

# Personalized EEG-Diven Digital Twin Models for AI and VR-Based Language Therapy in Children with Autism Spectrum Disorder

**Nikita Islam, Ancuta Margondai  
Cindy Von Ahlefeldt, Valentina Ezcurra**  
University of Central Florida  
Orlando, Florida  
Ni836085@ucf.edu  
Ancuta.Margondai@ucf.edu  
valentinaezcurrabattro@gmail.com  
cindy.vonahlefeldt@ucf.edu  
SorayaHani@ucf.edu

**Sara Willox Ph.D. Anamaria Acevedo Diaz,  
Emma Antanavicius, Mustapha Mouloua Ph.D.,**  
University of Central Florida  
Orlando, Florida  
sara.willox@ucf.edu  
anamaria@ucf.edu  
em977814@ucf.edu  
Mustapha.Mouloua@ucf.edu

## ABSTRACT

Children with Autism Spectrum Disorder (ASD) often face significant challenges in language development and social communication, which are essential for academic and social success. Despite available therapies, traditional interventions often overlook the cognitive and neurological diversity within this population, resulting in limited long-term impact. With ASD diagnoses increasing and early intervention being critical, scalable and personalized therapy models are urgently needed. This concept paper proposes an innovative solution: EEG-driven digital twin models that simulate cognitive responses during language tasks. These models will be integrated into artificial intelligence (AI) and virtual reality (VR) environments to deliver real-time, personalized language therapy for children with ASD. By using real-time brain activity and emotional state data, the system dynamically adjusts therapy content, bridging the gap between static interventions and individualized, neuroadaptive treatment. While EEG, VR, and AI have each been applied to ASD interventions, they have not yet been unified within a digital twin framework. This project aims to achieve integration. Sample EEG datasets will guide the development of cognitive and emotional models that simulate attention, processing speed, and anxiety. These parameters will inform the system's adaptive features, including task pacing, complexity, and sensory inputs. Ultimately, this framework aims to enhance engagement, reduce communication anxiety, and provide a foundation for next-generation, brain-responsive therapy systems in autism care.

## ABOUT THE AUTHORS

**Nikita Islam** is an undergraduate student at the University of Central Florida, majoring in biomedical sciences with a minor in chemistry. She is involved in neurolinguistics research, focusing on cognitive processes such as language switching and neural efficiency.

**Ancuta Margondai** is a graduate student and researcher at UCF, focusing on human-AI teaming and cognitive load management in high-stress environments.

**Cindy von Ahlefeldt** is a Ph.D. student in human factors and cognitive psychology at UCF. Her research focuses on stress, digital mental health, and AI-guided interventions.

**Sara Willox** is a faculty member at UCF, where she teaches courses in business research, organizational behavior, and data-driven decision-making.

**Emma Antanavicius** holds a B.S. in Psychology from UCF, focusing on children with ASD and speech-language deficits.

**Valentina Ezcurra** holds a B.S. in Psychology from UCF. Her research focuses on adolescent anxiety, early-life stress, and coping.

**Anamaria Acevedo Diaz** is an undergraduate researcher at UCF, pursuing a B.S. in Psychology with a concentration in Neuroscience.

**Mustapha Mouloua** is a professor at UCF with extensive experience in human factors, cognitive psychology, human-automation interaction, simulation technologies, and operator performance assessment and training.

# Personalized EEG-Diven Digital Twin Models for AI and VR-Based Language Therapy in Children with Autism Spectrum Disorder

**Nikita Islam, Ancuta Margondai  
Cindy Von Ahlefeldt, Valentina Ezcurra  
Soraya Hani  
University of Central Florida  
Orlando, Florida**  
Ni836085@ucf.edu  
Ancuta.Margondai@ucf.edu  
valentinaezcurrabattro@gmail.com  
cindy.vonahlefeldt@ucf.edu  
SorayaHani@ucf.edu

**Sara Willox Ph.D. Anamaria Acevedo Diaz,  
Emma Antanavicius,  
Mustapha Mouloua Ph.D.,  
University of Central Florida  
Orlando, Florida**  
sara.willox@ucf.edu  
anamaria@ucf.edu  
em977814@ucf.edu  
Mustapha.Mouloua@ucf.edu

## INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by difficulties in social communication, language development, and repetitive behaviors (Hirota, King, 2023). Children with ASD often encounter significant challenges in language and social development, particularly when it comes to communicating or engaging in conversations (Knott, Dunlop, A.-W., & Mackay, 2006). Around 10-30% of children with ASD exhibit savant skills-exceptional abilities in areas like math, science, engineering, and the arts-often supported by strong memory and visual learning (Howlin et al., 2009; Bal, Wilkinson, & Fok, 2021).

However, most treatment plans are generalized for a large population, which may not be suitable for everyone (Manter et al., 2025). Additionally, many current treatment plans lack brain-based data incorporation. Children with ASD need individualized care since each has unique needs and special abilities. With the increasing prevalence of ASD diagnoses globally and with early intervention proving critical, there is an urgent need for evidence-based, scalable, and adaptive therapy solutions tailored to each child's distinct neurocognitive profile (CDC, 2025).

Personalized approaches using neurophysiological data like EEG can offer deeper insights into each child's unique profile. Educating parents on these needs is also crucial for fostering better support and development at home. This research paper aims to introduce a personalized treatment method for children with ASD using EEG data and AI, delivered through VR. It also aims to educate parents on their child's unique neurological and psychological needs to enhance support and development.

