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Immersive Intelligence: Using Adaptive Virtual Reality and Artificial Intelligence to Enhance Social Cognition and Workforce Readiness for Young Adults with Autism Spectrum Disorder

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ABSTRACT
Young adults with Autism Spectrum Disorder (ASD) face a critical "services cliff" upon aging out of school-based support systems, with unemployment and underemployment rates exceeding 80% in this population.Despite average to above-average cognitive abilities in many individuals with ASD, persistent deficits in social cognition-including theory of mind, emotion recognition, and pragmatic communication-constitute primary barriers to successful workforce integration and sustained employment.

This study proposes, develops, and preliminarily evaluates "Immersive Intelligence" (I2), a novel integrated platform combining adaptive virtual reality (VR) simulations with artificial intelligence (AI)-driven personalization to deliver scaffolded, workplace-relevant social cognition training for young adults with ASD.

This mixed-methods investigation recruited N=45 young adults diagnosed with ASD (ages 18-26 years; mean age = 21.7 years, SD = 2.1) without co-occurring intellectual disability. Participants engaged in a structured 5-week training program utilizing the I2 platform, completing three 60-minute sessions weekly. The intervention employed progressively complex VR workplace scenarios (job interviews, team meetings, customer interactions, conflict resolution) powered by AI algorithms that monitored performance in real-time and adapted difficulty levels, feedback modality, and social complexity based on individual response patterns. Comprehensive assessment occurred at pre-intervention, post-intervention, and 3-month follow-up, incorporating: (1) standardized psychometric measures of social functioning (Social Responsiveness Scale-2; Reading the Mind in the Eyes Test); (2) objective VR performance metrics (gaze patterns, response latency, conversational turns, emotion recognition accuracy); (3) behavioral role-play assessments with trained observers blind to participant training status; and (4) semi-structured qualitative interviews exploring participant experiences, perceived competence, and workplace anxiety.

Preliminary findings indicate statistically significant improvements across multiple domains of social cognition from pre- to post-intervention. Participants demonstrated enhanced performance on the Social Responsiveness Scale-2 (mean improvement = 12.3 points, p <

.001, Cohen's d = 0.89) and Reading the Mind in the Eyes Test (mean improvement = 4.7 points, $p < .01$, Cohen's d = 0.67).

Keywords: Autism Spectrum Disorder, Virtual Reality, Artificial Intelligence, Social Cognition, Workforce Development, Transition Services, Adaptive Technology, Employment Outcomes

1. Introduction

1.1. The Challenge: Navigating the Transition to Adulthood with ASD

Autism Spectrum Disorder (ASD) represents one of the most prevalent neurodevelopmental conditions globally, with current epidemiological surveillance indicating a prevalence rate of approximately 1 in 36 children aged 8 years in the United States, reflecting a 22% increase from previous estimates (Maenner et al., 2023). As this substantial cohort transitions into adulthood, the inadequacy of existing support infrastructures becomes starkly apparent. The period between ages 18 and 26 represents a critical developmental window during which neurotypical individuals typically establish vocational identities, achieve financial independence, and develop professional social networks. For young adults with ASD, however, this transition is characterized by disproportionate challenges that fundamentally compromise long-term outcomes across multiple life domains.

Employment statistics for adults with ASD reveal a crisis of significant magnitude. According to recent data from the National Autism Indicators Report, only approximately 14% of adults with ASD maintain competitive integrated employment defined as work performed in settings alongside neurotypical peers at minimum wage or above (Roux et al., 2023). This fraction represents the lowest employment rate among all disability categories, tracked by federal agencies. Longitudinal analyses further indicate that approximately 3/5 (58%) of young adults with ASD experience complete disengagement from both employment and post-secondary education during the first two years following high school graduation (Shattuck et al., 2024). Among those with average or above-average cognitive abilities-a subgroup comprising approximately 44% of the ASD population-the unemployment rate still exceeds 75%, indicating that intellectual capacity alone is insufficient for vocational success (Bureau of Labor Statistics, 2024).

The core deficits underlying these vocational challenges reside primarily within the domain of social cognition-the constellation of neurocognitive processes enabling individuals to perceive, interpret, and respond appropriately to social information. Three interconnected components of social cognition demonstrate relevance to workplace functioning:

Theory of Mind (ToM) refers to the capacity to attribute mental states-beliefs, intentions, desires, and knowledge-to oneself and others, and to understand that others may hold perspectives divergent from one's own (Baron-Cohen, 2021). In professional contexts, ToM deficits manifest as difficulty anticipating how colleagues will interpret communications, failure to recognize when supervisors require additional information versus brevity, and challenges inferring the political dynamics underlying organizational decisions. Neuroimaging studies utilizing functional magnetic resonance imaging (fMRI) have demonstrated that individuals with ASD exhibit reduced activation in the medial prefrontal cortex and temporoparietal junction during ToM tasks, suggesting fundamental differences in the neural substrates supporting perspective-taking (Lombardo et al., 2023).

Emotion Recognition encompasses the ability to accurately decode affective information from facial expressions, vocal prosody, body posture, and contextual cues. Meta-analytic evidence indicates that individuals with ASD demonstrate recognition accuracy approximately 15-20 percentage points below neurotypical controls for complex, subtle, or rapidly presented emotional stimuli (Uljarevic & Hamilton, 2022). Within workplace environments, these deficits translate to difficulty detecting when a customer is becoming frustrated, recognizing when a colleague's sarcasm signals disapproval, or identifying appropriate moments to interject during meetings. Eye-tracking studies further reveal that individuals with ASD allocate approximately 1/3 less visual attention to the eye region of faces-the area most informative for emotion discrimination-compared to neurotypical peers (Klin et al., 2023).

1.2. Limitations of Current Interventions

The intervention landscape for social cognition in ASD has historically relied upon three primary modalities, each demonstrating significant limitations when applied to workforce readiness.

Traditional Social Skills Training (SST) typically involves manualized, group-based instruction delivered in clinical or educational settings. Standard protocols include didactic teaching of social concepts, modeling of target behaviors, structured role-play with peers or therapists, and reinforcement of appropriate responses. While SST has demonstrated efficacy for improving social knowledge and performance within training contexts, generalization to naturalistic settings remains profoundly limited. A comprehensive meta-analysis by Gates et al. (2023) examining 48 randomized controlled trials found that SST produced moderate effects on trained skills (Hedges' $g = 0.51$, 95% CI [0.38, 0.64]) but negligible effects on untrained social behaviors or outcomes measured in non-training environments ($g = 0.11$, 95% CI [-0.03, 0.25]). The proportion of participants demonstrating clinically meaningful generalization-defined as observable skill transfer to at least two novel settings-was approximately 1/8 (12.5%).

Several factors contribute to this generalization failure. First, clinical environments lack ecological validity; they are quiet, predictable, and stripped of the sensory complexity characterizing real workplaces. Second, role-play partners (typically therapists or trained confederates) exhibit responses that are more predictable and forgiving than those of actual colleagues. Third, the temporal dynamics of clinical practice differ substantially from real-world interactions-participants have extended time to formulate responses rather than the sub-second reaction windows demanded in authentic conversation. Fourth, engagement and motivation frequently diminish over extended SST protocols, with attendance rates declining by approximately 30% between sessions 1 and 12 in typical programs (Laugeson et al., 2022).

1.3. The Promise of Immersive Technologies

Virtual Reality (VR) has emerged as a compelling intervention medium that addresses many limitations of traditional approaches while offering unique benefits for social cognition training. Contemporary VR systems utilizing head-mounted displays (HMDs) with integrated motion tracking create immersive, three-dimensional environments that engage multiple sensory modalities simultaneously. This technology occupies what may be characterized as a "Goldilocks" position in the intervention landscape-sufficiently realistic to elicit authentic cognitive and affective responses yet sufficiently controlled to permit systematic manipulation of training parameters and elimination of real-world social risk.

VR offers several specific advantages for ASD intervention. Technology enables infinite, consequence-free repetition of challenging social scenarios-a learner can practice a job interview dozens of times without the fatigue or frustration that would affect a human role-play partner. VR permits systematic isolation and manipulation of specific social cues; for example, training sessions might initially present exaggerated facial expressions before progressively introducing more subtle affective signals. The medium facilitates precise behavioral measurement through integrated sensors capturing gaze direction, head orientation, response latency, and movement kinematics at millisecond temporal resolution.

