



Systematic Review

Affective User Experience (AUX) in Immersive Environments: A Systematic Review of Affective Computing in Immersive Environments for Individuals with Autism Spectrum Disorder (ASD)

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Abstract

This study examines the integration of affective computing within immersive environments, virtual reality (VR), augmented reality (AR), and mixed reality (MR), to support affective user experience (AUX) in individuals with autism spectrum disorder (ASD). Twenty-eight published empirical studies were analyzed following PRISMA guidelines, focusing on affective modalities, immersive technologies, methodological approaches, and intervention outcomes. Results indicate that immersive systems increasingly incorporate physiological sensing, eye-tracking, behavioral analytics, and, to a lesser extent, facial and speech recognition. Although 89% of studies rely on unimodal affective signals, emerging multimodal frameworks demonstrate enhanced adaptability and real-time emotional responsiveness. VR remains the predominant platform due to its high immersive capacity and controlled manipulation of social stimuli, while AR support interaction in everyday contexts, offering higher accessibility. Across studies, immersive affective systems show consistent benefits in emotion recognition, anxiety reduction, engagement, and social communication. However, the field is limited by small sample sizes, restricted real-world contextual relevance, and a lack of standardized AUX evaluation frameworks. This review identifies methodological gaps and proposes future research directions involving adaptive affective systems, low-cost sensors, and inclusive, longitudinal designs aimed at achieving emotionally intelligent, scalable, and context-aware immersive interventions for people with ASD.

Keywords: affective user experience; autism spectrum disorder; immersive environments; virtual reality and augmented reality



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1. Introduction

Autism spectrum disorder is a neurodevelopmental condition characterized by differences in social communication, restricted interest, atypical patterns and emotional processing [1]. Individuals with ASD often face challenges in understanding social cues, regulating emotions, and navigating complex environments, factors that can limit their

participation in educational, social and therapeutic activities. These challenges can significantly limit participation in educational, social, and therapeutic activities, particularly in contexts that demand adaptive emotional and social interaction.

Immersive environments such as virtual reality (VR), mixed reality (MR) and augmented reality (AR) represent a significant evolution in human–computer interaction by enabling experiences that bridge digital and physical worlds [2]. In the context of autism interventions, these technologies have gained relevance as tools for user experience (UX) through controlled, interactive, and customizable environments. In particular, VR systems can be designed to simulate daily life situations, facilitate exposure to sensory stimuli, and scaffold the learning of social, emotional, and cognitive skills [3] in a personalized manner. AR, in turn, extends these opportunities into everyday contexts by overlaying digital information and affective cues onto real-world settings, increasing portability and real-world contextual relevance. MR combines the immersive depth of VR with the contextual realism of AR, allowing for real-time interaction between physical and virtual elements [4]. This hybrid approach enables users to engage with both tangible and digital components simultaneously, fostering embodied learning, situational awareness, and empathic understanding. Evidence suggests that individuals with ASD are not only capable of engaging effectively with virtual environments but can also benefit from simulated social scenarios, with the potential to transfer these skills into real-life interactions [5]. For example, studies using Oculus Rift have shown improvements in teaching social skills to adults with ASD [6].

Affective computing refers to the design of systems that can recognize, interpret, and respond to human emotions [7]. Affective computing could integrate with VR to create emotionally immersive experiences [7]. Detecting emotional states in real time through facial expressions [8], vocal tone, physiological signals [9], body posture [10] or gaze-VR systems [11] can dynamically adjust their content, difficulty, feedback, or environmental context.

This capacity is particularly relevant for individuals with ASD, who often experience difficulties in recognizing their own emotional states and interpreting the emotions of others. In this context, AR/VR/MR systems can integrate real-time feedback loops that respond dynamically to users' emotional and physiological cues, such as heart rate and skin conductance. This closed-loop interaction enables adaptive experiences in which task demands, sensory stimulation, or feedback are continuously adjusted to users' affective states. Such adaptivity is particularly critical for individuals with ASD, for whom emotional elicitation and regulation are highly context-dependent and strongly influence engagement and learning.

Despite the rapid expansion of immersive technologies for autism interventions, most existing research continues to assess user experience primarily through usability metrics [12], affective state measurements [13], emotion recognition accuracy (e.g., facial expressions, physiological characteristics, body language, and voice analysis) [14], eye-tracking [15], and task performance outcomes. Within this literature, emotional processes are typically treated as indirect or secondary variables—measured post hoc or inferred from behavioral improvement—rather than being explicitly modeled as integral components of the interaction loop. As a result, affective data are frequently used for retrospective evaluation rather than to inform real-time interaction design or adaptive system behavior. This methodological orientation limits the potential of immersive systems to function as emotionally responsive and personalized environments, particularly for users whose affective states play a central role in engagement, regulation, and learning.

Affective computing (AC) is an interdisciplinary field concerned with the design and development of computational systems capable of identifying, comprehending, processing

and simulating human emotions [16]. Emerging from the field of human–computer interaction (HCI), AC is grounded in the premise that emotion is not peripheral to interaction but constitutes a fundamental component of how users perceive, engage with, and respond to interactive systems. Within this context, affective user experience (AUX) is not a re-labeling of traditional UX with emotional variables. Rather, AUX reframes immersive interaction as a closed affective loop in which emotional sensing, interpretation, and system response are structurally coupled.

From a methodological perspective, AUX enables the analysis of *how* affective data are embedded within system logic—specifically, whether and how emotional signals inform interaction dynamics, feedback mechanisms, or adaptive behavior—rather than merely assessing whether emotional outcomes improve. Theoretically, AUX shifts the focus from outcome-oriented evaluation to process-oriented interaction, allowing affect to be understood as a dynamic mediator between user, system, and context.

By applying the AUX lens, this review contributes an interpretive synthesis that explains why certain immersive technologies consistently support specific affective outcomes while others do not. It reveals trade-offs between immersion, contextual realism, and affective adaptivity that are obscured in descriptive comparison. In doing so, the review advances the field toward emotionally responsive, inclusive, and methodologically coherent immersive systems for individuals with ASD.

This systematic review aims to synthesize the current state of the art in affective computing within immersive environments for people with ASD. Specifically, it addresses the following research questions: (1) Which immersive technologies are applied for affective user experience in ASD interventions? (2) What affective computing modalities (physiological, facial, behavioral, or multimodal) are implemented in these environments? (3) What outcomes are reported in terms of emotional recognition, emotional regulation, and user engagement? And (4) what challenges, limitations, and future research directions are identified in the literature?

This article is structured as follows: Section 2 introduces theoretical concepts related to immersive technologies, affective computing and autism spectrum disorder. Section 3 details the methodology employed in the literature search, including databases, inclusion criteria, and the PRISMA process. Section 4 presents the main findings derived from the selected studies. Section 5 offers a critical discussion of the reviewed literature, highlighting trends, limitations, and challenges. Finally, Section 6 summarizes the conclusions and suggests directions for future research.

2. Background

2.1. Immersive Environment in Autism Interventions

Currently, psychological and behavioral interventions for people with ASD have progressively incorporated the use of technological tools, one of which is the use of immersive environments to teach skills in which they have difficulties and prepare them for scenarios that can be very demanding or stressful due to external factors [17]. Among the advantages mentioned for using this type of virtual reality tool in interventions with people with ASD are [17–19]:

1. Control and safety of the environment, as it allows professionals to precisely regulate stimuli so that individuals can develop their skills in a safe space.
2. Cognitive and pedagogical alignment, as it allows professionals to adapt the environment based on the person's learning needs.
3. Promotion of participation and skills, as it is recent technology and presents a gamification format, thus people are attracted to using this type of tool in their interventions.

In this way, by incorporating these elements, it is possible to work with a person with ASD in an environment where they feel safe, while at the same time preparing them for complex environments without damaging their mental health. In order to design these tools, it was found that most followed a design process that took into account the needs of people on the spectrum and coincided with the following steps [17–19]:

2.2. Affective Computing in Immersive Environments

The term affective computing encompasses several fields of study, such as Machine Learning, Deep Learning, and human–computer interaction, as its objective is to understand users' emotions by detecting physical changes when using technology. For this reason, a wide range of affective signal modalities are used for emotion recognition in immersive environments [20–22] (summarized in Table 1), including eye movement (EMO), Electrocardiogram (ECG), Blood volume pulse (BVP), galvanic skin response (GSR), Respiratory patterns (RESPs), heart rate (HR), facial detection, and vocal signals.

Table 1. Affective computing signal modalities commonly used in immersive environments.

Abbreviation	Full Term	Description/Purpose in Affective Computing	
EMO	Eye Movement	Analysis of eye movements (e.g., fixations, saccades, and blink rate) to infer attention, engagement, and emotional processing.	[23]
ECG	Electrocardiogram	Measures cardiac electrical activity; used to derive heart rate and heart rate variability for stress and arousal detection.	[24]
HR	Heart Rate	Number of heartbeats per minute; indicator of arousal, stress, or anxiety.	[25]
HRV	Heart Rate Variability	Variability between consecutive heartbeats; reflects autonomic nervous system regulation and emotional state.	[26]
BVP	Blood Volume Pulse	Optical measurement related to blood flow; commonly used to estimate heart rate and arousal.	[27]
GSR	Galvanic Skin Response	Measures skin conductance changes due to sweat gland activity; indicator of emotional arousal.	[28]
EDA	Electrodermal Activity	Broader measure of skin conductance including tonic and phasic components; widely used for stress and arousal detection.	[29]
RESPs	Respiratory Patterns	Analysis of breathing rate and rhythm; associated with relaxation, stress, or anxiety.	[30]
SKT	Skin Temperature	Peripheral temperature changes related to emotional arousal and stress responses.	[31]
EMG	Electromyography	Measures muscle electrical activity; used to infer tension, stress, or facial expression activation.	[32]
FER	Facial Expression Recognition	Computer vision-based detection of facial expressions to classify emotional states.	[33]
Speech/Prosody	—	Analysis of vocal features, such as pitch, intensity, and rhythm, to infer affective states.	[34]

When it comes to analyzing users' emotions while they are using virtual reality tools, the task becomes more complicated, as the most widely used technique in this field is facial detection, which is blocked by the use of virtual reality glasses [22]. Because of this, two main types of solutions have been proposed to analyze user emotions, namely:

- Performing training using a dataset that edits the eye and eyebrow area to simulate people's faces when wearing virtual reality glasses [21].
- Use multimodal analysis, which means combining several techniques used to detect what emotion the person is feeling, such as EMO in conjunction with an ECG [20,22].