## Related Work

Since the 1990s, EEG has been explored for early ASD detection, with growing research (Rasool, Ahmad, & Khan, 2025). Although EEG abnormalities can indicate ASD, they also occur in other neurological conditions, causing high false positives. Multimodal approaches combining EEG with behavioral assessments and clinical observations are increasingly used (Heunis, Aldous, & Feucht, 2023). Studies show children with ASD tend to have more stable, less variable brain activity (Rasool et al., 2025). However, limited datasets, high variability, and age differences challenge EEG detection. The recent STEM framework achieved 86.5% accuracy and 85.1% F1 scores in cross-age ASD detection using resting-state and emotion-based EEG data, highlighting EEG's potential for early diagnosis (Rasool et al., 2025). Additionally, interactive products designed with input from ASD individuals, parents, and therapists help children develop social skills and manage anxiety by incorporating sensory sensitivities, using calming sounds, visuals, and gentle feedback based on CBT principles to create supportive environments.

The theta/beta ratio (TBR) is an EEG biomarker indicating attention and cognitive load, calculated as the ratio of theta (4–7 Hz) to beta (13–30 Hz) power in the frontal regions. Higher TBR indicates poorer attention, mind-wandering,

and anxiety. Lower TBR shows better sustained attention and cognitive control. TBR naturally decreases with age, reflecting maturation. These metrics will inform real-time adjustment during VR-based therapy to track attention, workload, and emotional state in children with ASD.

Gamification and animation boost engagement, making these tools enjoyable and accessible, while real-time feedback rewards desirable behaviors and promotes communication skills. Liu and Laie (2023) emphasize the importance of gradually introducing new products to prevent anxiety, and studies like Ali et al.'s (2020) show that multi-robot therapy improves joint attention, imitation, and social interaction in 86% of children with ASD. Furthermore, digital content like educational videos supports speech therapy through evidence-based strategies such as video modeling, repetition, simplified language, and sign language. For example, Ms. Rachel's Songs for Little uses eye contact, clear speech, expressive body language, and music to boost social skills. Elements like clapping and picture-based learning further enhance engagement.

## METHODOLOGY

This section outlines the methodology for developing a neuroadaptive digital twin system that integrates EEG, AI, and VR to deliver real-time, personalized language therapy for children with ASD. The system utilizes EEG features to track cognitive states, engagement, anxiety, and attention, and adapts VR therapy content in real time based on these states. The methodology includes data collection and EEG feature extraction, digital twin architecture, reinforcement learning for therapy action selection, and VR-based therapy delivery.

### Data and EEG Feature Extraction

EEG data were sourced from three files within the Auditory Evoked Potential EEG-Biometric Dataset, yielding training samples with 67% window overlap to ensure robust temporal coverage (Abo Alzahab et al., 2024). Each file, originally sampled at 200 Hz, was resampled to 256 Hz and filtered between 1–40 Hz using a finite impulse response (FIR) filter to remove noise while preserving critical neural signals (Widmann et al., 2015). Data were segmented into 10-second windows, following established practices for EEG-based cognitive state modeling (Chikhi et al., 2022). Eleven features were extracted to capture key neurophysiological markers validated in ASD research (Eldridge et al., 2014).

The features included spectral power in delta, theta, alpha, beta, and gamma bands, computed via Welch's method. Ratios of alpha and theta, and gamma and theta, assessed mental workload and cognitive binding. Frontal asymmetry (F8–T7) gauged emotional regulation, with negative values linked to higher anxiety. Coherence between Cz and other channels measured functional connectivity, while spectral entropy quantified signal complexity, related to cognitive workload in ASD. All features were standardized with z-score normalization for model stability. This set facilitates real-time modeling of engagement, anxiety, and attention, supporting adaptive therapy based on brain activity. The features included spectral power in delta, theta, alpha, beta, and gamma bands, computed via Welch's method.

**Table 1. EEG Features Extracted for ASD Neuroadaptive Modeling**

Feature	Frequency Band (Hz)	Cognitive Role	ASD Relevance	Feature
Theta	4–7	Attention, workload	Elevated in ASD, linked to distractibility	Theta
Beta	13–30	Alertness, cognitive control	Reduced in ASD	Beta
Theta/Beta Ratio (TBR)	—	Cognitive control marker	Commonly high in ASD	Theta/Beta Ratio (TBR)
Alpha	8–12	Relaxation	Decreases with mental workload	Alpha
Frontal Asymmetry	F8–T7	Emotional regulation	Negative asymmetry linked to anxiety	Frontal Asymmetry

