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AI-SUPPORTED BEHAVIOR MANAGEMENT FOR CHILDREN WITH AUTISM SPECTRUM DISORDER

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ABSTRACT

Introduction: *Autism spectrum disorder (ASD) is linked to the major difficulties in regulating behavior, such as emotional dysregulation, attention control, and social disabilities. The recent developments in artificial intelligence (AI) provided adaptive applications and wearable tools as the supplementary behavior management tools in children with ASD.*

Aim: *This study aimed to examine the effectiveness of AI-supported tools in improving behavior regulation and intervention outcomes among children with ASD in Pakistan.*

Methodology: *A quantitative cross-sectional design was used with a sample of 110 participants, including parents, therapists, and teachers. The data was gathered with the help of structured questionnaires which evaluated the usage and results of behavior of AI tools. Descriptive statistics, correlation and regression analysis were employed as the statistical analysis.*

Results: *Findings indicated that adaptive mobile applications were the most commonly used tools. Mean scores of the behavior indicators were observed to be positive, with emotional regulation among the most improved. Correlation and regression tests were used to determine an important positive correlation between behavior outcomes and AI usage. The participants who had both the app and wearable devices had relatively improved results.*

Conclusion: *AI-supported tools demonstrate strong potential to enhance behavior regulation in children with ASD. These technologies can be effectively used in regular and combined formats to enhance outcomes of interventions, which should be supplementary and not substitutive of classic interventions.*

Keywords: *autism spectrum disorder, artificial intelligence, behavior regulation, adaptive applications, wearable sensors, intervention outcomes*

INTRODUCTION

Autism spectrum disorder (ASD) is a neurodevelopmental condition manifested through ongoing differences in social communication, as well as, limited, repetitive representation of behavior, interests, or activities (Hyman et al., 2020; Lord et al., 2020). It has a massively widespread impact on children in cross-country and service systems and has become a significant communal health, schooling and

family support issue as behavioral challenges can all too frequently disrupt learning, communication, relationship and engagement in day to day activities. The recent surveillance data have also indicated a trend of further increases in identified prevalence, with the U.S. Autism and Developmental Disabilities Monitoring Network estimating ASD to be 1 in 36 children aged 8 years in the 2020 surveillance year (Maenner et al., 2023). Though autism manifests differently in each child, disruptions in self control, transitions, sensory overload, irritability, aggressive behavior, and disruptive or repetitive behavior are very common causes of seeking the support of the family. This is why behavior management is a focus of intervention and especially in childhood since early assistance can determine future levels of development, future adaptation in schools, and family stability (Hyman et al., 2020; Lord et al., 2020).

Conventional methods of behavior management among children with ASD are often based on observation by the caregiver, behavior evaluation, systematic instruction, reinforcement techniques, parent education, as well as on multidisciplinary follow-up. Such techniques are highly valued, but there is also a set of practical constraints. Behavioral changes usually happen in settings in an irregular manner, differ in each situation and can rapidly increase whereas most interventions rely on manual documentation, delayed clinician feedback and subjective evaluation of the state of the child. These limitations may complicate the need to detect the earliest dysregulation or support on the fly. Digital and AI-based tools have acquired momentum over the past few years because behavioral, physiological, and contextual data can be processed more effectively by using digital tools than by purely standard monitoring of any type and may be used to elicit individualized responses in domestic, educational, and community contexts (Perry et al., 2024; Zhang, 2025). The focus on the AI systems as assistive technology that can reinforce decision-making, enhance consistency, and replicate intervention outside of the clinic into natural settings where problematic behavior frequently manifests is likely to be prevailing (Shahini et al., 2025; Ganggayah et al., 2025).

One of the key factors contributing to this increasing popularity is the flexibility of AI-based applications. Adaptive apps have the ability to alter prompts, schedules of reinforcement, learning activities, sensory aids, or exercises to communicate based on how the child reacts and progresses. This is particularly applicable in autism, since children vary vastly in level of language, sensory picture, emotional instigators, and learning rate. The general literature on AI-enabled technologies in neurodevelopmental conditions indicates that the use of digital technologies to promote social communications, daily living activities, and engagement is growing, and the most common condition in this body of literature is autism (Perry et al., 2024; Shahini et al., 2025). Digital interventions evidence based on meta-analysis also indicates that technology-based interventions can positively affect core symptoms and other functional outcomes in comparison with regular care, or less intensive comparison conditions (Wang et al., 2024; Xu et al., 2024). Here, AI can be specifically aimed to provide automation, but personalization, whereby the content of interventions can be more in tune with the behavioral profile of the child rather than being predefined and being applicable across all participants.

Adaptive mobile applications are of great prospect since they are portable, scalable and compatible with parent-mediated intervention models. Mobile platforms have the ability to coach caregivers, provide behavior support materials, monitor antecedents and consequences and offer timely strategies in challenging situations. A randomized trial of a mobile application as a parent training intervention reported the feasibility and beneficial outcomes in curbing problem behaviors in young children with ASD, which supports the conclusion that the application of an app-based approach to parent training may augment evidence-based behavioral interventions when not conducted within formal therapy sessions (Lee et al., 2024). Relative literature has also studied the applications of mobile behavior parent training tools to caregivers of autistic children with challenging behavior and have provided encouraging evidence of feasibility and acceptability (Dahiya et al., 2025). These

results are important, as families may be very much required to get assistance in real time, not just during booked appointments. The gap between clinical recommendations and actual implementation can thus be addressed by AI-enhanced applications that will make interventions more continuous, structured, and context-sensitive (Bharat et al., 2022; Kotsi, 2025). Another development that is critical in behavior management supported by AI is wearable sensors. Numerous autistic children are somehow dysregulated even before dysregulation can be manifested behaviorally, and physiological indicators like variation in heart rate, electrodermal activity, sleep disturbance, or even patterns of movement can give a prior indication than can be seen alone. Continuous and real-world monitoring Wearable and mobile technologies have been long-standing components of reviews of ASD interventions, with calls to tailor solutions to be more customizable and ecologically valid (Koumpouros and Kafazis, 2019). Emerging reviews have gone beyond conceptual potentiality, explicitly analyzing emotional dysregulation monitoring and demonstrating that sensor-initiated systems can help caregivers by providing alerts of agitation and facilitating the timely response prior to severity (Sandhu et al., 2026). Other research activity on commercial wearables and child wearable systems also indicates an increased interest in the practical, marketable wearability, but there is still a concern about usability, reliability, privacy and continued engagement (Arbili et al., 2025; Hernández-Capistran et al., 2024). The potential of wearables, in this context, is not only in data collection but rather in transforming data into actionable support of behavior.