Among the limitations mentioned in the articles when using these types of techniques for emotional recognition are the following:

- Head-Mounted Display restrictions, since, as mentioned above, it limits facial detection, which is commonly used in this field, in addition to limiting the user's head movement, since to achieve good detection using this technique, the head must be kept in front of the camera without moving [21].
- Problems when using EMO for analysis in immersive environments, due to high instability in recording caused by interference and movement of the user's head [20].
- Complexity of sensor installation, as this limits the subject's behavior during testing, where other types of portable devices for recording physiological characteristics would be preferred [22].

Table 1 summarizes the affective signal modalities and abbreviations used throughout this review, ensuring consistent terminology and facilitating interpretation of affective computing methods applied in immersive environments for individuals with ASD.

2.3. Affective User Experience

In the current literature, combining affective computing (AC) and user experience has been considered crucial in order to transform systems so that they are not purely functional for the user but rather aware of users' emotions and able to adapt to them [35]. The aim of this union is to move from static systems that only predict emotions so that the developer can then work on improvements through the feedback obtained, to systems that adapt dynamically according to the emotions felt by users [36], adjusting their content and behavior during use, such as providing simpler responses or reducing the list of tasks, leaving only those that are essential.

This union began to emerge when it was identified that it was not enough to focus solely on the prediction rates obtained through machine learning classification processes, but that it was essential to understand why the user behaved in a certain way in a given situation in the tools, which is where UX comes in as it is based on the type of errors the user makes when working with the interface, providing context for accuracy to be evaluated qualitatively [37].

By integrating UX into the emotional analysis of interactive systems, several measurable outcomes and essential design considerations were identified:

- Improved engagement and performance when using the application, with e-learning results showing tasks completed 15% faster and scores that were 12% higher. Meanwhile, results using EmoLand showed increased participation and motivation among children, with a high level of attention [36].
- Enhanced system accuracy achieved through multimodal emotion detection approaches, enabling more personalized and adaptive interactions.
- Privacy and ethical considerations identified as essential requirements when working with affective user data, as 43% of participants in the study reported concerns regarding data usage and analysis [36].
- Improved effectiveness of interventions for children with ASD through UX— and emotion—aware design, allowing immersive environments to be adapted to users' individual needs and emotional states [36].

2.4. State of the Art

Studies have examined the use of immersive technologies in ASD [38], addressing aspects such as usability, feasibility, clinical effectiveness, and educational outcomes. These studies have contributed valuable syntheses of technological trends and reported intervention effects, particularly highlighting the potential of virtual reality (VR) and, to a lesser extent, augmented reality (AR) for supporting social, emotional, and cognitive skills in individuals with ASD. However, the analytical perspectives adopted in prior reviews remain largely outcome-oriented or technology-centric.

Affective processes are typically treated as secondary outcomes (e.g., improvements in emotion recognition or anxiety reduction) or as implicit components of user experience rather than as central elements shaping interaction dynamics. Some reviews acknowledge the role of affective computing or physiological sensing; they rarely examine how affective signals are embedded within system logic or used to drive adaptive interaction in real time. As a result, prior syntheses provide limited insight into the interactional mechanism through which immersive systems support emotional regulation and engagement.

Table 2 presents representative studies on immersive technologies proposed for interventions in autism spectrum disorder (ASD), providing an overview of the technological approaches and application contexts reported in the literature.

Table 2. Studies on immersive technologies proposed for interventions in ASD.

Reference	Primary Focus	Affective Analysis	Notes
[39]	VR assessment/intervention in ASD and ADHD.	Limited affective evaluation	Scoping review predominantly reporting observational evidence and further generalizations.
[40]	VR- & AR-based joint attention training for ASD.	Limited affective analysis.	Empirical intervention study focusing on social communication (joint attention) using eye-gaze-based AR/VR interaction; affect is not explicitly operationalized beyond task engagement.
[41]	Immersive VR systems for accessibility in ASD.	Limited or implicit affective consideration.	Case study-based exploration of immersive technologies aimed at improving accessibility and interaction for autistic adolescents; affective processes are discussed implicitly in relation to engagement and comfort rather than being systematically evaluated.
[42]	School-based immersive VR for pragmatic language and social communication in children with ASD.	Not explicitly reported.	Empirical intervention study investigating a culturally adapted, gamified VR program to enhance pragmatic language, social reciprocity, and daily living skills in primary school-aged children with ASD through authentic contextual simulations.
[43]	VR/AR/MR social skills training in ASD.	Limited affective analysis.	Empirical intervention study combining AR and MR with concept maps.

3. Research Methodology

This study adopts a systematic review design to synthesize and critically evaluate the existing literature on the application of affective computing within immersive virtual environments for individuals with autism spectrum disorder. A systematic review enables a rigorous, transparent, and replicable analysis of multiple empirical studies, allowing for the identification of emerging trends, methodological challenges, and knowledge gaps in the field.

The review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [44], which provide a structured framework for the identification, screening, eligibility assessment, and inclusion of studies. A PRISMA flow diagram (Figure 1) was used to visually document each stage of the selection process, thereby enhancing transparency, traceability, and reproducibility. Records labeled as excluded in Figure 1 correspond to studies removed during the title/abstract screening and full-text eligibility assessment stages for reasons such as the absence of ASD populations, lack of immersive technologies (VR, AR, or MR), non-affective interventions, or insufficient methodological detail.

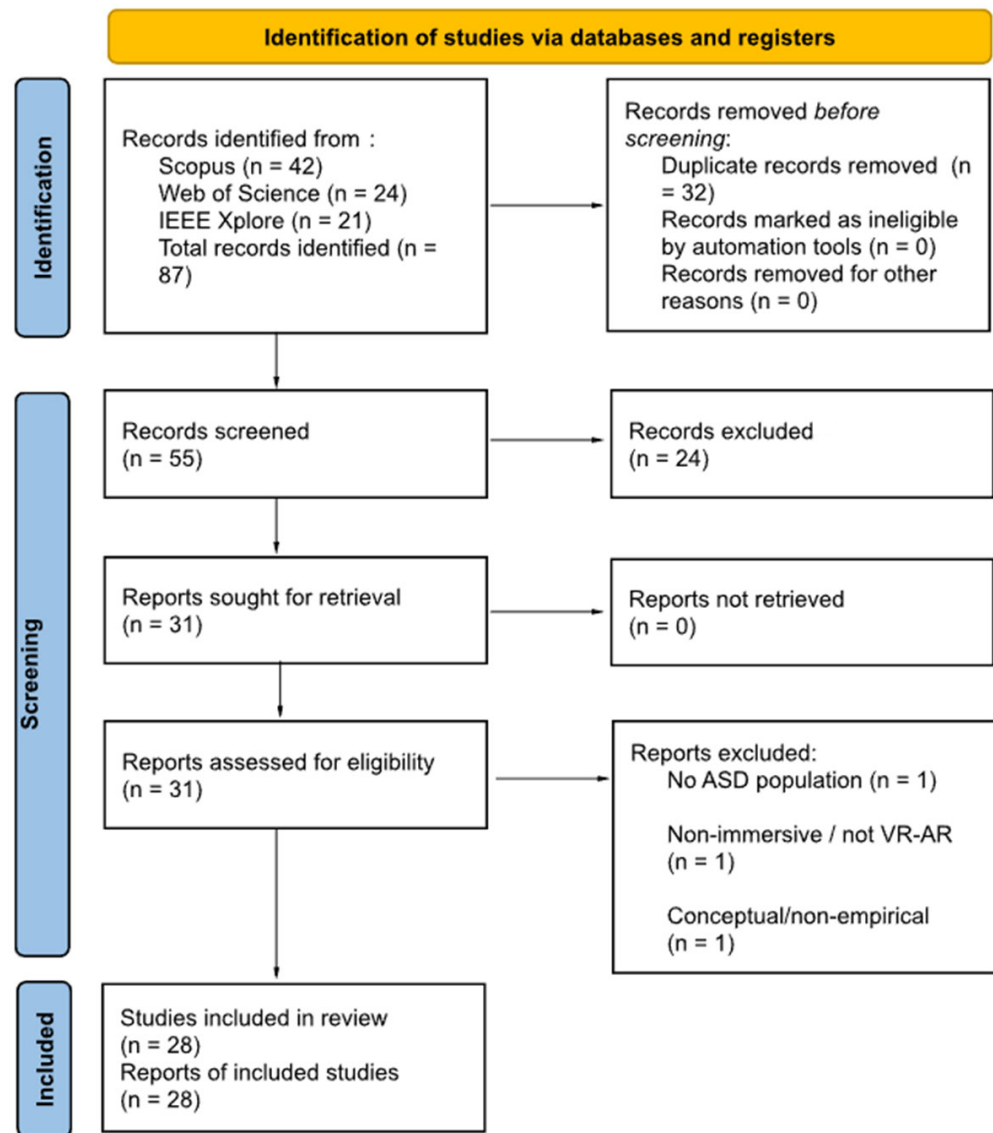


Figure 1. Flow diagram of studies selected using PRISMA methodology.

The relevant literature was retrieved from three major academic databases: Web of Science (WoS), Scopus, and IEEE Xplore. The search did not impose a predefined temporal range and employed a combination of keywords related to *affective computing*, *immersive technologies*, and *autism spectrum disorder*, in order to capture all relevant empirical studies available in this emerging research area. Following the screening and eligibility process, a total of 28 articles met the inclusion criteria and were selected for qualitative synthesis and critical analysis.

Additionally, the review was structured according to the PICO framework [45], which defines four essential components of systematic inquiry—Population, Intervention, Comparison, and Outcomes—to ensure conceptual coherence and methodological consistency across the selected studies. Table 3 shows the components of the PICO framework applied in this review.

Table 3. Application of the PICO framework used to define the population, intervention, comparison and outcome criteria guiding the systematic review of affective computing in immersive ASD interventions.

Element	Description
Population (P)	Individuals with autism spectrum disorder (ASD), across all ages and severity levels.
Intervention (I)	Immersive virtual, augmented, or mixed reality environments integrating affective computing technologies.
Comparison (C)	Non-immersive interventions, traditional methods, or control conditions (if available).
Outcome (O)	Affective user experience, emotion recognition and regulation, engagement, motivation, and reduction in anxiety or stress.