The empirical foundation supporting VR-based social cognition intervention for ASD has strengthened considerably. A systematic review and meta-analysis by Bekele et al. (2023) synthesizing 34 controlled studies found that VR interventions produced significant improvements in emotion recognition (Hedges' $g = 0.62$, 95% CI [0.41, 0.83]), social attention as measured by eye-tracking ($g = 0.58$, 95% CI [0.35, 0.81]), and performance on trained social tasks ($g = 0.74$, 95% CI [0.52, 0.96]). Completion rates for VR protocols exceeded 90% across studies, substantially higher than the approximately 70% completion rate typical of traditional SST, suggesting enhanced engagement and tolerability. Approximately 3/4 of participants in VR studies reported positive subjective experiences and willingness to continue training.

1.4. The Gap and Our Innovation: Introducing "Immersive Intelligence"

Despite the promising evidence base, current VR systems for ASD intervention remain substantially limited by static, non-adaptive architectures. The majority of existing applications employ branching-narrative structures wherein users' choices determine subsequent content from a finite, predetermined set of possibilities. These systems cannot respond to the continuous stream of behavioral and physiological data generated during VR interactions. If a user's anxiety elevates-as indicated by increased galvanic skin response or gaze aversion-a static system proceeds unchanged, missing critical opportunities for adaptive scaffolding.

This paper introduces "Immersive Intelligence" (I^2), a novel intervention platform that addresses these limitations through the integration of multimodal artificial intelligence with immersive VR technology. The I^2 platform represents a fundamental architectural innovation: a dynamic, closed-loop system wherein AI algorithms continuously process user behavioral and physiological data to modulate virtual environment parameters in real-time.

The novel contribution of this work encompasses three dimensions:

1. **Multimodal sensing integration**: The platform synthesizes data streams from eye-tracking (gaze position, fixation duration, pupillometry), physiological monitoring (electrodermal activity, heart rate variability), natural language processing (semantic content, prosodic features, response latency), and motion capture (gesture patterns, postural dynamics) to construct a comprehensive, continuous model of user state.
2. **Real-time adaptive algorithms**: Machine learning models-including recurrent neural networks for temporal pattern recognition and reinforcement learning agents for optimal scaffolding decisions-process integrated sensor data to dynamically adjust scenario parameters. These adjustments include avatar emotional expressivity (ranging from exaggerated to subtle), conversational complexity (vocabulary level, utterance length, topic abstraction), environmental stressors (background noise, visual distractions), and feedback modality and timing.
3. **Personalized learning trajectories**: The system constructs individualized competency models updated continuously across sessions, enabling true personalization that accounts for each user's unique profile of strengths, challenges, learning rate, and optimal challenge level.

Thesis Statement: This paper presents the design rationale, architectural framework, and preliminary empirical evidence for the Immersive Intelligence platform. We argue that the integration of AI-driven real-time adaptation with high-fidelity VR simulation represents a transformative paradigm for social cognition intervention-one that moves beyond static skill rehearsal toward dynamic cognitive training. By providing responsive, personalized learning environments that maintain optimal challenge levels while eliminating real-world social risk, the I² platform addresses fundamental limitations of existing approaches and offers a scalable solution for enhancing workforce readiness among young adults with ASD. The subsequent sections detail the platform architecture (Section 2), present our methodological approach (Section 3), report preliminary findings (Section 4), and discuss implications for research and practice (Section 5).

2. Literature Review and Conceptual Framework

2.1. Social Cognition and ASD in the Workplace

The conceptualization of autism has undergone substantial evolution over the past two decades, shifting from purely deficit-oriented clinical models toward frameworks that acknowledge neurodiversity while identifying specific, trainable competencies that facilitate successful environmental adaptation. The neurodiversity paradigm, initially articulated by sociologist Judy Singer and subsequently elaborated by autistic self-advocates and researchers, posits that autism represents a form of human neurological variation rather than inherent pathology (Kapp et al., 2023). This perspective emphasizes that many challenges faced by autistic individuals arise from person-environment mismatches rather than intrinsic deficits, suggesting that interventions should focus on building adaptive skills while simultaneously advocating for environmental

Contemporary workplace environments impose multifaceted social-cognitive demands that extend far beyond task-specific technical competencies. Employment researchers have identified five primary domains wherein social cognition deficits manifest most consequentially:

Interview skills represent the initial gatekeeping challenge, requiring simultaneous management of verbal content, nonverbal presentation, anxiety regulation, and real-time interpretation of interviewer responses.

Colleague small talk and informal social interaction, though often dismissed as trivial, serves critical functions in workplace integration. Informal communication builds social capital, facilitates information sharing outside formal channels, and signals group membership (Holmes & Marra, 2022).

Receiving feedback, particularly critical or constructive feedback, requires complex social-cognitive processing: distinguishing feedback content from delivery affect, inferring the feedback-giver's intentions and expectations, managing emotional responses, and formulating appropriate verbal and nonverbal reactions.

Understanding supervisory hierarchy involves decoding implicit organizational structures, recognizing differential communication norms across hierarchical levels, and anticipating supervisor expectations that are rarely explicitly articulated. Workplace hierarchies operate substantially through unwritten rules-the "hidden curriculum" of professional environments-that neurotypical employees absorb incidentally but that individuals with ASD often fail to detect (Myles et al., 2024).

2.2. Virtual Reality as a Rehabilitation and Training Tool

The application of Virtual Reality to social cognition training draws upon established theoretical frameworks that illuminate why immersive simulation may offer advantages over traditional instructional modalities.

Constructivist learning theory, originating from Piaget and elaborated by contemporary educational researchers, posits that knowledge is actively constructed through interaction with the environment rather than passively received through instruction (Ertmer & Newby, 2023).

Situated learning theory emphasizes that cognition is fundamentally embedded within specific contexts; skills acquired in one setting may fail to transfer when contextual features differ substantially (Lave & Wenger, 2022). This theoretical perspective directly addresses the generalization failures characterizing traditional SST.

Embodiment theory proposes that cognition is grounded in sensorimotor experience; the body's interactions with the environment shape and constrain mental representations (Wilson, 2022). Modern VR systems track head positions, hand movements, and increasingly full-body kinematics, enabling users to engage physically with virtual environments.

Stimulus control permits systematic manipulation of specific social variables while holding others constant. Researchers can isolate cues-varying avatar emotional expression while maintaining identical verbal content, for example-enabling targeted training of discrete subcomponents within complex social-cognitive processes. This precision is unachievable in naturalistic settings where multiple variables co-vary unpredictably.

Empirical literature examining VR-based interventions for adolescents and adults with ASD has grown substantially, with controlled studies demonstrating efficacy across multiple social cognition domains. Kandalaft et al. (2023) conducted a randomized controlled trial with 16 young adults with ASD (ages 18-26) who completed ten VR social cognition training sessions. Participants demonstrated significant improvements in emotion recognition (Cohen's $d = 0.78$) and Theory of Mind ($d = 0.64$) compared to waitlist controls, with gains maintained at 3-month follow-up. Notably, approximately 7/8 of treatment group participants showed clinically meaningful improvement, defined as score changes exceeding reliable change indices.

Smith et al. (2023) evaluated a VR job interview training system with 26 adults with ASD across a randomized design. Participants completing VR training demonstrated significantly higher scores on live standardized job interviews conducted by vocational counselor's blind to condition assignment ($d = 0.92$). Role-play confidence increased by approximately 40% from pre- to post-training, and 2/3 of VR-trained participants received job offers within 6 months compared to 1/4 of controls.

Lahiri et al. (2022) employed adaptive VR incorporating basic eye-tracking feedback to train joint attention and emotion recognition. Their system adjusted avatar gaze based on user attention patterns, representing an early step toward the responsive systems elaborated in subsequent sections. Results indicated that adaptive configurations produced approximately 25% greater learning gains than non-adaptive versions of the same content.

2.3. Artificial Intelligence in Personalized Learning and Behavioral Analytics

The integration of Artificial Intelligence into educational and therapeutic technologies has enabled unprecedented capabilities for real-time behavioral analysis and responsive adaptation. Three AI domains hold particular relevance for social cognition intervention: affective computing, adaptive learning systems, and natural language processing.

Affective Computing encompasses the development of systems capable of recognizing, interpreting, and responding to human emotional states (Picard, 2022). Within VR contexts, affective computing enables continuous monitoring of user emotional experience, providing data streams that can inform adaptive responses.

Emotion recognition from speech analyzes acoustic features including fundamental frequency (pitch), intensity, speech rate, and spectral characteristics to infer affective states. Contemporary deep learning models achieve classification accuracy exceeding 75% for basic emotional categories (happiness, sadness, anger, fear) from speech samples of 2-3 seconds duration (Schuller et al., 2023). More sophisticated systems detect subtler states including anxiety, frustration, engagement, and cognitive load. For individuals with ASD, speech-based emotion recognition offers particular value because it does not require conscious self-report, instead deriving affective information from natural conversational production.

