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Human task performance and associated internal states in extended reality: a systematic review of cognitive, psychophysiological, and physiological dimensions

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Human task performance in extended reality (XR) environments is a critical area of study due to the growing use of these technologies in fields such as healthcare, education, manufacturing, and training, as XR has the potential to influence both how well people complete tasks (e.g., accuracy, speed) and underlying human states such as cognitive load, stress, and physiological responses. A plethora of research has explored the benefits of XR across these domains, as well as research to investigate potential negative impacts on cognition and task performance. However, the findings regarding task performance remain inconclusive, and the factors contributing to enhanced versus diminished performance are poorly defined. In this paper, we conduct a systematic literature review of 79 research papers from 2015 to 2024, following the PRISMA guidelines, selected from an initial pool of 6,878 search results from the Publish or Perish database. Our review reveals that a key gap exists in understanding how specific XR factors, such as immersion levels, interaction modalities, and user interface design, influence both task performance and associated cognitive, psychophysiological, and physiological outcomes. We also report how these different factors influence the performance of cognitive, psychophysiological, and physiological tasks in different XR environments. We conclude by proposing potential research gaps and future research directions to focus on controlled experimental studies targeting these factors to gain deeper insights into their impact on human performance in XR settings.

KEYWORDS

extended reality, human task performance, psychomotor tasks, virtual reality, augmented reality, mixed reality

1 Introduction

Interest in eXtended Reality (XR) (i.e., umbrella term for virtual reality [VR], augmented reality [AR], and mixed reality [MR]; Rauschnabel et al. (2022)) is rapidly increasing as these technologies have widespread applications across diverse fields, including education (Radianti et al., 2020), defense (Harris et al., 2023), experiential learning (Mystakidis and Lypouridis, 2024), skills training (Philippe et al., 2020), and healthcare (Son et al., 2022). Figure 1 shows different applications of XR technologies, illustrating the use cases in immersive learning, virtual training, and professional development. These examples present how XR can create engaging and useful experiences in many different areas. The growing integration of XR technologies across various fields has fueled a surge in research investigating human task performance (HTP) in cognitive, physiological, and psychophysiological tasks within XR environments. Extensive experimental studies have been conducted to understand the impact of XR technologies on human task performance (Scharinger et al., 2023; Lin et al., 2020; Teng, 2022). These studies mostly report the beneficial aspects of XR compared to real-world settings. However, downsides, such as high cognitive demand and low task performance due to cybersickness, have also been reported (Au, 2022; He et al., 2022; Descheneaux et al., 2020). These discrepancies present significant hurdles in providing unified design criteria for researchers, designers, and developers, and a thorough understanding of the possible correlations between XR and human task performance is essential but still unclear. To address this knowledge gap, this paper examines the current state of XR in human performance through a systematic investigation of the factors, including system factors (Khalid et al., 2023), design factors (Nenna et al., 2022), and individual factors (Stanney et al., 2002), influencing human task performance in XR environments (Harzing, 2007).

Task performance in XR is influenced by system factors (e.g., hardware, software, display), individual differences (e.g., age, gender,

experience), content design (e.g., complexity, immersion, characters), and contextual elements (e.g., environment, motivation) (Shaw et al., 2016). Despite the volume of research, these findings are scattered across numerous publications, necessitating a consolidated overview for better understanding and future research direction. A comprehensive literature review can help identify common themes, emerging trends, and areas for further investigation. Organizing these insights into a cohesive framework would enable a clearer understanding of how various factors interact to affect performance in XR environments and could guide future research and system design to optimize human task performance across different applications.

To address this issue, in this paper, we conducted a systematic literature review of 79 papers selected from an initial pool of 6,878 search results using the Publish or Perish (PoP) database. The review explored the current research trends related to human task performance in XR systems, the factors affecting the performance, the negative impacts of XR, and potential research gaps for future studies. Following the PRISMA guidelines (Moher et al., 2009), we utilized the PoP database (Harzing, 2007) to collect relevant articles from various publishers and libraries. The selected papers covered a range of topics, including physiological, psychophysiological, and cognitive tasks, cognitive load, negative effects of XR, and performance factors. We also conducted a meta-analysis of the current papers from 2015 to 2024 and reported our key findings, the research gaps, and future research directions in this paper. Empirical studies related to human task performance, cognitive load, negative impacts of XR, and factors for HTP were the principal criteria for selecting the papers. This review focused on multiple objectives from three different types of tasks: cognitive, psychophysiological, and physiological. Our key contributions are but are not limited to:

- Contribution 1: Comprehensive Literature Review - Conducted a thorough review of existing research on

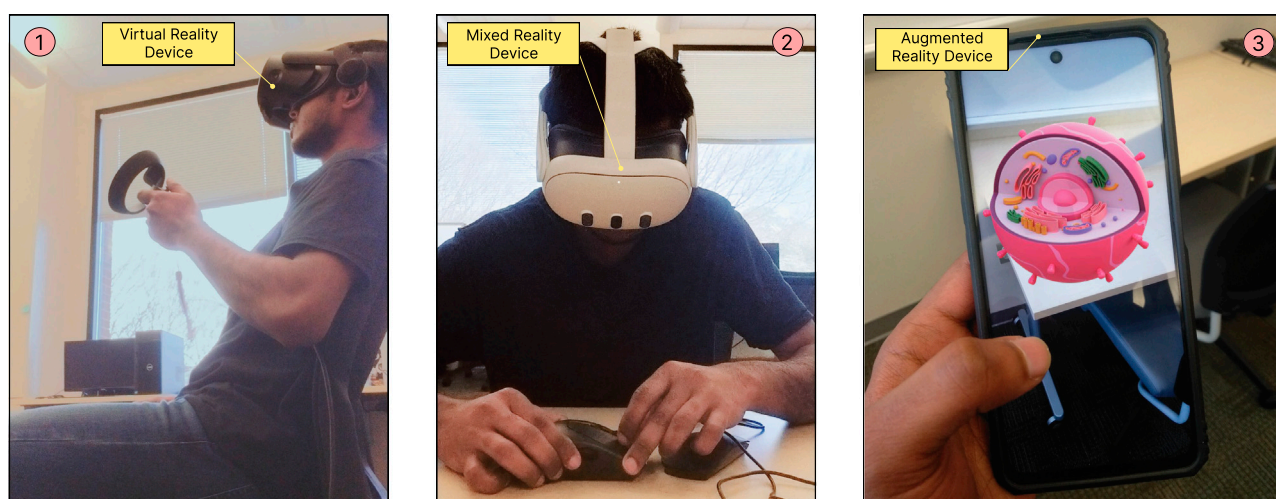


FIGURE 1
Applications of XR technologies in diverse fields. (1) The user is performing training in a virtual reality (VR) environment. (2) A user is performing an assembly task in a mixed reality (MR) environment. (3) The user is in a learning environment using the Smartphone-based Augmented Reality (AR) technology.

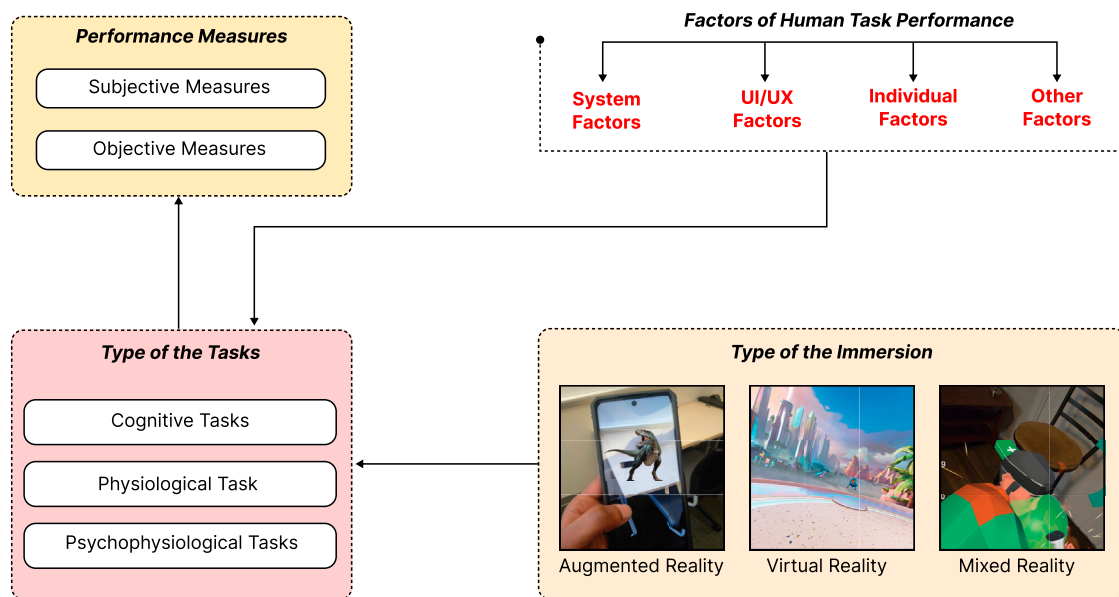


FIGURE 2
Overview of XR task design concepts, factors of human task performance, subjective and objective measurements, and immersion types.

human task performance in XR, focusing on studies involving procedural experiments. The findings were analyzed and systematically organized into a taxonomy for clarity and meaningful interpretation.