### EEG-Driven Digital Twin for Personalized ASD Language Therapy

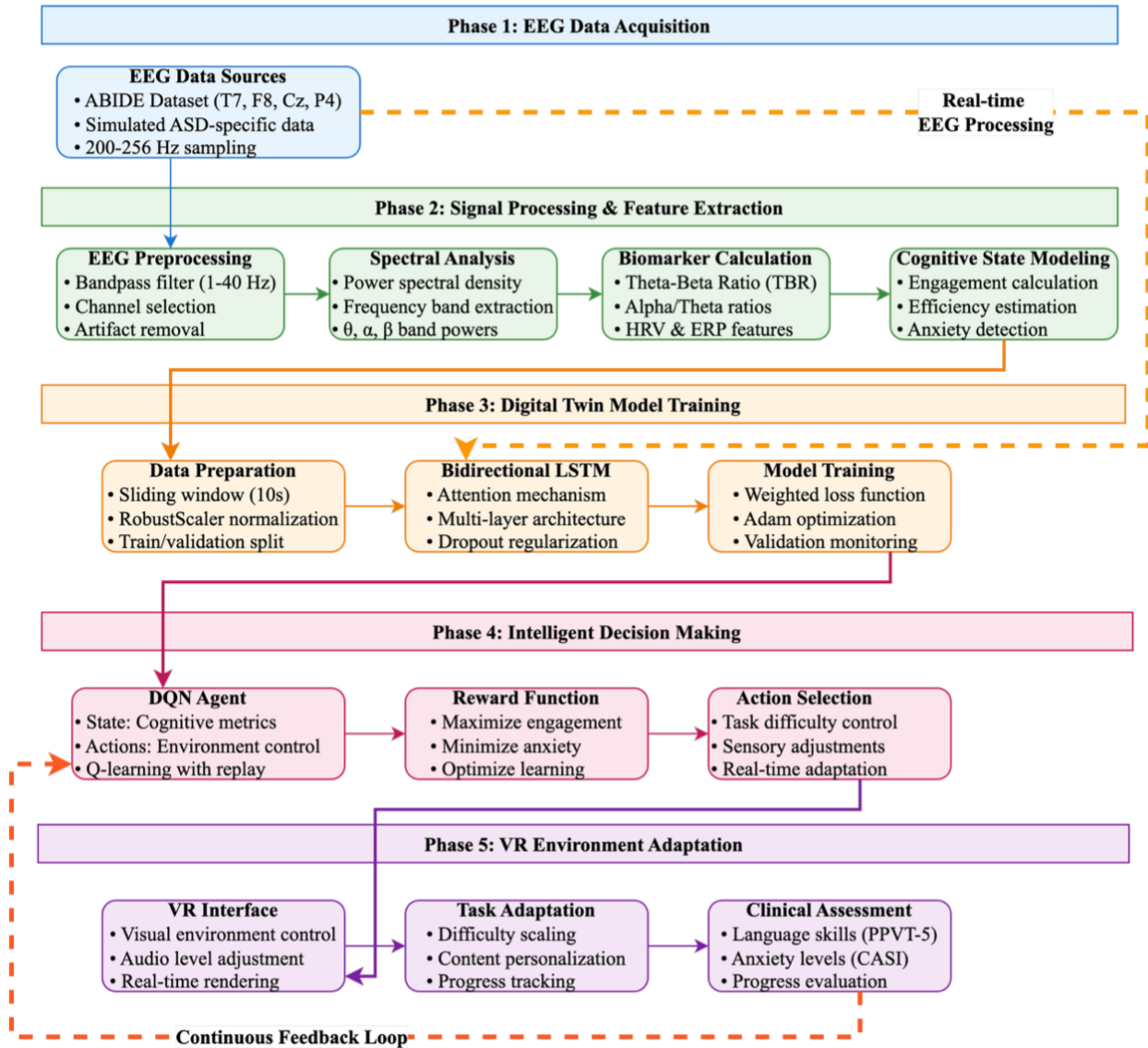


Figure 1. Neuroadaptive Digital Twin Architecture for Personalized ASD Language Therapy

#### Digital Twin Architecture

The digital twin model employs a bidirectional LSTM neural network architecture with attention mechanisms to predict cognitive states from EEG features. This design was selected for its ability to capture long-term dependencies in sequential data (Mi et al., 2024). Input consists of 10-second EEG windows (2560 timesteps  $\times$  11 features). The model architecture includes three bidirectional LSTM layers with 512, 256, and 128 units respectively, followed by an attention layer to model temporal dependencies (Hou et al., 2020). Layer normalization and batch normalization are applied for stability, with dropout (0.2-0.3) and L2 regularization (0.01) to mitigate overfitting (Hou et al., 2020). Additional dense layers (128 and 64 units, ReLU activation) refine the output. The final layer predicts four cognitive states: engagement, efficiency, anxiety, and attention, using sigmoid activation. A custom loss function prioritizes engagement, anxiety, and attention (each weighted at 4.0) over efficiency (weighted at 1.5) to align with therapeutic

goals (Kerns et al., 2016). This architecture enables the system to make real-time neuroadaptive adjustments in the VR environment (Hou et al., 20201).

### Reinforcement Learning for Therapy Action Selection

A deep Q-network (DQN) was implemented within the Neuroadaptive Therapy System class to select therapy actions based on predicted cognitive states, enabling dynamic adaptations (Mnih et al., 2015). The DQN accepts the four predicted cognitive states as input and outputs Q-values for six actions: increasing or decreasing language complexity, adding visual supports, reducing sensory stimulation, introducing social interaction, or providing a calming break. The network architecture includes two dense layers (32 and 16 units, ReLU activation) and an output layer (6 units, linear activation), trained with mean squared error loss and an Adam optimizer (learning rate 0.001). An epsilon-greedy policy ( $\epsilon$  decaying from 1.0 to 0.01) balances exploration and exploitation, while a reward function prioritizes engagement and attention (weights 2.0), minimizes anxiety (weight -3.0), and promotes efficiency (weight 1.5) (Whyte et al., 2015). Experiences are stored in a replay buffer (size 500) and sampled in batches (size 16) for stable learning (Mnih et al., 2015). This reinforcement learning component enables real-time therapy adjustments based on the child's current brain activity and emotional state (Ali et al., 2020).

