-XR and psychological and cognitive theory is an opportunity to provide users with suitable and adaptive task difficulty.

Compatibility between sensors and VR headsets: Applying various bio-data acquisition techniques is beneficial for analyzing users' interests/emotions in the XR environment, which is essential to personalization. However, some data acquisition techniques have compatibility issues with the VR headsets. For example, Izountar et al. [76] uses DeepFace [121] to identify users' emotions according to users' facial expressions from a set of images in the rehabilitation game. However, some VR applications cover users' faces and heads by HMDs, meaning facial data are not available when using VR headsets. Even though advanced headsets like the Varjo XR3, Varjo XR4, and Meta Quest Pro offer support for eye-tracking technique, they have not yet been extensively leveraged, while most other HMDs still do not enable eye-tracking. We believe that addressing the conflicts and compatibility issues between VR headsets and other sensors in data collection is a topic worth ongoing research.

Physical interaction with XR: Interaction accuracy affects the precision with which users interact with other users or scenes in XR. This increases users' attention and cognitive load in interaction behaviors. For instance, inaccurate gesture algorithms take users more attention to control their actions to interact with virtual objects, which may break immersion because of the extra attention cost compared with the same action in the real world.

The reasons are varied. On the one hand, users' sense of spatial distance in VR differs from that in the real world [142]. Thus, users must pay attention to determine whether their virtual hand has reached the desired spatial position. On the other hand, users have difficulty controlling their actions to correctly interact with objects. For instance, users need to observe whether their virtual hand has touched or selected an object, and this additional attention cost directly affects user experience and immersion. In the real world, grabbing an object is so intuitive that people are sometimes unaware that their brain has controlled their hand to reach out, thus incurring no noticeable attention cost.

Moreover, interactions in the real world provide strong tactile feedback, which is a significant challenge to replicate in the virtual environment. For example, Zhang et al. [114] use semantic analysis of the scene to provide tactile feedback through a haptic glove. However, even for the same object type, different materials result in different tactile sensations, which shows that only considering the rigidity of objects to simulate tactility is insufficient. We believe that further research providing users with realistic haptic feedback when interaction occurs represents a significant opportunity to achieve PSI-XR.

Additionally, the lack of accuracy in gesture recognition algorithms brings the problem of nesting gestures. When users must perform several different gestures in rehabilitation or training operations, the lack of precision easily leads to recognition and operation errors. This forces users to monitor whether their gestures are being correctly recognized while performing continuous gestures, which in turn impacts the immersion and user experience in the virtual environment. Accuracy gesture recognition algorithms which can avoid nesting gestures between different gestures could be beneficial to an immersive and human-centered interaction in PSI-XR.

The application of GenAI: Generated content created by GenAI has great application potential in healthcare and education. We believe that GenAI can offer personalized dialogue therapy and customized immersive treatment environments for mental health patients, allowing them to interact with AI-generated assistants in XR environments to discuss emotional issues or address anxiety and stress. Additionally, GenAI benefits from creating an environment where students engage in dialogue-based interactions with virtual tutors or peers, dynamically generating personalized content based on each student's learning progress and interests.

The use of GenAI in personalization has emerged rapidly since 2024. LLMs has a strong ability to communicate and understand users, providing personalized feedback with virtual content generated by GenAI. We believe that GenAI holds great potential for innovation in PSI-XR.

Ethics and privacy: The reviewed studies emphasize the critical importance of adhering to ethical standards and ensuring data privacy in XR research. Many studies obtained ethical approval from relevant ethics committees for their experiment. Valenza et al. [47] highlight the use of data privacy in their research, with the approval of the local ethics committee. Ghaznavi et al. [94] secure approval from the Imperial College London Ethics Committee. Similarly, Casoria et al. [78] and Khatri et al. [25] ensure that participants agree with the experiment process by providing their written informed consent. Khatri et al. [25] also obtain approval from the Ethical Committee of the Polytechnic University of Valencia in accordance with the Declaration of Helsinki. Mazhar et al. [74] explicitly stated compliance with the Code of Ethics of the World Medical Association (Declaration of Helsinki), while Liebers et al. [112] recommend that all VR applications should adhere to ethical development standards [143]. Additionally, Yu [58] and Pfeiffer et al. [26] underscore the broader significance of ethics and privacy in the development and deployment of XR applications, reflecting a collective commitment within the research community to upholding trust and responsibility in this emerging field. Adhering to ethical standards and ensuring data privacy in XR research presents a critical opportunity to build user trust and drive the broad adoption of these technologies. However, balancing privacy protection with technological innovation remains a significant challenge in the rapidly evolving XR landscape.

6 Conclusions

In this review, we have explored the developments in PSI-XR. The application areas were reviewed systematically using various technologies and smart techniques to achieve personalization. Building on this, these techniques were further classified and analyzed from the perspective of AI to explore the involvement of AI or non-AI methods and how they support personalization. This review suggested that PSI-XR effectively provides personalized experiences to users across different domains, such as education, entertainment, and healthcare. Integrating multiple smart techniques within XR environments enables the effective acquisition, analysis, and perception of user needs, allowing for the prediction and delivery of personalized experiences tailored to users.

Despite the significant progress in enhancing personalized experience through immersive smart XR environments, several challenges remain in realizing their potential fully. The data limitation within some XR applications that are developed with limited adopted devices has hindered progress in personalization. Further research and exploration into difficulty adjustment of XR tasks could benefit users' experience, especially in rehabilitation and training systems. Additionally, the compatibility issues between sensors and VR headsets limit multi-sensor fusion in XR, which could be a valuable research topic. Furthermore, GenAI holds immense potential for enabling personalization across various applications, making it a promising area for further exploration.

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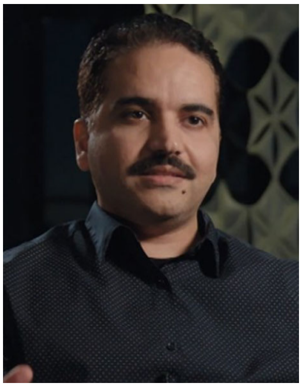

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