3.1. Research Questions

The review was guided by the following research questions:

1. Which immersive technologies (VR/AR) are applied for affective user experience in ASD interventions?
2. What affective computing modalities (physiological, facial, behavioral, or multimodal) are implemented in these environments?
3. What outcomes are reported regarding emotional recognition, emotional regulation, and user engagement?
4. What challenges, limitations, and future research directions are identified in the literature?

3.2. Extraction and Evaluation of Literature

This study selection process followed a predefined review protocol based on PRIMA guidelines. After duplicate removal, studies were screened in two stages: (i) title and abstract screening and (ii) full-text eligibility assessment. Screening decisions were based on the inclusion and exclusion criteria reported in Table 4. To minimize potential reviewer bias, all screening steps were conducted independently by the authors, and any disagreements regarding study inclusion were resolved through discussion until consensus was reached.

Table 4. Exclusion and inclusion criteria.

Criteria	Description
Inclusion	<ul style="list-style-type: none"> • Empirical studies applying affective computing in immersive MR/VR/AR environments involving individuals with ASD. • Studies reporting quantitative or qualitative outcomes related to affective user experience, emotion recognition, regulation, or engagement. • Peer-reviewed journal articles or conference papers published in English.

Table 4. *Cont.*

Criteria	Description
Exclusion	<ul style="list-style-type: none"> • Studies not involving ASD populations. • Non-immersive interventions. • Studies not addressing affective computing or emotional processes. • Reviews, opinion papers, editorials, or non-peer-reviewed publications. • Non-English publications.

The following Boolean search string was applied consistently across all databases:

(“user experience” OR UX OR usability OR accessibility)
 AND (“virtual reality” OR VR OR “augmented reality” OR AR OR “mixed reality” OR MR
 OR XR OR “extended reality” OR “immersive environments” OR “immersive technologies”)
 AND (“affective computing” OR emotion OR affective OR “emotional response” OR
 “affective user experience”)
 AND (“autism” OR “ASD” OR “autism spectrum disorder”)

Following the screening and eligibility process, a total of 28 studies (Table A1) met the inclusion criteria and were selected for qualitative synthesis and analysis.

To ensure transparent interpretation of the findings, the included studies were qualitatively appraised according to evidentiary maturity rather than treated as methodologically equivalent. Specifically, studies were grouped into: (i) feasibility and usability studies, primarily assessing acceptability, interaction viability, and short-term engagement; (ii) exploratory or pilot evaluative studies reporting preliminary affective or behavioral outcomes with small samples and limited controls; and (iii) structured evaluative studies employing comparative designs, validated outcome measures, or more robust methodological frameworks.

This appraisal does not constitute a formal risk-of-bias assessment. Instead, it provides a transparent interpretive lens through which the robustness, validity, and generalizability of reported outcomes are considered, and through which the strength of subsequent analytical claims is explicitly weighted.

The inclusion and exclusion criteria applied during the screening process are presented in Table 4.

4. Results

A detailed summary of all 28 empirical studies included in the review—covering study objectives populations, immersive technologies, affective computing methods, and reported outcomes—is provided in Tables A1 and A2 (Appendix A), which constitute the empirical basis for the synthesis presented in this section.

4.1. Data Extraction and Synthesis

The extracted data were qualitatively synthesized to identify common trends, methodological approaches, and thematic patterns across studies. Particular attention was given to the types of immersive environments (VR, AR, and MR); the affective computing techniques employed (e.g., emotion recognition, physiological sensing, affective feedback); and their reported impact on user engagement, emotional regulation, and learning outcomes in individuals with ASD.

Table A2 (Appendix A) serves as a core analytical instrument in this synthesis, enabling systematic comparison across immersive technologies, affective modalities, and evaluation logic across the reviewed studies. By cross-referencing the immersive platform, affective

signal modality, and presence of adaptive interaction, this table reveals systematic patterns that are not evident from outcome reporting alone. In particular, Table A2 shows that the majority of studies combining physiological or gaze-based measures do not operationalize these signals within adaptive interaction loops, relying instead on post hoc evaluation. This pattern explains why affective sensing is widespread while affect-driven interaction remains limited across the literature.

Where quantitative indicators such as effect sizes, physiological measures, or engagement metrics were available, aggregate comparisons were performed to explore consistent trends and potential relationships between affective computing modalities and user experience outcomes. This mixed analytical approach enabled a comprehensive understanding of how immersive environments contribute to affective user experience and emotional learning ASD interventions.

To enhance clarity, several visual analyses were conducted (Figures 2–6). Figure 2 presents the temporal distribution of the studies included in the review, revealing a growing research interest between 2018 and 2025, coinciding with the rapid expansion of accessible VR/AR technologies. This trend coincides with the broader availability and affordability of VR and AR technologies and reflects growing interest in immersive solutions for educational and therapeutic applications in ASD. A prior work has similarly noted the dominance of mobile and VR-based systems due to their accessibility and adaptability in intervention contexts [46].

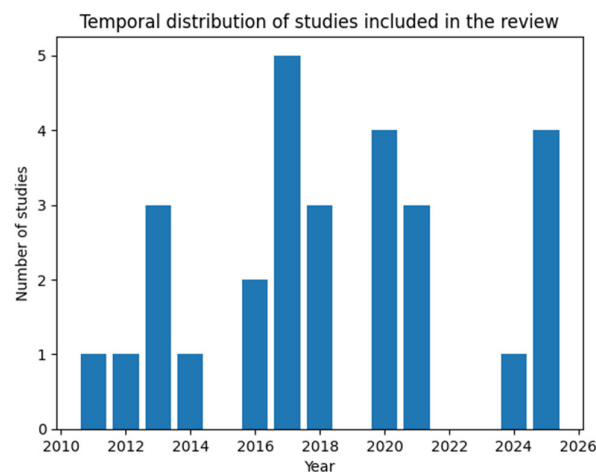


Figure 2. Temporal distribution of studies included in the review.

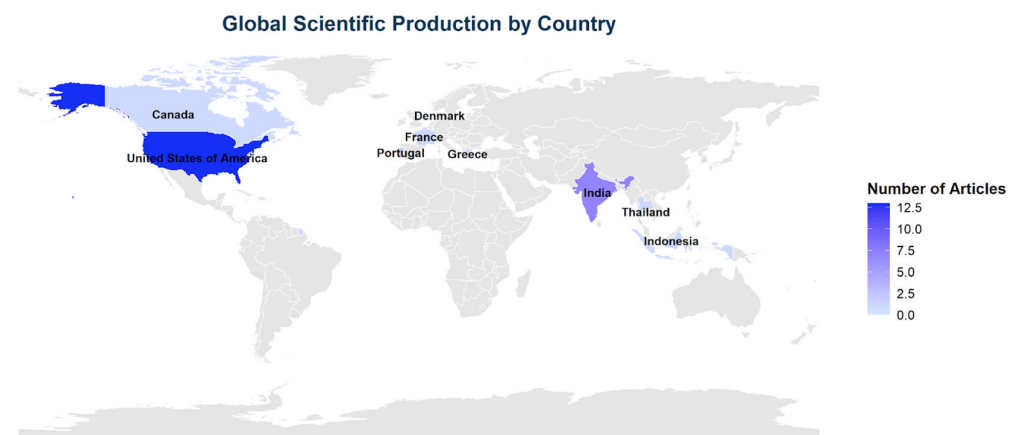


Figure 3. Geographic distribution of the reviewed studies.

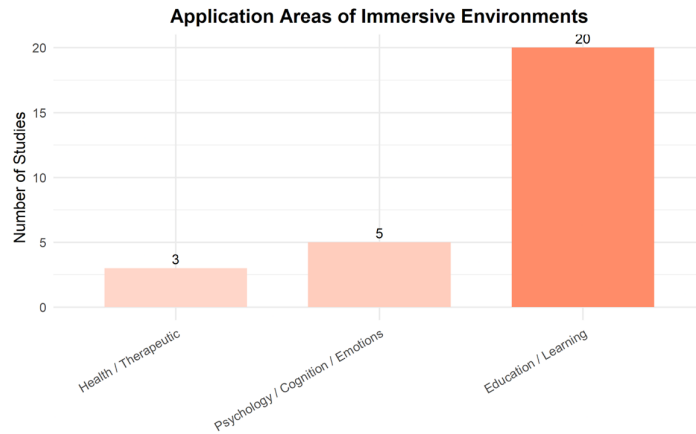


Figure 4. Distribution of immersive technologies applied in ASD interventions.

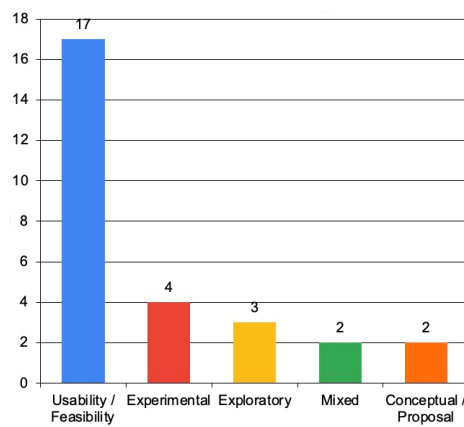


Figure 5. Type of studies included in the review.



Figure 6. Main outcomes reported in the reviewed interventions.

Figure 3 shows the geographic distribution of the selected publications, with most contributions originating from the United States, Europe, and East Asia, reflecting global but uneven research activity. Three countries (United States, India and Portugal) constitute 75% or the reviewed publications.

Figure 4 shows the application domains of immersive environments in ASD interventions. Most studies are situated in educational contexts (20 studies), followed by psychology (5 studies) and therapy (2 studies). The predominance of educational settings may be attributed to the alignment between immersive technologies and technology-enhanced learning approaches, as well as the suitability of VR and AR for structured yet flexible teaching of social, cognitive, and emotional skills. Additionally, most studies focus on children and adolescents rather than adults, reflecting the emphasis on early intervention in ASD research [47].

Figure 5 presents the distribution of the study types among the 28 articles included in the review. The majority correspond to usability and feasibility studies ($n = 17$), followed by experimental ($n = 4$), exploratory ($n = 3$), mixed-method ($n = 2$), and conceptual or proposal-based studies ($n = 2$). Importantly, 26 of the 28 studies report empirical evaluations involving user interaction, while the two conceptual studies are design-oriented and do not include outcome data.