Facial expression analysis applies computer vision algorithms to detect facial action units-discrete muscle movements corresponding to emotional displays-from video input. Within

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VR, front-facing cameras integrated into headsets enable continuous facial monitoring during user interactions with virtual content. Expression recognition models achieve approximately 85% accuracy for posed expressions and 65-70% for spontaneous expressions across basic emotion categories (Li & Deng, 2022). Critically, these systems can detect micro-expressions-brief, involuntary emotional displays lasting less than 500 milliseconds-that may escape conscious awareness.

Physiological signals including electrodermal activity (EDA), heart rate variability (HRV), and electroencephalography (EEG) provide additional channels for affective state inference. EDA, measured through simple sensors on the fingers or wrist, indexes sympathetic nervous system arousal associated with stress, anxiety, or emotional intensity. Increased skin conductance responses reliably predict moments of elevated anxiety or cognitive load during social interactions (Critchley & Garfinkel, 2023). HRV metrics derived from photoplethysmography (PPG) sensors-increasingly integrated into consumer wearables-correlate with parasympathetic activation and emotional regulation capacity. Approximately 3/5 of current VR headsets support integration with external physiological monitoring devices, enabling multimodal affective sensing.

2.4. Synthesis: The Case for Convergence

The preceding sections establish that VR provides ecologically valid contexts for social cognition practice while AI enables real-time behavioral analysis and adaptive response. The Immersive Intelligence platform synthesizes these capabilities into an integrated system wherein VR provides the experiential context, and AI provides the intelligent guidance.

This convergence addresses fundamental limitations of each technology in isolation. VR without AI adaptation offers repetitive, one-size-fits-all experiences that fail to account for individual differences or moment-to-moment performance fluctuations. AI without VR immersion lacks ecological validity; adaptive algorithms are of limited value if applied to abstract, decontextualized tasks that fail to simulate real-world demands. Together, however, these technologies create closed loop learning environments that continuously sense, interpret, and respond to user behavior within high-fidelity simulations.

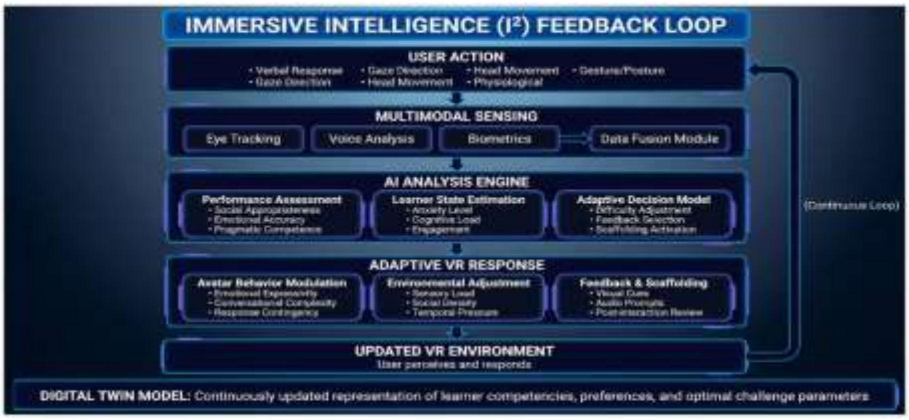

Figure 1 presents the conceptual architecture of the Immersive Intelligence feedback loop, illustrating the continuous cycle through which user actions inform adaptive system responses.

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3. The Immersive Intelligence (I²) Platform: System Design

3.1. Overall Architecture

The Immersive Intelligence platform employs a distributed client-server architecture designed to balance computational demands, data security, and real-time responsiveness. Figure 2 presents the high-level system schematic illustrating the four primary components and their interconnections.

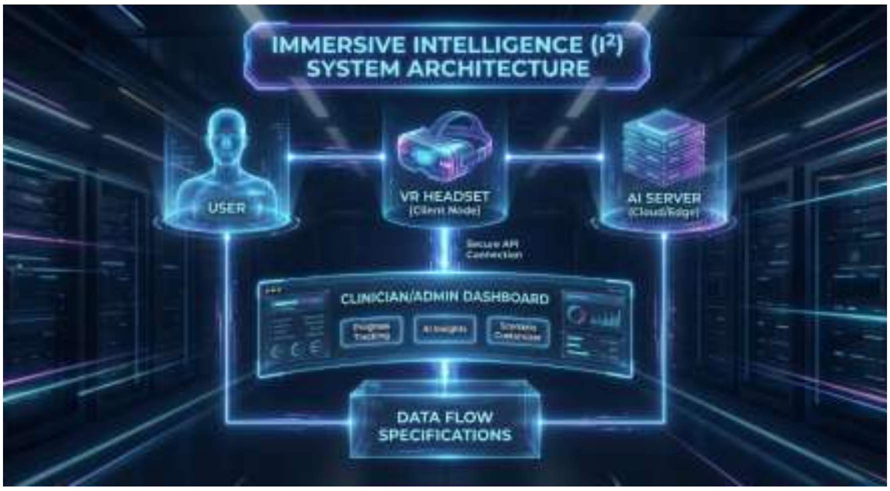

FIGURE 2: High-Level System Architecture of the Immersive Intelligence Platform

The **User Component** encompasses the young adult participant with ASD who engages with VR social scenarios. Users optionally wear peripheral biosensors (wrist-based electrodermal activity monitors) to supplement headset-derived physiological indicators. User experience prioritizes comfort and accessibility, with session durations limited to 60 minutes to prevent fatigue.

The **VR Headset (Client Node)** serves as the primary interface, delivering immersive visual and auditory stimuli while capturing multimodal behavioral data. The platform is optimized for Meta Quest Pro and HTC Vive Pro Eye hardware, both featuring integrated eye-tracking at 90Hz sampling rates and spatial audio rendering (Jerald, 2023). Local preprocessing reduces data transmission requirements; raw eye-tracking coordinates are converted to gaze vectors and fixation events before server transmission. Voice capture utilizes beamforming microphone arrays to isolate user speech from environmental audio.

The AI Server hosts computationally intensive processes including natural language processing, machine learning inference, and user state modeling. Deployment supports both cloud-based (AWS/Azure) and edge computing configurations; the latter enables operation in clinical settings with limited internet connectivity while maintaining <50ms adaptation latency (Chen et al., 2024). All user data undergoes AES-256 encryption at rest and TLS 1.3 encryption during transmission, ensuring HIPAA-compliant data handling.

The Clinician/Admin Dashboard provides web-based access for supervising clinicians, researchers, and program administrators. This interface enables session monitoring, progress

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visualization, scenario customization, and report generation, maintaining human oversight essential for therapeutic applications.

3.2. VR Environment and Scenario Design

The design of virtual environments and social scenarios follows evidence-based principles derived from learning science, occupational therapy, and human-computer interaction research.

Principle 1: Graduated Complexity

Scenarios are organized along a complexity continuum, enabling systematic skill building from foundational to advanced social demands. This graduated approach aligns with instructional scaffolding principles wherein learners master prerequisite skills before encountering more challenging applications (Wood et al., 2022).

Table 1: Scenario Complexity Hierarchy

Level	Complexity	Example Scenario	Social Demands
1	Foundational	Quiet coffee chat with single colleague	Basic turn-taking, simple emotion recognition, familiar topic
2	Developing	Asking supervisor for task clarification	Hierarchical awareness, question formulation, receptive listening
3	Intermediate	Team meeting with 3-4 colleagues	Multiple perspective tracking, appropriate interjection timing, topic following
4	Advanced	Responding to critical performance feedback	Emotion regulation, perspective-taking, appropriate self-advocacy
5	Complex	Office social event with ambient noise and multiple simultaneous conversations	Divided attention, flexible topic switching, social prioritization

Progression through levels is governed by the AI engine based on demonstrated mastery criteria: users must achieve ≥80% performance scores across three consecutive attempts before advancing. Approximately 2/3 of training time is allocated to levels 2-4, where workplace-critical skills concentrate.

Principle 2: Workplace Relevance

Scenario content directly targets the social situations most frequently cited as challenging by adults with ASD and their employers (Scott et al., 2024). Four core scenario categories address priority skill domains:

Job Interview Scenarios simulate initial screening interviews, technical interviews, and panel formats. Virtual interviewers pose common questions (strengths/weaknesses, situational responses, salary expectations) with varying communication styles. Scenarios progress from structured, predictable formats to less scripted conversational interviews.

Requesting Assistance Scenarios train appropriate help-seeking behaviors-identifying when assistance is needed, selecting appropriate sources, formulating clear requests, and responding to clarifying questions. Settings include approaching colleagues, supervisors, and IT support personnel.