- Contribution 2: Identification of Key Performance Factors in XR Environments - Identified the key factors from the literature that influence human task performance across various XR environments. These factors were categorized into four primary groups to provide a clearer, more structured understanding of their impact on performance.
- Contribution 3: Analysis of Research Gaps and Proposed Solutions - Conducted a detailed literature analysis on human task performance and its influencing factors in XR systems. Synthesized previous findings to identify research gaps and proposed actionable solutions, including recommendations for future studies and developing new methodologies to enhance understanding in this field.

The paper is organized as follows. **Section 1** outlines the basic introduction to human task performance in XR systems, cognitive load, and factors and aspects of their applications. **Section 2** details the relationship between human task performance and XR systems, while **Section 3** details the review methodology, including the process of paper selection and data extraction. The key findings are presented in the subsequent sections.

2 Human task performance in extended reality

Human task performance is influenced by various factors, including system characteristics, user interface design, and individual differences, and is typically evaluated through performance metrics such as task pace and accuracy, alongside

measures of cognitive and physical workload (Wickens et al., 2021). For instance, increasing task pace can reduce precision and lead to errors (Vekony et al., 2022), while tasks requiring high precision may take longer and impose greater cognitive load (Fleming et al., 2023). Cognitive demands, shaped by task complexity, expertise, and environmental conditions, also play a role (Darvishi-Bayazi et al., 2023). In XR environments, sensory feedback (e.g., visual, auditory, tactile) impacts human task performance. Figure 2 illustrates the key factors as well as task setups affecting performance, discussed in detail in this section.

2.1 Human-performed task categories in XR

We classified studies using the following decision rules:

1. Cognitive tasks: The primary manipulation and outcomes target mental processes (e.g., memory, attention, decision-making) with no required continuous or coordinated motor program beyond simple responses (e.g., button press), and without analysis of physiological signals as primary outcomes.
2. Physiological tasks: The primary outcomes are objective bodily signals or physical performance (e.g., gait, balance, exertion) without an explicit cognitive-load manipulation; at least one physiological signal (HR/HRV, RR, BP, EDA, skin temperature, EMG, pupil diameter) is recorded and interpreted as an outcome.
3. Psychophysiological tasks: Both (a) a cognitive or affective manipulation and (b) coordinated motor action are integral to task success, and at least one physiological signal is analyzed as an outcome.

Tie-breakers: When a study plausibly fits multiple categories, we prioritized psychophysiological if both cognitive manipulation and

motor coordination were essential and a physiological signal was analyzed; otherwise cognitive if outcomes were purely performance/accuracy/RT without physiological analysis; otherwise physiological. For example, fear-induction paradigms that combine affective manipulation, task performance, and recorded physiological responses were classified as psychophysiological.

2.1.1 Cognitive tasks

A cognitive task in an XR system refers to any task that requires mental processes such as perception, memory, attention, problem-solving, decision-making, or learning while interacting with immersive environments (Li et al., 2019). Research highlights that XR offers unique opportunities to manipulate environmental variables in ways that traditional learning environments cannot, thus enhancing human task performance in cognitive learning or training. Well-designed immersive environments can enhance learning by providing support for human cognitive limitations, reducing cognitive load, and increasing learning outcomes (De Back et al., 2021). Furthermore, immersive learning environments provide customized learning experiences, simulate real-world situations, improve memory retention, and reduce cognitive workload (Maroukhas et al., 2024). However, the effects are not always positive. Issues such as cybersickness, acute stress, and visual fatigue involved in immersive environments diminish cognitive performance and impede learning and task performances (Han et al., 2017).

2.1.2 Physiological tasks

A physiological task in an XR system involves physical responses or bodily functions, such as movement, balance, coordination, or exertion, while interacting with a virtual environment (Lee and Kim, 2024). Physiological task performance in XR examines how responses like heart rate, eye movement, and muscle activity change to assess stress levels during task completion (Roy et al., 2019). This metric also evaluates physiological responses with changes in the virtual environments (Neo et al., 2021). XR can be shaped to meet users' physiological needs, enhancing both safety and realism. For example, such customization enhanced hand-eye coordination in medical training, and helped medical students and surgeons perform minimally invasive surgeries guided by medical imaging (Rosenfeldt Nielsen et al., 2021). Research also shows that XR can reduce physiological discomfort during medical procedures by diverting attention to relaxing immersive content (Calogiuri et al., 2018). XR has potential in domains beyond healthcare, such as sports training. Thus, exploring physiological task performance across diverse setups in XR systems is crucial.

Operationalization of physiological change: In this review, "physiological change" refers to objectively recorded autonomic or somatic signals (e.g., heart rate, heart rate variability, respiratory rate, blood pressure, electrodermal activity/skin conductance, skin temperature, electromyography), and where relevant, ocular physiology (pupil diameter/eye openness). For each included study, we extracted and report which specific physiological measures were collected.

2.1.3 Psychophysiological tasks

A psychophysiological task in an XR environment refers to activities that require cognitive functions and physiological

movements. These activities require synchronizing mental processes with motor actions, frequently requiring participants to react to visual stimuli in a virtual environment by manipulating their arms, legs, or other parts of their bodies (Ghrouz et al., 2019). Measuring the performance for a psychophysiological task in an XR system integrates simultaneous monitoring of mental load and physiological reactions such as heart rate and eye movement. These tasks often get affected by several external factors including some individual factors such as age, gender, prior respectability to an XR environment, etc. For instance, older adults face reduced performance compared to other age groups when texting and walking (Krasovsky et al., 2018).

2.2 Factors of human task performance

A variety of factors influence human task performance in an XR system. These factors can be categorized into system factors, user interface (UI) and user experience (UX) factors, individual factors, etc.

2.2.1 System factors

System factors encompass the technical aspects that influence both task performance and immersion in XR systems. These include hardware components such as display resolution, latency, and input devices, as well as software elements like the user interface and feedback systems (Yang et al., 2024). Key factors that significantly impact task performance include field of view (FoV), optical flow (OF), and latency, while factors such as user movement control and exposure duration have demonstrated marginal effects in the literature. For instance, network latency can negatively affect cognitive tasks by increasing participants' mental workload (Khalid et al., 2023). Similarly, optical flow plays a crucial role in movement-based physiological tasks by enhancing detection and enabling redirected walking, thereby leading to more natural interactions in virtual environments (Lee et al., 2024). These system factors are discussed in detail in the Results Section 4.

2.2.2 UI/UX factors

UI/UX factors refer to the design of the virtual environment and its interaction with real-world elements like lighting and noise, which can either enhance or hinder task performance depending on the user's capabilities and experience with XR systems. A well-designed UI, featuring intuitive controls, clear navigation, and responsive feedback, can reduce cognitive load and improve interactions (Alazmi and Alemtairy, 2024). Conversely, a poorly designed interface may cause confusion, frustration, and increased mental workload, all of which diminish task performance. Cybersickness is a critical issue within UI/UX design, often arising from mismatches between sensory inputs—particularly visual and vestibular cues (Stanney et al., 2020). Symptoms such as fatigue, nausea, and dizziness disrupt immersion and significantly impair user performance in tasks requiring sustained focus or physical interaction (Garrido et al., 2022).

2.2.3 Individual factors

Individual factors, such as gender, age, ethnicity, and prior experience, show varying levels of influence on human task

TABLE 1 Subjective and objective measures used to assess task performance and related internal states^a. *N* denotes the number of papers reporting each measure.