This distribution indicates that current research on affective computing and immersive ASD interventions is largely oriented toward early-stage validation rather than large-scale experimental or longitudinal evaluation. From an analytical perspective, this evidence profile constrains the strength of effectiveness claims and necessitates cautious interpretation of reported affective outcomes.

The prevalence of usability-focused empirical studies reflects well-documented ethical, methodological, and practical constraints associated with working with ASD populations—particularly children—including small sample sizes, heterogeneity of needs, and the need to minimize participant burden. At the same time, it highlights the developmental maturity of the field, which remains in a formative phase characterized by system prototyping, interaction design exploration, and proof-of-concept validation rather than consolidated clinical or educational efficacy.

Figure 6 summarizes the primary outcomes reported across the reviewed studies. This figure was obtained by systematically coding the outcomes described in the results sections of the 28 included articles and grouping them into recurrent categories, namely emotion recognition and regulation, user engagement and motivation, anxiety reduction, and social communication skills. Each study could contribute to more than one outcome category when applicable. The resulting distribution reflects the relative frequency with which these outcomes are reported across the literature. The predominance of affective and behavioral indicators highlights the strong emotional and psychological focus of immersive interventions for individuals with ASD. A word cloud was generated through a keyword frequency analysis of titles, abstracts and author keywords from the 28 included studies. Textual data were preprocessed (lowercasing, stopword removal, and term normalization), and term frequency was computed. This visualization reflects the relative prominence of recurring concepts and is intended to be an exploratory thematic overview rather than a quantitative analysis.

Figure 7 shows the distribution of reviewed studies across levels of methodological maturity and affective user experience (AUX) integration. Most studies cluster around feasibility-level designs with post hoc affective measurement, while affect-driven adaptive interaction remains limited to a small subset of exploratory systems, highlighting a structural gap between affect recognition and affect utilization.

As shown in Figure 7, 61% of the reviewed studies (17/28) correspond to feasibility or usability evaluations, while only 14% (4/28) employ structured evaluative designs. Regarding AUX integration, 71% studies (20/28) rely exclusively on post hoc affective measurement, 18% (5/28) combine UX evaluation with affective indicators, and only 11% (3/28) operationalize affect within adaptive interaction loops. Notably, all studies implementing adaptive AUX remain exploratory or proof-of-concept studies, with none reaching structured evaluative maturity. This distribution highlights a systematic gap between affect recognition and affect-driven interaction and underscores the provisional nature of current conclusions regarding emotional regulation and adaptive personalization.

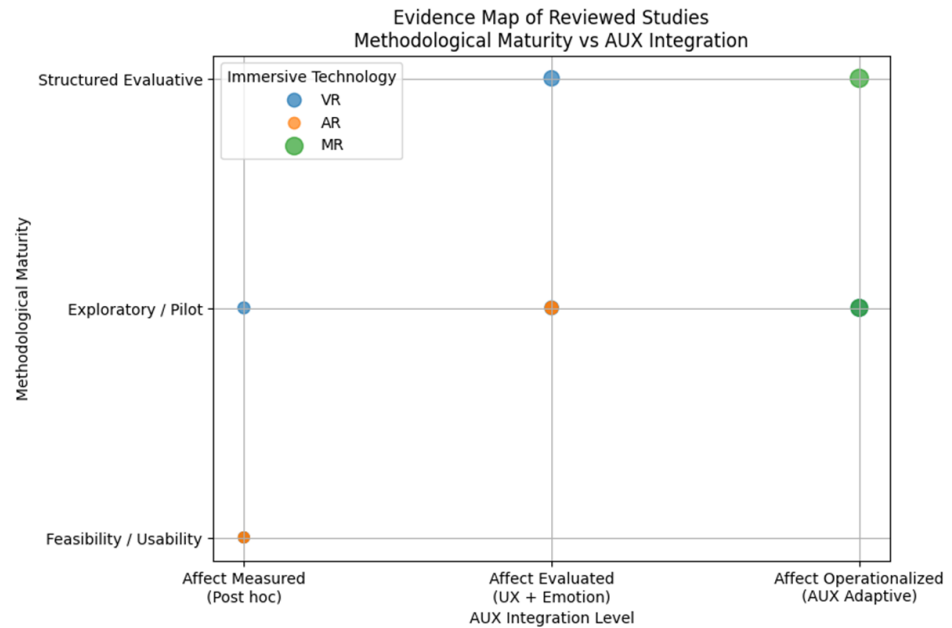


Figure 7. Evidence map of reviewed studies according to levels of methodological maturity and affective user experience (AUX) integration.

Table 5 summarizes the distribution of the reviewed studies according to methodological maturity and level of affective user experience integration. The table makes explicit that the current evidence base is dominated by early-stage research, with 61% of studies (17/28) corresponding to feasibility or usability evaluations and only 14% (4/28) employing structured evaluative designs. This distribution indicates that most reported findings reflect design viability and short-term engagement rather than validated effectiveness.

Table 5. Distribution of reviewed studies by methodological maturity and AUX integration.

Category	n	%
Methodological maturity		
Feasibility/usability	17	61%
Exploratory/pilot	7	25%
Structured evaluative	4	14%
AUX integration		
Affect measured (post hoc)	20	71%
Affect evaluated (UX + emotion)	5	18%
Affect operationalized (adaptive AUX)	3	11%

With respect to AUX integration, the table further shows that 71% of studies (20/28) rely exclusively on post hoc affective measurement, while only 11% (3/28) operationalize affective signals within adaptive interaction loops. Notably, all studies implementing adaptive AUX belong to exploratory or proof-of-concept categories, and none reach structured evaluative maturity. This pattern highlights a systematic gap between affect recognition and affect-driven interaction and explains why conclusions regarding emotional regulation, adaptive personalization, and real-world transfer remain provisional.

By making these distributions explicit, Table 5 supports an evidence-calibrated interpretation of the results and reinforces the analytical distinction introduced by the AUX framework between systems that measure affect and those integrate affect as a driver interaction.

4.2. Comparative Analysis of Outcomes Across VR, AR, and MR

The results reported in this section reveal not only differences in technological implementation but also underlying design assumptions about affective interaction. Rather than representing interchangeable solutions, VR, AR, and MR systems embody distinct priorities regarding emotional regulation, contextual relevance, and user autonomy. Interpreting these patterns through an AUX lens clarifies why specific affective outcomes systematically emerge within certain technologies while remaining limited or absent in others.

Virtual reality (VR) interventions predominantly report improvements in emotion recognition, emotional regulation, and anxiety reduction. These outcomes are largely attributed to the high level of immersion and precise control over sensory stimuli that VR environments afford. Several studies demonstrate that VR enables safe exposure to emotionally demanding social scenarios, supporting structured affective learning and regulation [5,48–50]. However, these advantages are often accompanied by limited real-world contextual relevance, as VR interactions typically occur in laboratory or simulated environments, which may restrict the transfer of learned emotional skills to real-world contexts [47,51,52].

In contrast, augmented reality (AR) interventions tend to emphasize user engagement, acceptability and real-world applicability. By overlaying digital affective cues onto real-world environments, AR systems support affective learning and social interaction in naturalistic contexts, such as socioemotional communication [53,54]. Reported outcomes frequently include increased attention to social cues, improved engagement, and moderate gains in emotion recognition. Although AR-based interventions generally show less pronounced effects on emotional regulation and anxiety reduction compared to VR, their portability, low intrusiveness, and contextual integration facilitate sustained use and real-world transfer. These characteristics make AR particularly suitable for inclusive educational and everyday affective support settings.

Mixed reality (MR) interventions, while less represented in the reviewed literature, combine immersive depth with contextual realism and demonstrate promising outcomes related to self-awareness, stress regulation, and adaptive behavior. MR systems such as InterViewR [55] and MASI-VR [56] integrate multimodal affective signals—including physiological responses, gaze behavior, speech, and behavioral cues—to provide adaptive feedback in real time [11,21,57]. Nevertheless, MR findings remain largely exploratory due to small sample sizes, higher technical complexity, and limited empirical validation [37,42].

Overall, this comparison highlights a trade-off between experimental control and real-world contextual relevance across immersive technologies. VR offers strong affective regulation outcomes within controlled environments, AR facilitates engagement and real-world applicability, and MR represents a promising yet underexplored pathway toward adaptive and context-aware affective interaction. These findings suggest that the selection of immersive technology should be guided by the targeted affective outcomes, user context, and deployment environment rather than by immersion level alone.

Table 6 presents a comparative synthesis of VR, AR, and MR interventions supporting affective user experience in ASD. Rather than functioning as a purely descriptive overview, the table highlights systematic differences across immersive technologies in terms of interaction logic, affective outcomes, and evidence maturity.

Table 6. Comparative summary of VR, AR and MR interventions for affective user experience (AUX) in ASD.

Dimension	Virtual Reality (VR)	Augmented Reality (AR)	Mixed Reality (MR)
Level of immersion	High immersion; full virtual environments [47,56].	Partial immersion; digital overlays on real-world context [55,58].	High immersion combined with real-world interaction [4,55].
Typical deployment context	Laboratory-based training, serious games, and social simulations [5,47,56].	Classrooms, homes, and everyday environments [54,58].	Vocational training, interview simulations, and professional contexts [55,59].
Primary affective outcomes	Strong improvements in emotion recognition, emotional regulation, and anxiety reduction (primarily exploratory/feasibility evidence) [48,50,56,60].	Moderate improvements in emotion recognition and engagement [53,61].	Promising outcomes in self-awareness, stress regulation, and adaptive behavior [55,56].
User engagement & acceptability	High engagement; sometimes limited by hardware intrusiveness [12,62,63].	High acceptability due to portability and low intrusiveness [54,58].	High perceived realism and engagement; limited deployment [5,55].
Real-world contextual relevance	Low to moderate; controlled but artificial settings [47,52].	High; supports real-world transfer and sustained use [53,61].	Moderate to high; combines realism with immersive feedback [5,55].
Common affective signals	Eye-tracking, physiological signals (HR and EDA), and behavioral analytics [48,56,62].	Facial expression recognition, behavioral cues; limited physiology [61,64].	Multimodal signals (gaze, physiology, speech, and behavior) [55,56].
Affective adaptivity	Mostly offline or limited real-time adaptation [48,56].	Rare real-time affective adaptation [58,64].	Higher potential for real-time adaptive feedback [55,56].
Typical evaluation methods	SUS (System Usability Scale), physiological measures, gaze metrics, and performance [12,62,63].	Usability, behavioral observation, and performance metrics [54,58].	Multimodal biofeedback, usability, and self-awareness measures [55,56].
Key strengths	Precise control; safe exposure to emotionally demanding scenarios [5,47,56].	Portability; accessibility; and real-world applicability [54,58].	Integration of immersion and context; adaptive interaction [5,55].
Main limitations	Limited real-world; hardware constraints [47,56].	Limited depth of affective regulation [61,64].	Small samples; higher technical complexity [5,55].
Maturity of evidence	Moderate (largest body of empirical studies) [47,48,56].	Moderate (strong feasibility and acceptability evidence) [54,58].	Low (exploratory and proof-of-concept studies) [55,56].