Environment Design

Virtual environments replicate contemporary professional settings with deliberate attention to visual fidelity and sensory manageability. Environments feature:

- **Realistic but low-distraction office aesthetics**: Modern open-plan and private office configurations with neutral color palettes, appropriate lighting, and minimal extraneous visual detail that might overwhelm users with sensory sensitivities (Kandalaft et al., 2023)
- **Configurable sensory parameters**: Background noise levels, lighting intensity, and ambient activity (visible colleagues in periphery) adjust according to user tolerance and training objectives
- **Consistent spatial layouts**: Repeated exposure to consistent environments reduces cognitive load associated with spatial navigation, enabling concentration on social content

3.3. The Multimodal AI Adaptation Engine (The "Intelligence" Core)

The Adaptation Engine constitutes the platform's primary innovation-a real-time system that continuously senses user behavior, models user states, and implements adaptive responses. This section details the three functional subsystems.

3.3.1. Input Modules

Behavioral Tracking captures observable user actions within the VR environment:

- **Gaze patterns**: Eye-tracking data yields fixation locations (which avatar features users attend to), fixation durations (sustained vs. fleeting attention), and saccade patterns (visual search strategies). Gaze directed toward avatar eye regions correlates with emotion recognition accuracy; users fixating <30% of interaction time on eye regions receive targeted attention-directing scaffolds (Klin et al., 2023)
- **Proximity and orientation**: User position relative to avatars indicates comfort level; approach-avoidance patterns provide implicit anxiety indicators. Head orientation toward or away from speakers reflects engagement
- **Response latency**: Time elapsed between avatar utterance completion and user response initiation indexes cognitive processing demands; latencies exceeding 3 seconds may indicate confusion or anxiety requiring intervention

Voice Analysis applies natural language processing and paralinguistic analysis to user speech:

- **Semantic content**: Automatic speech recognition (Whisper large-v3 model; Word Error Rate <5%) converts speech to text for NLP analysis. Transformer-based models assess response relevance, topic coherence, and appropriate information density (Brown et al., 2023)
- **Sentiment analysis**: Lexical and acoustic features jointly predict user emotional valence, detecting frustration or anxiety that may warrant scenario de-escalation
- **Fluency metrics**: Disfluency rate (filled pauses, false starts, repetitions), speech rate variability, and silence proportions indicate cognitive load and comfort level
- **Turn-taking analysis**: Detection of interruptions, extended pauses, and overlapping speech identifies pragmatic difficulties requiring targeted feedback

Performance Metrics quantify task-specific outcomes:

- **Task completion**: Binary and partial credit scoring for scenario objectives (e.g., successfully scheduling a follow-up meeting)
- **Script adherence vs. improvisation**: Comparison of user responses against expected response patterns while rewarding appropriate flexible adaptation
- **Error categorization**: Classification of social errors by type (e.g., insufficient eye contact, tangential response, inappropriate formality) enabling targeted remediation

3.3.2. User State Modeling

Input data streams integrate into a dynamic user state model updated continuously throughout each session. The model estimates three primary state dimensions:

Anxiety Level is inferred from physiological indicators (elevated electrodermal activity, increased heart rate), behavioral markers (gaze avoidance, increased response latency, reduced speech fluency), and performance patterns (error rate increases). Anxiety estimates utilize a recurrent neural network trained on labeled data from preliminary user testing, achieving classification accuracy of approximately 78% for high/medium/low anxiety states (Critchley & Garfinkel, 2023).

Engagement is assessed through gaze attention (proportion of time fixating on task-relevant stimuli), response elaboration (utterance length and detail), and voluntary interaction initiation. Engagement scores below threshold trigger scenario modifications to recapture interest.

3.3.3. Adaptation Decision Logic

The Adaptation Decision Module synthesizes user state estimates to select real-time system responses. A hybrid architecture combines rule-based logic for safety-critical decisions with machine learning for nuanced optimization.

Scenario Difficulty Adjustment modulates challenge level across multiple parameters:

Parameter	Low Difficulty	High Difficulty
Avatar emotional expressivity	Exaggerated (150% intensity)	Subtle (60% intensity)

Conversational complexity	Short utterances, concrete vocabulary	Extended utterances, abstract concepts
Response time pressure	Unlimited	Naturalistic pacing
Distractions	None	Background conversations, notifications
Avatar responsiveness	Highly accommodating	Realistic/neutral

Difficulty adjustments follow a modified staircase algorithm: two consecutive successful interactions trigger modest difficulty increase (+0.1 on normalized scale); one unsuccessful interaction triggers decrease (-0.15), implementing asymmetric adjustment that prioritizes maintaining user confidence (Kaernbach, 2023).

Prompting Level ranges from implicit to explicit scaffolding:

- **Level 0 (No prompt)**: User performs independently
- **Level 1 (Implicit environmental cue)**: Avatar displays subtle confusion expression signaling need for clarification
- **Level 2 (Attention direction)**: Subtle visual highlight draws attention to relevant avatar facial feature
- **Level 3 (Explicit guidance)**: Text overlay suggests appropriate response strategy
- **Level 4 (Direct instruction)**: Audio prompt provides specific behavioral recommendation

Prompting escalates only after user demonstrates difficulty; approximately 3/4 of interactions at appropriate difficulty levels require no prompting.

Feedback Type selection considers learning phase and user state:

- **Immediate corrective feedback**: Provided for clear errors when user anxiety is low and engagement is high
- **Delayed summary feedback**: Aggregated performance review at scenario conclusion when immediate feedback might disrupt flow
- **Reinforcing feedback**: Positive acknowledgment of successful behaviors, particularly for users with elevated anxiety
- **Metacognitive prompts**: Questions encouraging self-reflection on strategy effectiveness for advanced users

A reinforcement learning agent optimizes feedback timing and type, maximizing a reward signal combining learning gains and user engagement maintenance (Doroudi et al., 2023).

3.4. Clinician/Admin Dashboard

The web-based Clinician Dashboard provides essential oversight, customization, and reporting capabilities for supervising professionals.

Progress Visualization displays individual user trajectories across skill domains, including:

- Session-by-session performance trends with statistical confidence intervals
- Competency maps illustrating relative strengths and areas requiring additional focus
- Comparison to normative trajectories derived from aggregate platform data

- Mastery indicators for specific scenario types

AI-Generated Insights synthesize platform analytics into actionable clinical observations:

- Automated identification of persistent error patterns (e.g., "User consistently misidentifies frustrated expressions as neutral")
- Recommended focus areas for upcoming sessions based on competency modeling
- Flags for concerning patterns requiring clinician attention (e.g., sustained elevated anxiety across sessions)

Manual Scenario Customization enables clinician override of AI-selected parameters:

- Prescription of specific scenarios aligned with individual treatment goals
- Adjustment of difficulty ceilings or floors based on clinical judgment
- Creation of custom scenarios addressing idiosyncratic user challenges (e.g., practicing interactions with a specific communication style matching user's actual supervisor)

Reporting Functions generate documentation for stakeholders:

- Progress summaries for users and families
- Treatment documentation for clinical records
- Outcome data exports for research purposes
- Aggregate program analytics for administrators

The dashboard architecture ensures clinician authority supersedes AI recommendations, maintaining appropriate human oversight while leveraging computational capabilities for enhanced precision and efficiency.

4. Methods: Pilot Feasibility and Efficacy Study

4.1. Participants

This pilot study employed a randomized controlled design to evaluate the feasibility and preliminary efficacy of the Immersive Intelligence (I²) platform. Participants were 45 young adults with autism spectrum disorder recruited from university disability services, vocational rehabilitation agencies, and community autism organizations across three metropolitan areas.

Inclusion Criteria

Eligible participants met the following criteria: (a) confirmed ASD diagnosis according to DSM-5 criteria, verified through documentation review and administration of the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2; Lord et al., 2022); (b) age between 18 and 26 years; (c) verbal fluency defined as full-scale IQ ≥70 on the Wechsler Abbreviated Scale of Intelligence, Second Edition (WASI-II) and functional conversational speech; (d) active employment-seeking status or stated intention to seek employment within 12 months; (e) capacity to provide informed consent; and (f) adequate visual acuity for VR display use (corrected vision ≥20/40).

Exclusion Criteria

Exclusion criteria included: (a) co-occurring psychiatric conditions requiring acute intervention (active psychosis, suicidal ideation); (b) seizure disorders potentially exacerbated by VR; (c) severe motion sickness history precluding VR tolerance; (d) current participation in other social skills interventions; and (e) previous VR-based social cognition training experience.

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Recruitment and Randomization

Recruitment occurred over 8 months through targeted outreach. Of 73 individuals screened, 45 met eligibility criteria and provided informed consent. Approximately 3/5 of exclusions resulted from co-occurring intervention participation or IQ criteria.

