Adaptive virtual reality systems employed for children with autism spectrum disorder interventions: a systematic review

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Abstract

Background: Adaptive systems serve to personalize interventions or training based on the user's needs and performance. The adaptation techniques rely on an underlying engine responsible for processing incoming data and generating tailored responses. Adaptive systems in virtual reality (VR) have proven to be efficient in data monitoring and manipulation, as well as in their ability to transfer learning outcomes to the real world. In recent years, there has been significant interest in applying these systems to treat deficits in autism spectrum disorder (ASD). This is driven by the heterogeneity of symptoms among the affected population, which leads to the need for an early customized intervention that targets specific symptom configurations for each individual.

Objective: Recognizing these technology-driven therapeutic tools as efficient solutions, this systematic review aims to explore the application of VR adaptive systems in interventions for young individuals with ASD.

Methods: A systematic review of the past ten years literature was conducted using three different databases. Overall, a total of 10 articles were included. Relevant information extracted from studies was the sample size and mean age, the study's objectives, the skill trained, the implemented device, the adaptive strategy employed, the engine techniques, and the signal utilized to adapt the systems

Results: Studies have included level switching and/or adaptive feedback strategies, weighing the choice between a machine learning–adaptive engine (ML) and a non-machine learning–adaptive engine (non-ML). Adaptation signals ranged from explicit behavioral indicators like task performance to implicit biosignals such as motor movements, eye gaze, speech, and peripheral physiological responses.

Conclusions: Findings reveal promising trends in the field, suggesting that VR-automated systems leveraging real-time regression switching levels and/or multimodal feedback driven by machine learning (ML) techniques on embodied signal processing have the potential to enhance interventions for young individuals with ASD. Limitations and future directions are also discussed.

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Review

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Abstract

Background: Adaptive systems serve to personalize interventions or training based on the user's needs and performance. The adaptation techniques rely on an underlying engine responsible for processing incoming data and generating tailored responses. Adaptive systems in virtual reality (VR) have proven to be efficient in data monitoring and manipulation, as well as in their ability to transfer learning outcomes to the real world. In recent years, there has been significant interest in applying these systems to treat deficits in autism spectrum disorder (ASD). This is driven by the heterogeneity of symptoms among the affected population, which leads to the need for an early customized intervention that targets specific symptom configurations for each individual.
Objective: Recognizing these technology-driven therapeutic tools as efficient solutions, this systematic review aims to explore the application of VR adaptive systems in interventions for young individuals with ASD.
Methods: An extensive search was conducted across three different databases—PubMed Central, Scopus, and Web of Science—to identify relevant studies from approximately the past decade. Each author independently screened the included studies to assess the risk of bias. Studies satisfying the following inclusion criteria were selected: (a) the experimental tasks were delivered via a VR system; (b) system adaptation was automated; (c) the VR system targeted intervention or training for ASD symptoms; (d) participants' ages ranged from 6 to 19 years; (e) the sample included at least one ASD group; and (f) the adaptation strategy was thoroughly explained. Relevant information extracted from studies was the sample size and mean age, the study's objectives, the skill trained, the implemented device, the adaptive strategy employed, the engine techniques, and the signal utilized to adapt the systems.
Results: Overall, a total of 10 articles were included, involving 129 participants, 76% of whom had ASD. Studies have included level switching (7) and/or adaptive feedback strategies (9), weighing the choice between a machine learning–adaptive engine (ML; 3) and a non-machine learning–adaptive engine (non-ML; 8). Adaptation signals ranged from explicit behavioral indicators (6) like task performance to implicit biosignals such as motor movements, eye gaze, speech, and peripheral physiological responses (7).
Conclusions: Findings reveal promising trends in the field, suggesting that VR-automated systems

leveraging real-time progression switching levels and/or verbal feedback driven by non-machine learning (non-ML) techniques on explicit, or better yet, implicit signal processing have the potential to enhance interventions for young individuals with ASD. The discussed limitations mainly arise from the lack of technological tools for data handling, potentially causing bias due to human error.

Keywords: Adaptive system; Virtual reality; Autism spectrum disorder; Intervention; Training; Children; Machine learning; Biosignal

Introduction

The research on assessment, training, and intervention applied to technologies has recently focused on creating complex adaptive systems [1–5]. Drawing from Almirall et al. [6], an adaptive intervention is characterized by a set of clinical decision rules that offer guidance on when and how to adjust the dosage and nature of the treatment, considering specific measures. In this way, adaptivity can be defined as the system's capability to alter its actions in response to the preferences and needs of the user [4,7]. Moreover, adaptive systems have the potential to enhance the individualized training experience and prevent issues like overtraining, undertraining, cognitive overload, frustration, and boredom [5]. This differs from the non-adaptive approach, where the same settings are used throughout training or adjustment based on game settings that are unrelated to the participant’s performance [8].

Technologies, such as robots, mobiles, and screens, provide controlled and engaging environments that facilitate adaptive training and support the development of multiple interaction abilities in a secure and predictable manner [9]. The conventional computer is the predominant hardware choice for adaptive and personalized systems [3,4] because adaptive systems have been built upon existing development tools and infrastructure designed for traditional computers and devices. This approach aims to streamline the development process, ultimately reducing the human effort and time required for implementation. In contrast with traditional computer-based therapies, virtual reality (VR) excels in promoting ecological validity by delivering immersive, lifelike experiences, thus creating a strong sense of presence and facilitating the transfer of learning outcomes to real-world situations[10–13]. VR is intended as a computer-generated simulation of an environment that allows users to interact with and experience an artificial world as if it were real. VR aims to create a sense of presence, where users feel as though they are physically present within the virtual environment, enabling them to explore, manipulate objects, and engage with the surroundings in a lifelike manner [12]. Indeed, VR technology can achieve varying degrees of immersion, categorized into three levels—non-immersive, semi-immersive, and fully immersive—depending on the capabilities of the device being utilized. VR offers various avenues for adaptation, including adjusting the complexity of content, tailoring evaluations, and modifying autonomous virtual agents [14]. Another form of adaptation could involve integrating system input, such as utilizing voice commands or haptic feedback. Moreover, VR enables the recording of not just real-time information but also facilitates the integration of data collected from various devices, each dedicated to monitoring distinct psychophysiological activities [15]. Several studies have yielded significant training findings in implementing adaptive VR interfaces. Among them are interventions related to mental health or neuro-psychiatric conditions such as emotional and affective training [16], phobias [17], pathological stress [18], or posttraumatic stress disorder [19].