From an AUX perspective, these differences reflect underlying trade-offs between environmental controllability, contextual realism, and affective adaptivity. These trade-offs help explain why specific affective outcomes are more consistently reported in some technologies than in others. Consequently, Table 6 supports an interpretive reading of the literature, linking technological affordances to the types and robustness of affective outcomes observed.

Figure 8 shows the distribution of primary affective outcomes across immersive technologies, revealing distinct outcome profiles for VR, AR, and MR interventions.

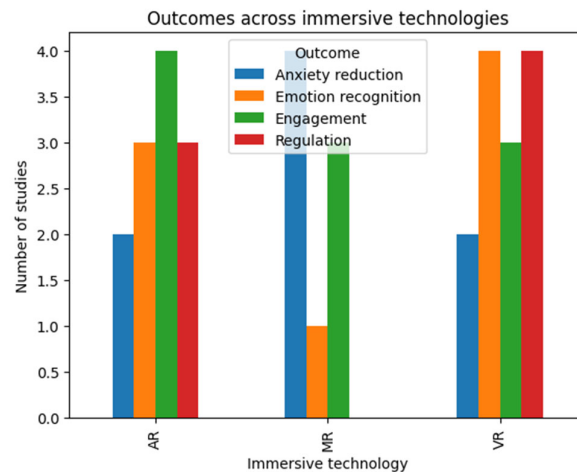


Figure 8. Outcomes across immersive technologies.

4.3. User Experience and Affective Evaluation Methods

In this review, affective user experience (AUX) is operationalized as an analytical construct defined by three core dimensions: (1) affective sensing, referring to how emotional signals are captured (e.g., physiological, behavioral, gaze-based, or multimodal); (2) affective integration, denoting whether and how these signals are interpreted within the system logic; and (3) affective operationalization, indicating whether affective information actively shapes real-time interaction, feedback, or adaptation. Unlike conventional UX frameworks that primarily assess post hoc perceptions of usability or satisfaction, AUX focuses on affect as a dynamic mediator within the interaction loop. This distinction enables evaluation of not only whether users report positive experiences, but whether emotional states meaningfully influence system behavior during interaction.

The results presented in this subsection are interpreted from an AUX perspective to clarify how affective design choices shape interaction outcome in immersive ASD interventions. Rather than representing interchangeable solutions, VR, AR, and MR systems (see Table A2) embody distinct assumptions about emotional regulation, contextual relevance, and user autonomy. These assumptions influence not only the type of affective outcomes reported but also the evaluation logic through which user experience is assessed.

From an AUX standpoint, the relevance of evaluation methods lies in whether they capture affect as an interaction process or merely as a post hoc outcome. Accordingly, this subsection examines how different UX and affective evaluation approaches operationalize affect within immersive interaction, distinguishing between methods that assess usability and engagement after interaction and those that enable analysis of affective dynamics during interaction. This distinction is critical for understanding how affective computing contributes to emotionally adaptive, user-centered immersive systems rather than functioning solely as an auxiliary measurement layer.

Table 7 categorizes the UX and AUX evaluation methods employed across the reviewed studies and serves as an analytical framework rather than a descriptive inventory. These methods range from behavioral observation and usability questionnaires to physiological monitoring, eye-tracking, and adaptive biofeedback systems. While traditional usability instruments (e.g., SUS and Likert scales) are widely used to assess ease of use, satisfaction, and perceived engagement, they provide limited insight into users' affective experience during interaction, as they rely on retrospective self-reports.

Table 7. Categorization of user experience and affective user experience (AUX) evaluation methods used in immersive ASD interventions.

Category	Primary Affective Signals	UX/AUX Evaluation Methods	Advantages	Disadvantages	References
Behavioral-based methods	Observable behaviors (gaze shifts, turn-taking, and task interaction).	Direct behavioral observation	Captures real-time interaction, engagement, and spontaneous affective responses during VR/AR tasks. Useful for children with limited verbal skills.	Subjective interpretation requires expert observers and can miss internal emotional states.	[5,12,61,65]
Self-reports & usability-based methods	Subjective perceptions (comfort, engagement, and satisfaction).	Usability testing (questionnaires, SUS, and Likert scales)	Provides structured quantitative evaluation of satisfaction, ease of use, and engagement; easy to implement.	Limited depth on affective experience; self-report bias, especially in children or individuals with ASD.	[49,55,66]
Participatory & qualitative methods	Verbalized thoughts, preferences, and interaction narratives.	Think-aloud protocol/co-design	Provides insight into user perceptions and cognitive processes; promotes inclusive and participatory design.	Requires verbal ability and may interfere with task performance.	[12,59]
Visual-attention methods	Fixations, saccades, blink rate, and pupil dilation.	Eye-tracking	Provides objective measures of attention and emotion recognition (fixations, saccades, blink rate, and pupil dilation).	Expensive and sensitive to calibration errors; limited use with lower-functioning participants.	[15,49,50]
Physiological-based methods	HR, HRV, EDA, SKT, EMG, and ECG.	Physiological monitoring (EDA, HR, SKT, ECG, and EMG)	Captures implicit affective states, such as stress, anxiety, or arousal; enables adaptive VR interventions.	Requires sensors and complex signal processing; may cause discomfort or distraction.	[48,50]
Expert-based methods	Heuristic judgments of interaction quality.	Heuristic evaluation/expert review	Efficient for identifying interface design issues early in development; complements user testing.	Depends on evaluator expertise; limited real-world contextual relevance.	[55,59]
Contextual qualitative methods	Emotional reactions reported by caregivers or therapists.	Interviews and focus groups (therapists, caregivers, and users)	Provides contextual qualitative insights into usability, emotional impact, and social acceptance.	Time-consuming and subjective; may be influenced by observer or parent bias.	[54,58,65]
Performance-based methods	Accuracy, latency, and task success.	Task completion, accuracy, and latency	Quantitative indicators of learning, recognition accuracy, or social performance improvement.	May not fully reflect emotional engagement; lacks affective depth.	[48,60,66]
Adaptive affective methods	Multimodal affective states (physiology + gaze + behavior).	Biofeedback/adaptive systems	Enables real-time personalization by adjusting task difficulty or stimuli based on physiological feedback.	Requires sophisticated integration and calibration; limited generalization across users.	[48,50,55]
Experiential affective methods	Emotional resonance and empathy-related responses.	Empathy-based experiential assessment (VR perspective-taking)	Useful for evaluating emotional resonance and empathy in neurotypical users; supports awareness training.	Not directly applicable to ASD therapeutic outcomes; subjective self-reports.	[60,67]

In contrast, physiological—and gaze—based measures offer more objective indicators of emotional arousal and attention engagement, such as heart rate variability, electrodermal activity, fixation duration, and pupil dilation. However, these approaches often require specialized hardware, careful calibration, and complex signal processing, which may limit their scalability and applicability in real-world ASD contexts.

The observed heterogeneity in UX and AUX evaluation methods reflects the absence of a standardized framework for assessing affective user experience in immersive systems for individuals with ASD. Notably, only a small subset of reviewed studies integrates affective signals into real-time adaptive interaction loops, revealing a persistent gap between affective measurement and affect-driven interaction design. This finding underscores the need for coherent, multimodal, and integrative AUX evaluation frameworks capable of supporting emotionally adaptive and inclusive immersive interventions.

It is important to distinguish between direct behavioral observation and heuristic evaluation, as these methods serve different purposes within UX and AUX assessment. Direct behavioral observation involves the systematic observation and recording of participants' real-time behaviors while interacting with immersive systems, such as gaze patterns, task engagement, turn-taking, or spontaneous affective response. This method is user-centered, and data are derived from actual user interaction. In contrast, heuristic evaluation is an expert-based inspection method in which specialists evaluate the interface and interaction design against established usability and interaction principles, without direct involvement of end users. While behavioral observation captures manifested user behavior, heuristic evaluation focuses on identifying potential design issues and usability violations from an expert perspective. Table 7 explicitly differentiates between UX-oriented and AUX-oriented evaluative logics based on the functional role of affect within the evaluation process. Rather than presenting an exhaustive list of assessment techniques, the table highlights how different methods operationalize affect within the evaluation process. Traditional UX-oriented approaches—such as usability questionnaires, task performance metrics, and heuristic evaluations—primarily assess post hoc perceptions of interaction quality and user satisfaction. While valuable for establishing system usability and acceptability, these methods provide limited insight into the dynamic of emotional experience during interaction. Crucially, only those systems that use affective information to inform real-time adaptive behavior meet the operational criteria of AUX as defined in this review.

Figure 9 presents the distribution of affective signal modalities employed across immersive technologies, illustrating how emotional states are operationalized in VR, AR and MR interventions. The figure shows a clear predominance of unimodal affective sensing approaches—such as physiological monitoring, gazed-based measures, or behavioral observation—across all platforms, with comparatively limited adoption of multimodal strategies. This pattern suggests that, although affective signals are frequently collected, they are often treated in isolation rather than integrated into comprehensive affective user experience (AUX) frameworks. The scarcity of multimodal approaches highlights an important methodological gap, given the heterogeneity of emotional expression in ASD populations and potential benefits of combining complementary affective signals for more robust and personalized interaction.

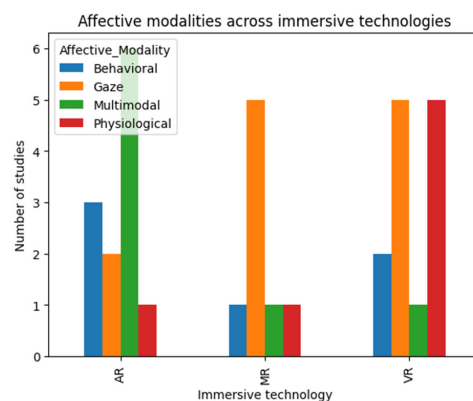


Figure 9. Affective modalities across immersive technologies.