Category of task	Subjective measures	Objective measures
Cognitive	NASA-TLX (<i>N</i> = 15), SUS (<i>N</i> = 15), SSQ (<i>N</i> = 2), FMS (<i>N</i> = 2)	EDA (<i>N</i> = 4), Heart rate (<i>N</i> = 6), EEG (<i>N</i> = 5), Reaction time (<i>N</i> = 5)
Physiological	RPE (<i>N</i> = 10), VAS (<i>N</i> = 8), PES (<i>N</i> = 5)	Heart rate (<i>N</i> = 10), EDA (<i>N</i> = 7), Respiration rate (<i>N</i> = 8), Blood pressure (<i>N</i> = 6), Skin temperature (<i>N</i> = 4)
Psychophysiological	NASA-TLX (<i>N</i> = 10), Perceived Stress Scale (<i>N</i> = 2)	EEG (<i>N</i> = 8), ECG (<i>N</i> = 5), EDA (<i>N</i> = 6), Heart rate variability (HRV) (<i>N</i> = 7), Cortisol levels (<i>N</i> = 4)

^aWhile some measures directly capture task performance (e.g., reaction time, accuracy), many assess related internal states (e.g., mental workload, stress) that can influence performance.

performance, depending on the task type and environmental conditions. For instance, age can affect performance in specific cognitive tasks, such as the Montreal Cognitive Assessment (MoCA) (Tan et al., 2022), while gender may not have a significant impact. Prior experience is another critical factor, as individuals with previous experience tend to perform better in complex, skill-based tasks by reducing cognitive load and improving efficiency. However, prior experience may be less relevant for more intuitive or simpler tasks.

2.2.4 Other factors

Other factors affecting task performance in XR systems do not fit neatly into the categories of system, UI/UX, or individual factors but still play a role. For example, disruptions in time perception may not universally detract from performance but can have substantial impacts on tasks requiring immediate responses (Cometti et al., 2018). Collaboration is another pivotal factor as effective coordination and shared situational awareness are crucial for success in collaborative XR tasks. The absence of shared objectives, seamless interaction, and task synchronization can hinder teamwork and consequently reduce overall task performance in such environments (De Back et al., 2021).

2.3 Measures of human task performance

Human task performance in XR can be assessed using both subjective and objective metrics, providing a comprehensive view of how XR affects cognitive, physiological, and psychophysiological tasks. Subjective measures evaluate user engagement with XR systems (Wong et al., 2023), while objective measures provide empirical data, such as response time, accuracy, and physiological indicators (Tussyadiah et al., 2018). These methods complement each other, as subjective insights often impact performance reported by objective data. Table 1 outlines the techniques used in the reviewed papers.

2.3.1 Subjective measures

Subjective assessments rely on user-reported data, often via questionnaires (Schwind et al., 2019). Common tools include the NASA Task Load Index (NASA-TLX) (Hart and Staveland, 1988) for physical and cognitive workload, the Presence Questionnaire (PQ) Witmer and Singer (1998) for immersion, and the System Usability Scale (SUS) (Brooke, 1996) for usability and satisfaction. Other measures like the Borg RPE (Borg, 1998), VAS (McCormack et al., 1988), and PSS (Cohen et al., 1983) assess physical effort,

stress, and physiological responses. Cybersickness, impacting task performance, is evaluated using the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) and Fast Motion Sickness (FMS) Scale (Kichkaylo and O'Neill, 1998). These tools offer valuable insights into subjective task performance in XR (Lewis, 2018).

2.3.2 Objective measures

Objective measures assess user experience through biological signals, providing quantifiable data on cognitive and emotional states (Zhang, 2020). Common tools include an electrocardiogram (ECG), electrodermal activity (EDA), electroencephalogram (EEG), heart rate, blood pressure, and reaction time. Many studies used EDA, EEG, and ECG to classify emotions and assess physiological workload (Tremmel et al., 2019; Mondellini et al., 2023; Marucci et al., 2021; Chiossi et al., 2023), while others focused on user experience and cognitive load with blood pressure and heart rate (Hinricher et al., 2023; Archer and Steed, 2022). Another example is a dual-task paradigm consisting of a primary task (direct interaction with XR) and a secondary task (inducing distraction or cognitive load) (De Back et al., 2021), offering crucial insights into the effects of immersion on cognitive and psychophysiological abilities and task performance. When studies are grouped under *physiological tasks*, at least one of the following was explicitly measured as an outcome: HR/HRV, RR, BP, EDA, skin temperature, EMG, or related ocular physiology (e.g., pupil diameter). If no such signal was collected or reported, the study was not treated as assessing physiological change.

3 Review method

In this section, we highlight the review methods following the PRISMA (Moher et al., 2009) guideline for our paper. A brief overview of the review method is illustrated in Figure 3.

3.1 Keyword and search criteria

We followed the PRISMA guidelines (Moher et al., 2009) for this review to collect and synthesize the papers. The process started by identifying and organizing keywords to facilitate the search for relevant articles. We developed a comprehensive set of keywords and search terms aimed at locating studies focused on human task performance in the XR environment. Table 2 presents the keyword categories used to collect research

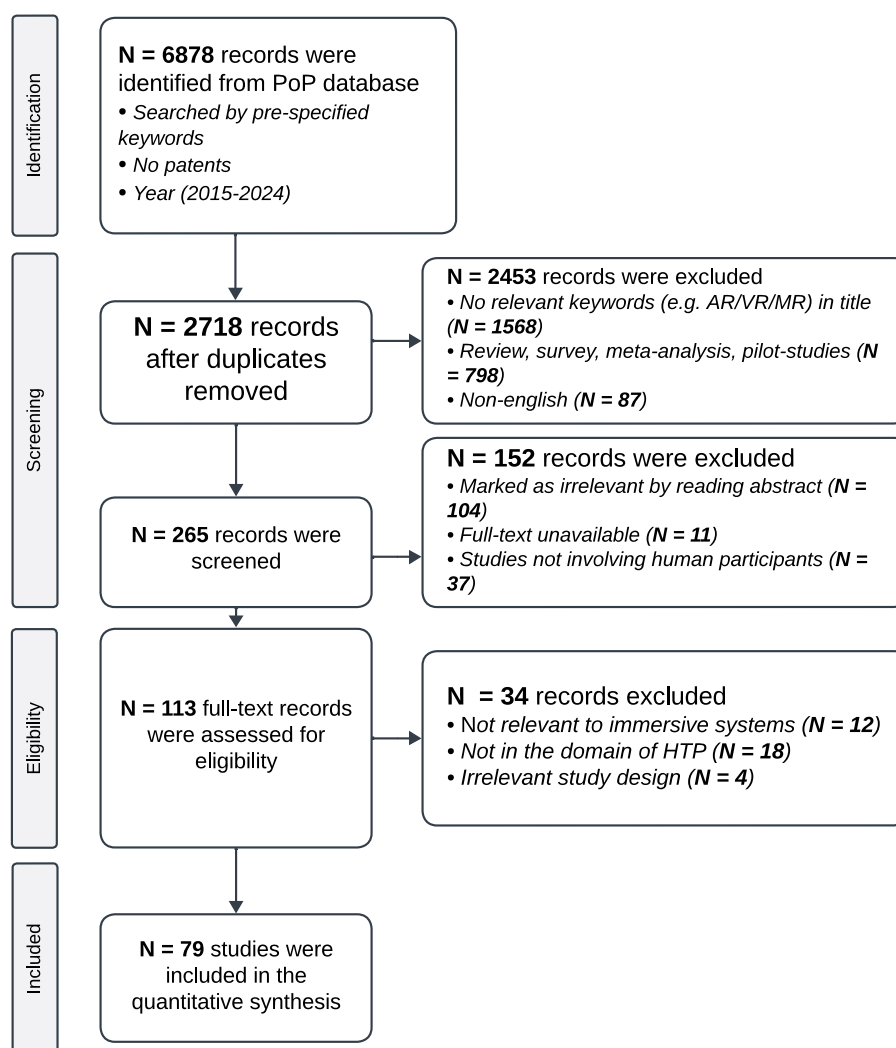


FIGURE 3
PRISMA (Moher et al., 2009) Flow Diagram of the Paper Selection Process for XR-Related Research on Human Task Performance (HTP) from the year 2015 to 2024.

TABLE 2 Categorization of keywords associated with XR task types, immersive environments, and challenges.