In recent decades, research has focused on using VR in the assessment, treatment, and training of neurodevelopmental disorders such as autism spectrum disorder (ASD) [13,20–25]. Studies increasingly focus on this disease due to the escalating worldwide incidence and the high demand for early interventions [26]. Moreover, extensive research demonstrated that training with VR can lead to notable enhancements in various domains among the young ASD population [14,21,23–25]. ASD is a neurodevelopmental condition characterized by impairments in social communication and the presence of restrictive and repetitive behaviors [27]. One distinguishing aspect of ASD is its spectrum nature, indicating significant variability in symptom severity among affected individuals. This heterogeneity results in clinical phenotypes that differ substantially from one person to another while sharing common underlying features. The heterogeneity in symptom severity observed in ASD needs the implementation of personalized treatment approaches that target specific symptom configurations for each individual. By designing early interventions tailored to each child's characteristics, it becomes possible to provide targeted training and improvements in areas of deficit commonly associated with ASD [14,28]. Addressing this need, adaptive VR technologies appear to have the potential to pave the path for a new generation of highly efficient technology-driven therapeutic tools for the young ASD population.

Following this approach, a variety of ASD adaptive technologies have been proposed. Among them, Bian et al. [29] presented a VR training system for improving driving skills that autonomously adapted its difficulty according to participants' engagement and performance metrics. A further adaptive system has been applied to a VR job training interview platform, which was able to adjust the conversation upon users' responses dynamically and their stress levels [30]. Research has demonstrated that employing this solution for rehabilitation yields favorable outcomes in enhancing certain abilities of ASD children [31]. Specifically, the VR system was able to tailor the intervention in accordance with the user's actions.

Given the body of evidence that studies have demonstrated the effectiveness of employing adaptive VR systems for addressing deficits in individuals with ASD and the showcased advantages of early intervention, there arises a need to dig into the technical aspects of system adaptation and the complexity of user data handling. To do this, it is crucial to dissect the components of an adaptive system generally used to train or treat ASD symptoms. The following taxonomy will facilitate the reading of the present work.

Adaptive strategy: level-switching, feedback, and time

A system can be adapted through different strategies, between them: level-switching techniques or feedback. Level switching follows a logic of level difficulty, and the choice of switching can be based on progression or regression choices. The progression technique can be considered the core training principle, as it is necessary to increase the difficulty level to continue training certain skills, improve them, and prevent the occurrence of learning effects. Therefore, in this scenario, training is adapted through a gradual increase of difficulty based on the individual's abilities. Unlike progression, the regression technique allows for a finer, more flexible, and more nuanced difficulty level adaptation according to the arising needs. Rooted in traditional therapy practices, this strategy allows for dynamic adjustments that increase or decrease the difficulty based on the observed performance of the individual [8]. This would ensure that the individual is able to perform satisfactorily at an easier level before increasing the difficulty, allowing more time to learn the content [8].

Conversely, feedback consists of a system response transmitted visually, audibly, verbally, or haptically to enhance user understanding. Both strategies can be transmitted in two temporal dimensions: real-time or deferred. The first adaptation occurs based on real-time measures during training, while the other happens before the training or session begins, and it depends on the trainee's prior knowledge, level, preferences, or experience [5]. Underlying these, an engine is responsible for processing the information it receives (see *Signals: explicit and implicit* section) to transmit an ad hoc response regarding level switching and/or feedback. The engine role can be performed either by a professional, making a person-automatized technology, or directly by the system itself, being a system-automatized technology.

The adaptive engine: person-automatized technologies and system-automatized technologies

Within the engine's framework, it is defined as person-automatized when a professional is in charge of analyzing the engine input signals and making decisions about the type of adaptation needed according to each case. Often, clinicians adapt the interaction by observing the user without playing any active role in the virtual environment (e.g., [28]). However, on other occasions, users tend to interact in a virtual environment with main avatars controlled by real people who adapt the system responses according to the user (e.g., [32,33]). Although this is a valid choice of adaptation, the limitation lies in need for technical expertise to effectively use these systems [32]. According to person-automized systems, a professional should be able to make clinical decisions by integrating behavioral and/or psychophysiological subject data to adapt the system. However, it could imply time and/or bias problems. Conversely, advanced systems that automate clinical integrations through multi-computer interactions stand out as a promising choice [32].

A cost-effective and streamlined approach involves employing a system-automized adaptive engine [5]. In this configuration, the system autonomously processes input signals and directly makes decisions to tailor the intervention. Thereby, together with reducing the signal processing time and adaptation decision, there is a lower risk of errors or attention problems for professionals [9,34]. In this context, non-machine learning (non-ML) techniques can be strategically employed to adapt the engine. These techniques rely upon explicitly defined rules or heuristics to guide decision-making and system adaptation. These rules are typically designed by professionals and are based on a set of predetermined conditions and actions. The process involves an analysis of the input signals, and the adaptive decisions are made based on the application of rule-based methods, handcrafted algorithms, or expert knowledge [35,36]. Besides non-ML, engines can be designed through machine learning (ML) techniques to adapt based on learned patterns from data rather than rigid explicit rules. ML models are trained on stored data to make predictions or decisions. These systems then refine their knowledge through data-driven methodologies, automated learning processes, and continuous improvement mechanisms, enabling them to learn and make strategic adaptive decisions autonomously [29,30].

In recent years, the focus has been moving increasingly toward system-automized technologies that use real-time adaptative techniques (e.g., [34,37]). Indeed, these adaptive systems are capable of responding in real-time to behaviors with accuracy beyond human observation [34]. Real-time responses appear to confer advantages in creating effective and realistic interventions [35,38]. To enhance user experience, comfort, or task efficiency, systems may apply ML techniques to recognize patterns in the data, allowing them to adapt in real-time [29,39]. This is often achieved by using sensors and algorithms to interpret and analyze the data effectively, leveraging the input signals of the system effectively.

Signals: explicit and implicit

Concerning what has been reported about adaptive strategies and their features (level switching, feedback, time, engine), it is now important to explain what kind of information is processed by the engine in order to make an adaptive decision. A signal refers to any user's information or data that is used as input to the engine that guides the adaptive decision-making. The adaptation process occurs through the recording, analyzing, and interpreting collected signals to make informed decisions about how the system should adjust its behavior, settings, or functionality. Based on the available information, the underlying goal is to improve the system's performance, efficiency, efficacy, and user experience. These signals can have either explicit or implicit nature, and they play a crucial role in enabling the system to adapt and respond effectively to changing conditions. Only through the analysis of the user's own signals can an intervention be adapted according to the user's needs. The signal is named explicit when it corresponds to visible behaviors such as verbal responses or task performance. The latter typically involves quantifiable metrics of how effectively a user is performing a specific task, with the purpose of informing the system about the quality or efficiency of the task execution [40,41]. On the other hand, the implicit signal (or biosignal) refers to data or information inputs that are not explicitly provided by a user but are inferred or recorded by the system. These implicit biosignals often include non-verbal behaviors such as eye gaze, motor movements, speech patterns, and peripheral physiological responses [30,36,42,43]. Implicit biosignals are valuable because they can provide hidden insights not visibly shown by the user.

Moreover, real-time processing of behavioral, biological, and psychological information is used to continuously assess the user's state and adapt the human-machine interface. Adaptive virtual systems establish robust communication with users, detecting their current state and adjusting activities to support specific behavioral goals.