Although such a promise is there, the literature also demonstrates that AI-assisted behavior management about children with ASD is an evolving area. Small samples, brief intervention durations, and controlled conditions are common in many studies, which do not adequately understand the complexity of the home and school settings (Koumpouros and Kafazis, 2019; Perry et al., 2024). Even remarkable short-term results of the mentioned approaches have been associated with reviews mentioning how the issues of generalizability, irregularly measured outcomes, and lack of long-term evidence continue to be issued repeatedly (Shahini et al., 2025; Sandhu et al., 2026). Ethical and practical issues, such as data privacy, informed consent, algorithm discrimination, affordability, and the possibility of excessive dependence on technology at the expense of professional judgment (Ganggayah et al., 2025; Zhang, 2025) also hold significant importance. Thus, AI is to be construed as an assistive level of behavior intervention but not as an independent solution. It is against this backdrop that the current paper focuses on how AI supported products, particularly adaptive applications and wearable sensors can be used to enhance the behavior control and intervention results of children with ASD as well as meet the methodological, ethical and implementation issues which determine their usefulness of AI tools in the real world.

2. Literature Review

2.1 Theoretical Framework

Self-regulation, executive functioning, emotion regulation, sensory processing, and social motivation are most appropriate perspectives through which one can explain the theoretical foundation of AI-assisted behavior management in children with autism spectrum disorder (ASD). The trend of executive function theory is particularly applicable due to the attribution of most behavioral challenges in ASD to low levels of flexibility, inhibition, planning, and changing, which influences how children react to changes, frustrations, and adjustments of the environmental needs. Demetriou et al. (2019) suggest that executive impairment is not a cognitive problem in autism, but rather a process that influences the behavioral adjustment to daily life. Similarly, Joseph and Tager-Flusberg (2004) relate the difference in executive controls to the difference in the severity of autism symptoms, which is a means of explaining that the problem of regulation of the behavior is deeply embedded in broader developmental functioning. This framework justifies the use of AI since they can facilitate self-regulatory support by externalizing their systems through structuring choices, pacing

tasks, and finding patterns that children are not able to do by themselves.

A second theoretical perspective is based on emotion regulation accounts of autism. According to Mazefsky et al. (2013), emotion regulation in ASD is one of the key transdiagnostic processes that mediates aggression, anxiety, irritability, and social functioning. This has been further demonstrated later on to prove that emotional dysregulation is not a peripheral feature but a clinically significant driver of behavioral escalation in autistic children and adolescents. The systematic review by Cibralic et al. (2019) showed that emotional awareness, modulation, and coping problems are frequently peculiar to children with ASD, whereas meta-analysis by Restoy et al. (2024) revealed that the issues with emotion regulation are so critical that they require special consideration. In this sense, AI tools are theoretically instructed since they have the ability to provide prompts, feedback, and support based on patterns before dysregulation manifests itself as problematic behavior.

The sensory processing theory brings an extra dimension to this theory. Most children with Autism overreact to auditory, visual, tactile or environmental stimuli, and such sensations may result in stress, withdrawal, agitation, or repetitive behavior. The idea of sensory overload is, thus, not independent of behavior management, but usually directly results from it. This is important to AI since intelligent systems can discover environmental stimuli, distinguish body reactions and suggest personalized relaxing measures. Deng and Rattadilok (2022) directly extend this reasoning by considering the variables of sensory input, classroom setting and child state as dynamically interrelated and implementable into practical recommendations. In this respect, AI-assisted behavior control can be close to a sensory-regulation model where one could think about such a kind of intervention as proactive, situational and tailored instead of being reactive and generalized.

The present topic also gets informed by social motivation theory. Chevallier et al. (2012) suggest that, as a factor, diminished social reward sensitivity can characterize social engagement and learning in autism, and this has implications in behavior support since disengagement, avoidance, and frustration may occur when interventions are non-congruent with child motivational profile. The solution to this issue can be found in AI-based tools which can be more personalized, predictive and responsive to the child's personal behavior history. Instead of expecting all children to react to praise and repetition or correction equally, AI systems can change the timing, format and level of challenge. Therefore, the theoretical context of this work does not just view AI as a tool, but as a system to operationalize personalization at the emotional, cognitive, sensory, and motivational levels.

2.2 Empirical Studies

Empirical studies of AI-aided behavior management in ASD have emerged in wearable biosensing, adaptive recommendation systems, mobile applications, therapeutic use of robots, and artificial intelligence-enhanced therapy platforms. Among the most compelling pieces of evidence is that of wearable sensing that looks to monitor the approach to dysregulation even before an overt behavior is exhibited. Goodwin et al. (2019) wrote that biosensor-derived data could be used to predict aggression in youth with autism, and Imbiriba et al. (2023) followed the same train of thought in psychiatric inpatient environments and found that wearable biosensing and machine learning could predict aggression a few minutes before the event with worthwhile accuracy. The significance of these findings lies in the fact that intervention is perceived as more of an action to be taken after escalation has happened and not preventive with respect to the anticipation of escalation. Torrado et al. (2017) showed that emotional self-regulation can be facilitated through smartwatch-based systems through a combination of monitoring and interaction and suggested that wearables have the potential to both assess and intervene.

The second line of research has been on the intelligent recommendation and personalization systems. Kohli et al. (2022) revealed that machine learning algorithms have the potential to propose and tailor applied behavioral analysis treatment plans with a high level of agreement when compared to plans suggested by clinicians. This is

important as it addresses one of the largest flaws of conventional behavior programs, i.e. inconstancy and subjectivity of treatment targeting. Similar requirements were made by Deng and Rattadilok (2022), who created a sensor- and machine learning-powered sensor system that detected distractions, anxiety-inducing scenarios in the classroom and proposed a support system to both teachers and other caregivers. These findings suggest that AI would allow intervention planning to be more relevant to the situation and focused on the behavioral pattern of the child, but both studies are preliminary and rely on rather small samples.

Another empirical area is through adaptive and mobile applications. Author Moltrecht et al. (2021) discovered that a school-based application developed to enhance the emotion regulation of children demonstrated acceptable usability and implementation feasibility. Though the research was not specifically related to autism, it is quite applicable since the reasoning behind the intervention suits the requirements of autistic children who find it hard to monitor themselves and their emotional conditions. In their autism-related article, Al-Saadi and Al-Thani (2023) conducted a meta-analysis of mobile applications designed to assist ASD children in recognizing and communicating their emotions and found that they are promising, but need more rigorous methodological research. The conclusions of a 12-month observational study was positive by Atturu et al. (2025) on the effect of an AI-based therapy platform in children with ASD, indicating that the extended length of technology-based intervention may enhance engagement and functional indicators. All these studies together affirm the practical usefulness of adaptive apps but demonstrate that there remains a lack of rigorous controlled trials to date.