4.4. Response to Research Questions

RQ1: Which immersion technologies are applied for affective user experience in ASD interventions?

Immersive technologies applied in ASD interventions span across VR, AR, and MR, each contributing differently to affective user experience. Early explorations relied on desktop-based VR platforms that presented avatars displaying controlled emotional expressions, allowing researchers to study facial expression recognition and affective processing in adolescents with ASD [5,50]. These environments gradually evolved into gaze-sensitive VR platforms that integrated real-time eye-tracking to provide adaptive feedback and personalize social communication tasks [15,49]. Later systems expanded into physiology-sensitive VR environments, where physiological signals such as heart rate, skin conductance, and temperature were monitored and incorporated into adaptive frameworks capable of predicting anxiety and regulating task difficulty [5,13,48].

Beyond laboratory-based VR, immersive serious games were designed to train emotion recognition and perspective-taking, leveraging gamification to sustain motivation and engagement [12,60,66]. In parallel, AR has gained significant traction as a portable and context-aware tool. Smartglasses-based interventions, including the Brain Power System and Google Glasses, demonstrated high levels of acceptability, low stress, and potential for use in schools and homes, showing promise as socio-affective coaching aids [42,54,58,68]. AR has also been implemented in gamified learning environments, such as the ARE-motion Book and FaceMe, which integrate expressive agents and emotion recognition algorithms, as well as AR therapy apps and cognitive-skill platforms designed for everyday contexts [3,61,69].

Figure 10 presents the distribution of immersive environment technologies applied across the reviewed studies. Virtual reality (VR) accounted for the majority of implementations (68%), followed by augmented reality (AR) at 18%; mixed reality (MR) at 4%; and other technologies, such as desktop-based simulations or hybrid platforms, representing 11%.

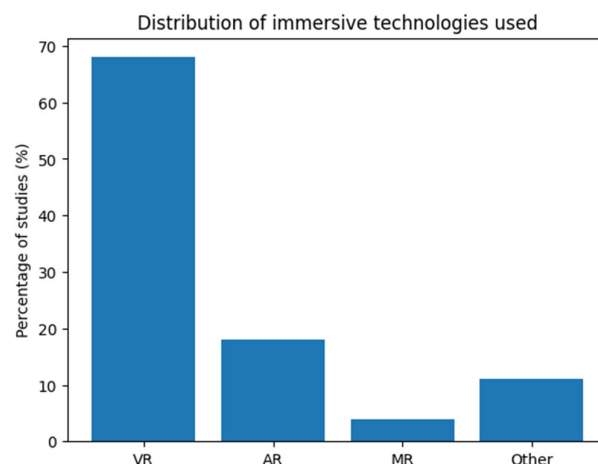


Figure 10. Distribution of immersive environments technologies used.

This distribution confirms that VR remains the dominant medium for affective and cognitive interventions in ASD research, primarily due to its high level of immersion, control over sensory stimuli, and capacity to simulate social scenarios safely. The growing use of AR reflects increasing interest in portable and context-aware applications, while MR remains in its early experimental stage, limited by technical complexity and cost.

RQ2: What affective computing modalities (physiological, facial, behavioral, or multimodal) are implemented in these environments?

The reviewed studies reveal a wide array of affective computing modalities, reflecting the multimodal nature of affective experience. However, the majority of studies (approximately 89%) relied on unimodal affective signals, focusing on either physiological or ocular indicators rather than on integrated multimodal systems. Physiological modalities were among the most prevalent, with measures such as heart rate variability, electrodermal activity, respiration, electromyography, and skin temperature frequently recorded to infer stress, arousal, and anxiety states [5,13,48]. Ocular metrics also played a central role: fixation duration, blink rate, saccades, and pupil diameter were systematically analyzed to evaluate attention to social cues and emotional engagement, providing reliable indicators of anxiety and social processing differences in ASD [5,48,49].

Facial and speech-based modalities appeared primarily in AR applications. Systems such as FaceMe and the AREmotion Book implemented automatic facial emotion recognition through convolutional neural networks and expressive-agent modelling, while Empathic System integrated voice-based emotion analysis and prosodic cues to support affective coaching [61,68]. Behavioral modalities were consistently evaluated through task performance, interaction logs, and observable social behaviors, such as gaze shifts, turn-taking, and spontaneous emotional responses in serious games [12,54].

In contrast, only a limited number of studies ($\approx 11\%$) pursued multimodal affective integration, combining gaze, physiology, and behavioral data within adaptive frameworks. Examples include the Affect-Recognizer [13] and Multimodal Adaptive Social Interaction in Virtual Environment (MASI-VR) [50], which jointly analyzed eye-tracking, electrodermal activity, heart rate, respiration, and task performance to dynamically adjust social scenarios according to the user's affective state. Similarly, InterViewR [55] combined biofeedback on gaze, speech, and physiological signals during immersive vocational training, demonstrating the potential of real-time multimodal feedback for self-awareness and stress regulation.

Figure 11 shows that the distribution underscores the predominance of visual-attention and physiological-based measures in ASD research, reflecting their reliability, non-invasiveness, and capacity to provide continuous, objective indicators of affective and cognitive states. Conversely, the limited adoption of facial and speech recognition techniques may stem from technical constraints, such as occlusion, lighting variability, and individual differences in expressivity among individuals with ASD. Overall, the integration of multimodal affective signals remains an emerging but promising direction toward more adaptive, personalized, and empathetic interaction in immersive learning and therapeutic environments.

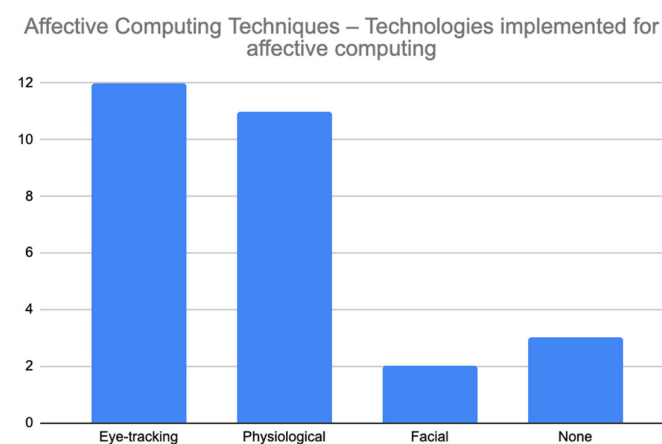


Figure 11. Distribution of affective computing modalities (physiological, facial, behavioral, and multimodal) implemented in immersive environments for people with ASD.

RQ3: *What outcomes are reported in terms of emotional recognition, emotional regulation, and user engagement?*

The outcomes reported across these studies converge on positive effects for emotional recognition, emotional regulation, and user engagement. VR-based serious games and social simulations consistently improved emotion recognition, with evidence of generalization from avatars to photographs of real people [60,66]. AR platforms such as FaceMe and AREmotion demonstrated that children achieved higher attention to faces, better imitation of emotional expressions, and improved performance compared to 2D systems, confirming the value of immersion for emotion learning.

Emotion regulation and anxiety reduction were particularly evident in physiology-sensitive VR interventions. Adaptive systems that integrated physiological markers successfully reduced anxiety responses while sustaining performance, highlighting the potential of biofeedback-driven personalization [5,48]. Similarly, AR smartglasses interventions showed high tolerability, calmness, and reduced stress in naturalistic settings, supporting their role as low-burden affective tools [54,58]. Engagement and motivation were also consistently enhanced through gamification and immersive features. MR systems such as InterViewR were perceived as realistic, helping users become aware of their behaviors under stress and providing practical training for job interviews, while empathy-focused VR, such as the Autism TMI VR Experience, successfully elicited affective responses from neurotypical participants, improving their awareness of autistic sensory experiences. Collectively, these outcomes suggest that immersive VR/AR/MR interventions not only improve emotion recognition and regulation in individuals with ASD but also foster sustained motivation and social engagement.

RQ4: *What challenges, limitations, and future research are identified in the literature?*

Despite encouraging findings, several challenges and limitations constrain the current body of evidence. Many studies involved small sample sizes, often with fewer than ten participants, which reduces statistical power and generalizability [48,49,54]. Hardware intrusiveness and cost also emerged as barriers, as early VR systems relied on chin-rests for eye-tracking or expensive physiological acquisition systems, such as Biopac, limiting real-world deployment and use [13,50]. Additionally, several interventions were static, without adaptive responses to real-time affective states, reducing their ability to replicate naturalistic social interactions [50]. More recent adaptive designs, such as MASI-VR and Affect-Recognizer, demonstrate the importance of multimodal adaptation, but these approaches remain in early proof-of-concept stages.

Another persistent challenge is the transferability of lab-based improvements to real-world social contexts. While VR interventions show promising effects on emotion recognition and anxiety reduction, evidence for long-term generalization is scarce. AR studies highlight portability and real-world contextual relevance, yet longitudinal trials remain limited [58,69]. Furthermore, most research has focused on high-functioning adolescents, leaving minimally verbal individuals, younger children, and those with severe ASD underrepresented. Future research should prioritize inclusivity, ecological integration, and scalability. Advances in low-cost, unobtrusive sensors and AI-driven adaptive frameworks [54,68] suggest promising avenues, while multi-site randomized controlled trials and longitudinal evaluations will be essential to establish robust evidence of efficacy.

Figure 12 illustrates the future research directions identified across the reviewed studies on affective and immersive technologies for ASD. The figure highlights emerging priorities, such as the development of AI-driven adaptive systems, the integration of low-cost wearable sensors, and the inclusion of more diverse participant groups in research. These directions reflect a collective effort to enhance personalization, accessibility, and real-

world contextual relevance in immersive interventions, moving toward scalable, ethically grounded, and context-aware applications in both educational and therapeutic settings.