Aim of the study

In accordance with the above, in recent years, the utilization of adaptive VR systems as a therapeutic tool for individuals with ASD has gathered increasing attention [20,23–25]. Due to the diverse nature of ASD, which manifests differently in individuals and evolves over the lifespan, intervention requirements differ significantly between pediatric and adult populations. Acknowledging the substantial evidence endorsing the advantages of early intervention [44], this systematic review concentrates specifically on the pediatric population affected by ASD. Therefore, considering the relevance of using adaptive systems in ASD to improve the customization of treatment based on young individuals' characteristics and their progress, this systematic review primarily aims to comprehensively investigate and analyze the existing literature on the application of adaptive VR systems in the context of ASD children's interventions. Specifically, the goal is to discuss those studies that have implemented VR adaptive systems, analyze the study objectives, the methodologies chosen for the functioning of the adaptive engine, and the types of signals implemented. This review focuses merely on system-automized adaptive engines due to their convenience compared to the person-automatized ones [5,32]. Therefore, the methodology investigated refers to level switching, feedback, time, the autonomous adaptation of systems engines, and the signals processed. Secondly, this review aims to identify the current body of research on the VR-based adaptive systems for ASD children's intervention, highlight methodological considerations, and propose directions for future research to guide the development and refinement of adaptive VR interventions for young individuals on the autism spectrum.

To our knowledge, there are no systematic reviews or meta-analyses on this topic. The only similar work is Alcañiz et al. [9], which, however, did not employ a systematic approach for the comprehensive screening and revision of the existing literature. Furthermore, it not only considered those adaptive interventions in VR but followed a broader gaze aimed at any type of technology.

Methods

The literature search adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis guidelines (PRISMA; [45]), ensuring a rigorous search process for a systematic review.

Literature Search Strategy

A comprehensive search was conducted on March 13th, 2024, to identify relevant studies in three different databases: PubMed Central, Scopus, and Web of Science. Electronic databases were searched using a combination of keywords and MeSH terms related to the research question, as well as the literature was searched for English peer-reviewed articles and conference articles with full-text available, published starting on January 1, 2013, to March 13, 2024. Considering the recent increase of interest in the field and the continuous evolution of hardware and software, a literature review that includes sources published around the last 10 years would provide an up-to-date state-of-the-art, ensuring the inclusion of the most advanced technologies and the latest methodologies [23,46,47]. The first author used the following Boolean string to search the databases: (“virtual” OR “VR”) AND (“adaptive” OR “personalized” OR “customized” OR “individualized” OR “tailored”) AND (“training” OR “intervention” OR “therapy” OR “clinical*”) AND (“toddler” OR “children” OR “infant” OR “teen*” OR “young adult*”) AND (“autistic spectrum disorder” OR “autism” OR “ASD”). Studies that fulfilled the following inclusion criteria were selected: (a) experimental tasks were presented through a VR system; (b) adaptation was system-automized; (c) VR system aimed at intervention or training of ASD symptoms; (d) participants’ age may vary between 6 and 19 years old; (e) sample included at least one ASD group; (f) the adaptive strategy is comprehensively explicative. Accordingly, the following criteria were used to exclude studies from this systematic review: (a) studies not employing VR system for experimental tasks; (b) absence of automated adaptation mechanisms within the VR system; (c) studies whose objective was not specifically aimed at intervention or training in relation to ASD symptoms; (d) studies involving participants outside the age range of 6 to 19 years, or absence of specified age; (e) absence of any group with ASD diagnosis within the study sample; (f) studies failing to provide a sufficient or clear explanation of the adaptive strategy employed. Applying these criteria aimed to ensure the selection of studies meeting stringent standards for relevance to the review objectives and rigor in methodology.

The selection of studies was divided into six stages. Stage One: the first author conducted the literature search of the databases and manually removed duplicates. The data were recorded into a template to ensure consistency in the data collection process and organized for subsequent analysis. Under PRISMA recommendations to avoid bias and reduce errors, the five authors operated independently from the second stage onward. Step Two: titles and abstracts of the retrieved studies were reviewed to identify potentially eligible ones. Reasons for excluding studies were documented. Step three: a full-text assessment based on predefined inclusion and exclusion criteria was performed. Any discrepancies between reviewers were resolved through discussion and consensus. Reasons for excluding studies were documented. Step four: the quality of the selected studies was assessed through the JBI Critical Appraisal tool [48] to avoid the risk of bias. To do so, the selected articles were evaluated according to standardized criteria, such as study design, findings based on sound evidence, and potential sources of bias. Step five: relevant data from each included study were systematically collected using a predefined data extraction form. Relevant information categories extracted from the studies were chosen and defined by the 5 authors following the aim of this systematic review. Step six: the extracted data were combined and analyzed to provide an overall summary of the evidence. The data synthesis involved a narrative synthesis that was tabulated to facilitate the further interpretation of the findings. The selection process was documented using a PRISMA flow diagram (Figure 1). No technological or automatic tool was used to manage the collected records. Relevant information that has been extracted from studies was the sample size and mean age, the objective of the study, the skill trained, the implemented device, the adaptive strategy performed, the engine chosen, and the signal involved. The adaptive strategy findings are classified through the mode they adapted the intervention, such as through level switching (progression or regression) and/or feedback, as the time when adaptation occurs (real-time or deferred), and as the engine executing the adaptation (ML-based or non-ML-based). Feedback is meant on a verbal, auditive, visual, and haptic basis. The signal reported in the results refers only to those feeding the adaptive engine. Signals recorded for subsequent analyses that did not refer to the adaptive strategy were not reported.