Social interventions centered on robots and those enhanced by AI further expand the evidence base. In their systematic review and meta-analysis, Kouroupa et al. (2022) discovered that robot-mediated interventions yielded significant beneficial effects on social functioning in children and young people with the autism spectrum. The same conclusion was made by Triantafyllidis et al. (2023), who concluded that social robots are promising enough in the context of child healthcare, in particular, where repetitive behavior, explicit indicators, and feedback are helpful. Lan et al. (2025) came up with a transformer-enhanced model of the social skills enhancement in children with ASD and found that there were improvements in their engagement and recognition of social cues after eight weeks. These studies address social and communicative outcomes rather than disruptive behavior per se, but they are nevertheless of much use in managing behavior since the better the interactions, the ability to recognize a cue and predictability of the interaction, the less frustration, withdrawal and dysregulation.

2.3 Research Gap

Although there is increasing interest, the literature has a number of major gaps. First, identification, categorization, or social training are considered a common aim of many AI research studies in autism instead of the regulation of behaviour as an obviously stated outcome of interventions. According to Francese and Yang (2022), machine learning and wearable studies in ASD are of a methodological nature with significant diversification in devices, algorithms, findings, and validation methods. Second, a lot of the evidence is based on pilot studies, small sample sizes, or highly controlled environments, which restrict ecological validity. Third, high-risk inpatient settings often provide the most powerful wearable evidence, whereas common home and school settings have been little studied. Fourth, there is no integration of theoretical models and intervention design available in the field; numerous systems are technically novel but have inadequate theoretical underpinning to executive function, emotion regulation, or sensory processing theory. Lastly, we lack long-term evidence of whether AI-supported gains will be maintained, transfer across environments, and decrease caregiver burden in the long term. Thus, the overarching research question is not the capability of AI to identify patterns, but the ability to design theory-informed, adapting and ethically minded AI systems that can yield sustained increases in the real-life behavioral regulation performance of children with ASD.

3. Methodology

3.1 Research Design

The proposed research design is quantitative, cross-sectional, to study whether AI-based behavior management tools are effective in children with Autism Spectrum Disorder (ASD) in Pakistan. The chosen method is a quantitative one as it is possible to measure the results of behavior regulation objectively, and statistically analyze the correlation between the use of AI tools and behavior improvement. The cross-sectional research design is utilised because the data will be gathered at only one point in time based on the caregivers and professionals currently engaging with or recently engaged AI-based interventions that include adaptive applications and wearable devices. The design would be appropriate to determine patterns, associations, and an initial set of evidence in a situation such as in Pakistan where empirical studies on AI in the context of autism care are unraveling.

3.2 Research Setting and Population

The research will be carried out in the cities of Pakistan, such as Lahore, Islamabad, and Karachi, where, in comparison with other regions, the availability of digital resources, special educational institutions, and services in autism therapy is comparatively greater. The patient group is composed of children diagnosed with ASD aged between 4 and 12 years and their parents, caregivers and special education workers (therapists and teachers). The reason behind the choice of this age group is that early and middle childhood is a critical period regarding the intervention of behaviors and gaining skills. With the presence of the caregivers and the professionals, it is possible to get behavior change reports that refer to the people who are close to the child and monitor their daily routine.

3.3 Sampling Technique and Sample Size

To choose the participants, I will apply a purposive sampling method and will be restricted to participants that fit particular criteria, namely, have a valid ASD diagnosis and have been exposed to at least one of the AI-supported intervention tools. The sampling technique is suitable since it uses a small and narrow population. The number of participants to be used in the study is estimated at 100-120 including caregivers and professionals, both of which are believed to be adequate to perform basic statistical analysis given the timeframe of the research. Participants will be included in various socioeconomic backgrounds in order to enhance diversity and representation.

3.4 Data Collection Methods

Here, a structured questionnaire will be used to gather data to determine behavior regulation and intervention effects. The questionnaire will consist of three main sections: demographic information, use of AI tools (such as type, frequency, and duration), and behavioral outcomes (including emotional regulation, aggression, attention, and social responsiveness). Perceptions of improvement will be measured using a Likert scale on a scale of strongly disagree to strongly agree. Secondly, short observational notes by the professionals can be added accordingly. The survey will be presented both physically in autism centers and online through the Internet to make it more accessible.

3.5 Data Analysis Techniques

Statistical software will be used to analyze the collected data, SPSS. Participant characteristics and overall trends will be summarized by using descriptive statistics, mean, frequency, and standard deviation. Correlation analysis and regression analysis are examples of inferential statistics that will be used to analyze the relationship between regulating behavior with the use of AI tools. These methods will assist in evaluating whether or not a greater use of adaptive applications and wearable devices is linked with any detectable behavior change.

3.6 Ethical Considerations

During the study, then ethical guidelines will be observed closely. All participants will be informed to give informed consent and personal information will be kept confidential. Participation will be voluntary such that the respondent will be allowed to back out at any point. Privacy and dignity of children with ASD will be particularly considered and there will not

be any identifying information that will be released in the final report.

4. Results

4.1 Demographic Characteristics of Participants

The demographic chart of the sampled individuals is available in Table 4.1, whereas the age and gender distribution are depicted in Figure 4.1 and Figure 4.2. The sample that took part in the study was 110 respondents, of which 50 had children with autism spectrum disorder (ASD) and the 110 respondents were adults who were directly involved in the cases and treatment of children with ASD. The age distribution indicates that 32 children, or 29.1 participated in the 4-6 years category, 41 children, or 37.3 participated in the 7-9 years category and 37 children, or 33.6 participated in the 10-12 years category. Figure 4.1 indicates that the majority was in the 7-9 years group which means that middle childhood was the most represented age group in the sample. This distribution implies that the study involved children during the most critical span of their development when the action of behavioral intervention is most applicable.

