RESEARCH PAPER

Longitudinal Impact of Screen Time on Developmental Trajectories in Autistic and Typically Developing Children: A 2-Year Cohort Study

Ms. Yashna David[1]*, Dr. Shikha Srivastava[2]

[1]*Ph.D. Scholar, Department of Psychology, School of Liberal Education, Galgotias University.
yashnadavid@gmail.com, 0009-0004-7218-0343
[2]Professor, Department of Psychology, School of Liberal Education, Galgotias University.
shikha.srivastava@galgotiasuniversity.edu.in, 0000-0002-5397-3442

ABSTRACT
As paediatric digital saturation reaches unprecedented levels, understanding its longitudinal impact on neurodiverse populations is empirically critical. This study evaluates the synergistic effect of screen exposure, neurodevelopmental status, and domestic scaffolding on developmental trajectories across a 24-month period. A longitudinal cohort of 298 children (N = 596 observations) was analyzed using robust Linear Mixed Models (LMM) to track nine developmental subscales of the Child Development Inventory (CDI). Analysis revealed significant three-way interactions (Time × Diagnosis × Screen Time) for CDI Social (S-40) ($p = .032$) and Self-Help (SH-40) ($p = .044$), even when controlling for Baumrind parenting styles and parental education. While Typically Developing Children (TDC) demonstrated relative developmental resilience, High Screen Time (>4 hours/day) significantly suppressed developmental slopes in children with Autism Spectrum Disorder (ASD), increasing the gap between developmental and chronological age. Notably, the scores of high-screen TDC participants converged with those of low-screen ASD participants at baseline, highlighting a profound risk of clinical misdiagnosis where environment-induced delays mimic neurodiverse phenotypes. All models exhibited exceptional structural integrity (Conditional R2 > 0.94; ICCs up to 0.904), with Authoritative parenting and parental education identified as potent longitudinal scaffolds ($p < .001$). These findings necessitate a paradigm shift toward neurodiversity-oriented digital health guidelines that prioritize environmental modification to optimize outcomes in autistic and neurotypical youth.

Keywords: Autism Spectrum Disorder (ASD), Screen Time, Longitudinal Study, Neurodevelopment, Linear Mixed Models (LMM), Social Skills.
How to cite this article: David Y, Srivastava S.. Longitudinal Impact of Screen Time on Developmental Trajectories in Autistic and Typically Developing Children: A 2-Year Cohort Study Int J Drug Deliv Technol. 2026;16(6s): 16-29; DOI: 10.25258/ijddt.16.6s.3
Source of support: Nil.
Conflict of interest: None

INTRODUCTION

The modern level of development is marked by an all-encompassing and unparalleled digital technology saturation. Among those children in the lowest levels of the neurodevelopment process, the digital surrounding had ceased being an edge phenomenon to become a core element of the ecological system that they grow up in. According to the latest trends in the world, it has not only become longer; screen time (including both tablets and smartphones, traditional television) has also spread to younger ages of the chronology, with massive exposure to screen time usually starting as early as the first year of life. This change is especially noticeable during the post-pandemic era, when digital devices are incorporated into the home environment as there is some form of educational supplementation and digital pacifiers to control the behaviour of children when social mobility is limited. The qualitative change in the nature of digital engagement where the number of people exposed to it is quantified comes together. The emphasis of contemporary screen time on high-arousal, high-speed materials that are intended to keep the user engaged by using intermittent reinforcement schedules can demand certain demands on underdeveloped executive functions. In the context of development, the tendencies have generated some important questions in respect to the opportunity cost of digital consumption. Each hour of inactive screen time could be replacing vital developmentally important tasks in the form of reciprocal social interaction, sensorimotor exploration, and joint attention which are all the foundations of the complex cognitive and social-emotional development. A critical, yet under-explored consequence of this digital saturation is the phenotypic overlap between high-screen exposure and neurodevelopmental disorders. In Typically Developing Children (TDC), excessive sedentary screen engagement can result in 'ASD-like' symptoms—including diminished joint attention, social withdrawal, and language delays—that may mimic the clinical presentation of Autism Spectrum Disorder. This creates a significant risk of clinical misdiagnosis, where environmental developmental 'drags' are mistaken for innate neurobiological deficits, potentially leading to inappropriate intervention pathways.