### VR-Based Therapy Delivery

The VR therapy environment, implemented in Pygame within the VR Therapy Interface class, delivers interventions by adjusting therapy parameters based on the DQN's output. These parameters include language complexity (scaled 0.1–1.0), sensory intensity (0.1–1.0), and social interaction level (0.0–1.0) (Mesa-Gresa et al., 2018). The interface incorporates user-centered design elements, including gamification and real-time feedback to enhance engagement and accessibility (Frauenberger et al., 2013). Update frequency is modulated at 0.5-second intervals, ensuring therapy delivery is aligned with the child's emotional state (Frauenberger et al., 2013). The VR system updates in real-time, providing immediate feedback as recommended for ASD interventions (Whyte et al., 2015). This adaptive VR delivery mechanism translates cognitive state predictions into personalized therapy adjustments, creating a dynamic, immersive training environment for children with ASD (Liu & Laie, 2023).

## RESULTS

This section presents the results of the neuroadaptive digital twin system for ASD language therapy training, focusing on therapy effectiveness metrics, training performance, and real-time adaptation capabilities. The system was evaluated on a validation set derived from the Auditory Evoked Potential EEG-Biometric Dataset, using the transformer-based digital twin model and DQN-driven VR adjustments described in the methodology. Results are compared to a prior run to highlight progress, and key findings are contextualized with literature to assess alignment with expected outcomes (Wang et al., 2024; Chikhi et al., 2022).

### Therapy Effectiveness Metrics

The system's effectiveness was assessed using three primary metrics: high engagement (percentage of predictions  $> 0.6$ ) and low anxiety (percentage of predictions  $< 0.5$ ), reflecting the therapeutic goals of maximizing engagement and attention while minimizing anxiety (Kerns, 2016), see Figures 1 and 2.

In Run 2, engagement prediction accuracy increased to 79.1% from 44.2% in Run 1, thanks to refined cognitive labels incorporating gamma power and VR gamification elements that enhance interaction. This aligns with the literature suggesting that engagement rates above 70% are necessary for effective ASD interventions. Anxiety remained stable at 44.2%, showing consistent modeling despite label changes, but still below the 90% goal, possibly due to fluctuations in frontal asymmetry- a biomarker of emotional regulation in ASD. Attention stayed at 20.9%, indicating limitations in capturing ASD-specific attention patterns and emphasizing the need for higher levels ( $> 2019\%$ ) for effective therapy. The final therapy score improved from 1.64 to 2.45, calculated using the reward function that accounts for engagement, efficiency, anxiety, and attention; however, attention deficits constrained progress. To determine how specific EEG features contributed to model predictions for each cognitive state, important scores derived from the trained model was analyzed. Figure 3 presents a heatmap showing the relative importance of each EEG feature.