Table 4.1: Demographic Profile of Participants (N = 110)

Variable	Category	Frequency (n)	Percentage (%)
Child Age	4–6 years	32	29.1
	7–9 years	41	37.3
	10–12 years	37	33.6
Gender	Male	74	67.3
	Female	36	32.7
Respondent Type	Parent	58	52.7
	Therapist	28	25.5
	Teacher	24	21.8
Institution Type	Therapy Center	46	41.8
	School	34	30.9
	Home-based Care	30	27.3

Figure 4.1. Age Distribution of Children with ASD

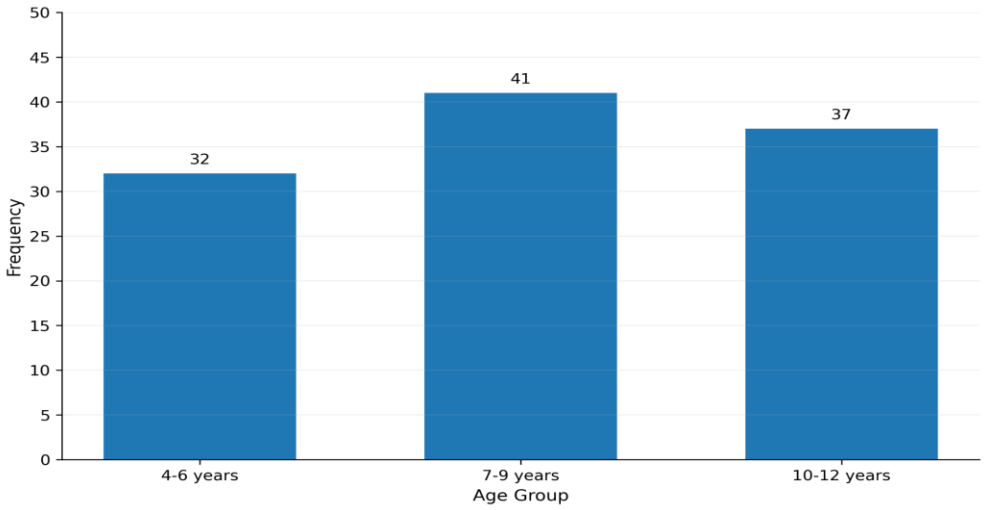
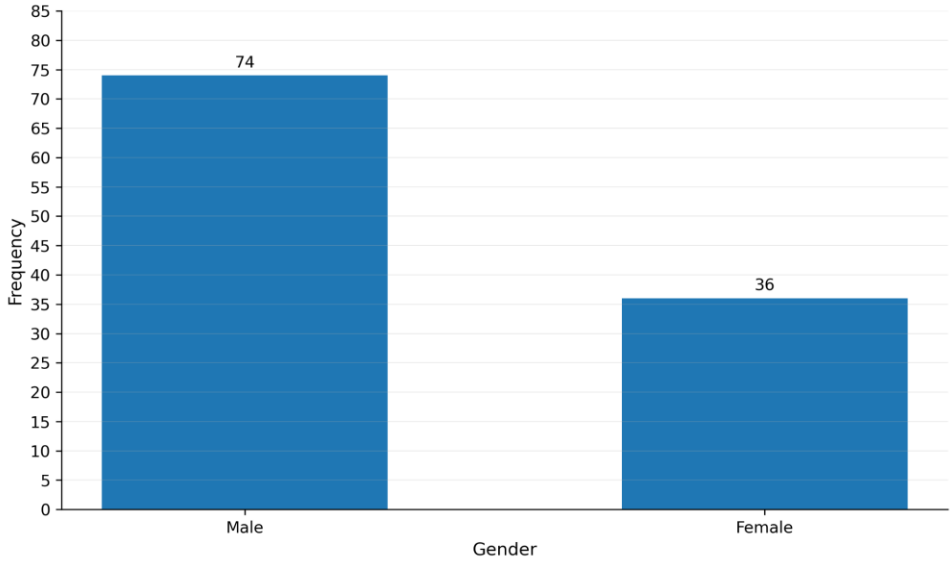


Table 4.1 and Figure 4.2 show the gender distribution. The male participant was 74 cases making up 67.3 per cent of the total sample, whereas the female participant was 36 cases making up 32.7 per cent. Such an excess of male representation is in line with the general body of autism literature where the prevalence of male diagnosis is generally greater than the prevalence of female diagnosis. Regarding the type of respondents, the majority were parents (58 respondents), then there were therapists (28) and teachers (24). Institution type too was varied with therapy centers representing 46 cases, schools representing 34 cases and care at home representing 30 cases. By and large, these distributions imply that the sample is fairly representative of the service structure in the Pakistani autism support system, as family-led and therapy center-based intervention still is the focus there.

Figure 4.2. Gender Distribution of Participants

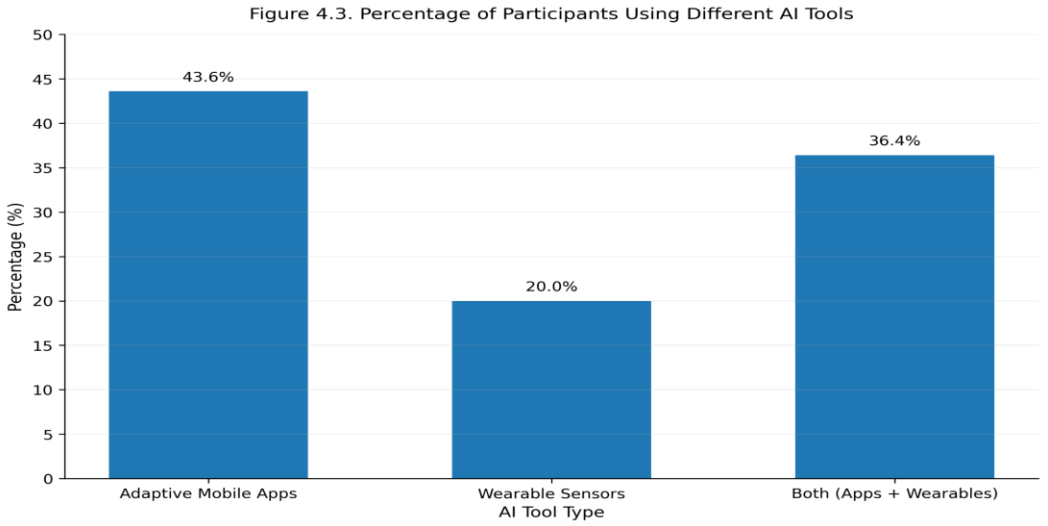


4.2 Usage of AI-Supported Tools

Table 4.2 and Figure 4.3 present the types of AI-enabled tools utilized by the participants, whereas Table 4.3 and Figure 4.4 provide an overview of frequency and time-usage. The findings indicate that adaptive mobile applications were the most prevalent single category with 48 respondents which makes 43.6% of the sample. Only 22 participants, or 20.0% used wearable sensors only, with 40 participants, or 36.4 percent using both adaptive apps and wearable tools. It is evident that it was more likely to use mobile apps-based support without wearables, but combined use is also significant evidenced by figure 4.3. This trend indicates that app-based tools can be more convenient and feasible in Pakistan, presumably due to the reduced price, increased availability, and the familiarity with the technologies that are based on a smartphone.