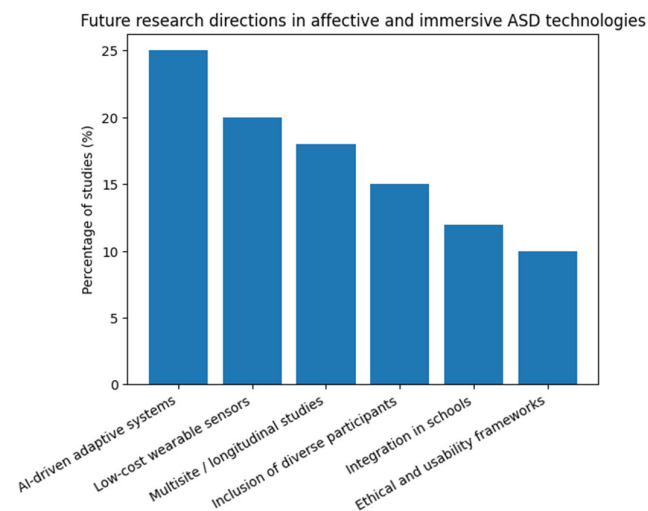


Figure 12. Future research directions in affective and immersive ASD technologies.

5. Discussion

The analysis of twenty-eight empirical studies indicates that affective user experience in immersive ASD interventions is shaped less by the presence of affective sensing technologies than by how affective information is integrated into interaction design. Across the reviewed studies, emotional signals—such as physiological arousal, gaze patterns, or behavioral indicators—are frequently collected yet seldom used to modulate system behavior in real time. This recurring pattern reveals a structural gap between affect recognition and affect utilization that constrains the experiential and regulatory potential of immersive systems.

The interpretation of these findings must be situated within the methodological maturity of the available evidence. The reviewed literature is dominated by feasibility and exploratory studies, often based on small samples, short-term interventions, and heterogeneous outcome measures. As a result, many reported benefits—such as improvements in engagement, emotion recognition, or anxiety reduction—should be interpreted as indicators of design promise and short-term viability rather than as evidence of sustained or generalizable effectiveness.

Evidence supporting affect-driven adaptation, emotional regulation, and real-world transfer is comparatively limited and derives almost exclusively from exploratory or proof-of-concept systems. Consequently, conclusions related to adaptive affective interaction and personalization remain provisional and should be considered hypothesis-generating rather than confirmatory. More robust conclusions will require a larger sample, validated affective outcome measures, and longitudinal or comparative study designs.

From an AUX perspective, this gap reflects a fundamental theoretical limitation in current design practices. Many immersive systems treat affect as an evaluative construct rather than as a constitutive element of interaction. As a result, affective computing is positioned as a measurement layer appended to usability assessment rather than as a driver of adaptive, emotionally responsive interaction. This orientation is particularly restrictive in ASD contexts, where affective states fluctuate rapidly and directly influence attention, engagement, and learning.

Comparative analysis further exposes trade-offs across immersive technologies. VR environments consistently support emotional regulation and anxiety reduction due to their high degree of environmental controllability, yet this strength is offset by limited ecological

validity and uncertain generalization beyond laboratory settings. AR systems prioritize contextual integration and accessibility but provide less capacity for deep affective modulation. MR systems attempt to reconcile these dimensions by combining immersion with real-world interaction; however, their higher technical complexity and limited empirical validation currently constrain broader adoption. Viewed through the AUX lens, these trade-offs demonstrate that immersion alone does not determine affective effectiveness; rather, it is the coupling between affective sensing interpretive logic and adaptive responses that shapes experiential outcomes.

Figure 13 shows studies that incorporate affective sensing mechanisms with those that implement real-time adaptive interaction based on affective signals, highlighting a structural gap between emotion measurement and affect-driven system behavior.

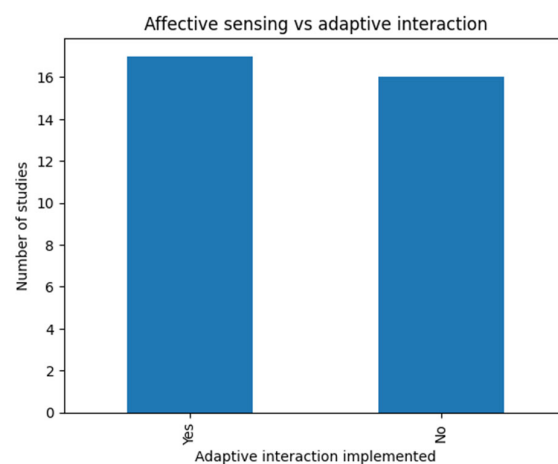


Figure 13. Affective sensing vs. affect-driven adaptive interaction in immersive ASD interventions.

From a technological perspective, VR remains the most widely applied immersive modality, frequently combined with affective computing techniques, such as eye-tracking, physiological sensing, and behavioral analytics [5,15,48–50]. These systems enable the real-time estimation of affective states, including anxiety, engagement, or stress, through indicators such as gaze duration, pupil dilation, heart rate variability, or galvanic skin response. AR, although less prevalent, shows high acceptability and relatively low cognitive demand, especially in systems using smartglasses or tablet-based interfaces for social and emotional learning [18,54,58,70]. MR applications, including InterViewR [55] and adaptive multimodal systems, such as MASI-VR (Bekele et al., 2016 [56]), represent more advanced integrations, allowing for dynamic adaptation of the environment based on users' affective and physiological responses. However, these systems remain largely experimental due to technical complexity and cost.

Despite these technological advances, UX evaluation practices remain largely traditional. Most studies rely on usability-focused instruments, such as the System Usability Scale (SUS), task performance, metrics, heuristic inspection, and self-reported satisfaction [52,55]. Only a limited number of studies implement real-time affective UX assessment that integrates physiological, behavioral, and contextual data. This methodological gap restricts our understanding of how affective computing can meaningfully enhance emotional inclusivity and cognitive accessibility in immersive system design. Furthermore, the predominance of short, laboratory-based sessions without longitudinal follow-up limits real-world relevance and transfer, weakening claims regarding sustained emotional or behavioral change.

A consistent trend across the reviewed literature is the strong developmental orientation of interventions. The majority target pediatric populations with moderate to

high-functioning ASD [5,51,59,60]. In contrast, studies involving adolescents or adults, such as those using InterViewR [55] or WorkplaceVR [52], remain rare and primarily oriented toward vocational training or interview practice. This imbalance highlights a significant research gap in affective and accessible UX design for adult neurodivergent users, particularly in higher education and professional contexts, where emotional regulation, stress management, and self-efficacy are equally critical [54].

Although multimodal affective sensing technologies have demonstrated results in terms of emotional regulation and engagement, their generalizability and scalability remain limited. Sample sizes in the reviewed studies typically ranged from 5 to 20 participants, and longitudinal evaluations or controlled experimental designs are largely absent [5,18,48]. As a result, while these systems successfully demonstrate feasibility and user acceptance, they do not yet provide robust evidence of long-term effectiveness or real-world transfer.

Furthermore, the accessibility dimension of UX remains underexplored. Although several systems explicitly consider sensory sensitivities and physical comfort [58,70], few adopt universal design principles or systematically assess cognitive accessibility as part of their UX framework. Consequently, affective UX in immersive systems often remains optimized for technical performance rather than for holistic user inclusion across the autism spectrum.

Collectively, the reviewed literature portrays a field with high innovation potential but low methodological maturity. Current efforts effectively bridge affective computing and immersive design to promote emotional learning in ASD; however, they remain fragmented and context specific. Future research should aim to:

- Establish standardized affective UX evaluation frameworks integrating behavioral, physiological, and emotional indicators.
- Expand empirical investigations to adult and higher-education populations to promote inclusivity across the lifespan.
- Adopt longitudinal and ecologically valid methodologies capable of assessing emotional adaptation and learning transfer over time.

Ultimately, immersive affective systems, particularly those combining VR and AR, hold considerable promise for emotion-sensitive, adaptive, and inclusive user experiences. Realizing this potential will require moving beyond pilot prototypes toward validated, scalable, and ethically responsible affective UX models, capable of accommodating the cognitive diversity and emotional complexity that is characteristic of the autism spectrum [5,18,55].

Implications for the Design of Affective UX in Immersive ASD Systems

The findings of this systematic review have several implications for the design of immersive systems aimed at supporting affective user experience (AUX) in individuals with autism spectrum disorder. First, the results highlight the need to move beyond static, task-oriented immersive applications toward emotion-aware and adaptive interaction systems. Although many reviewed interventions successfully measure affective signals—such as physiological responses or gaze behavior—these signals are frequently used only for post hoc analysis rather than as active inputs for real-time system adaptation [12,48,55,56,65]. Adaptive frameworks, such as MASI-VR and Affect-Recognizer, demonstrate that integrating affective data into closed-loop interaction can enhance emotional regulation and engagement, yet such approaches remain underrepresented in current research [55,65].

Second, the predominance of unimodal affective sensing identified in the reviewed studies (Table 5) highlights an important design limitation. While single-modality approaches—particularly physiological monitoring or eye-tracking—provide reliable indicators of arousal, attention, and anxiety [48,61,65], they offer a partial representation of users' emotional states. Given the heterogeneity of emotional expression in ASD pop-

ulations, future immersive systems should prioritize multimodal affective integration, combining physiological, behavioral, and visual-attention signals to support more robust, personalized, and emotionally responsive interactions [55,56].

Third, the review underscores the importance of low-intrusiveness, accessibility, and real-world contextual relevance in affective UX design. AR-based systems and wearable solutions, such as smartglasses and lightweight sensors, demonstrate higher acceptability and lower cognitive and sensory burden compared to more restrictive VR setups [54,58,68]. Designers should therefore favor portable, low-cost, and unobtrusive technologies that minimize discomfort while preserving affective sensitivity, particularly for individuals with sensory sensitivities commonly reported in ASD [54,58]. This design orientation is especially relevant for real-world educational and therapeutic deployment.

Fourth, the heterogeneity of AUX evaluation methods identified across studies (Table 7) highlights the necessity of integrated affective UX assessment frameworks. Effective design should incorporate complementary evaluation layers, including behavioral observation, physiological sensing, and subjective feedback from users, caregivers, or therapists [58–60]. Embedding AUX evaluation throughout the design lifecycle—rather than treating it as a final validation step—can support iterative refinement and more inclusive, user-centered system development [35,37].

Fifth, the strong emphasis on pediatric populations observed in the reviewed literature suggests that future design efforts must explicitly address lifespan inclusivity. While most immersive affective systems target children and adolescents [5,60], there is growing evidence of the relevance of affective UX in adult-focused contexts, such as vocational training, interview preparation, and stress management [52,55]. Designing flexible interaction paradigms and customizable affective feedback mechanisms can extend the applicability of immersive systems across different age groups and functional profiles.