Keywords on type of the tasks	Keywords on immersive environment	Keywords on challenges of XR
"Cognitive task", "Mentally demanding", "Psychomotor", "Psychophysiological", "Collaborative", "Decision making", "Surgery", "Sports", "Multi-task", "Physiological task"	"Virtual reality", "VR", "Augmented reality", "AR", "Mixed reality", "MR", "Extended reality", "XR", "Immersive Systems"	"Cognitive load", "Mental demand", "Mental workload", "Attention capacity", "Cognitive strain", "Mental effort", "Physical demand", "Physical workload", "Cybersickness", "Simulator sickness"

papers. The keywords for paper searches covered many topics, including human task performance, types of immersion, cognitive and physiological factors influencing task performance, mental workload, and associated challenges such as cognitive load, physiological workload, cybersickness, etc. Since "Task performance" was the key focus in this review, it was the common keyword for each search episode. A balanced number of papers were selected for each category to ensure a well-distributed taxonomy. The Publish or Perish (PoP) database was utilized for paper extraction (Harzing, 2007), offering an

easy-to-use interface that allowed filtering by keywords, publication year, and category (e.g., patents or research papers).

3.2 Paper extraction process

Since all of the papers collected were not relevant to the review objectives, and to maintain balance over the taxonomies, it was crucial to follow structured steps to extract the most relevant papers. Figure 3 shows the high-level overview of the paper extraction for

the review methods following the PRISMA guidelines (Moher et al., 2009). There were four fundamental steps for the paper extraction process. Each of these steps is discussed below:

3.2.1 Identification

Papers were searched and collected using the Harzing PoP database (Harzing, 2007). This database provided papers based on the given keywords and filtration regardless of the publisher. The resulting papers were then collected and saved in comma-separated value (CSV) format. It yielded a total of 6,878 papers initially using the search criteria. Patents were excluded during the extraction, also, the publication year was in or after 2015 set for the records. Our last search was performed on 07 April 2024. So, these 6,878 records were identified for further synthesis to remove duplicates.

3.2.2 Screening

After eliminating 4,160 duplicate papers (60.48% of the initial search), 2,718 records remained for analysis. To focus on procedural quantitative studies of human task performance in XR systems, we excluded review papers, surveys, pilot studies, and doctoral consortium papers. We developed a Python program (to be publicly accessible later) to streamline this process by performing keyword analysis, filtering out the specified types, and compiling the results into a CSV file. By reviewing titles, we removed an additional 2,453 irrelevant records (35.66% of the initial search), leaving 265 papers for screening. We then carefully reviewed the abstracts, excluding 152 papers (2.20% of the initial search) that were irrelevant or unnecessary for our taxonomy.

3.2.3 Eligibility

During the screening stage, we further narrowed down the number of papers through multiple assessments. The full text of each article was thoroughly read and summarized, focusing on their findings and methodologies. After summarization, the papers were categorized taxonomically based on factors affecting human task performance, mental workload, types of tasks, and study design. At this stage, an additional 34 papers (0.49% of the initial search) were excluded due to irrelevance to XR environments or misalignment with our taxonomy.

3.2.4 Inclusion

In the final stage of the paper extraction process, we conducted an intensive manual review of all selected papers. After the eligibility assessment, the previous stage yielded a total of 79 papers, each evaluated against predetermined criteria to ensure relevance and quality. The full text of each paper was thoroughly re-examined, focusing on their taxonomy, field, and findings. After double-checking the data, all 79 papers were deemed suitable and included in the review.

4 Results

In this section, we present the findings of our systematic literature review, organized into three key categories: task performance in XR, the impact of XR (both positive and

negative) on human task performance, and the factors within XR that influence human task performance.

4.1 Tasks performance in XR

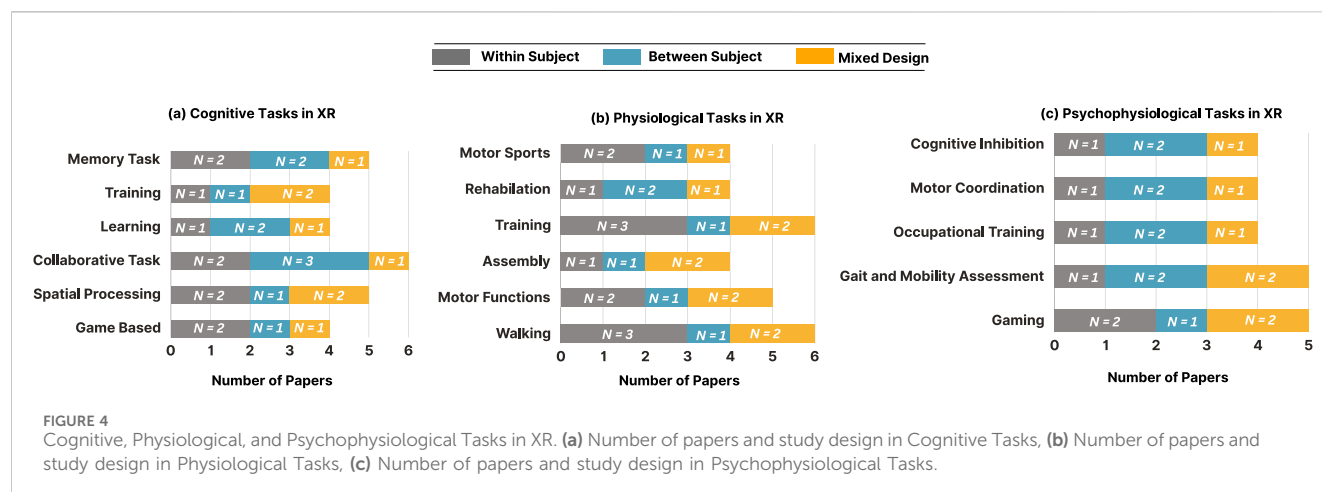
As we collected various papers from various domains around human task performance in an immersive system, a diverse list of topics was identified for this review.

4.1.1 Cognitive task performance in XR

A total of 28 papers (35.44% of the total) discussed the task and various aspects of cognitive task performance in an immersive system specifically. Regardless of the types of immersion and study design, most studies found inconsistent task performance in XR and the real world. Most of the research (10, 12.65% of the total) chose *within-subject* and *between-subject* (10 papers) as their study design, while 8 adopted the *mixed-design*. Figure 4a highlights the variety of cognitive tasks used in XR studies. Willemssen et al. (2018) compared participants' performance in the same task in both AR and VR modalities across AR, VR, and the real world, finding that task completion took longer in AR and the real world than in VR. Redlinger et al. (2022) examined the influence of game-like visual features in a VR environment but found no significant effect on participants' cognitive performance, with only minor changes in accuracy. Pan et al. (2018) explored the effect of fear induced by an undersea virtual environment on cognitive tasks of varying difficulty, discovering that fear impacted task performance with medium difficulty levels. Wu et al. (2019) investigated the use of Spherical Video-based Virtual Reality (SVVR) to enhance elementary students' cognitive problem-solving skills, and their finding revealed an improved performance while using SVVR rather than the traditional methods. Deshpande and Kim (2018) used Microsoft HoloLens for object assembly tasks in AR and found that performance was better in AR than in the real world. Dasdemir (2022) tested the effects of AR applications on brain oscillations using the BOOKAR dataset, and the results indicate that emotion recognition is more successful when using AR reading. Lastly, Stanney et al. (2021) conducted a comprehensive study on XR-based military medical training, demonstrating its advantages for enhancing cognitive performance.

4.1.2 Physiological task performance in XR

A total of 29 papers (36.70% of the total) focused on physiological task performance within immersive systems. *Mixed-design* and *within-subject* approaches were the most common study designs used. Figure 4b highlights the scope of studies investigating physiological task performance in XR environments. Results varied across AR, VR, and MR settings. Some studies, such as Bugdadi et al. (2019), found no significant impact on task performance during VR-based surgical training with force feedback devices. They compared two haptic devices (Omni and Entact) and found no notable difference in performance. In contrast, Kalkan et al. (2021) reported a 25% improvement in VR-based assembly task performance compared to real-world training on a hydraulically-controlled clutch system. Similarly, Yang et al. (2019) found that AR assistance reduced task time, errors, and cognitive load during assembly tasks. However, Wells and Miller (2020) observed no



significant difference between real-world and VR-based welding training, suggesting mixed results for task performance in immersive environments. [Ali et al. \(2023\)](#) reported significant improvements in student performance in a VR-based chemistry lab, where different aids in the simulation enhanced task performance and reduced cognitive load. In dual motor tasks, studies found no significant impact of immersive environments, regardless of participant age or task type ([Krasovsky et al., 2018](#); [Habibnezhad et al., 2020](#)).