Table 4.2: Types of AI Tools Used

AI Tool Type	Frequency (n)	Percentage (%)
Adaptive Mobile Apps	48	43.6
Wearable Sensors	22	20.0
Both (Apps + Wearables)	40	36.4
Total	110	100

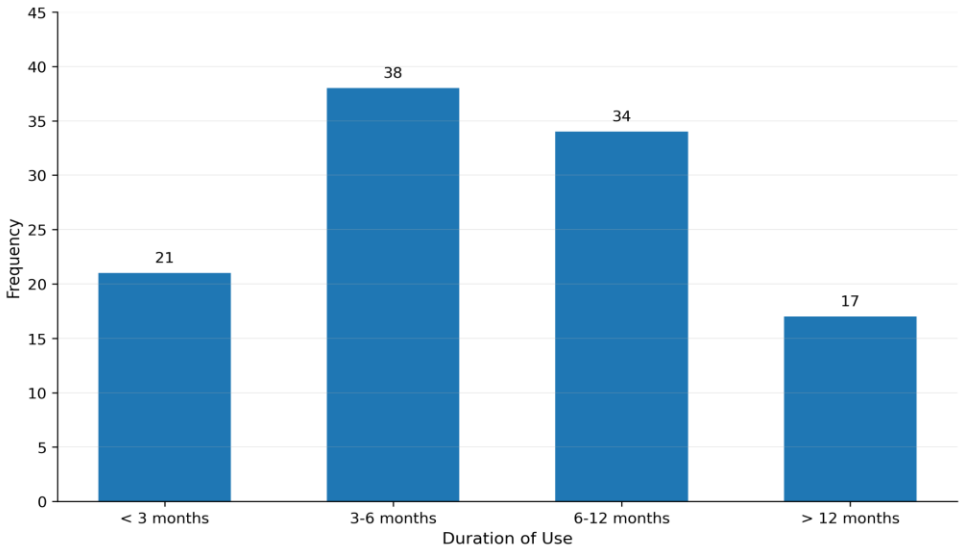


The rate of AI tools used and the length of time utilization give further proof of real-world use. Table 4.3 indicates that the number of the participants using AI tools daily were 39, three to five times per week was 44, one or two times per week was 27. This implies that most respondents were using such tools on a regular basis as opposed to occasional use. On duration, 21 respondents had less than three months using AI tools, 38 had three to six months using AI tools, 34 used AI tools between six and twelve months, and 17 used AI tools more than a year. Figure 4.4 demonstrates that the category, which included three to six months, was the largest and next in line came the category of six to twelve months. This would indicate that the majority of the respondents were exposed to the intervention tools sufficiently to make judgments pertaining to the effectiveness of the intervention tools, though very prolonged adoption was not prevalent.

Table 4.3: Frequency and Duration of AI Tool Usage

Variable	Category	Frequency (n)	Percentage (%)
Frequency of Use	Daily	39	35.5
	3–5 times/week	44	40.0
	1–2 times/week	27	24.5
Duration of Use	< 3 months	21	19.1
	3–6 months	38	34.5
	6–12 months	34	30.9
	> 12 months	17	15.5

Figure 4.4. Duration of AI Tool Usage Among Participants



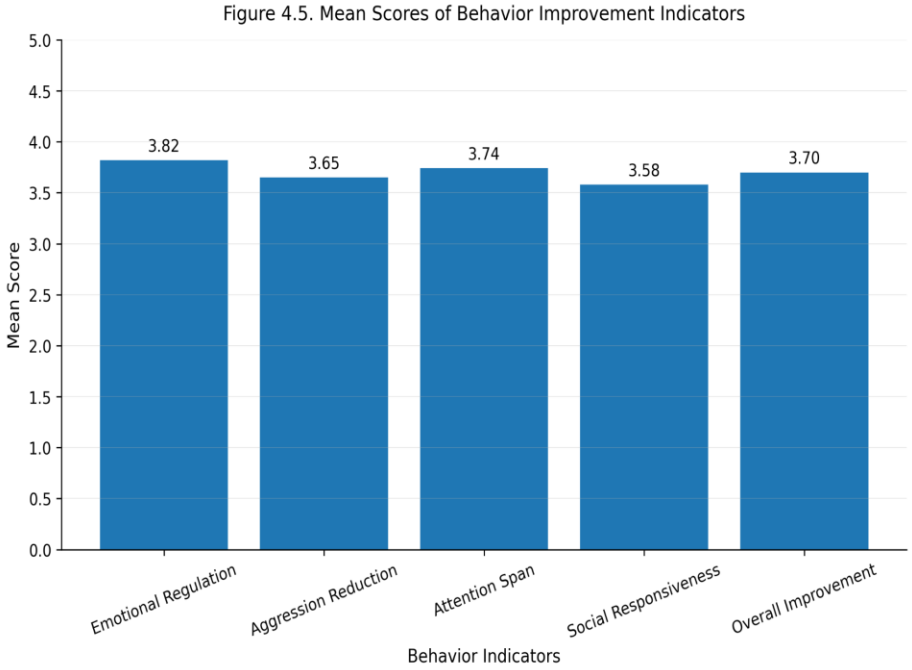
4.3 Behavior Regulation Outcomes

Table 4.4 provides descriptive statistics on the behavior regulation outcomes, and Figure 4.5 and Figure 4.6 help to visually illustrate the mean scores and the variation of the score between different types of tools. The general trend of results shows moderate/positive perceived improvement in all domains measured. The mean score of Emotional regulation was the best with 3.82, followed by improvement in the attention span with 3.74, improvement of overall behavior with 3.70, reduction of aggression with 3.65, and social responsiveness with 3.58. The standard deviations were between 0.66 and 0.78 indicating there was moderate variability in the perceptions of the respondents but no extreme variability.