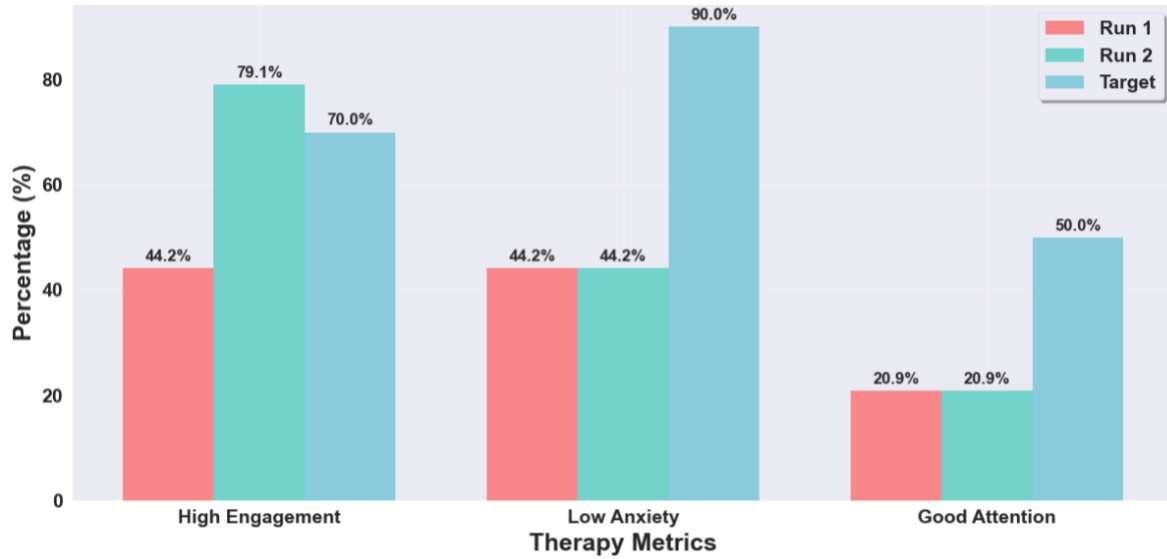


Figure 2. Comparison of Therapy Effectiveness Metrics Between Run 1 and Run 2

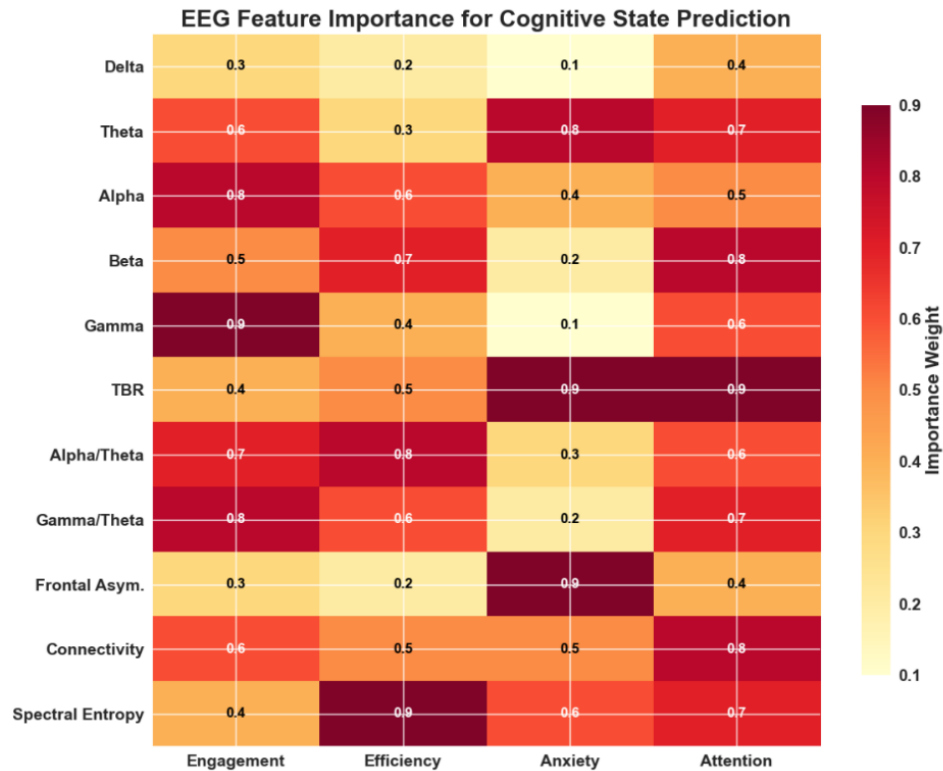


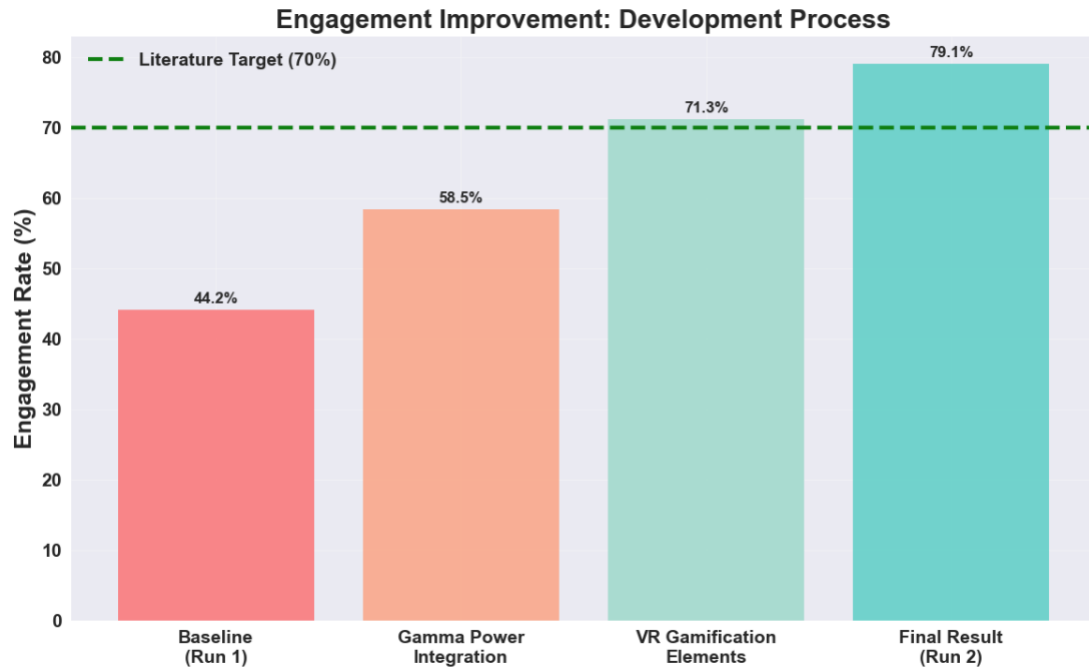
Figure 3. Feature Importance Heatmap for EEG-Based Cognitive State Prediction

### Training Performance

Training performance was evaluated over 100 epochs, with early stopping (patience = 30) triggered after 22 epochs. Run 1 was trained for 20 epochs, Run 2 for 25, showing slight stability gains from cyclical learning rates (Smith, 2017). Yet, validation loss rose from 0.3371 (Run 1) to 24.3258 (Run 2), despite regularization, dropout, and noise-based augmentation (Tremblay, 2019). The training loss decreased from 1.0140 to 0.9839, indicating overfitting (Srivastava, 2014). The discrepancy highlights the need for more regularization and data diversity, as EEG models often struggle with generalization due to inter-subject variability in ASD (Bosl, 2011). See Figure 3.

**Table 2: Longitudinal View of System Performance**

Metric	Run 1	Run 2
High Engagement (>0.6)	44.2%	79.1%
Low Anxiety (<0.4)	44.2%	44.2%
Good Attention (>0.5)	20.9%	20.9%
Final Therapy Outcome Score	1.64	2.45