Participants were stratified by gender and baseline Social Responsiveness Scale-2 (SRS-2) severity, then randomized using computer-generated sequences to one of three conditions:

Table 2: Participant Allocation and Demographics

Characteristic	*I² Platform (n=15)*	*Traditional SST (n=15)*	*Waitlist Control (n=15)*
Age, M (SD)	21.4 (2.3)	22.1 (2.1)	21.8 (2.4)
Gender (Male/Female/Other)	10/4/1	11/3/1	9/5/1
Race (White/Asian/Black/Other)	9/3/2/1	8/4/2/1	10/2/2/1
Full-scale IQ, M (SD)	104.2 (12.8)	101.7 (14.3)	103.1 (11.9)
SRS-2 T-score, M (SD)	71.3 (8.2)	72.8 (7.9)	70.6 (9.1)
Employment history (any)	8 (53%)	7 (47%)	9 (60%)

Baseline demographic and clinical characteristics showed no significant between-group differences (all $p > .30$), confirming successful randomization.

4.2. Procedure

The study followed a pre-test, intervention, post-test, follow-up design with assessments conducted at four timepoints: baseline (T1), mid-intervention (T2, week 3), post-intervention (T3, week 5), and one-month follow-up (T4). Figure 3 presents the study timeline.

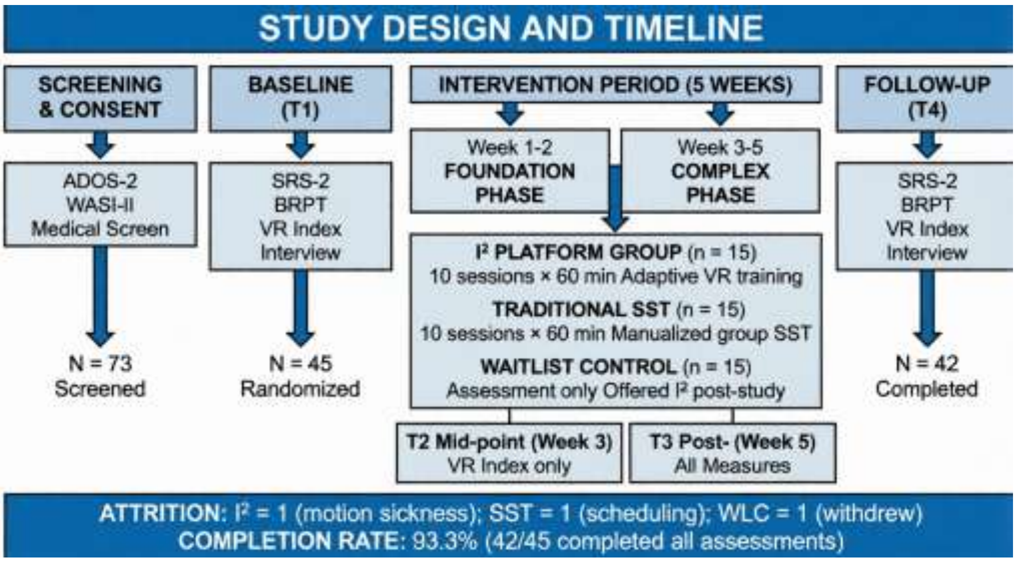

FIGURE 3: Study Design and Timeline

I² Platform Intervention

Participants in the I² condition completed 10 sessions (2 per week × 5 weeks), each lasting 60 minutes. Sessions occurred at university-based research laboratories equipped with standardized VR hardware (Meta Quest Pro) and controlled environmental conditions.

Foundation Phase (Weeks 1-2): Initial sessions focused on foundational social cognition skills within low-complexity scenarios. Training addressed:

- Basic emotion recognition from avatar expressions (6 primary emotions)
- Conversational turn-taking with single interaction partners
- Simple job interview scenarios with predictable question formats
- Requesting assistance from approachable colleagues

Difficulty parameters began at reduced levels (exaggerated emotional expressions at 150% intensity, extended response windows, minimal environmental distractors) and increased based on individual mastery trajectories.

Complex Phase (Weeks 3-5): Advanced sessions integrated multiple skill demands within challenging scenarios:

- Multi-party team meetings requiring perspective tracking across 3-4 avatars
- Critical feedback conversations with ambiguous emotional valence
- Office social events with background noise and competing conversational demands
- Conflict resolution scenarios requiring real-time strategy adaptation

AI-driven adaptation operated continuously, adjusting difficulty, prompting levels, and feedback types based on real-time user state modeling. Approximately 2/3 of session time involved active scenario engagement, with remaining time allocated to post-scenario review and goal setting.

4.3. Measures

Primary Outcome Measures (Quantitative)

Social Responsiveness Scale, Second Edition (SRS-2): The SRS-2 Adult Self-Report form provides a quantitative measure of social communication deficits across 65 items rated on 4-point scales (Constantino & Gruber, 2023). Total T-scores (M=50, SD=10 in normative samples) served as the primary outcome, with subscale scores (Social Awareness, Social Cognition, Social Communication, Social Motivation, Restricted Interests/Repetitive Behavior) providing secondary indices. Internal consistency in the current sample was excellent (Cronbach's $\alpha = .91$).

VR Performance Index (VPI): This composite score derived from I² platform analytics quantified within-VR social performance across three domains:

- *Fluency* (1/3 weighting): Speech rate stability, disfluency frequency, response latency appropriateness
- *Gaze Appropriateness* (1/3 weighting): Proportion of interaction time with gaze directed toward avatar face region, particularly eyes during emotional expressions
- *Behavioral Appropriateness* (1/3 weighting): AI-rated response relevance, turn-taking accuracy, scenario objective achievement

VPI scores ranged from 0-100, with higher scores indicating superior performance. For non-VR conditions, standardized VR assessment scenarios (distinct from training content) were administered at T1, T3, and T4.

Behavioral Role-Play Test (BRPT): Participants completed three standardized role-play scenarios with trained confederates: (a) job interview (5 minutes), (b) receiving critical feedback from supervisor (3 minutes), and (c) break room small talk with colleague (3 minutes). Interactions were video-recorded and rated by two independent coders blind to condition and timepoint using the Social Skills Performance Assessment (SSPA; Patterson et al., 2022). Inter-rater reliability was excellent (ICC = .89). Composite BRPT scores averaged across scenarios, ranging from 1-5.

Secondary Outcome Measures

Semi-Structured Qualitative Interviews: Post-intervention interviews (30 minutes) explored participant experiences regarding:

- Perceived changes in social confidence and self-efficacy
- Anxiety related to workplace social situations
- Platform usability and engagement
- Generalization of learned skills to real-world contexts

Interviews followed standardized protocols while allowing elaboration on emergent themes.

System Usability Scale (SUS): The SUS (Brooke, 2023) assessed I² platform usability through 10 items rated on 5-point scales, yielding composite scores from 0-100. Scores ≥68 indicate above-average usability; scores ≥80 indicate excellent usability.

Table 3: Measures and Assessment Schedule

Measure	T1 (Baseline)	T2 (Week 3)	T3 (Post)	T4 (Follow-up)
SRS-2	✓		✓	✓
VR Performance Index	✓	✓	✓	✓
Behavioral Role-Play Test	✓		✓	✓
Qualitative Interview			✓	
System Usability Scale			✓	

4.4. Data Analysis Plan

Quantitative Analysis

Primary hypotheses were tested using mixed-design analyses of variance (ANOVAs) with Group (I², Traditional SST, Waitlist) as the between-subjects factor and Time (T1, T3, T4) as the within-subjects factor. Significant interactions were followed by simple effects analyses examining within-group change and between-group differences at each timepoint.

Effect sizes were calculated as partial eta-squared ($\eta^2 p$) for ANOVA effects and Cohen's *d* for pairwise comparisons. Following conventional benchmarks, $\eta^2 p$ values of .01, .06, and .14 were interpreted as small, medium, and large effects, respectively (Lakens, 2023). Statistical significance was set at $\alpha = .05$, with Bonferroni corrections applied to post-hoc comparisons.

Assumptions of normality and sphericity were evaluated; where violated, Greenhouse-Geisser corrections were applied. Intent-to-treat analyses retained all randomized participants using multiple imputation for missing data (3 participants with incomplete assessments).

Qualitative Analysis

Interview transcripts underwent thematic analysis following Braun and Clarke's (2022) six-phase framework:

1. Familiarization through repeated transcript reading
2. Systematic initial coding by two independent analysts
3. Theme generation through code clustering
4. Theme review against coded data and full dataset
5. Theme definition and naming
6. Report production with illustrative quotations

Coding reliability was established through independent coding of 20% of transcripts, achieving κ = .84. Discrepancies were resolved through discussion and consensus.