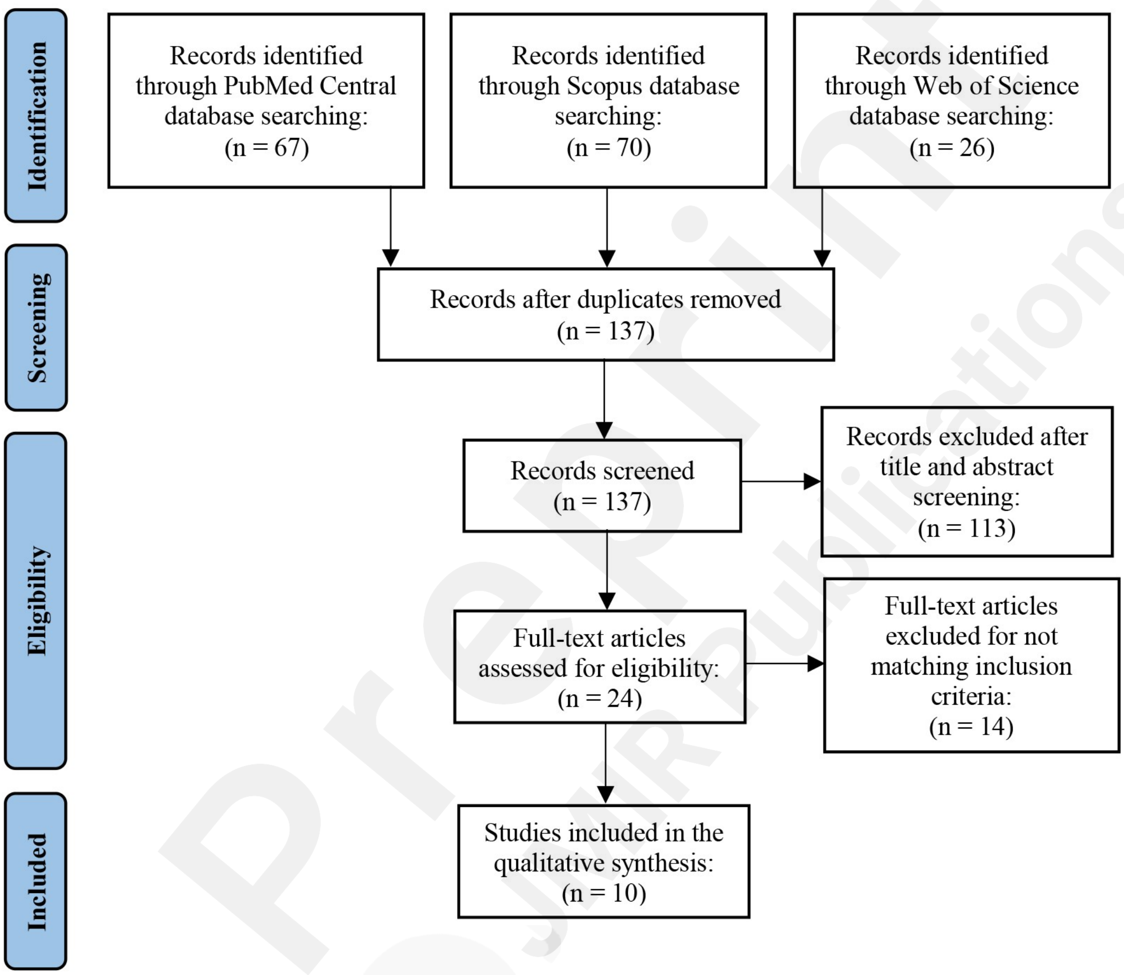

Figure 1. Flow diagram of literature search selection

Results

Review Flow

The search strategy used in the literature review yielded a total of 163 records, with 67 articles retrieved from PubMed Central, 70 from Scopus, and 26 from the Web of Science database. After removing duplicate articles found in multiple databases (26 articles), 137 unique articles remained. Among these, 113 articles were excluded based on screening titles and abstracts, and an additional 14 articles were excluded following a full-text screening to ensure they met the inclusion criteria. Some studies initially appeared to meet the inclusion criteria; however, subsequent analysis revealed discrepancies leading to their exclusion. For instance, some studies were excluded due to the implementation of person-automized systems rather than system-automated processes as required

[32,33]. Among other reasons, certain articles were excluded because they lacked an experimental design [49]. Finally, a total of 10 articles satisfied the above criteria and were thus included in the review. The data collected were analyzed following a systematic approach employed to identify and synthesize the findings.

Selected Studies of the Systematic Review

Selected studies are presented in Table 1 in alphabetic order. The studies involved 129 participants, of whom 76% were ASD. The mean age ranges within the ten articles' groups span from 8 to 16 years, inclusive. Concerning the objective of the study, either were usability studies (6) [36,38,40,42,50,51], had a further objective aimed at treatments (3) [35,37,41], or aimed merely at treatment (1). All included studies designed training through serious games, thus having the purpose of teaching or educating through a game. Most studies were focused on training social skills (7) [35,36,40,42,43,50,51], in minority on motor skills (2) [37,38] and executive functions (1) [41]. The devices that have been implemented are the computer desktop (8) [35,36,38,40–43,50], head-mounted display (1) [37], and tablet (1) [51].
Regarding the adaptive strategy, level switching was based either on a progressive strategy (4) [37,41,50,51] or a regressive strategy (3) [36,40,42]. Moreover, systems provided adaptive feedback through the use of verbal (8) [36,38,40–43,50,51], audio (4) [38,41,50,51], visual (3) [35,38,51], and haptic (1) [38] cues. A real-time adaptative strategy was employed in most of the studies (9) [35–38,40–42,50,51], except two studies that used a deferred time strategy [41,43]. Finally, regarding the adaptive engine performed, either a non-ML-based method was implemented (8) [35,36,38,40–43,50,51], or an ML-based method was applied (3) [37,51]. The cases counted are higher or lower than the total number of studies because some employed different adaptive strategies for level switching and feedback, or they did not employ both of them.
The studies adapted their system through an explicit behavioral signal, such as task performance (6) [36,40–42,50,51], or an implicit biosignal, such as motor movements (3) [37,38,51], eye gaze (2) [35,42], speech (1) [43], and peripheral physiological (1) [36].

Table 1. Selected studies.

Authors	Sample size, mean age (SD)		Study objective	Training	Device	Adaptive strategy				Signal
	ASD	TD				Level switching	Feedback	Time	Engine	
Bekele et al., 2016 [35]	N=6 15.77 (1.87)	N=6 15.20 (1.68)	▪ Treatment ▪ Usability	Social skills	Desktop	/	Visual	Real-time	Non-ML-based	Eye gaze
Hocking et al., 2022 [37]	N=10 14.10 (2.6)	N= /	▪ Treatment ▪ Usability	Motor skills	HMD	Progression	/	Real-time	ML-based	Motor movements
Jyoti & Lahiri, 2020 [50]	N=20 8.7 (2.2)	N=20 8.7 (2.3)	Usability	Social skills	Desktop	Progression	▪ Audio ▪ Verbal	Real-time	Non-ML-based	Task performance
Jyoti & Lahiri, 2022 [51]	N=20 8.61 (2.03)	N=/	Usability	Social skills	Tablet	Progression	▪ Audio ▪ Visual ▪ Verbal	Real-time	▪ Level switching: non-ML-based	▪ Task performance ▪ Motor movement

									▪ Feedback: ML-based	s
Kuriakose & Lahiri, 2016 [36]	N=9 14.10 (2.6)	N=/	Usability	Social skills	Desktop	Regression	Verbal	Real-time	Non-ML-based	▪ Task performance ▪ Peripheral physiological
Lahiri et al., 2013 [42]	N=8 16.07 (2.08)	N=/	Usability	Social skills	Desktop	Regression	Verbal	Real-time	Non-ML-based	▪ Task performance ▪ Eye gaze
Moon & Ke, 2023 [43]	N=4 12.25 (0.5)	N=/	Treatment	Social skills	Desktop	/	Verbal	Deferred	ML-based	Speech patterns
Pradeep Raj & Lahiri, 2016 [40]	N=2 16.25 (3.4)	N=2 11.9 (2.7)	Usability	Social skills	Desktop	Regression	Verbal	Real-time	Non-ML-based	Task performance
Vallefuoco et al., 2022 [41]	N=10 11.9 (2.7)	N=/	▪ Treatment ▪ Usability	Executive functions	Desktop	Progression	▪ Audio ▪ Verbal	▪ Level switching: deferred ▪ Feedback: real-time	Non-ML-based	Task performance
Zhao et al., 2018 [38]	N=6 9.66 (1.36)	N=6 10.73(1.91)	Usability	Motor skills	Desktop	/	▪ Audio ▪ Visual ▪ Verbal ▪ Haptic	Real-time	Non-ML-based	Motor movements

ASD: autism spectrum disorder, HMD: head-mounted display, ML machine learning, N: sample size, SD: standard deviation, TD: typical development

Discussion

The main findings indicate a trend of balanced use among adaptive strategies such as level switching, with slight preferences towards progression techniques, and feedback, with a preference for verbal mode. Furthermore, a widespread use of non-ML techniques was found in engines that utilized explicit and implicit signals, with a slight tendency towards the latter. Finally, the results showed significant advantages for real-time adaptations.