Finally, the lack of longitudinal and real-world validation across the reviewed studies has direct implications for design and deployment. Most interventions rely on short-term laboratory evaluations with small samples, limiting evidence of sustained emotional learning and real-world transfer [12,18,65]. Designers should therefore anticipate long-term use and ecological integration, incorporating adaptive learning mechanisms, continuous affective monitoring, and real-world evaluation strategies to support generalizability and ethical robustness [58,69].

In summary, the design of affective UX in immersive ASD systems should be guided by principles of emotional adaptivity, multimodal affective integration, accessibility, and lifespan inclusivity. By embedding affective computing within user-centered and context-aware design frameworks, immersive technologies can evolve from experimental prototypes into scalable, emotionally intelligent tools capable of addressing the diverse emotional needs of individuals across the autism spectrum [35,55,58].

6. Conclusions

This systematic review examined 28 studies addressing affective computing in immersive environments for individuals with ASD through the analytical lens of affective user experience (AUX). The synthesis indicates that immersive technologies—particularly VR and, to a lesser extent, AR and MR—are consistently associated with improvements in usability, engagement, and emotion recognition. These findings are supported primarily by feasibility and exploratory studies and therefore reflect design viability and short-term interaction benefits rather than validated effectiveness.

Evidence supporting emotional regulation, affect-driven personalization, and real-world transfer is more limited and methodologically fragile. Such outcomes are reported almost exclusively in exploratory or proof-of concept systems that integrate affective sens-

ing with adaptive interaction logic. As a result, claims regarding adaptive emotional regulation and sustained behavioral change should be interpreted as promising but provisional, pending confirmation through structured evaluative and longitudinal research designs.

A central contribution of this review lies in its explicit operationalization of affective user experience (AUX) as a process-oriented analytical framework. By distinguishing between systems that measure affect post hoc and those that operationalize affect as an interactional mediator, AUX enables a more precise interpretation of reported outcomes and prevents the conflation of usability, engagement, and affective adaption. This distinction clarifies why affective sensing is widespread across immersive systems, while genuinely affect-driven interaction remains rare.

From a design perspective, the review identifies clear implications that should be regarded as exploratory design guidelines rather than evidence-confirmed prescriptions. These include the need to couple multimodal affective sensing with real-time adaptive logic to prioritize low-intrusiveness and contextual relevance—particularly in AR-based systems—and to align affective adaptation strategies with users' cognitive and sensory profiles. While these recommendations are grounded in cross-study patterns, their effectiveness has not yet been systematically validated.

From a research perspective, the findings underscore the necessity of moving beyond feasibility-oriented evaluations toward methodologically robust studies that incorporate larger samples, validated affective outcome measures, and ecologically valid deployment contexts. Longitudinal designs will be essential to assess whether affect-driven interaction produces sustained benefits in emotional regulation and learning transfer for individuals with ASD.

In summary, this review advances the field by providing an analytically grounded synthesis that is explicitly calibrated to the strength and limitations of current evidence. Rather than overextending claims of effectiveness, it delineates what is currently supported, what remains provisional, and where future research efforts should be directed. In doing so, it positions AUX as a coherent framework for guiding the next generation of emotionally responsive and inclusive immersive systems for ASD.

Future research should incorporate multimodal affective sensing, longitudinal and ecologically valid designs, and inclusive sampling across the autism spectrum. Advances in AI-driven adaptation, low-cost wearable sensors, and mixed-reality interaction pipelines may enable immersive environments to dynamically adjust to users' emotional states, creating more accessible, personalized, and ethically grounded affective experiences. Moving toward standardized AUX methodologies and cross-context evaluation is essential for transforming current prototypes into robust, scalable technologies capable of supporting social-emotional development and promoting meaningful participation for individuals with ASD.

In this sense, the present work does not aim to establish definitive claims but rather to contribute to the conceptual and methodological clarification of affective user experience (AUX), offering a critical framework to support the development of more rigorous and comparable evaluations in future research.

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Appendix A

Table A1. Summary of the empirical studies included in the review, detailing publication year, study, objectives, participant characteristics, immersive technology employed, affective computing methods, and reported outcomes.

Year	Ref	Main Objective	Population	Type of Intervention	Main Outcomes
2013	[50]	Analyze gaze and physiological cues in immersive environments	Children with ASD	VR affect assessment	Emotion recognition
2013	[71]	Improve social interaction through VR games	Children with ASD	VR game-based training	Social interaction
2014	[5]	Evaluate VR-based affect recognition	Adolescents with ASD	VR emotion recognition tasks	Emotion recognition
2016	[56]	Develop and evaluate an adaptive VR system for social interaction	Children with ASD	VR-based adaptive social interaction	Emotion regulation; social interaction
2016	[72]	Enhance emotional skills using immersive VR	Children with ASD	VR emotional skills training	Social communication
2017	[48]	Assess physiological response during VR interaction	Adolescent with ASD	VR with physiological monitoring	Anxiety reduction; emotion recognition
2017	[60]	Train emotion recognition through serious games	Children with ASD	VR serious games	Emotion recognition
2018	[58]	Support social communication using AR smartglasses	Children with ASD	AR-based social cues	Engagement; social communication
2018	[73]	Improve emotional and social adaptation	Children with ASD	VR social-emotional training	Emotion recognition
2018	[63]	Evaluate usability of VR interventions	Adolescents with ASD	VR usability study	Engagement
2019	[68]	Enhance social interaction through AR activities	Children with ASD	AR interactive activities	Social interaction
2019	[74]	Support social skill development using VR	Children with ASD	VR social skills training	Social skills; engagement
2020	[62]	Enable multiplayer interaction with gaze tracking	Adolescents with ASD	VR gaze-based interaction	Social interaction; engagement
2020	[38]	Support communication skills with VR	Children with ASD	VR educational intervention	Communication skills
2020	[48]	Measure anxiety using VR-based tasks	Adolescents with ASD	VR physiological assessment	Anxiety reduction
2022	[12]	Evaluate engagement in VR-based activities	Children with ASD	VR-based activities	Engagement

Table A1. *Cont.*

Year	Ref	Main Objective	Population	Type of Intervention	Main Outcomes
2020	[75]	Increase engagement through VR tasks	Children with ASD	VR engagement training	Engagement; task performance
2020	[76]	Reduce anxiety through VR exposure	Adolescents with ASD	VR exposure tasks	Anxiety reduction
2021	[55]	Support interview training using mixed reality	Adolescents/adults with ASD	MR interview simulation	Stress regulation; self-awareness
2021	[64]	Promote engagement using AR learning activities	Children with ASD	AR experiential learning	Engagement; motivation
2023	[61]	Improve emotion recognition using AR	Children with ASD	AR emotion-learning application	Engagement; motivation
2023	[77]	Improve attention using VR	Children with ASD	VR attention training	Attention improvement
2024	[73]	Support affect expression in VR	Children with ASD	VR affective interaction	Affect expression; social reciprocity
2024	[52]	Enhance self-efficacy via VR	Adolescents with ASD	VR training tasks	Self-efficacy; social skills
2024	[78]	Improve gaze behavior using VR	Children with ASD	VR gaze training	Gaze fixation
2025	[65]	Support socioemotional learning using VR narratives	Adolescents with ASD	VR narrative-based learning	Engagement; emotion recognition
2025	[79]	Support social skills using VR	Adolescents with ASD	VR social skills intervention	Social skills

Table A2. Analytical coding of immersive technology, affective modalities, UX/AUX evaluation methods, and outcomes.

	Immersive Technology	Affective Signal Modality	UX/AUX Evaluation Methods	Adaptive Interaction	Primary Outcomes
[56]	VR	Multimodal (physiology + gaze + behavior)	Physiological analysis; performance metrics	Yes	Emotion regulation; social skills
[55]	MR	Multimodal (behavioral and physiological)	Performance metrics; interview outcomes	Yes	Stress regulation; self-awareness
[48]	VR	Physiological	Physiological monitoring; task performance	No	Anxiety reduction; emotion recognition
[58]	AR	Behavioral	Observation; questionnaires	No	Engagement; social communication
[61]	AR	Behavioral	Observation; usability questionnaires	No	Engagement; motivation
[65]	VR	Behavioral	SUS; task performance	No	Engagement; emotion recognition
[12]	VR	Physiological	Physiological analysis; observation	No	Engagement
[68]	AR	Behavioral	Questionnaires; observation	No	Social interaction
[49]	VR	Physiological	Physiological analysis	No	Anxiety reduction

Table A2. Cont.

	Immersive Technology	Affective Signal Modality	UX/AUX Evaluation Methods	Adaptive Interaction	Primary Outcomes
[60]	VR	Behavioral	Game performance; behavioral observation	No	Emotion recognition
[68]	AR	Behavioral	Observation; questionnaires	No	Engagement; social communication
[5]	VR	Physiological; behavioral	Physiological monitoring; task performance	No	Emotion recognition
[74]	VR	Behavioral	Observation; performance metrics	No	Social skills; engagement
[76]	VR	Physiological	Physiological analysis	No	Anxiety reduction
[50]	VR	Physiological; gaze	Eye-tracking; physiological analysis	No	Emotion recognition
[64]	AR	Behavioral	Observation; interviews	No	Engagement; motivation
[71]	VR	Behavioral	Game performance metrics	No	Social interaction
[72]	VR	Behavioral	Observation; questionnaires	No	Social communication
[73]	VR	Behavioral	Performance metrics; questionnaires	No	Emotion recognition
[62]	VR	Gaze	Eye-tracking; performance	No	Social interaction; engagement
[38]	VR	Not reported	Observation; questionnaires	No	Communication skills; problem solving
[75]	VR	Behavioral	Observation; engagement metrics	No	Engagement; task performance
[63]	VR	Behavioral	Questionnaires; usability	No	Engagement
[77]	VR	Physiological	Physiological data; performance	No	Attention improvement
[79]	VR	Behavioral; physiological	Behavioral observation; physiological	No	Social skills; effectiveness
[78]	VR	Gaze	Eye-tracking; parent questionnaires	No	Gaze fixation ability
[52]	VR	Physiological	Mixed methods; physiological	No	Self-efficacy; social skills
[73]	VR	Behavioral	Questionnaires; observation	No	Affective expression; social reciprocity

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