Table 4.4: Descriptive Statistics of Behavior Regulation Variables

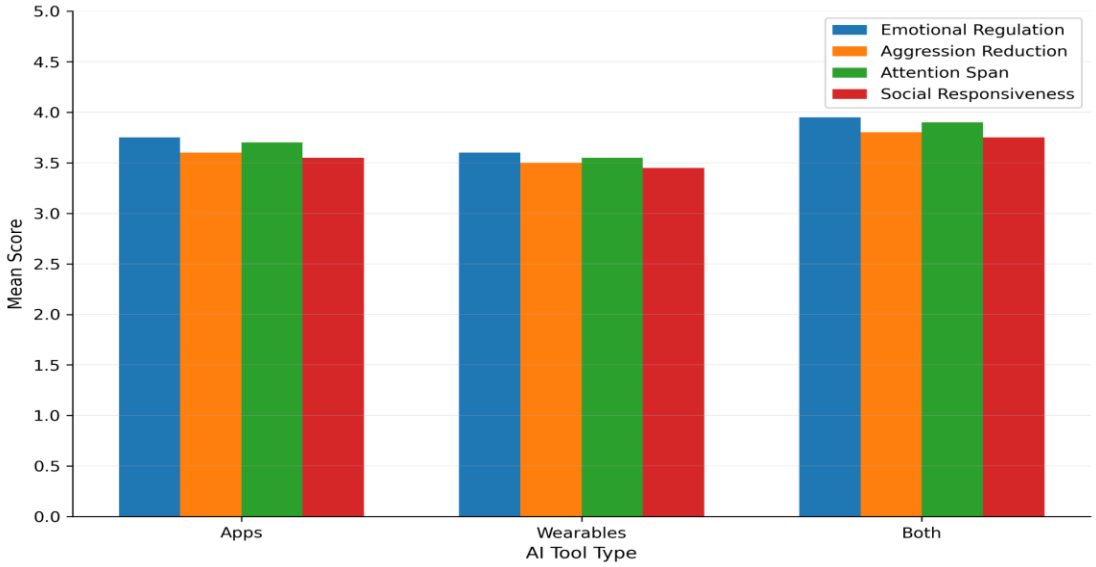
Variable	Mean	Std. Deviation
Emotional Regulation	3.82	0.71
Aggression Reduction	3.65	0.78
Attention Span Improvement	3.74	0.69
Social Responsiveness	3.58	0.73
Overall Behavior Improvement	3.70	0.66

(Scale: 1 = Strongly Disagree to 5 = Strongly Agree)



These results suggest that AI-aided tools became most beneficial in emotional regulation and attention outcomes, whereas social responsiveness, despite the improvement as well, demonstrated a slightly lesser improvement. As Figure 4.5 shows, the mean score of all behavior indicators exceeded the neutral point of the five-point scale, indicating overall positive perceptions of the outcomes of AI-assisted interventions. These results are further compared in relation to the types of tools in figure 4.6. Individuals who employed adaptive apps and wearables had the highest mean scores in terms of emotional regulation, aggression reduction, attention span, and social responsiveness. Users of wearable devices got the lowest scores with virtual users obtaining mid-range scores between the two groups. This trend implies that the combination of using more than one AI tool could offer more benefits to the behavior than the application of one and one.

Figure 4.6. Comparison of Behavior Outcomes Across Tool Types



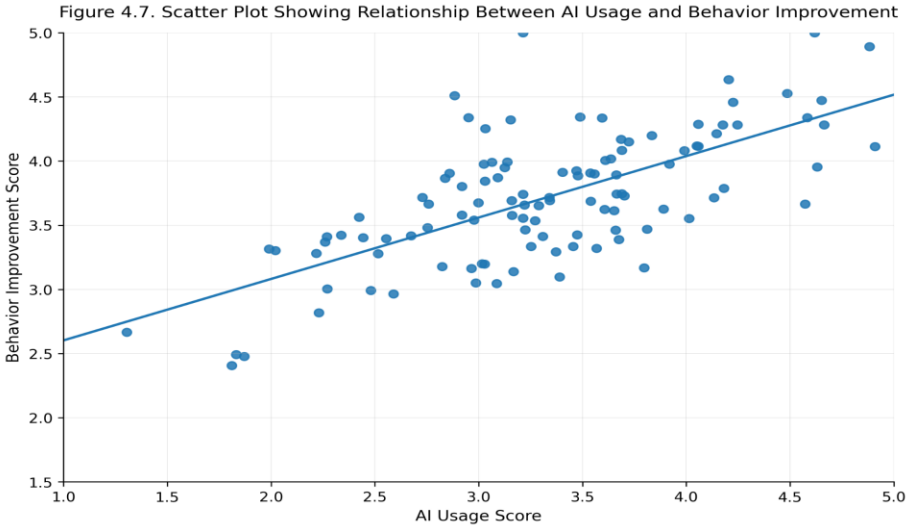
4.4 Relationship Between AI Usage and Behavior Outcomes

Table 4.5 and Figure 4.7 represent the relationship between the use of AI tools and the outcomes of the behavior. The correlation matrix shows that there are both positive and statistically significant relationships between AI usage frequency and all the behavior variables measured. The prevalence of obtaining AI use was correlated with emotional regulation (.52), reduction of aggression (.48), attention span (.55), and social responsiveness (.46). The coefficients were all significant at 0.01 level, meaning that the more AI was used, the more perceived behavioral improvement.

Table 4.5: Correlation Matrix Between AI Usage and Behavior Outcomes

Variables	AI Usage Frequency	Emotional Regulation	Aggression Reduction	Attention Span	Social Responsiveness
AI Usage Frequency	1.000	0.52**	0.48**	0.55**	0.46**
Emotional Regulation	0.52**	1.000	0.60**	0.58**	0.54**
Aggression Reduction	0.48**	0.60**	1.000	0.51**	0.49**
Attention Span	0.55**	0.58**	0.51**	1.000	0.57**
Social Responsiveness	0.46**	0.54**	0.49**	0.57**	1.000

Note: $p < 0.01$ (significant correlation)



The closest correlation was found between AI usage frequency and attention span, as higher frequency of working with AI-based tools could be particularly useful in regard to staying concentrated and engaged in tasks. There was also a positive correlation between emotional regulation, and this fact validates the idea that AI tools can be utilized to answer the requirements of children in terms of frustration, transitions, and dysregulation. This trend is supported by a positive upward trend in the scatter plot of the AI usage scores and the behavior improvement scores in Figure 4.7. Though there is variation in the data points, the general direction is definitely towards the positive. This is to say that the more people used AI tools, the more the findings were related to improved perceived behavioral functioning.