Overall, the mean age ranges between the selected studies (8-16 years) suggest a tendency to prefer a sample composed of adolescents rather than young children. Extended studies [44,52] underlie the benefits of early intervention (on children younger than adolescents) in achieving significant improvements by targeting the fundamental behavioral and skill deficits linked to ASD. Indeed, younger children tend to make better progress in their treatment, even with lower-intensity programs, compared to older children [44]. Considering the theoretical foundations and the benefits that early intervention brings to ASD children, future studies involving VR adaptive systems should consider a younger age sample, as reported in other research fields on ASD treatment, like interventions using robots (e.g., [53–55]). In this context, when designing an early intervention, it is crucial to consider pediatric recommendations advocating for a maximum screen time of one hour per day for children aged 2 to 5 years, as this contributes to establishing a high-quality program [56]. Consequently, the implementation of any technological tools must be carefully crafted and controlled.

Furthermore, concerning the study objectives, findings indicated that most of the articles primarily focused on usability [35–38,40–42,50,51]. This confirms the relatively recent emergence of research in applying VR adaptive systems in ASD interventions [20,23–25]. Indeed, an emerging field must first validate the new methods and technologies through usability studies. Moreover, a few among them had another clinical goal of validating the designed treatment, which is valuable considering these are innovative and previously untested adaptive systems [35,37,41]. In addition, the prevalence of training targeting social skills is observed in more than half of cases [35,36,40,42,43,50,51], aligning with a well-established focus in ASD intervention literature that emphasizes the importance of addressing social challenges faced by individuals with ASD [57,58].

Another prominent trend observed relates to the device deployed. Notably, among the selected articles, there is a consistent preference for desktop computers and similar devices like tablets [35,36,38,40–43,50,51], which is coherent with the broader literature on adaptive VR training [5]. The prominent decision to opt for non-immersive VR devices showcases a practical choice grounded in considerations of accessibility, affordability, cost-effectiveness, and the avoidance of potential discomfort [36,42,50,51,59]. Yet, it is likely to have been chosen because evidence suggests that non-immersive VR systems could also support individuals with ASD, particularly in addressing comorbidities such as attention-deficit/hyperactivity disorder or anxiety disorders [60,61]. Further research targeting non-immersive VR's impact on comorbid conditions within ASD would be valuable for elucidating its full potential and applications.
The subsequent sections are delineated as follows: Section 1 delves into findings regarding the adaptive strategy in terms of mode and time. Section 2 delineates the techniques chosen to adapt their engine. Ultimately, Section 3 presents a detailed discussion about the involved signal. Each section includes a segment aimed to highlight methodological considerations and guide future research development.

Adaptive strategy: regression, multimodal, real-time

The examination of the adaptive systems in the selected articles reveals a critical interplay between level switching and feedback strategies, both essential components for addressing the challenges associated with individualized training. Yet, not all studies have implemented both adaptive strategies in their intervention. Considering the level switching strategy, in studies employing progression-based adaptations [37,41,50,51], the difficulty level was automatically increased following sufficient performance, and the same level was repeated following insufficient performance. For example, Jyoti & Lahiri [50] considered a performance threshold ≥70% score criterion as satisfactory for increasing the difficulty level. In this application, the performance score was scored based on accuracy in recognizing regions of the virtual character's face during a maximum amount of time available for responding. Another instance is the one of Hocking et al. [37], in which this level was raised to ≥75% to continuously update the challenge. Differently, in this study, performance was quantified by calculating the efficiency, synchrony, and symmetry of the movement performed. Contrastingly, studies that adopted the regression technique [36,40,42], which were slightly less, increased the level of difficulty following sufficient performance and remained the same or decreased in the case of semi-insufficient or insufficient performance, respectively. Specifically, Kuriakose & Lahiri [36] designed rules to determine whether the difficulty level should increase (performance ≥70% and anxiety level <6 units, or performance $<70\%$ and anxiety level <6 units), remain the same (performance ≥70% and anxiety level ≥6 units, or performance $<70\%$ and anxiety level <6 units), or decrease (performance $<70\%$ and anxiety level ≥6 units, or performance

≥70% and anxiety level ≥6 units) based on the performance score along with the predicted anxiety level. In the study conducted by Pradeep Paj & Lahiri [40], performance was assessed on cognitive and emotional tasks, with adjustments made solely based on the possibility of increasing the difficulty when performance was sufficient (≥70%) and decreasing in level when performance was not sufficient.

In the training context, feedback plays a pivotal role in guiding and enlightening the system's user regarding their performance, providing responses to both explicit and implicit behaviors. Except for one case [37], all selected studies implemented at least one feedback mode in their system. The decision to employ one mode over the other appears contingent upon the specific training goals and the nature of the skills being developed. Findings reveal that a majority adopted verbal mode feedback [36,38,40–43,50,51]. This phenomenon can be supported by the fact that listening (audio-message) or reading communication in words allows complex information to be transmitted. Moreover, evidence showed that a good percentage of studies, where applied, opted for a combination of the feedback mode [38,41,50,51]. In fact, it is well known that multimodal communication is more likely to be received effectively and has a greater informational effect [62]. For example, in Jyoti & Lahiri's [51] study, according to criteria governed by performance and face orientation, at the end of each task was proportioned a verbal, visual (i.e., number of stars), and auditory (i.e., clapping hands) feedbacks in a positive or negative connotation following a reinforcement perspective. The exploration of multimodal feedback, as exemplified by Zhao et al. [38], introduces a compelling dimension to the discussion by successfully implementing complex multimodal feedback. Zhao et al.'s [38] incorporation of four different feedback modes —verbal (i.e., written message), auditive (i.e., crash audio, achievement jingle), visual (i.e., reward or warning images), and haptic (i.e., friction, spring force)— represents a sophisticated approach to enhancing user engagement. The synergistic effect of multiple sensory modalities, as supported by previous literature [63], suggests that integrating diverse feedback elements can have a cumulative positive impact on the user's learning experience.