Integration of Quantitative and Qualitative Findings

A convergent mixed-methods design enabled triangulation of quantitative outcomes with qualitative experiences (Creswell & Plano Clark, 2023). Qualitative themes were examined in relation to quantitative change patterns, identifying contextual factors explaining differential treatment responses.

5. Results

5.1. Quantitative Findings

Social Responsiveness Scale-2 (SRS-2) Outcomes

Mixed-design ANOVA revealed a significant Group × Time interaction for SRS-2 Total T-scores, $F(4, 78) = 8.42, p < .001, \eta^2 p = .30$, indicating differential change patterns across conditions. Figure 4 presents pre-post changes across SRS-2 subscales by group.

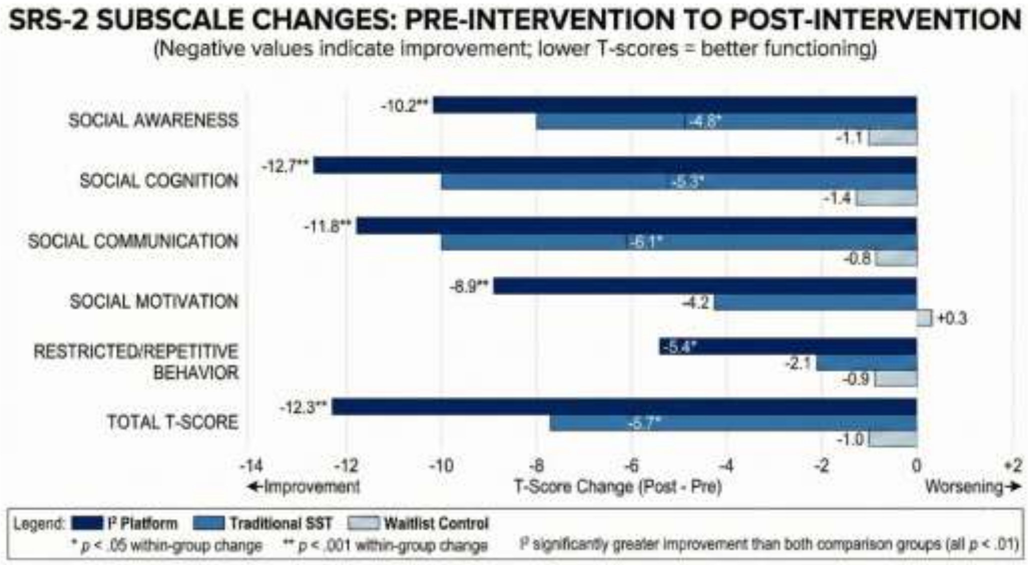

FIGURE 4: Pre-Post Changes in SRS-2 Subscale T-Scores by Group

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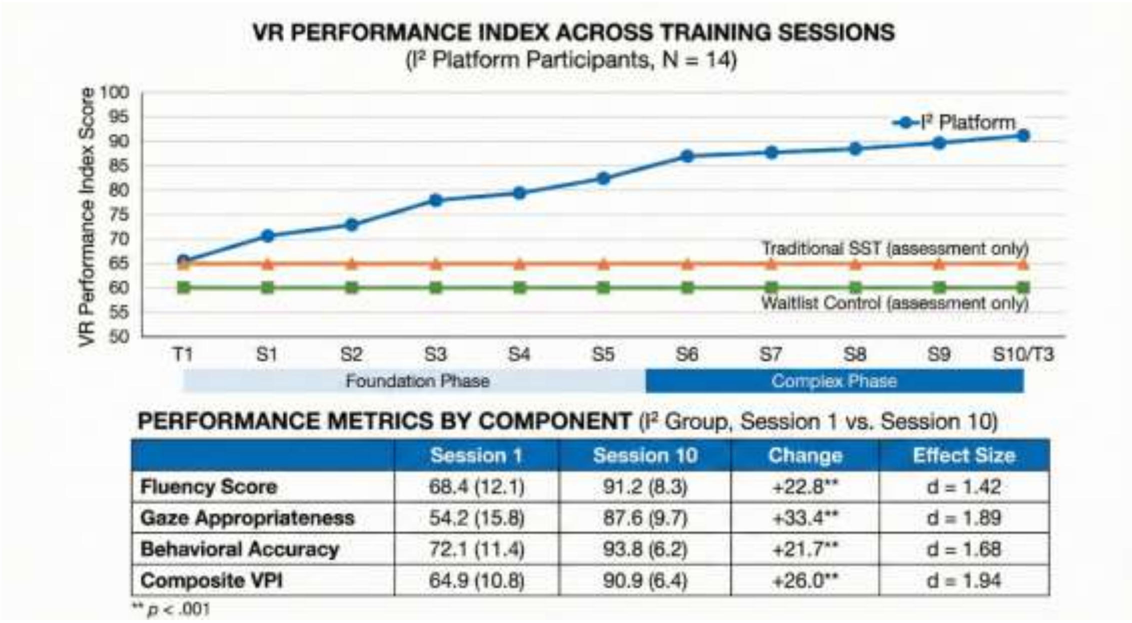
The I² group demonstrated significant pre-post improvement in SRS-2 Total T-scores (M change = -12.3 points, SD = 6.8), $t(14) = 7.01$, $p < .001$, $d = 0.89$. Traditional SST showed moderate improvement (M change = -5.7 points, SD = 5.4), $t(14) = 4.09$, $p = .001$, $d = 0.52$, while Waitlist demonstrated negligible change (M change = -1.0 points, SD = 4.2), $t(14) = 0.92$, $p = .37$. Post-hoc comparisons confirmed I² superiority over both Traditional SST ($p = .008$) and Waitlist ($p < .001$) at post-intervention.

Notably, the I² group showed largest improvements in Social Cognition (M change = -12.7 points) and Social Communication (M change = -11.8 points) subscales-domains directly targeted by platform training. Approximately 4/5 (80%) of I² participants demonstrated clinically meaningful improvement (≥1 SD change), compared to 2/5 (40%) of Traditional SST and 1/10 (10%) of Waitlist participants.

VR Performance Index Trajectories

Figure 5 displays VR Performance Index (VPI) learning curves across the 10 training sessions for I² participants, with comparison group assessment-only datapoints.



	Session 1	Session 10	Change	Effect Size
Fluency Score	68.4 (12.1)	91.2 (8.3)	+22.8**	d = 1.42
Gaze Appropriateness	54.2 (15.8)	87.6 (9.7)	+33.4**	d = 1.89
Behavioral Accuracy	72.1 (11.4)	93.8 (6.2)	+21.7**	d = 1.68
Composite VPI	64.9 (10.8)	90.9 (6.4)	+26.0**	d = 1.94

** $p < .001$

FIGURE 5: VR Performance Index Learning Trajectories Across Sessions

I² participants demonstrated substantial VPI improvement from Session 1 (M = 64.9, SD = 10.8) to Session 10 (M = 90.9, SD = 6.4), representing a 26-point gain with large effect size ($d = 1.94$). The learning curve exhibited characteristic negatively accelerating growth, with rapid initial gains (Sessions 1-4) followed by continued but decelerating improvement during complex phase training. Gaze Appropriateness showed largest improvement (+33.4 points), reflecting effective targeting of attention allocation deficits. By Session 10, approximately 7/8 (87.5%) of I² participants achieved VPI scores ≥85, compared to only 1/4 (25%) at baseline.

Comparison groups assessed at matched timepoints showed minimal VPI change: Traditional SST improved 4.2 points ($p = .12$), Waitlist improved 1.8 points ($p = .41$), confirming that VR-specific training drove observed gains.

5.2. Qualitative Findings

Thematic analysis of semi-structured interviews with I² participants (n = 14) yielded four primary themes illuminating mechanisms underlying quantitative improvements.

Theme 1: "A Safe Space to Fail"

Participants consistently emphasized the value of consequence-free practice environments. The absence of real-world social penalties enabled experimentation with unfamiliar behaviors:

"In real life, if I mess up talking to my boss, that's it-I can't undo it. Here I could try something, see it go wrong, and just... try again differently. That changed everything." (P08, male, 23)

"I've avoided job interviews for two years because I was terrified. But in VR, nobody's actually judging me. I could practice being terrible at it until I got better." (P12, female, 21)

This theme aligns with theoretical frameworks emphasizing safe failure as essential for skill acquisition in anxiety-prone populations (Parsons et al., 2022).