4.1.3 Psychophysiological task performance in XR

A total of 22 (27.84% of the total) papers described specifically the psychophysiological task performance in XR systems, highlighting how immersive environments might impact individual motor abilities and coordination. Several studies have found that XR systems are effective for training and evaluating psychophysiological skills, particularly in fields such as medical training, rehabilitation, and sports performance ([Schmid and Wagner-Hartl, 2023](#); [Barata et al., 2015](#)). Moreover, studies have shown that psychophysiological performance in XR systems can translate to real-world improvements, making XR a valuable tool for skill acquisition and training ([do Couto, 2023](#)). These findings highlight the potential of XR for psychophysiological tasks, especially in applications that require precise motor control and coordination. [Figure 4c](#) shows the number of papers along with their study design and aspect of the task in this review. The tasks were divided into five key areas: Cognitive Inhibition, Motor Coordination, Occupational Training, Gait and Mobility Assessment, and Gaming.

4.2 Impacts of XR on human task performance

This section examines the positive and negative impacts of XR environments on human task performance, as reported in the reviewed papers. As shown in [Table 3](#), the impact of XR systems can vary significantly depending on the context. The immersive nature of XR enhances engagement, learning, and memory retention, particularly in fields such as aviation, surgery ([Buttussi and Chittaro, 2018](#)), and industrial training, where high-risk scenarios can be safely simulated ([Rubio-Tamayo](#)

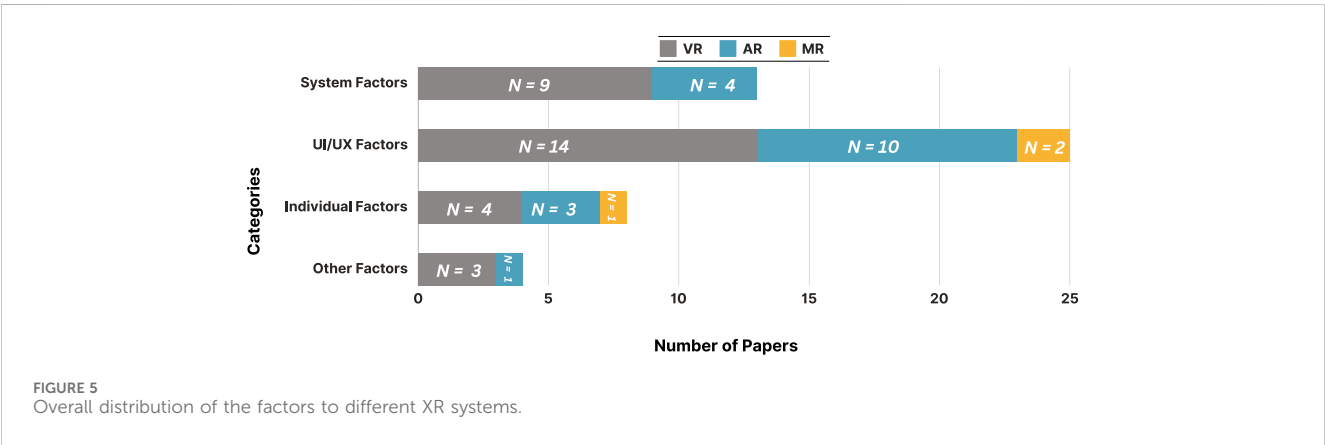
[et al., 2017](#)). Additionally, the ability to visualize abstract concepts or manipulate virtual objects in real-time has been linked to improved cognitive and psychophysiological performance, allowing users to engage more deeply with material ([Al-Ansi et al., 2023](#)). For instance, XR has been shown to improve spatial awareness and problem-solving skills in architectural design and urban planning ([Darwish et al., 2023](#)). However, as outlined in [Table 3](#), the impact of XR is not always positive. Some users experience serious issues that negatively affect task performance. Immersive environments can lead to discomfort, which in turn reduces cognitive and physiological performance ([Lavoie et al., 2021](#)). Common issues such as motion sickness, disorientation, and eye strain, can significantly impair task effectiveness ([Hein et al., 2023](#)). Additionally, immersive virtual environments may cause unpleasant and painful experiences, reducing engagement and the sense of presence ([Quesnel and Riecke, 2018](#)). In some cases, these negative effects can persist even after the immersion ends ([Mittelstaedt et al., 2019](#)), limiting the ability to transfer skills to real-world tasks ([Dobrowolski et al., 2021](#)). This review also considered these negative impacts to better understand the potential factors contributing to performance impairments.

4.3 Factors of human task performance in an XR system

Identifying and analyzing the key factors affecting human task performance in immersive systems was a central objective of this review. The papers were comprehensively analyzed based on these factors using various study designs and techniques. [Figure 5](#) illustrates the number of papers from various factor categories related to human task performance in XR systems. A significant portion (25 papers, 31.64%) focused on UI/UX factors, emphasizing elements that influence user interface and experience in XR environments, particularly system design, interaction ease, and user satisfaction. Another 13 papers (16.45%) investigated the impact of system factors, mainly addressing technical aspects like display resolution, frame rate, input devices, and latency, which are critical to user experience and task performance. While these categories play a vital role in XR task performance, individual

TABLE 3 Positive and negative impacts of XR technologies on human task performance for different types of tasks.

Type of immersion	Tasks	Positive impact (with citation)	Negative impact (with citation)
AR	Assembly task Yang et al. (2019) ; Deshpande and Kim (2018) ; General tasks in construction, architecture, operation industries Fazel and Adel (2024) ; Bademosi and Issa (2019) ; Localizing virtual objects using a distance matching Au (2022) ; Repeating and generating words during driving Kenemans et al. (2021)	Reduced task completion time, cognitive workload Yang et al. (2019) ; Enhanced performance Deshpande and Kim (2018) ; Improvements in accuracy, productivity, safety Fazel and Adel (2024) ; Bademosi and Issa (2019)	Increased spatial error, reduced auditory susceptibility Au (2022) ; Kenemans et al. (2021)
MR	Learning in an educational setup Yi et al. (2024) ; Training Tang et al. (2020) ; Choi and Kim (2024) ; Executive functioning Svarverud (2022)	Improved understanding of historical stories, cultural connotations Yi et al. (2024) ; Creativity, geometric analysis, model visualization Tang et al. (2020) ; Critical-thinking, motivation in emergency-nursing training Choi and Kim (2024)	Potential long-term visual disadvantages Svarverud (2022)
VR	Cognitive tail-making task Mostajeran et al. (2023) ; Recalling items while walking Girardeau et al. (2023) ; Learning through a VR application Lin et al. (2020) ; Teng (2022) ; Spatial n-back working memory task Scharinger et al. (2023) ; Zhang and Robb (2021) ; Walking Birenboim et al. (2021) ; Assembly task Kalkan et al. (2021) ; Tasks in a virtual chemistry lab Ali et al. (2023) ; Shooting Game Maloney (2019) ; Tutoring during training Andersen et al. (2020) ; Prosthetic case planning Liebermann et al. (2024) ; Playing a challenging computer game with neck length biofeedback Baer et al. (2022) ; VR bike application Mittelstaedt et al. (2019)	Higher cognitive performance, restorativeness, positive affect, lower stress Mostajeran et al. (2023) ; Improved memory, learning outcomes, cognitive paths Girardeau et al. (2023) ; Lin et al. (2020) ; Teng (2022) ; Positive effects on cognitive task performance, reduced cognitive load Scharinger et al. (2023) ; Zhang and Robb (2021) ; High-resolution physiological walking parameters, wellbeing indicators Birenboim et al. (2021) ; Improved task performance Kalkan et al. (2021) ; Ali et al. (2023)	Increase in implicit racial bias, cognitive load, potential for cybersickness, poorer game performance, deterioration in reaction times Maloney (2019) ; Andersen et al. (2020) ; Liebermann et al. (2024) ; Baer et al. (2022) ; Mittelstaedt et al. (2019)
AR and VR	Spatial design visualization Jin et al. (2020) ; Edler and Kersten (2021) ; Fitt's law experiment: Move to a target area, such as pointing, clicking, or tapping Batmaz et al. (2019) ; Mathematic education Cevikbas et al. (2023) ; Immersive shopping He et al. (2022)	Enhanced spatial awareness and problem-solving abilities Jin et al. (2020) ; Edler and Kersten (2021)	Impaired depth perception and virtual hand interaction in close spaces Batmaz et al. (2019) ; Unclear overall impact on learning outcomes, technological glitches, and reliability issues Cevikbas et al. (2023) ; Mismatch between consumer expectations and technology capabilities He et al. (2022)



factors were explored less frequently, with only 8 papers (10.12%) focusing specifically on this area. [Table 4](#) provides a detailed visualization of the key factors, along with task and environment design elements found in the reviewed papers. The impact of each factor varied depending on perspective, so the table includes the type of immersion, task design, and its effect on human task performance.