This review also delves into the temporal considerations of the implementation of adaptive strategies. Either of these strategies can be transmitted from the engine to produce an ad hoc adaptive decision in session (real-time) or between sessions of the study (deferred). The review's results indicated a preference for adapting the level or the feedback in real-time rather than deferred ones [35–38,40–42,50,51]. Real-time adaptation seems promising because aligns with the potential to enhance the training experience by tailoring content in response to the user's performance [5]. For instance, Bekele et al. [35] designed a stimuli occlusion paradigm in which the stimuli were revealed gradually along with the eye gaze performance of the participants. Therefore, the more attentively subjects turned their gaze toward the stimulus, the more visually clear and sharp it became — giving visual feedback to the participant. A particular case has been identified in Vallefuoco et al. [41], wherein feedback was given in real-time according to the accuracy of participants' actions; instead, the first session level was chosen based on the DSM V severity levels of ASD symptoms [27] and seemed to be increased with the progression of the game levels along with the level of symptoms. In addition to the duplicity of real-time (feedback) and deferred (level switching) adaptivity of the two strategies, there was further duplicity inherent in level switching: the initial level was set by the therapist and then automated by the system. Indeed, this study has been included in this review because, at first, the system was person-automatized and then became system-automatized (see *The adaptive engine: non-ML and ML techniques section*), following the advantages of cost-effective and streamlined involved.

Given these premises, it seems advantageous to introduce at least one strategy in real-time when designing an adaptive automized system. Training employing a scaffolding strategy that recognizes the need to adapt the level switching up and down when necessary (regression technique) has consistently demonstrated better learning outcomes [8]. In the same way, feedback is considered a scaffolding strategy useful to adapt intent and capabilities during the training by promoting critical thinking [64]. Considering the findings, the power of verbal and multimodal feedback [62], and the benefits of in-session administration of these two adaptive strategies [5,64], future studies should include progression level switching and/or real-time verbal feedback in their adaptive interventions. Future research should carefully consider the interplay between these adaptive strategies and their potential synergistic effects on training efficacy. Practitioners and policymakers involved in designing training interventions should recognize the complementary nature of these strategies and strive to incorporate them synergistically. In conclusion, the comprehensive analysis of adaptive strategies sheds light on their intricate dynamics within individualized training environments. By incorporating these insights into practice frameworks, future researchers can work towards enhancing the effectiveness, accessibility, and scalability of adaptive training interventions across various domains.

The adaptive engine: non-ML and ML techniques

A system-automatized adaptive engine can independently analyze signals and decide when to apply level switching or feedback to customize the intervention for each individual.

In this frame, the deployment of an adaptive engine within the reviewed studies confirms the dichotomy in the techniques employed for decision-making—non-ML and ML. A significant majority of the reviewed studies lean towards non-ML techniques for adaptive engine design [35,36,38,40–42,50,51]. This approach involves establishing predefined rules, often binary in nature, to determine the appropriateness of the participant's performance. Decisions are made through established cut-offs to determine whether the performance is sufficient in terms of duration, successes, gazed area, accurate movements, or physiological activity levels. For instance, Kuriakose & Lahiri [36] designed an adaptive rationale engine based on the composite effect of physiological indexes level (high/low) through the fuzzy logic classification method and the quality of task performance (adequate/inadequate). Similarly, Lahiri et al. [42] adapted their VR system through complex fixed rules that blended information from viewing patterns (fixation duration), eye physiology (pupil diameter, blink rate), and task performance. The inflexibility of non-ML techniques is evident in their reliance on a priori knowledge and fixed rules. While effective for binary decisions, the limitation lies in their inability to adapt to more intricate data nuances not easily discernible by human observation. In contrast to non-ML techniques, the primary goal of ML is to predict future observations as accurately as possible and increase efficiency and reproducibility [65,66]. Despite the advantages of adopting ML techniques, a limited number of selected studies opted for ML techniques to drive adaptive engine decisions [37,43,51]. The utilization of artificial neural networks by Hocking et al. [37] exemplifies the capacity of ML to objectively quantify kinematic features by tracking the biomechanical changes and adapting the level of challenge in real-time. Specifically, they applied a normalized exponential transformation translated into a discrete probability assignment over the potential labels — and trained this model until no further enhancements were observed. Another ML illustration is the one of Moon & Ke [43], who analyzed the participant's speech and utilized a supervised ML method to categorize the probability values into threshold conditions (high to low emotional state). A certain type of feedback was given based on the individual's threshold condition. The novel integration of ML and non-ML approaches within a single study, as seen in Jyoti & Lahiri [51,67], showcases the potential for a hybrid model. While the task performance level switching remained non-ML, ML-based feedback signaled a nuanced approach to harnessing the strengths of both techniques. The latter relied on image processing using a Haar feature-based cascade frontal face classifier [67] to calculate the percentual of the user's face (gross motor movement) oriented toward the area of interest. However, the method proposed by Viola & Jones [67] is now considered obsolete, as it has been replaced with deep learning methods, such as Convolutional Neural Networks [68,69].

Given the considerations made until now, the distinct characteristics of non-ML and ML techniques raise critical considerations for their application in adaptive systems. Non-ML techniques, reliant on predetermined rules, demonstrate efficacy in scenarios where binary decision-making aligns with straightforward performance metrics. However, their limited ability to discern subtle patterns in data necessitates caution when confronted with complex and dynamic user interactions that are usually not detectable by humans. Conversely, ML techniques, driven by continuous objective analysis of datasets and pattern recognition, hold promise in offering adaptive systems that improve automatically over time. Considering a growing emphasis on adaptive systems based on ML [5], the ability to replicate outcomes and accurately predict future observations, as highlighted by Orrù et al. [65], positions ML as a potent tool to provide more refined and personalized interventions. Future research should carefully weigh the trade-offs between non-ML and ML approaches. The current review advocates for increased adoption of ML techniques in future research aiming to enhance ASD interventions.

However, it is notable that among the selected studies that used ML techniques, the sample ranged from 4 to 20 participants [37,43,51]. In ML models, predictions are made by employing versatile learning algorithms to find patterns in typically vast datasets; this is why extensive datasets are necessary to yield more accurate algorithm outcomes [65,66]. Acknowledging that larger datasets enhance the generalization performance of ML models [66], the limited sample sizes in these studies raise concerns about the robustness of the ML-based adaptive engines. Future research should prioritize expanding sample sizes to bolster the reliability and effectiveness of ML-driven interventions.

Among other advantages, the adaptive engine, functioning as the autonomous core of the system, exhibits the capability to make real-time decisions. Regardless of the chosen technique (non-ML or ML), an overarching theme within the reviewed studies is the pervasive use of real-time adaptive systems. This aligns with the growing interest in adaptive systems that employ ML techniques to recognize patterns in data, enabling real-time responses and an enhanced user experience [34,39]. This is frequently accomplished using sensors and algorithms for effective data interpretation and analysis, harnessing the input signals to optimize the system's performance. It is supported to implement this approach for future studies to enhance the system's ability to provide meaningful responses based on the gathered dynamic user inputs. Policymakers could support initiatives aimed at advancing sensor technology and algorithm development to facilitate real-time data interpretation and analysis in adaptive systems, as it could enhance their effectiveness in clinical settings.