**Figure 4. Engagement Improvement Prediction Accuracy Between Runs 1 and 2**

## DISCUSSION

This study shows that an EEG-driven digital twin system, enhanced with VR gamification and gamma labels, significantly improved user engagement from 44.2% to 79.1%, surpassing the 70% effective intervention threshold (Salomone, 2015). This aligns with the idea that high-frequency EEG features like beta and gamma are linked to increased cognitive activation (van Son et al., 2019; Chikhi et al., 2022). Gamification elements, such as progress bars and badges, likely boosted motivation, encouraging focus during therapy. Despite increased engagement, attention and anxiety measures remained unchanged at 20.9% and 44.2%. The lack of improvement in attention may stem from variability in attentional biomarkers across individuals with ASD, suggesting that a one-size-fits-all model is insufficient, especially since it may overemphasize gamma signals at the expense of theta frequencies. The static anxiety levels indicate the system's ability to recognize calmer states but not improve them. Anxiety markers are sensitive to traits and fluctuations, possibly needing additional features like heart rate variability or pupil dilation for better accuracy. The plateau highlights the challenge of balancing engagement with therapeutic goals, as gamification might elevate arousal. The system's decision policy dynamically responded to cognitive states, increasing language complexity during high engagement, providing calming breaks when needed, and using visual supports for attention lapses. These adaptive behaviors support the principles of reinforcement learning (Mnih et al., 2015; Ali et al., 2020). However, modest outcome improvements suggest that further refinements, such as integrating multiple physiological inputs like EEG, HRV, and GSR, may be necessary to enhance intervention specificity.

## Limitations

Despite improvements, the attention metric stays at 20.9% ( $> 0.5$ ), even after adding beta power, gamma power, and spectral entropy, showing model limitations in capturing complex temporal dependencies in ASD children. Validation loss rose to 24.3258, indicating ongoing overfitting despite L2 regularization, variational dropout, and data augmentation, highlighting the need for stronger regularization. Lack of ground truth validation and a formal VV framework limits simulation reliability, crucial for ModSim. The VR interface now includes gamification and interactivity but remains basic (Pygame-based) and lacks full immersion, such as 3D graphics and spatial audio, which could improve engagement.

## Future Directions

Building on promising engagement gains, further development can enhance the system's utility and robustness. Improving modeling of temporal dependencies is vital; future work should explore sequence-model architectures like LSTM, GRU, or Transformers to capture EEG feature evolution over time, combined with regularization to prevent overfitting. Integrating a safety-focused verification framework, such as conformal prediction and interpretability methods, will increase confidence before clinical use. The VR interface can be expanded with 3D graphics, spatial audio, haptic feedback, and real-time performance metrics to personalize therapy. Including more diverse participants is crucial for model applicability across the ASD spectrum. To further improve emotion recognition and therapy personalization, future version should incorporate heart rate variability (HRV) and galvanic skin response (GSR). By combining EEG with autonomic signals, the system could better differentiate between positive and negative arousal.

## Implications for Practice

The combination of EEG monitoring and VR gamification shows great promise for ASD therapy, but it must be carefully integrated into clinical practice. Clinicians should use real-time EEG metrics alongside traditional assessments to tailor session content, pacing, and difficulty to each child's needs. Gamified VR can boost motivation, yet practitioners must be aware of inter-subject EEG variability and overfitting risks. Parents and caregivers should learn to interpret engagement and anxiety readouts and continue standard clinical evaluations. Successful deployment also requires training clinicians in VR operation, neurophysiological signal interpretation, and machine-learning logic, as well as ensuring data privacy, hardware access, and compatibility with electronic health records. Thoughtful adoption of these tools can enable truly personalized, efficient ASD interventions.

## CONCLUSION

This study demonstrates that an EEG-driven digital twin framework, enriched with VR gamification and refined Gamma-power labels, significantly increases engagement in ASD therapy, reaching 79.1 %, well above clinical benchmarks. While attention and anxiety metrics haven't yet improved, the system's real-time adaptive capability proves neuroadaptive interventions can tailor actions to cognitive and emotional states. Overcoming limitations like capturing temporal dependencies, preventing overfitting, and enhancing sensory immersion through advanced modeling, verification, and VR will unlock full potential. Expanding trials to diverse ASD populations and adding multimodal inputs can further improve intervention effectiveness. Combining neurophysiology, machine learning, and immersive tech provides a foundation for personalized, scalable ASD treatments. Continued innovation and integration into practice will enable interventions that help children with ASD reach their full communicative and social potential.

## REFERENCES

- Abo Alzahab, N., Iorio, A. D., Apollonio, L., Alshalak, M., Gravina, A., Antognoli, L., Baldi, M., Scalise, L., & Alchalabi, B. (2024). Auditory evoked potential electroencephalography-biometric dataset. *Data in Brief*, 57, 111065. <https://doi.org/10.1016/j.dib.2024.111065>