4.3.1 Impact of system factors

This review revealed several key system factors that impact human task performance in the XR system. Increased latency was found to reduce task performance, though it slightly lowered error rates ([Khalid et al., 2023](#)). An enhanced field of view improved performance by up to 20% ([Ghasemi et al., 2021](#); [Trepkowski et al., 2019](#)), while shorter exposure durations in mixed reality enhanced

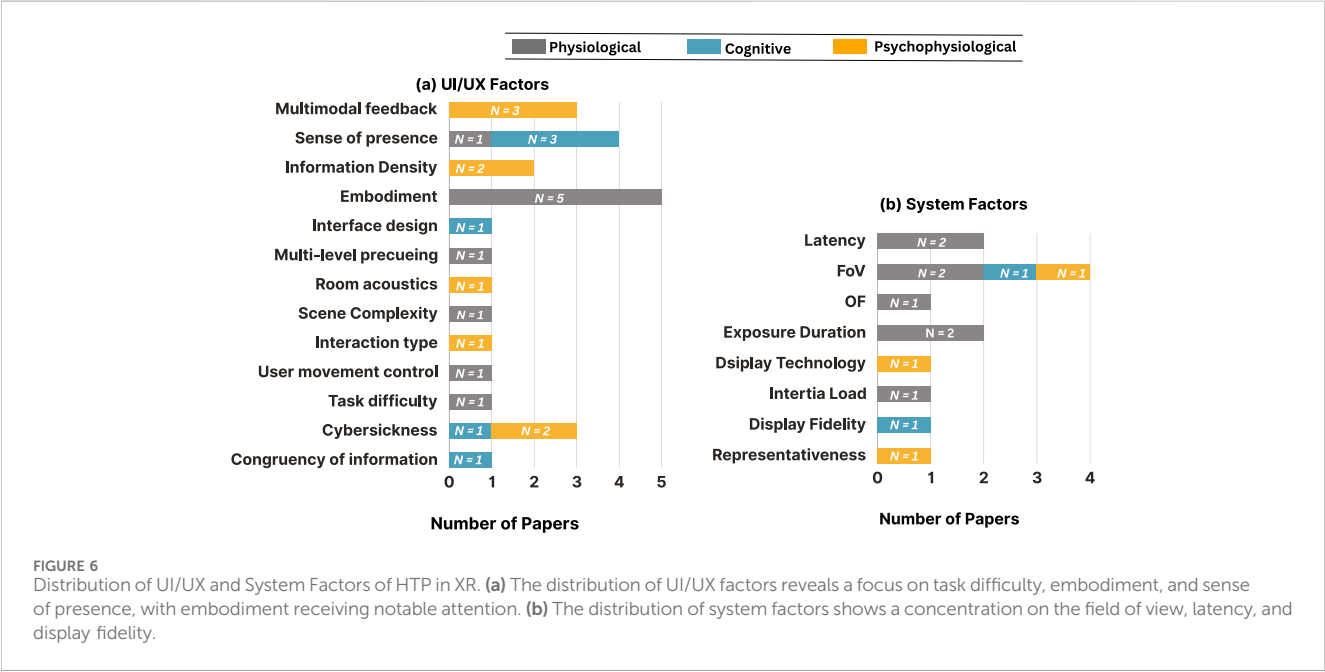
TABLE 4 Summary of Key Factors Influencing Human Task Performance in XR systems.

Category	Factor	Type of task	Correlation with performance (with citation)
System Factors	Latency	Psycho-physiological	Increased latency significantly reduces task performance, although it slightly decreased error rates Khalid et al. (2023)
	Field of View (FoV)	Physiological	Wide FoV (horizontal and vertical) increases physiological performances Wang et al. (2016) ; Ghasemi et al. (2021)
		Cognitive	Enhanced FoV increased performance up to 20% in both VR and AR Trepkowski et al. (2019)
	Exposure Duration	Physiological	Shorter exposures could enhance performance and reduce sickness Stanney et al. (2002) ; Wang et al. (2024)
	Display Technology	Psycho-physiological	Projection displays achieved the best task performance, while head-mounted displays (HMDs) performed worst across all criteria Lin et al. (2015)
	Inertia Load	Physiological	Removing inertial load led to poor motor control and reduced performance Tang et al. (2023)
	Optical Flow (OF)	Psycho-physiological	Optical flow enhances redirected walking (RDW) performance by adjusting the detection threshold (DT) range Lee and Kim (2024)
	Display Fidelity	Cognitive	Higher display fidelity significantly improves overall performance Bacim et al. (2013)
	Representativeness	Physiological	Presentation mode affected user preference and task efficiency Le Noury et al. (2020)
UI/UX Factors	Multimodal Feedback	Psychophysiological	Improved task accuracy and reduced completion time Marucci et al. (2021) ; Markov-Vetter et al. (2020) ; Yildirim (2022) ; Cooper et al. (2018)
	Sense of presence	Cognitive	Strong sense of presence enhanced cognitive task performance by increasing engagement, focus, and immersion Chen et al. (2021) ; Maneuvrier et al. (2020) ; Seeliger et al. (2022)
	Sense of presence	Physiological	Positive Moon et al. (2022)
	Information Density	Psycho-physiological	Information density significantly impacts cognitive and physiological task performance. Participants needed more time at high than at low density to complete a task Trepkowski et al. (2019) ; Van de Merwe et al. (2019)
	Body Visualization and Embodiment	Physiological	Whole-body visualization in VR improved accuracy in physiological tasks and influenced balance task performance, compared to other body visualization types. Missing a certain part of the body could significantly decrease task performance. Additionally, embodying a certain avatar affected task performance considerably Pastel et al. (2020) ; Kocur et al. (2020a) , (2020b) ; Borjon et al. (2021) ; Dudley et al. (2019)
	Interface Design	Cognitive	Diegetic interfaces improve performance compared to non-diegetic interfaces Marre et al. (2021)
	Multi-level precueing	Psycho-physiological	Performance increases with two to three precues, but decreases with four precues Liu et al. (2021)
	Room Acoustics	Cognitive	Positive Doggett et al. (2021)
	Scene Complexity	Physiological	Increased complexity affects performance negatively Stanney et al. (2002)
	Interaction Type	Psycho-physiological	Action-based VR controls lead to enhanced performance and lower mental workload compared to button-based controls Nenna et al. (2022)
	User movement control	Physiological	Enhanced control improved physiological task performance Stanney et al. (2002)
	Task Difficulty	Physiological	Variable effects for tasks with different levels of difficulty Parton and Neumann (2019)
	Cybersickness	Cognitive and Psycho-physiological	Cybersickness reduces cognitive and psychophysiological task performances Martirosov et al. (2022) ; Oh and Son (2022)

(Continued on following page)

TABLE 4 (Continued) Summary of Key Factors Influencing Human Task Performance in XR systems.