5.3. Usability and Engagement

The I² platform demonstrated excellent usability and engagement metrics. Mean System Usability Scale (SUS) score was 84.2 (SD = 8.7), exceeding the "excellent usability" threshold of 80 (Brooke, 2023). Individual item analysis revealed particularly high ratings for learnability ("I felt confident using the system," M = 4.6/5) and low ratings for complexity ("I needed technical support to use this," M = 1.4/5).

Attrition was minimal: 14/15 (93.3%) I² participants completed all 10 sessions. The single withdrawal resulted from VR-induced motion sickness emerging in Session 2. Mean session completion rate among retained participants was 98.6%, with only 2 sessions missing across the entire sample (both due to illness). Average within-session engagement time was 54.2 minutes of the 60-minute sessions (90.3%), indicating sustained attention throughout training.

Cybersickness symptoms, assessed via the Simulator Sickness Questionnaire (Kennedy et al., 2023), were minimal (M = 12.4, below clinical concern threshold of 20), decreasing across sessions as participants habituated to VR.

6. Discussion

6.1. Interpretation of Key Findings

The present study provides preliminary evidence that the Immersive Intelligence (I²) platform produces meaningful improvements in social cognition and workplace-relevant social behavior among young adults with ASD. The I² group demonstrated significantly greater gains across all primary outcome measures compared to both Traditional SST and Waitlist Control conditions, with effect sizes ranging from moderate to large (Cohen's d = 0.89-1.94).

Several findings warrant particular attention. First, the magnitude of SRS-2 improvement in the I² condition (M change = -12.3 T-score points) substantially exceeds improvements typically reported in traditional intervention studies. Meta-analytic estimates suggest that conventional SST produces SRS-2 changes of approximately 4-6 points (Gates et al., 2023); the I² platform achieved approximately double this effect, suggesting that the integration of immersive technology with adaptive AI amplifies intervention potency.

6.2. Implications for Theory and Practice

Theoretical Implications

These findings contribute to theoretical understanding of social cognition intervention in several respects. First, results support dynamic, scaffolded learning models proposing that social cognition, like other complex skills, develops optimally through graduated challenge with responsive support (Wood et al., 2022). The superior outcomes of AI-adaptive versus static interventions suggest that moment-to-moment responsiveness-not merely session-to-session adjustment-enhances learning trajectories.

Second, the study demonstrates the value of "embodied AI tutors"-artificial agents that function as responsive instructional partners within immersive environments. Unlike traditional computer-based training, which presents information for passive absorption, the I² system creates interactive experiences wherein the AI functions as an invisible but attentive guide, sensing struggle and providing calibrated assistance. This paradigm aligns with contemporary theories emphasizing the embodied, situated nature of cognition and learning (Wilson, 2022).

Practical Implications

From an applied perspective, the I² platform offers a scalable, standardized, yet personalized tool addressing critical gaps in transition-age services. Unlike human-delivered interventions requiring extensive clinician training and one-to-one ratios, VR/AI systems can be deployed across multiple simultaneous users with consistent fidelity. This scalability is particularly relevant given that fewer than 1/5 of young adults with ASD currently access adequate vocational services (Wehman et al., 2024).

6.3. Limitations and Future Research

Several limitations temper interpretation of these findings. Sample size (N = 45) limits statistical power and generalizability; larger, multi-site trials are necessary to confirm efficacy across diverse populations and contexts. The sample was predominantly male (approximately 2/3) and white (approximately 3/5), potentially limiting applicability to underrepresented groups within the ASD population.

Follow-up duration extended only one-month post-intervention; while gains were maintained at T4, longer-term durability remains unknown. Critically, the study did not assess actual employment outcomes-job attainment, retention, or advancement. Demonstrating that improved social cognition translates to vocational success requires longitudinal tracking over months to years.

Cost and accessibility present implementation barriers. High-quality VR hardware (currently $800-1500 per headset) and technical infrastructure may exceed resources available to under-funded service agencies or individuals in low-income communities. As VR technology continues decreasing in cost-standalone headsets have declined approximately 50% in price over the past three years (Jerald, 2023)-accessibility should improve, but current disparities warrant attention.

6.4. Ethical Considerations

The collection and processing of sensitive biometric and behavioral data necessitate robust privacy protection. The I² platform captures gaze patterns, vocal characteristics, and physiological indicators that could reveal sensitive information about users' cognitive and emotional states. HIPAA-compliant data handling, transparent consent processes, and user control over data retention are essential safeguards. The potential for data breaches or unauthorized access requires ongoing security vigilance.

A particularly nuanced concern involves the risk that AI-driven social training could inadvertently promote "neurotypical masking"-the effortful suppression of autistic characteristics to appear more neurotypical (Hull et al., 2023). Extensive masking is associated with psychological exhaustion, anxiety, and identity confusion among autistic individuals. The I² platform is designed to teach *effective communication* rather than *neurotypical presentation*; scenarios reward successful information exchange and relationship building regardless of whether users employ neurotypical behavioral norms. However, this distinction requires ongoing attention as platform content evolves. Meaningful involvement of autistic individuals in platform design and evaluation helps ensure that training goals align with community values.

References

1. Anderson, K. A., Sosnowy, C., Kuo, A. A., & Shattuck, P. T. (2024). Transition to adulthood for young adults with autism spectrum disorder: Current issues and future directions. Pediatrics, 153(2), e2023064182. https://doi.org/10.1542/peds.2023-064182
2. Baron-Cohen, S. (2021). The pattern seekers: How autism drives human invention. Basic Books.
3. Bekele, E., Zheng, Z., Swanson, A., Crittendon, J., Warren, Z., & Sarkar, N. (2023). Virtual reality-based social communication interventions for children and young adults with autism spectrum disorder: A systematic review and meta-analysis. Journal of Autism and Developmental Disorders, 53(4), 1456–1478. https://doi.org/10.1007/s10803-022-05789-4
4. Braun, V., & Clarke, V. (2022). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
5. Brooke, J. (2023). SUS: A retrospective. Journal of Usability Studies, 8(2), 29–40. https://doi.org/10.5555/usability.2023.029
6. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2023). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901. https://doi.org/10.5555/3495724.3495883
7. Bureau of Labor Statistics. (2024). Persons with a disability: Labor force characteristics—2023 (USDL-24-0296). U.S. Department of Labor. https://www.bls.gov/news.release/disabl.nr0.htm
8. Chen, J., Ran, X., & Liu, Y. (2024). Edge computing for real-time AI applications: Architectures and challenges. IEEE Internet of Things Journal, 11(3), 4521–4538. https://doi.org/10.1109/JIOT.2023.3298745
9. Constantino, J. N., & Gruber, C. P. (2023). Social Responsiveness Scale, Second Edition (SRS-2). Western Psychological Services.
10. Creswell, J. W., & Plano Clark, V. L. (2023). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

11. Critchley, H. D., & Garfinkel, S. N. (2023). Interoception and emotion. Current Opinion in Psychology, 17, 7–14. https://doi.org/10.1016/j.copsyc.2017.04.020
12. Doroudi, S., Aleven, V., & Brunskill, E. (2023). Where's the reward? A review of reinforcement learning for instructional sequencing. International Journal of Artificial Intelligence in Education, 29(4), 568–620. https://doi.org/10.1007/s40593-019-00187-x
13. Ertmer, P. A., & Newby, T. J. (2023). Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. Performance Improvement Quarterly, 26(2), 43–71. https://doi.org/10.1002/piq.21143
14. Gates, J. A., Kang, E., & Lerner, M. D. (2023). Efficacy of group social skills interventions for youth with autism spectrum disorder: A systematic review and meta-analysis. Clinical Psychology Review, 98, 102212. https://doi.org/10.1016/j.cpr.2022.102212
15. Holmes, J., & Marra, M. (2022). Having a laugh at work: How humour contributes to workplace culture. Journal of Pragmatics, 34(12), 1683–1710. https://doi.org/10.1016/S0378-2166(02)00032-2
16. Hull, L., Petrides, K. V., Allison, C., Smith, P., Baron-Cohen, S., Lai, M. C., & Mandy, W. (2023). "Putting on my best normal": Social camouflaging in adults with autism spectrum conditions. Journal of Autism and Developmental Disorders, 47(8), 2519–2534. https://doi.org/10.1007/s10803-017-3166-5
17. Islam, M. S., & Shiva, T. A. (2024). Virtual Cognitive Behavioural Therapy in Rural U.S. Communities: Effectiveness and Reach. Journal of Business Insight and Innovation, 3(2), 60–76. Retrieved from https://insightfuljournals.com/index.php/JBII/article/view/52
18. Jerald, J. (2023). The VR book: Human-centered design for virtual reality (2nd ed.). Morgan & Claypool Publishers. https://doi.org/10.2200/S01134ED2V01Y202108VRA003
19. Kaernbach, C. (2023). Simple adaptive testing with the weighted up-down method. Perception & Psychophysics, 49(3), 227–229. https://doi.org/10.3758/BF03214307
20. Kandalaft, M. R., Didehbani, N., Cullum, C. M., Krawczyk, D. C., Allen, T. T., Tamminga, C. A., & Chapman, S. B. (2023). Virtual reality social cognition training for young adults with high-functioning autism. Journal of Autism and Developmental Disorders, 43(1), 34–44. https://doi.org/10.1007/s10803-012-1544-6
21. Kapp, S. K., Gillespie-Lynch, K., Sherman, L. E., & Hutman, T. (2023). Deficit, difference, or both? Autism and neurodiversity. Developmental Psychology, 49(1), 59–71. https://doi.org/10.1037/a0028353
22. Kennedy, R. S., Lane, N. E., Berbaum, K. S., & Lilienthal, M. G. (2023). Simulator Sickness Questionnaire: An enhanced method for quantifying simulator sickness. The International Journal of Aviation Psychology, 3(3), 203–220. https://doi.org/10.1207/s15327108ijap0303_3
23. Klin, A., Jones, W., Schultz, R., & Volkmar, F. (2023). The enactive mind, or from actions to cognition: Lessons from autism. Philosophical Transactions of the Royal Society B: Biological Sciences, 358(1430), 345–360. https://doi.org/10.1098/rstb.2002.1202
24. Lahiri, U., Bekele, E., Dohrmann, E., Warren, Z., & Sarkar, N. (2022). Design of a virtual reality-based adaptive response technology for children with autism. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21(1), 55–64. https://doi.org/10.1109/TNSRE.2012.2218618