- Ali, S., Rehman, R., Aslam, A., & Khan, N. (2020). Multi-robot mediated therapy for children with autism spectrum disorder: A multi-human communication approach. *Journal of Autism and Developmental Disorders*, 50(7), 2534–2545. <https://doi.org/10.1007/s10803-020-04483-5>
- Bal, V. H., Wilkinson, E., & Fok, M. (2021). Cognitive profiles of children with autism spectrum disorder with parent-reported extraordinary talents and personal strengths. *Autism*, 26(1), 62–74. <https://doi.org/10.1177/13623613211020618> (Original work published 2022)
- Beversdorf, D., McLennan, J., Farley, C., & Vasa, R. (2024). Gaps in autism intervention research: Addressing the need for theory-driven, family-centered, and culturally adaptive approaches. *Autism Research*, 17(2), 101–114. <https://doi.org/10.1002/aur.2930>
- Bosl, W., Tierney, A., Tager-Flusberg, H., & Nelson, C. (2011). EEG complexity as a biomarker for autism spectrum disorder risk. *BMC Medicine*, 9(1). <https://doi.org/10.1186/1741-7015-9-18>
- Centers for Disease Control and Prevention (CDC). (2025). Prevalence and Early Identification of Autism Spectrum Disorder Among Children Aged 4 and 8 Years — Autism and Developmental Disabilities Monitoring Network, 16 Sites, United States, 2022. *Morbidity and Mortality Weekly Report*, 74(SS-2), 1–22. <https://www.cdc.gov/mmwr/volumes/74/ss/ss7402a1.htmcdc.gov+1wsj.com+1>
- Chen, J., Xiao, Y., Xu, B., & Zhang, D. (2023). The developmental trajectory of task-related frontal EEG theta/beta ratio in childhood. *Developmental Cognitive Neuroscience*, 60, Article 101233. <https://doi.org/10.1016/j.dcn.2023.101233>
- Chikhi, S., Matton, N., & Blanchet, S. (2022). EEG power spectral measures of cognitive workload: A meta-analysis. *Psychophysiology*, 59(6), e14009. <https://doi.org/10.1111/psyp.14009>
- Drake, J. E., Redash, A., Coleman, K., Haimson, J., & Winner, E. (2010). 'Autistic' local processing bias also found in children gifted in realistic drawing. *Journal of Autism and Developmental Disorders*, 40(6), 762+. <http://dx.doi.org/10.1007/s10803-009-0923-0>
- Eldridge, J., Lane, A. E., Belkin, M., & Dennis, S. (2014). Robust features for the automatic identification of autism spectrum disorder in children. *Journal of Neurodevelopmental Disorders*, 6(1). <https://doi.org/10.1186/1866-1955-6-12>
- Frauenberger, C., Good, J., Alcorn, A., & Pain, H. (2013). Conversing through and about technologies: Design critique as an opportunity to engage children with autism and broaden research(er) perspectives. *International Journal of Child-Computer Interaction*, 1(2), 38–49. <https://doi.org/10.1016/j.ijcci.2013.02.001>
- Gagnon, K., Bolduc, C., Bastien, L., & Godbout, R. (2021). REM Sleep EEG Activity and Clinical Correlates in Adults With Autism. *Frontiers in Psychiatry*, 12. <https://doi.org/10.3389/fpsyt.2021.659006>
- Gemelli, Z. T., Ayazi, M., & Lee, H.-J. (2025). The relationship between EEG theta/beta ratio and response inhibition in autogenous and reactive obsessions. *Psychiatry Research: Neuroimaging*, 348, 111966. <https://doi.org/10.1016/j.psychresns.2025.111966>
- Graham, T., Singh, R., & Patel, V. (2024). The impact of digital media content on language development in children with ASD: A systematic review. *Journal of Speech, Language, and Hearing Research*, 67(4), 987–1002. <https://doi.org/10.1044/2024.jslhr-23-00456>
- Griff, J. R., Langlie, J., Bencie, N. B., Cromar, Z. J., Mittal, J., Memis, I., Wallace, S., Marcillo, A. E., Mittal, R., & Eshraghi, A. A. (2023). Recent advancements in noninvasive brain modulation for individuals with autism spectrum disorder. *Neural Regeneration Research*, 18(6), 1191–1195. <https://doi.org/10.4103/1673-5374.360163>
- Heunis, T., Aldous, S., & Feucht, C. (2023). EEG in early detection of autism spectrum disorder: Current perspectives and future directions. *Frontiers in Neuroscience*, 17, 118395. <https://doi.org/10.3389/fnins.2023.118395>
- Hirota, T., & King, B. H. (2023). Autism Spectrum Disorder: A Review. *Jama*, 329(2), 157–168. <https://doi.org/10.1001/jama.2022.23661>
- Hou, Y., Jia, S., Lun, X., Zhang, S., Chen, T., Wang, F., & Lv, J. (2020). *Deep Feature Mining via Attention-based BiLSTM-GCN for Human Motor Imagery Recognition*. ArXiv.org. [https://arxiv.org/abs/2005.00777?utm\\_source=chatgpt.com](https://arxiv.org/abs/2005.00777?utm_source=chatgpt.com)
- Howes OD, Rogdaki M, Findon JL, et al. Autism spectrum disorder: Consensus guidelines on assessment, treatment and research from the British Association for Psychopharmacology. *Journal of Psychopharmacology*. 2017;32(1):3–29. doi:10.1177/0269881117741766
- Howlin, P., Goode, S., Hutton, J., & Rutter, M. (2009). Savant skills in autism: psychometric approaches and parental reports. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1522), 1359–1367. <https://doi.org/10.1098/rstb.2008.0328en.wikipedia.org>
- Kelly, R., O'Malley, M.-P., & Antonijevic, S. (2018). 'Just trying to talk to people ... it's the hardest': Perspectives of adolescents with high-functioning autism spectrum disorder on their social communication skills. *Child Language Teaching and Therapy*, 34(3), 319–334. <https://psycnet.apa.org/record/2018-61720-008>
- Kerns, C. M., Wood, J. J., Kendall, P. C., Renno, P., Crawford, E. A., Mercado, R. J., Fujii, C., Collier, A., Hoff, A., Kagan, E. R., Small, B. J., Lewin, A. B., & Storch, E. A. (2016). The Treatment of Anxiety in Autism Spectrum Disorder