In conclusion, the architectural choices for adaptive engines play a pivotal role in shaping the efficacy of interventions. The synthesis of real-time adaptability with a preference toward adopting non-ML techniques and consideration of the nuances of sample size regarding those adoptions with ML techniques should guide future endeavors in developing adaptive systems that seamlessly integrate cutting-edge technologies to enhance user experiences in ASD interventions.

Signals: an embodied adaptation

Given what has been discussed with respect to the adaptive strategies governed by the engine and the techniques used by the engine, it is pertinent to address what drives and prompts these adaptation decisions: signals.

The results of this review showed a similar reliance on explicit and implicit signals, with a slight preference for the latter, in shaping ASD training adaptations. In particular, three studies [40,41,50] exclusively utilized explicit signals, focusing on behavioral data such as task performance metrics (i.e., reaction time and success rates). Another set of studies [36,42,51] adopted a more integrated approach, combining explicit signals (task performance) with implicit biosignals like gross motor movements, peripheral physiological responses, and eye gaze. Jyoti & Lahiri [50,51] highlighted the importance of adapting training through an implicit measure complementary to performance data. Indeed, in their latest study [51], they introduced informative data on the duration of face orientation toward the stimulus presented, as it can infer whether a child is attending to the task stimulus. Adding implicit biosignals might augment the potential of explicit signals, providing a valid result. Similarly, Kuriakose & Lahiri [36] adapted their VR system to users' affective states, such as anxiety, through peripheral physiological signals (including galvanic skin response and pulse plethysmogram). Adaptive training based on implicit biosignals has been demonstrated to hold the potential to optimize physiological arousal to maximize the trainee's training [5]. Conversely, training programs that fail to adjust to users' affective states may negatively impact performance, leading to either low arousal levels (as in boredom) or high arousal levels (as in anxiety) [29]. To avoid so, it is essential to consider implicit biosignals together with explicit ones. A joined analysis of users' explicit and implicit biosignals is favorable in order to make refined adaptation decisions based on their needs. Implicit biosignals can offer a valuable analysis for recognizing the user's inner state during treatment, often imperceptible to human observation but easily deciphered by computers [36]. Indeed, compared to explicit signals, implicit biosignals emerge as pivotal in providing optimal challenges to users, increasing their engagement, and improving their performance [29,30]. Lahiri et al. [42] study stands out as a pioneer, in comparison with the other included studies, in anticipating the benefits of adapting through implicit biosignals. Indeed, it proposed to measure the engagement level through real-time viewing patterns, subtle eye physiological changes, and performance metrics to adaptively enhance responses for improved social communication skills. Here again, there is a clear need to incorporate an implicit biosignal when training or investigating a complex construct.

Recent studies suggested the integration of advanced technologies (e.g., eye gaze monitoring, peripheral responses monitoring, motion-sensing, speech input devices) to capture implicit biosignals, steering ASD interventions toward a more intuitive and embodied approach [29,35,40]. As discussed, implicit biosignals unveil hidden meanings and provide insights that extend beyond observable user behaviors. Into this gap lies the notion of embodied cognition [70], which claims that body and mind are not detached but rather maintain a continuous, tight, ongoing relationship. Embodied theories are based on the concept that every action or reaction is influenced by one's perception of any stimulus, typically during goal achievement [70,71]. VR interventions, as embodiments of learning paradigms, represent an illustration of how technology links the mind, body, and environment together and where individual perception plays a crucial role in shaping their bodily experience of the world [72]. The selected studies in this review reflect a growing body of evidence to adapt interventions to the implicit needs of ASD children, incorporating devices capable of collecting implicit biosignals of fine [38] or gross [37,51] motor movements, eye gaze [35,42], peripheral physiological responses [36], and speech [43]. For example, Moon & Ke [43]had driven adaptive feedback through speech data mining to identify the emotional states of children.

Based on the assumption that embodied cognition theories indicate that cognition is a continuous interplay of various modules, encompassing simulation, environmental, situated action, and bodily state factors [73], the implicit biosignals are at the core of the process of cognition, as they reflect and explain behaviors that are not directly observable. Thus, future adaptive interventions for ASD children should go beyond monitoring the performance as a stand-alone datum and adopt an embodied perspective by including implicit aspects, assuming that the arousal component influences the learning experience in training. Cognition rarely proceeds independently of the body; however, it is recognized that many researchers address other forms of cognition assumption [70]. Therefore, the suggestion is to implement the embodied adaptation framework but acknowledge that other adaptations may also be valuable. Practitioners could support initiatives aimed at promoting embodied perspectives in ASD interventions, recognizing their potential to enhance learning experiences and outcomes for individuals with ASD.

Lastly, attention should be shed on those included studies that processed the implicit biosignal in real-time to enhance ASD adaptive interventions [35–38,42,51]. Evidence suggests the ability of VR-automatized systems that dynamically adapt based on implicit biosignals are able to foster ongoing communication with users by identifying their present state and aligning activities with specific behavioral objectives [37,38]. For example, sophisticated algorithms have made it possible to quantify and qualify dynamic whole-body motor movement in real-time to adapt the motor skills intervention [37]. Even finer motor movements, such as force or precision/control, can be adapted in real-time to improve the performance of a kinetic task [38]. In conclusion, the spotlight on studies processing explicit and/or implicit biosignals in real-time underlines their potential to enhance the effectiveness of adaptive interventions for young ASD individuals. Moreover, as technology continues to advance, the integration of unobtrusive wearable devices that capture implicit biosignals, either independently or in combination with explicit signals, emerges as promising [5]. Based on the literature and the above reasons, it is recommended to embrace the embodied perspective to comprehensively understand and intervene in the unique needs of ASD children.

Overall findings

The literature search showed that there has been a growing emphasis on developing objective adaptive technologies to target the needs of individuals with ASD. This review primarily aimed to shed light on the methodologies of the included studies employed for the adaptive engine and the types of signals utilized. Secondly, this manuscript enabled the identification of methodological insights and offers guidance for improving adaptive VR interventions for individuals on the autism spectrum.

Findings suggested a tendency to focus on adolescent samples, underscoring the importance of exploring younger age groups on VR adaptive systems. A predominant focus on usability, social skills training, and a common use of desktop computers has been discussed.

The main findings showed the utilization of adaptive strategies varied among studies, with a noteworthy trend toward real-time adaptations. The nuanced application of progression techniques, coupled with the exploration of verbal feedback and real-time adaptations, provided a foundation for future research aimed at optimizing adaptive training systems for therapeutic contexts.

The review highlighted considerations associated with non-ML and ML techniques critical in the engine adaptation. The overarching theme in the reviewed studies underscores the widespread use of real-time adaptive systems, mostly non-ML, but also aligned with the growing emphasis in the past two years on employing ML techniques for refined and enhanced training. Moreover, when choosing an ML engine, a wider sample size should guide the development of future adaptive systems for ASD personalized interventions.

Finally, both explicit and implicit signals were identified as the driving force behind adaptive decisions, with a gained attention toward utilizing implicit biosignals for a more comprehensive understanding of user needs. Embracing an embodied adaptation framework is suggested for future ASD interventions, emphasizing real-time processing for optimal adaptation and contributing to improved performance.