Category	Factor	Type of task	Correlation with performance (with citation)
Individual Factors	Congruency of Information	Cognitive	Congruency of visuotactile information decreased reaction times and increased performance Odermatt et al. (2021)
	Cognitive competency	Cognitive and Psycho-physiological	Increased cognitive competency leads to reduced errors and slower reaction time Juliano et al. (2022) ; Norouzi et al. (2019)
	Gender	Physiological	Male participants show enhanced motor performance Kocur et al. (2020a)
	Age	Psycho-physiological	Older people face reduced task performance Liao et al. (2019) ; Krasovsky et al. (2018)
	Prior experience	Cognitive	Prior experience slightly increases task accuracy Schmid and Wagner-Hartl (2023)
	Physiological competency	Psycho-physiological	Increased physiological workload enhances stress level and reduces task performance Markov-Vetter et al. (2020)
Other Factors	Skill Level	Physiological	Higher competence enhances task performance due to familiarity with system interfaces Dobrowolski et al. (2021a)
	Coordination	Cognitive	Coordination in collaborative tasks motivates users and enhances performances Khalid et al. (2023)
	Spatial understanding	Cognitive	Better spatial understanding reduces task completion time Drey et al. (2023)
	Physical Training Intensity	Physiological	Marginal impact on human task performance Bauer and Andringa (2020)
	Task familiarization	Psycho-physiological	Task familiarization significantly reduce discomfort and increases task accuracy Cometti et al. (2018)



performance and reduced sickness ([Wang et al., 2024](#); [Stanney et al., 2002](#)). Among display technologies, projection displays led to the best task outcomes, while head-mounted displays (HMDs) performed the worst ([Lin et al., 2015](#)). The removal of inertial load negatively affected motor control and overall performance in physiological tasks ([Tang et al., 2023](#)), and optical flow improved redirected walking by optimizing the detection threshold range ([Lee et al., 2024](#)). Higher display fidelity consistently enhanced performance ([Bacim et al., 2013](#)), and the representativeness of physiological tasks influenced user preferences and efficiency ([Le Noury et al., 2020](#)). These factors underline the importance of optimizing system characteristics to maximize task performance

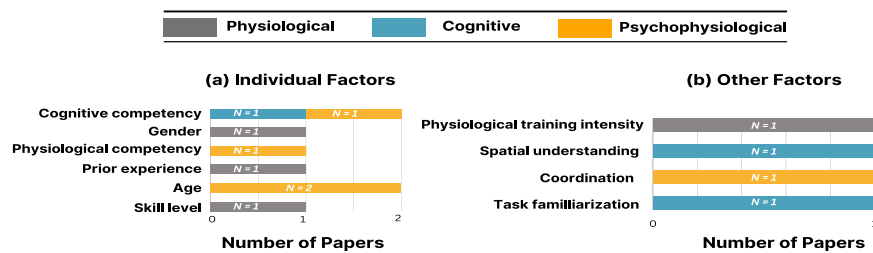


FIGURE 7
Distribution of Individual and Other Factors of HTP in XR. (a) The distribution of individual factors shows that age and cognitive load are the most frequently studied. (b) The distribution of other factors of HTP in XR shows limited studies on these types of factors.

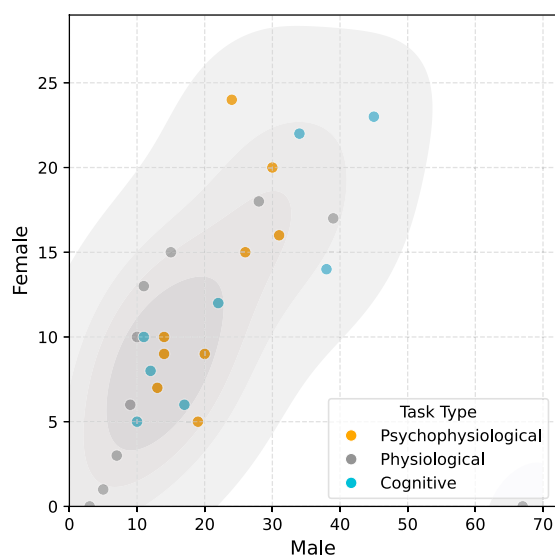


FIGURE 8
Distribution of male and female participants across three task categories: Psychophysiological, Physiological, and Cognitive tasks.

in immersive environments. Figure 6b shows the distribution of system factors over the papers with their specific task setup. It is clear from the chart that a limited number of papers (2 papers) found in this review for ‘cognitive tasks’ focus on the system factors, while it was 8 papers for physiological tasks.

4.3.2 Impact of UI/UX factors

The results of this review demonstrate that a variety of UI/UX factors have significant impacts on human task performance in virtual and augmented reality environments. As shown in Figure 6a, the embodiment stands out as a key factor that receives significant attention in the literature. It enhances the user’s sense of agency and engagement (Pastel et al., 2020; Kocur et al., 2020a,b). This, in turn, helps improve task performance. Multimodal feedback consistently improved task accuracy and shortened completion times throughout the studies (Marucci et al., 2021; Markov-Vetter et al., 2020; Yildirim, 2022; Cooper et al., 2018), while a strong sense of presence enhanced cognitive performance by increasing user engagement and attention (Chen et al., 2021; Maneuvrier et al., 2020; Seeliger et al., 2022). Information density was found to

influence both cognitive and physiological task performance, with higher densities leading to longer task completion times (Trepkowski et al., 2019; Van de Merwe et al., 2019).

4.3.3 Impact of individual factors

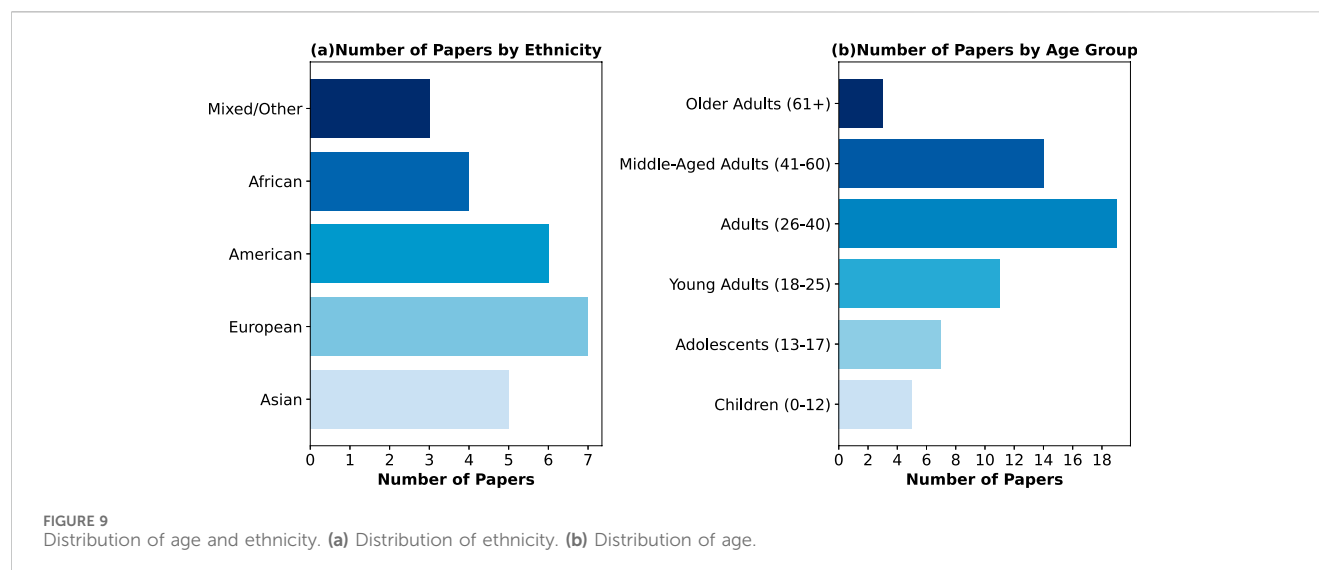
Although the studies in this review did not strongly emphasize individual factors, they remain important and could be a focus of future research. Figure 7a highlights the number of papers discussing individual factors such as cognitive competency, age, and gender. Notably, 27 papers (34.17% of the total) reported the gender distribution of participants. Figure 8 shows the breakdown of male and female participants, revealing that most studies involved a majority of male participants. This raises the possibility that results might differ if female participants were more dominant, even though some research has underscored ‘Gender’ as a significant factor in human task performance in XR systems (Kocur et al., 2020a). Additionally, several studies examined the influence of age on task performance (Banakou et al., 2018; Krasovsky et al., 2018; Ali et al., 2023). Figure 9 presents the distribution of age groups and ethnicities across the reviewed papers. It is clear from Figure 9 that studies primarily focused on adults (age: 26–40), and very less amount of research was conducted on older adults (age: 61+), with European (i.e., Caucasian) majority groups.

4.3.4 Impacts of other factors

Apart from system factors, individual factors, and UI/UX factors, there were some other factors identified in this review that were identified by the researchers during their studies but did not fall into any of these categories. For example, the physiological training intensity was marked influenced physiological task (Bauer and Andringa, 2020), even though it was not very significant. Spatial understanding and collaboration in a collaborative task had a significant impact on human task performance (Khalid et al., 2023; Drey et al., 2023). Additionally, Task familiarization improves human task performance as users get more comfortable with the system and tasks (Cometti et al., 2018). Figure 7b shows the number of papers in this review focusing on other factors except the aforementioned three categories along with their task setups.