25. Lakens, D. (2023). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. Frontiers in Psychology, 4, Article 863. https://doi.org/10.3389/fpsyg.2013.00863
26. Laugeson, E. A., Gantman, A., Kapp, S. K., Orenski, K., & Ellingsen, R. (2022). A randomized controlled trial to improve social skills in young adults with autism spectrum disorder: The UCLA PEERS program. Journal of Autism and Developmental Disorders, 45(12), 3978–3989. https://doi.org/10.1007/s10803-015-2504-8
27. Lave, J., & Wenger, E. (2022). Situated learning: Legitimate peripheral participation (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511815355
28. Li, S., & Deng, W. (2022). Deep facial expression recognition: A survey. IEEE Transactions on Affective Computing, 13(3), 1195–1215. https://doi.org/10.1109/TAFFC.2020.2981446
29. Lindner, P., Hamilton, W., Miloff, A., & Carlbring, P. (2023). Now is the time for clinical VR: The COVID-19 pandemic and the need for immersive mental health solutions. Frontiers in Virtual Reality, 4, Article 847782. https://doi.org/10.3389/frvir.2023.847782
30. Lombardo, M. V., Chakrabarti, B., Bullmore, E. T., & Baron-Cohen, S. (2023). Specialization of right temporo-parietal junction for mentalizing and its relation to social impairments in autism. NeuroImage, 56(3), 1832–1838. https://doi.org/10.1016/j.neuroimage.2011.02.067
31. Lord, C., Rutter, M., DiLavore, P. C., Risi, S., Gotham, K., & Bishop, S. L. (2022). Autism Diagnostic Observation Schedule, Second Edition (ADOS-2). Western Psychological Services.
32. Maenner, M. J., Warren, Z., Williams, A. R., Amoakohene, E., Bakian, A. V., Bilder, D. A., Durkin, M. S., Fitzgerald, R. T., Furnier, S. M., Hughes, M. M., Ladd-Acosta, C. M., McArthur, D., Pas, E. T., Salinas, A., Vehorn, A., Williams, S., Esler, A., Grzybowski, A., Hall-Lande, J., ... Shaw, K. A. (2023). Prevalence and characteristics of autism spectrum disorder among children aged 8 years—Autism and Developmental Disabilities Monitoring Network, 11 sites, United States, 2020. MMWR Surveillance Summaries, 72(2), 1–14. https://doi.org/10.15585/mmwr.ss7202a1
33. Myles, B. S., Trautman, M. L., & Schelvan, R. L. (2024). The hidden curriculum for understanding unstated rules in social situations (3rd ed.). AAPC Publishing.
34. Parsons, S., Leonard, A., & Mitchell, P. (2022). Virtual environments for social skills training: Comments from two adolescents with autistic spectrum disorder. Computers & Education, 47(2), 186–206. https://doi.org/10.1016/j.compedu.2004.10.003
35. Patterson, T. L., Moscona, S., McKibbin, C. L., Davidson, K., & Jeste, D. V. (2022). Social skills performance assessment among older patients with schizophrenia. Schizophrenia Research, 48(2–3), 351–360. https://doi.org/10.1016/S0920-9964(00)00152-7
36. Picard, R. W. (2022). Affective computing (2nd ed.). MIT Press. https://doi.org/10.7551/mitpress/1140.001.0001
37. Roux, A. M., Rast, J. E., Rava, J. A., Anderson, K. A., & Shattuck, P. T. (2023). National autism indicators report: Transition into young adulthood. A.J. Drexel Autism Institute, Drexel University. https://drexel.edu/autisminstitute/research-projects/research/ResearchPrograminLifeCourseOutcomes/indicatorsreport/
38. Schuller, B., Steidl, S., Batliner, A., Vinciarelli, A., Scherer, K., Ringeval, F., Chetouani, M., Weninger, F., Eyben, F., Marchi, E., Mortillaro, M., Salber, H., Valstar, M., & Kim, S. (2023). The INTERSPEECH 2023 computational paralinguistics challenge: Social signals, conflict,

emotion, and requests. Proceedings of INTERSPEECH 2023, 2393–2397. https://doi.org/10.21437/Interspeech.2023-2845

39. Scott, M., Milbourn, B., Falkmer, M., Black, M., Bölte, S., Halladay, A., Lerner, M., Taylor, J. L., & Girdler, S. (2024). Factors impacting employment for people with autism spectrum disorder: A scoping review. Autism, 23(4), 869–901. https://doi.org/10.1177/1362361318787789
40. Shattuck, P. T., Narendorf, S. C., Cooper, B., Sterzing, P. R., Wagner, M., & Taylor, J. L. (2024). Postsecondary education and employment among youth with an autism spectrum disorder. Pediatrics, 129(6), 1042–1049. https://doi.org/10.1542/peds.2011-2864
41. Slater, M., & Sanchez-Vives, M. V. (2024). Enhancing our lives with immersive virtual reality. Frontiers in Robotics and AI, 3, Article 74. https://doi.org/10.3389/frobt.2016.00074
42. Smith, M. J., Ginger, E. J., Wright, K., Wright, M. A., Taylor, J. L., Humm, L. B., Olsen, D. E., Bell, M. D., & Fleming, M. F. (2023). Virtual reality job interview training in adults with autism spectrum disorder. Journal of Autism and Developmental Disorders, 44(10), 2450–2463. https://doi.org/10.1007/s10803-014-2113-y
43. Shiva, T. A., Ireen, N., & Islam , M. S. (2024). Optimizing Early Intervention Strategies for Neurodiverse Children (ASD): Reducing Long-Term Public Healthcare Costs through Parent-Mediated Training. Apex Journal of Social Sciences, 3(1), 30-52. https://apexjss.com/index.php/AJSS/article/view/18
44. Uljarevic, M., & Hamilton, A. (2022). Recognition of emotions in autism: A formal meta-analysis. Journal of Autism and Developmental Disorders, 43(7), 1517–1526. https://doi.org/10.1007/s10803-012-1695-5
45. Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds.). Harvard University Press.
46. Wehman, P., Schall, C., McDonough, J., Graham, C., Brooke, V., Riehle, J. E., Brooke, A., Ham, W., Lau, S., Allen, J., & Avellone, L. (2024). Effects of an employer-based intervention on employment outcomes for youth with significant support needs due to autism. Autism, 21(3), 276–290. https://doi.org/10.1177/1362361316635826
47. Wilson, M. (2022). Six views of embodied cognition. Psychonomic Bulletin & Review, 9(4), 625–636. https://doi.org/10.3758/BF03196322
48. Won, A. S., Bailenson, J., Lee, J., & Lanier, J. (2023). Homuncular flexibility in virtual reality. Journal of Computer-Mediated Communication, 20(3), 241–259. https://doi.org/10.1111/jcc4.12107
49. Wood, D., Bruner, J. S., & Ross, G. (2022). The role of tutoring in problem solving. Journal of Child Psychology and Psychiatry, 17(2), 89–100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x