By synthesizing and evaluating the existing evidence, this study aims to contribute valuable insights that can inform the design and implementation of more targeted and effective interventions, ultimately enhancing the quality of life for individuals with ASD and their families[74]. In fact, an adaptive system holds the promise of improving outcomes for greater numbers of ASD children by guiding clinicians on how to take advantage of heterogeneity in response to treatment [6].

Limitations

This review is not without limits. No technological or automated tools were used to handle the collected data, which could have led to bias due to human error. However, the literature search is considered valuable because, given the small number of articles found, it was also easily analyzed manually without the use of specific automated techniques. The limitations of the selected studies primarily stem from the heterogeneity in study designs. Future reviews should focus on different inclusion-exclusion criteria with more consistent designs to reduce variation and improve comparability. Additionally, the availability of data in the selected studies poses another constraint. Certain studies lacked sufficient information regarding the adaptation of their systems, making it challenging to conduct specific analyses or fully assess the study's contribution. Finally,

Conclusion

In recent years, the field of ASD interventions has witnessed a significant shift towards the development of objective adaptive technologies. This evolving paradigm aims not only to enhance the overall effectiveness of interventions but also to customize them to better suit the unique needs of individuals with ASD. A systematic review was conducted to assess the current body of literature concerning the application of adaptive VR systems in ASD interventions.

The findings showed trends that align with theories, and similar studies focused on broader themes, such as the significant interplay between level switching strategies and feedback and a preference for adaptive engines operating in real-time [5,64]. However, throughout the manuscript, we also offer several reflections on how the methodological focus appears to be shifting. Specifically, we observe the qualities and opportunities that implementing multimodal feedback could bring to adaptive interventions [38,62,63]. We provide critical insight concerning the growth of adaptation studies implementing ML techniques. Indeed, among the included records, those from the past two years have primarily focused on this technique [37,43,51], likely due to its versatile and accurate nature [65,66]. Similarly, the importance of implicit biosignals is rationalized within the theoretical framework of embodied cognition [72,73] for a deeper understanding of unobservable behaviors.

This work can support researchers in designing and testing adaptive VR systems for ASD interventions and help software designers develop more engaging and targeted VR applications, thus improving the effectiveness of digital therapies. Additionally, it can contribute to the research of innovative methodologies for assessing and monitoring progress in ASD treatments using advanced VR tools. It can also provide valuable support to clinical professionals in better adapting interventions to patients' states and specific needs. Finally, it can guide practitioners toward a deep understanding of the potential of VR in ASD treatments, positively influencing decision-making in the formulation of healthcare and educational policies.

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critically reviewed the article for essential intellectual content, approved the final publication, and collectively accepted responsibility for addressing any questions regarding the work's accuracy and integrity.

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Ethical Approval. This systematic review adheres to the reporting guidelines set forth by PRISMA. The Polytechnic University of Valencia has verified that ethical approval is not required.

Conflicts of Interest

None declared.

Abbreviations

ASD: autism spectrum disorder
ML: machine learning
non-ML: non-machine learning
VR: virtual reality

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Supplementary Files

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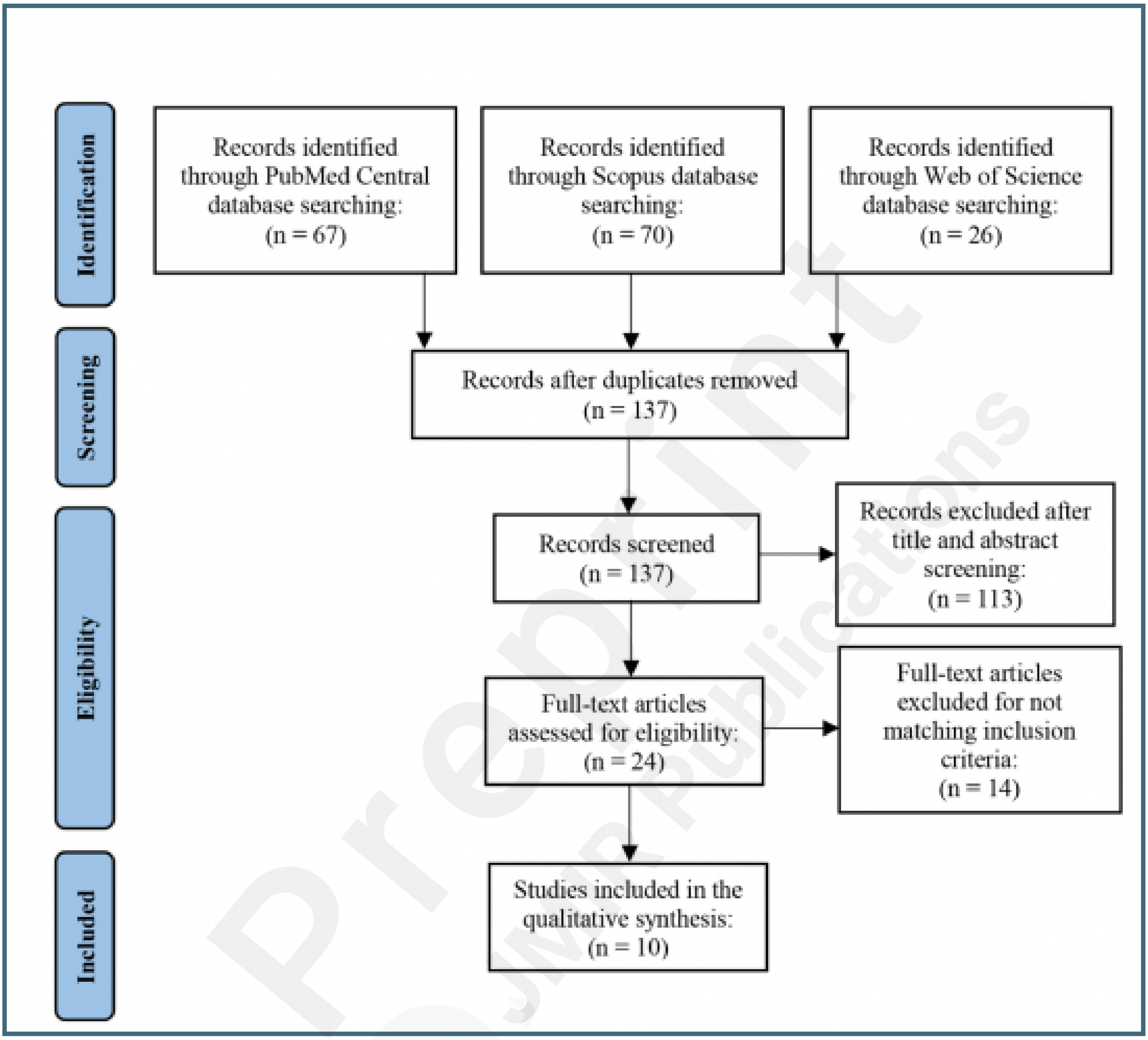
Figures

Flow diagram of literature search selection.



CONSORT (or other) checklists

PRISMA checklist.
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