5 Discussion

This review adopts a broad perspective on human task performance in XR, encompassing both observable performance



metrics (e.g., speed, accuracy, errors) and underlying cognitive, psychophysiological, and physiological outcomes that can influence or result from performance. In this section, we discuss potential research gaps (PRGs) related to human task performance in immersive virtual environments, analyzing the research questions from 45 VR papers, 23 AR papers, and 11 MR papers. This section identifies areas for further exploration within XR, highlighting gaps that need more research to understand human task performance in XR systems.

5.1 Major challenges in XR task performance

Human task performance in XR systems often declines due to factors such as increased cognitive and physiological load, cybersickness, and technological misalignments, all of which pose serious threats to performance. Cognitive load, frequently cited in this review (which is also described in a later section in detail), is a key factor that reduces performance by overwhelming mental capacity when users process large amounts of sensory information or handle complex interfaces (Chang et al., 2022). Physiological load, from prolonged XR use, leads to muscle fatigue, eye strain, and discomfort due to physical engagement or poorly optimized hardware (Wrzus et al., 2024). Cybersickness, caused by mismatches between visual and vestibular inputs, significantly disrupts performance, affecting accuracy, reaction time, and efficiency (Martirosov et al., 2022; Oh and Son, 2022). While real-time mitigation strategies have been explored (Islam and Islam, 2024), more research is needed, particularly regarding system factors of cybersickness, despite evidence for individual factors (Setu et al., 2024). These challenges can reduce XR's effectiveness for tasks such as training, simulation, and collaboration, limiting user engagement and adoption.

5.2 Potential research gaps (PRGs)

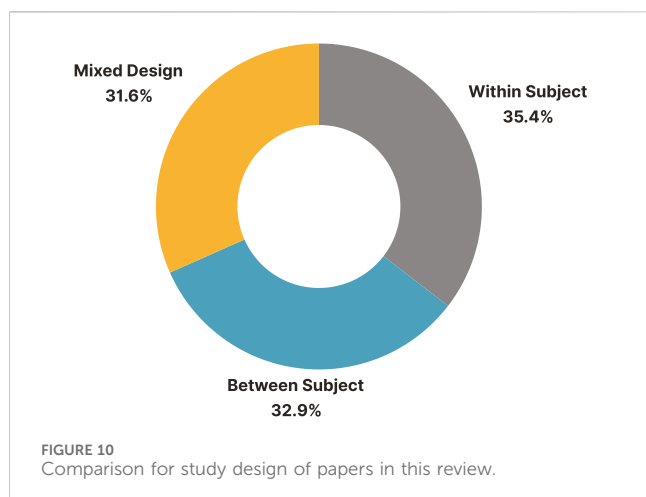
The potential research gaps are described in this section in detail, along with possible future study directions.

5.2.1 PRG1: factors influencing task performance in XR

Factors identified in this review were classified into four major categories: system factors, UI/UX factors, individual factors, and other factors. UI/UX factors were the most dominant, with 25 papers (31.64% of the total) explicitly or implicitly discussing these factors. Some papers found a severe impact of such factors (Cooper et al., 2018; Marucci et al., 2021), while others reported marginal impact (Parton and Neumann, 2019). The prevalence of this category highlights the significant amount of research focused on user interface and experience design and its role in enhancing performance in XR environments. In our analysis, we found limited research examined system factors, primarily in the MR domain (Figure 6). While the findings on system factors are well-supported in terms of latency, FoV, optical flow, etc., (Khalid et al., 2023; Ghasemi et al., 2021; Wang et al., 2016), further investigation is needed to assess their impact on task performance in other immersive technologies beyond VR. Similarly, research on individual factors is limited, indicating the need for more studies in this area. Most of the studies in this category focused on adults and younger participants (Juliano et al., 2022), with other groups underrepresented. This gap warrants further exploration in future research. While there were no direct findings related to the impact of "Ethnicity", it remains a factor that should be investigated in future studies (Figure 9). Additionally, some factors influencing task performance fall outside these categories (i.e., coordination, spatial Understanding, and such) but are nonetheless important (Figure 7). Comprehensive studies should address these overlooked factors to provide a more complete understanding of human task performance in XR systems.

5.2.2 PRG2: adaptability to different types of tasks

Minimal investigations have explored how different types of tasks influence user performance metrics in an immersive virtual environment. One of the recent papers utilized the research lack for decision-making collaborative time-critical tasks in the AR domain (Gower, 2022). Apart from that, Pan et al. (2018) found differential effects of sea-level-induced fears among users for



different types of tasks. Furthermore, a limited amount of research focused on learning-based tasks and gaming in an XR system for assessing human task performance. A thorough investigation of these areas could provide significant insights into the effects of task variety on user engagement, learning outcomes, and performance efficiency. For example, understanding how immersive technologies may be optimized for learning objectives or conditions that cause stress might result in more efficient designs of XR applications.

5.2.3 PRG3: experimental design on XR task performance

Many studies on human task performance in XR systems do not fully examine the effects of different experimental designs, such as within-subject, between-subject, and mixed designs. These experimental approaches are crucial for accurately assessing the relative effectiveness of XR systems versus traditional real-world environments (Belcher and Halliwell, 2021; Figure 10). However, practical constraints like difficulties finding participants and balancing demographics like age and gender might make it difficult to carry out thorough investigations. This review found that approximately 35.4% of studies used a within-subject design, while 32.9% employed between-subject designs, and 31.6% utilized mixed designs. These findings suggest that using various study designs opens the door to different insights, as study design can significantly influence outcomes and findings in human task performance research within XR environments (Matovu et al., 2022). Furthermore, experimental design is crucial for future research since appropriate participant distribution in study setups is essential to providing reliable outcomes (Grübel, 2023). Additionally, experimental research should also focus on diverse age groups and ethnicities to perform user studies so that the gaps in these criteria can be bridged.

5.2.4 PRG4: cognitive load in XR systems

Research on cognitive load in immersive virtual environments is still limited despite its critical importance. A high cognitive load can impair task performance, while too low a load may cause boredom and disengagement (Yin et al., 2020).

Studies emphasize the need to explore optimal levels of immersion that balance the cognitive load for better performance outcomes (Agbo et al., 2023; Norouzi et al., 2019). Few papers specifically focus on the cognitive load itself rather than its contributing factors. However, evaluating these factors is essential when developing XR systems. For example, increased cognitive load may result from additional sensory information in VR, which can negatively impact learning abilities (Li et al., 2022). There is significant potential for future research to investigate cognitive load factors during virtual immersion. Various elements of an immersive environment, such as interface complexity, interaction modes, and sensory engagement, all influence cognitive load. A complex interface, for instance, increases cognitive demand, diverting users' attention from primary tasks and diminishing task performance. Therefore, understanding these components is key to designing XR systems that optimize cognitive load and enhance user experience.

6 Conclusion

This review centered on human task performance within XR systems, exploring the various factors that influence it, the study designs employed, and the assessment techniques utilized. By conducting a comparative assessment between real-world and XR environments, this paper highlighted both the positive and negative impacts of XR systems on human task performance across different task settings. The analyses underscored how different study designs affect the reliability and validity of research findings in this domain. The evaluation methods discussed were essential not only for measuring performance outcomes but also for assessing participant engagement and satisfaction. A significant contribution of this review is the in-depth analysis of the factors impacting human task performance in XR systems. We extensively investigated these factors, representing their positive or negative effects based on several criteria, thereby providing valuable insights for future research. Notably, while much of the existing research has focused on system factors concerning human task performance, our review highlights the importance of other factors as well. Therefore, we recommend that future studies broaden their focus to include these additional factors to gain a more comprehensive understanding of human task performance in XR environments.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

NA: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review and editing. PW: Formal Analysis, Methodology, Validation,

Writing – review and editing. KH: Methodology, Validation, Writing – review and editing. SJ: Conceptualization, Formal Analysis, Investigation, Methodology, Validation, Writing – review and editing. HR: Methodology, Validation, Writing – review and editing. GT: Investigation, Validation, Writing – review and editing. MI: Investigation, Validation, Writing – review and editing. RI: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/frvir.2025.1589256/full#supplementary-material>

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