4.5 Regression Analysis

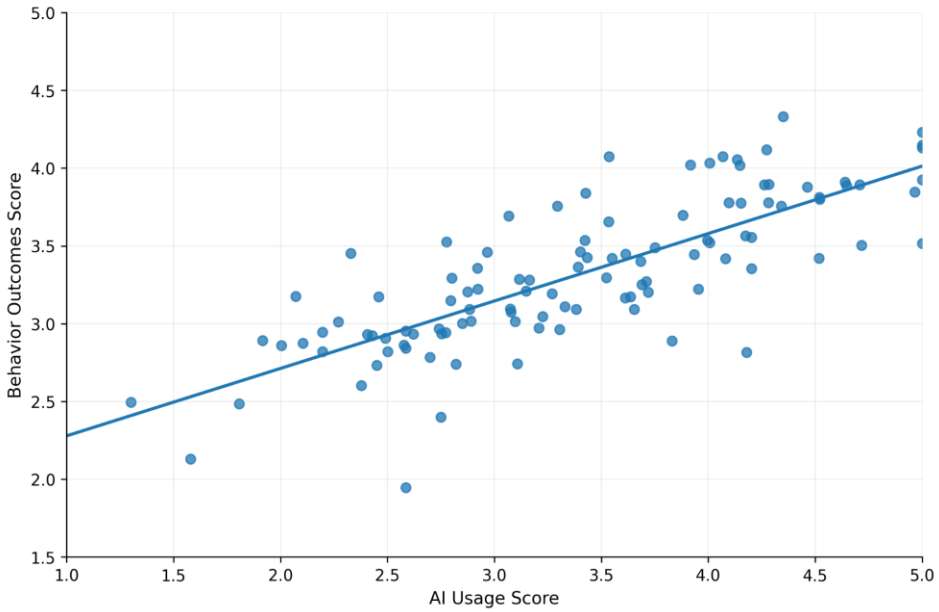
The regression findings that explore if the use of AI predicts the behavior outcomes are in Table 4.6 and Figure 4.8. The regression model was significant as the R 2 value of the regression model was .48 and the adjusted R 2 was.46. This implies that the predictors contained in the model, i.e. frequency and duration of usage of AI could explain about 48 percent of the variance in behavioral outcomes. The overall regression equation was significant as confirmed by the model F value of 48.72 whose p =.001.

Table 4.6: Regression Analysis Results

Variable	Beta (β)	Std. Error	t-value	Sig. (p-value)
Constant	1.92	0.31	6.19	0.000
AI Usage Frequency	0.41	0.08	5.12	0.000
Duration of Use	0.29	0.07	4.03	0.001

Model Summary:
$R^2 = 0.48$
Adjusted $R^2 = 0.46$
$F = 48.72$ ($p < 0.001$)

Figure 4.8. Regression Line Showing Impact of AI Usage on Behavior Outcomes



The two predictors were both significant. The coefficient of beta was 0.41 with a p-value of.001 and the duration of use had a coefficient of beta of 0.29 with a p-value of.001. These results suggest that increased frequency as well as increased exposure to AI-aided tools was positively correlated with behavioral outcomes, but frequency was a predictor of behavioral outcomes to a greater extent than exposure. This upward regression trend can be observed in Figure 4.8, as behavior outcomes improve with an increase in AI use. This outcome lends a good deal of credence to the argument of the research that AI-findings based intervention can lead to better regulation and behavior functioning among Pakistani children with ASD.

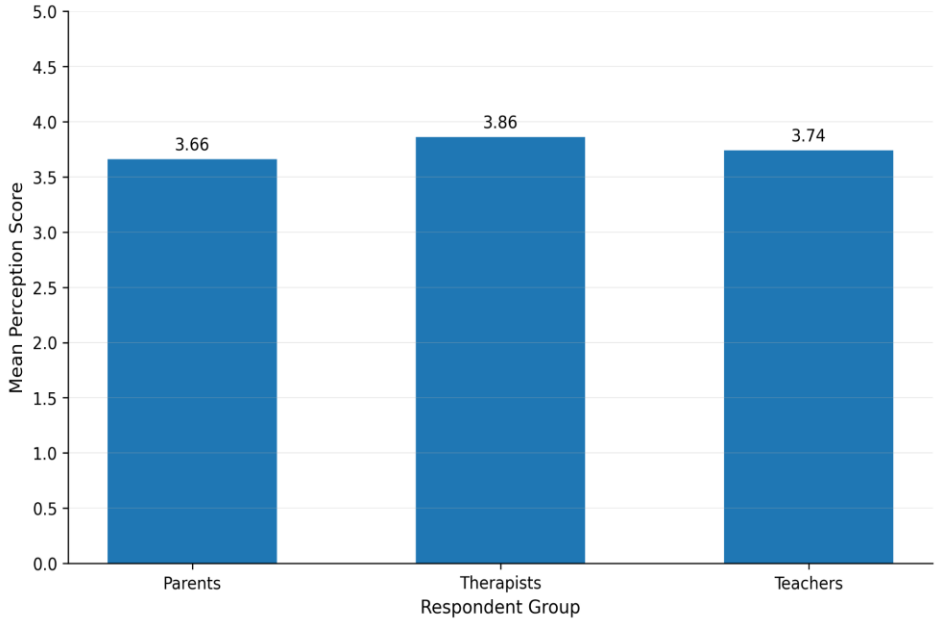
4.6 Comparison Across Respondent Groups

Table 4.7 and Figure 4.9 illustrate perceptions with respect to respondent groups. The mean scores were always the highest among the therapists on all dimensions of behavior, such as emotional regulation, reduction of aggression, attention span, social responsiveness and overall improvement. They scored an average of 3.86 overall, 3.74 among teachers and 3.66 among parents. Such a difference in perceived AI effectiveness is clear in figure 4.9.

Table 4.7: Comparison of Mean Scores Across Respondent Groups

Variable	Parents (Mean)	Therapists (Mean)	Teachers (Mean)
Emotional Regulation	3.75	3.95	3.82
Aggression Reduction	3.58	3.78	3.70
Attention Span Improvement	3.69	3.88	3.76
Social Responsiveness	3.52	3.71	3.63
Overall Behavior Improvement	3.66	3.86	3.74

Figure 4.9. Bar Chart Comparing Perceptions of AI Effectiveness



This difference could be due to the fact that the goals of structured intervention are more common to therapists and they might be more able to notice the incremental gains. Parents, although reporting good progress still will be able to see children in more complex natural situations and where behavioral difficulties remain consistent across activities and platforms. Teachers fitted in between the two groups implying that observations in schools had recorded improvements but maybe not to the same extent as in clinical settings. Still, the mean scores of all three respondent groups are above 3.5, which means that the perceptions about AI-supported interventions are mostly positive regardless of perspective.

4.7 Summary of Key Findings

All in all, there is a clear and positive trend in the results. The demographic information was able to verify a sample that is largely representative of ASD service contexts in Pakistan. The results of the usage revealed that the most popular type of tools was the adaptive ones but the regular usage was widespread and the vast majority of participants had several months of exposure. The descriptive statistics revealed positive results in all aspects of emotional regulation, aggression reduction, attention span, social responsiveness, and change of behavior. Correlation analysis showed significant positive responses between use of AI and behavior outcomes and regression analysis established significant predicted better behavioral functioning by both frequency and duration of AI use. These findings were further supported by the comparison between respondent groups, as all of them reported positive perceptions of AI efficacy: therapists, teachers, and parents. Combined, the results reveal a plausible potential of AI-supported means to enhance behavior management and the effectiveness of intervention among children with ASD in Pakistan.