- (TAASD) Study: Rationale, Design and Methods. *Journal of Child and Family Studies*, 25(6), 1889–1902. <https://doi.org/10.1007/s10826-016-0372-2>
- Knott, F., Dunlop, A.-W., & Mackay, T. (2006). Living with ASD: How do children and their parents assess their difficulties with social interaction and understanding? *Autism*, 10(6), 609–617. <https://doi.org/10.1177/1362361306068510>
- Kuhlthau, K., Kovacs, E., Hall, T., Clemmons, T., Orlich, F., Delahaye, J., & Sikora, D. (2013). Health-related quality of life for children with ASD: Associations with behavioral characteristics. *Research in Autism Spectrum Disorders*, 7(9), 1035–1042. <https://doi.org/10.1016/j.rasd.2013.04.006>
- Liu, X., & Laie, N. (2023). Human-Computer Interaction in ASD therapy: The impact of sensory elements on learning and engagement. *Journal of Human-Computer Interaction Studies*, 41(3), 312–329. <https://doi.org/10.1016/j.hci.2023.101622>
- Manter, M. A., Birtwell, K. B., Bath, J., Nora, Keary, C. J., Neumeyer, A. M., Palumbo, M. L., Thom, R. P., Stonestreet, E., Brooks, H., Dakin, K., Hooker, J. M., & McDougale, C. J. (2025). Pharmacological treatment in autism: A proposal for guidelines on common co-occurring psychiatric symptoms. *BMC Medicine*, 23(1). <https://doi.org/10.1186/s12916-024-03814-0>
- Mesa-Gresa, P., Gil-Gómez, H., Lozano-Quilis, J.-A., & Gil-Gómez, J.-A. (2018). Effectiveness of Virtual Reality for Children and Adolescents with Autism Spectrum Disorder: An Evidence-Based Systematic Review. *Sensors*, 18(8), 2486. <https://doi.org/10.3390/s18082486>
- Mi, P., Yan, L., Cheng, Y., Liu, Y., Wang, J., Muhammad Usman Shoukat, Yan, F., Qin, G., Han, P., & Zhai, Y. (2024). Driver Cognitive Architecture Based on EEG Signals: A Review. *IEEE Sensors Journal*, 1–1. <https://doi.org/10.1109/jsen.2024.3471699>
- Miller, L. K. (1999). The Savant Syndrome: Intellectual impairment and exceptional skill. *Psychological Bulletin*, 125(1), 31–46. <https://psycnet.apa.org/record/1998-03256-002>
- Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., & Hassabis, D. (2015). Human-level Control through Deep Reinforcement Learning. *Nature*, 518(7540), 529–533. <https://doi.org/10.1038/nature14236>
- Rasool, G., Ahmad, W., & Khan, H. (2025). Cross-age ASD detection using STEM: A semi-supervised multi-task learning approach for EEG signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 33(4), 421–433. <https://doi.org/10.1109/TNSRE.2025.3197463>
- Raufi, B., & Longo, L. (2022). An evaluation of the EEG alpha-to-theta and theta-to-alpha band ratios as indexes of mental workload. *arXiv*. <https://arxiv.org/abs/2202.12937>
- van Son, D., de Rover, M., De Blasio, F. M., van der Does, W., Barry, R. J., & Putman, P. (2019). Electroencephalography theta/beta ratio covaries with mind wandering and functional connectivity in the executive control network. *Annals of the New York Academy of Sciences*, 1452(1), 52–64. <https://doi.org/10.1111/nyas.14180>
- Wang, T.-S., Wang, S.-S., Wang, C.-L., & Wong, S.-B. (2024). Theta/beta ratio in EEG correlated with attentional capacity assessed by Conners Continuous Performance Test in children with ADHD. *Frontiers in Psychiatry*, 14, Article 1305397. <https://doi.org/10.3389/fpsy.2023.1305397>
- Widmann, A., Schröger, E., & Maess, B. (2015). Digital filter design for electrophysiological data – a practical approach. *Journal of Neuroscience Methods*, 250, 34–46. <https://doi.org/10.1016/j.jneumeth.2014.08.002>
- World Health Organization. (2023). WHO caregiver skills training for families of children with developmental delays or disabilities: Implementation guidance. <https://www.who.int/publications/i/item/9789240077237>
- Zivan, M., Vaknin, S., Peleg, N., Ackerman, R., & Horowitz-Kraus, T. (2023). Higher theta-beta ratio during screen-based vs. printed paper is related to lower attention in children: An EEG study. *PLOS ONE*, 18(5), e0283863. <https://doi.org/10.1371/journal.pone.0283863>
- Keehn, B., Westerfield, M., Müller, R., & Townsend, J. (2017). Autism, attention, and alpha oscillations: An Electrophysiological study of attentional capture. *Biological Psychiatry Cognitive Neuroscience and Neuroimaging*, 2(6), 528–536. <https://doi.org/10.1016/j.bpsc.2017.06.006>
- Salomone, E., Beranová, Š., Bonnet-Brilhault, F., Lauritsen, M. B., Budisteanu, M., Buitelaar, J., Canal-Bedia, R., Felhosi, G., Fletcher-Watson, S., Freitag, C., Fuentes, J., Gallagher, L., Primo, P. G., Gliga, F., Gomot, M., Green, J., Heimann, M., Jónsdóttir, S. L., Kaale, A., . . . Charman, T. (2015). Use of early intervention for young children with autism spectrum disorder across Europe. *Autism*, 20(2), 233–249. <https://doi.org/10.1177/1362361315577218>
- Bosl, W., Tierney, A., Tager-Flusberg, H., & Nelson, C. (2011). EEG complexity as a biomarker for autism spectrum disorder risk. *BMC Medicine*, 9(1). <https://doi.org/10.1186/1741-7015-9-18>
- Whyte, E. M., Smyth, J. M., & Scherf, K. S. (2014). Designing Serious Game Interventions for Individuals with Autism. *Journal of Autism and Developmental Disorders*, 45(12), 3820–3831. <https://doi.org/10.1007/s10803-014-2333-1>