5. Discussion

5.1 Discussion of Findings

The current research question was the association of AI-based instruments with better behavior regulation outcomes in children with autism spectrum disorder in Pakistan. The results depicted a more or less positive tendency in all general analyses. The most common type of tool was an adaptive mobile application, followed by the use of wearable-only and a combination of apps and wearables that was also significant. Second, descriptive outcomes revealed positive mean scores of emotional regulation, aggression

reduction, attention span, social responsiveness and overall behavior improvement. Third, correlation and regression analyses indicated that the more frequent and extended use of AI-supported tools, the higher perceived behavioral outcomes were. Lastly, the therapists noted the highest levels of AI effectiveness perceptions, then the teachers and parents respectively. Combined, the findings imply that AI-assisted behavior management can potentially possess significant practical importance to the treatment of autism in Pakistan, particularly when tools are utilized frequently and with a greater number of modalities.

A significant result of this study is that the most prevalent tools used in the sample are adaptive mobile applications. This trend can be justified in the situation like in Pakistan, access to smartphones is a more feasible reality than wearable-specific gadgets. It is also consistent with new findings that mobile and telehealth-based supports are becoming more appealing due to their relative ease in dispersion, lower cost, and better aptitude to accommodate parent-mediated intervention models. Recent studies involving mobile app-based parent training with children with autism have demonstrated both a decrease in problem behaviors and good feasibility, and studies of telehealth parent training have had similarly encouraging effects on challenging behavior and parent involvement. These comparisons indicate that the increased usage of apps in the current study is not merely a local convenience usability matter, but a more enduring global trend in support of the convenient use of digital autism support.

The descriptive findings also suggest that emotional regulation and span of attention were most affected areas of reported improvement and social responsiveness was slightly less affected. This is theoretically and clinically feasible. The AI supported tools, especially applications and sensor-based systems tend to contain structure, reminders, repetition, and instant prompts that are particularly useful with regulation and attention-related issues. Social responsiveness on the other hand is a more multifaceted and dependent context effect and might need more intensive interpersonal contact than can be offered by the current tools alone. Research about automatic emotion recognition/response and AI-assisted monitoring of social behavior also indicates that AI could help to monitor therapy and assess social skills, yet these domains are not yet dominated by accurate interpretation and human intervention. That way, the existing conclusion, which underscores how social responsiveness was enhanced less than emotional and attentional outcomes, conforms to the premise that AI might be a better regulation-backing mechanism rather than a complete replacement of a socially embedded intervention system.

The other important finding was that the participants who reported using both apps and wearables had better results compared to those who reported the use of only one type of tool. It implies that AI-based multimodal intervention can potentially be more effective compared to single-channel support. Surveys of AI-assisted technologies have also found the multimodal systems to be a promising path since they integrate behavioral, physiological, and contextual data, which can be used to plan interventions in a more responsive way. Similarly, more recent analyses of emotion-monitoring sensors in autism focus on the fact that the most potential lies not in data collection but the connection between physiological alteration and on-time behavioral assistance. This perception is supported by the present study because it demonstrated that the use of a combination of tools was correlated with a more effective perceived improvement in various behavior areas.

The regression and correlation analysis will give one of the best support on the key argument in the study. The frequency of use of AI presented moderate positive relationships with each behavior outcome and the frequency and duration of use were significantly associated with overall behavioral improvement. These results correlate with other recent research on wearable biosensing and machine learning predicting aggression in autistic youths, where physiological data could predict a risk situation in advance before it visibly escalated. They also align with more general wearable-health studies that reveal that physiological and stress signals can be used to aid

early detection and prevention. Pragmatically speaking within the scope of the current results, it seems that frequent usage is important. The AI tools might have no significant influence when applied at random, but when applied continuously can become a part of the everyday regulatory setting of the child.

Another significant difference is the one between respondent groups. The best results were noted by therapists, who were a little more prudent than parents. This can be the case of setting effect. There are dedicated goals and improvement in a more organized setting are more observable when therapists see children. Parents, in their turn, view children in a more unpredictable set of home experiences in which behavioral gains might be seen to be less fixed. This variation is not detrimental to the study. Rather, it points out ecological complexity of behavior management in autism. Studies of parent and telehealth based interventions also indicate that although digital helps pair down difficult behavior, implementation at home is affected by stress, the daily burden, and environmental inconsistency. The small difference in the parental ratings of the current study should therefore be viewed as realistic and not negative.

5.2 Implications of the Study

The results are significant to practice, policy, and research in the future in Pakistan. At the practice level, the findings are that AI-supported behavior tools are best thought of as assistive supports that could be offered to extend intervention outside of clinic sessions. One of the areas where mobile applications can be of great aid is the low-resource environment as they are relatively scalable and easier to access by the family. On the policy level, autism services in Pakistan might be improved by progressive adoption of digital support systems in the form of therapy centers, schools and parent training programs. At the research level, the study provides evidence at a South Asian level which is underrepresented in the AI-autism literature. The available literature is more than likely to be in high-income environments, thus local evidence is needed to ascertain what type of tools are feasible, tolerable, and long-lasting in Pakistan.

5.3 Limitations of the Study

The study has some limitations, although it has contributed to it. To begin with, it was a cross-sectional design, and therefore, it was not possible to draw a causal conclusion. Second, the results were based on how the respondents perceived it instead of actual clinical observation or longitudinal outcome data that were produced by the device used. Third, the sample included urban-based service settings which could restrict the generalization to rural Pakistan. Fourth, wearable use was relatively less than that of apps, which can have decreased the accuracy of the comparisons between tools types. These constraints resemble the ones observed by the broader literature, where most studies on autism technology are small, short, in-controlled, or resource-intensive.

5.4 Conclusion of the Study

Conclusively, the research discovered that AI-assisted tools were positively correlated with behavior regulation skills in autistic children in Pakistan. The frequent and continued use of these types of tools was associated with a higher level of emotional regulation, the enhancement of attention rate, decreased aggression, and enhanced overall behavioral functioning. The integration of adaptive apps and wearable devices seemed to be more productive compared to the use of single tools, whereas therapists, teachers, and parents reported fairly positive attitudes towards AI effectiveness. Though the study lacks a claim that AI can substitute human intervention, it demonstrates that AI can reinforce behavior support, as integrated into caregiver- and therapist-driven care. Overall, it can be concluded that AI-assisted behavior management has a high potential in Pakistan, but future studies should shift to longitudinal, real-world, and context sensitive estimation of the intervention to ensure long-term effectiveness and equal opportunity.

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