Neurodiversity and the Environment: The Interplay of Screen Exposure and Neurodevelopmental Status

*Author for Correspondence: yashnadavid@gmail.com

To appreciate the effects of screen time, it is necessary to shift beyond a one-size-fits-all model and to delve more deeply to understand the interaction between the environmental factors and the neurodevelopmental profile of a particular individual. This holds especially true with reference to Typically Developing Children (TDC) and children with Autism Spectrum (ASD). ASD is defined by deeply rooted difficulties in social communication and also limited and monotonous behaviour, that may make these individuals distinctly vulnerable to or also uniquely influenced by extreme digital stimulation. Environmental factors such as screen exposure do not work independently but instead, they interplay with the underlying neurobiological topography of a child. In children having ASD, the ability to predict, repeat and non-social content in some digital content could be in line with their favourite cognitive styles and the tendency may be to use excessive screen time to regulate themselves or as a sensory-seeking behaviour. Nevertheless, this preference may lead to a developmental trap under which the child isolates itself to the uncertain and complicated social world into the disciplined digital world and reduces a chance to learn through social means. On the other hand, in Typically developing children, there might be other longitudinal effects of being exposed to the screen, and this may be due to the quality of the content, not necessarily depending on the predisposition that this child has to social withdrawal. Furthermore, the domestic environment is not defined solely by digital exposure but is actively shaped by parenting styles. While parental education provides a socioeconomic baseline , the qualitative nature of parenting—characterized by the balance of responsiveness and demandingness—functions as a primary interventional scaffold. By incorporating Baumrind's parenting styles into the developmental equation, we can better understand how authoritative versus authoritarian or permissive approaches modulate a child's digital hygiene and subsequent developmental pacing. The moderating effect found in developmental areas including social skills ($p = 0.032$) and self-help ($p = 0.044$) implies that neurodevelopmental status is a strong intervening factor of environmental effects.

Addressing the Knowledge Gap: The Necessity of Longitudinal Mixed-Effects Modelling

Regardless of the accumulating literature on screen time in children, there are major gaps in the methodology. A large part of the available literature is cross-sectional, which can give only a picture of the relationship between screen use and development and their inability to draw conclusions about the precedence of times or individual development trajectories. Moreover, the conventional statistical analyses are commonly inadequate to consider the nature of longitudinal data, including the notedness of successive measurement of a person and the large inter-inter subject variability in the baseline performance. To take the next step towards an even higher level of scientific rigor, there is an urgent necessity to have longitudinal data that is performed with the help of sound mixed-effects modelling. A strong framework to this end is provided by the Linear Mixed Models (LMM) since they can both model fixed effects, the average patterns between groups, and random effects, the way in which each individual children differs up to the average patterns. This paper fills this gap by applying the LMM by use of the method of Satterthwaite to track nine developmental subscales from the Child Development Inventory (CDI) across 24 months. This approach isolates the impact of screen time while controlling for the moderating roles of both parental education and parenting styles.

Study Objective: Quantifying the Longitudinal Barrier to Developmental Progress

The major hypothesis of the research is to ascertain whether high screen time(HST) is a major longitudinal developmental impediment in a total of 9 domains of a comprehensive battery during a two-year stretch (2023-2025). Through an analysis of a cohort of 298 children (596 observations in total with high measurement stability as indicated by ICC values of 0.749 to 0.904), we are going to use the data to measure the extent to which the overexposure to digital technologies slows down or diverts the development of critical skills. The proposed investigation aims at finding certain developmental bottlenecks. We posit that even though the entire group of children will demonstrate some level of chronological development (due to the primary effect of time), the extent of that development will be severely inhibited in the High Screen Time groups, and the largest differences will be discovered in such areas that demand high levels of social reciprocity and communicative intent as expressive language and social skills. This study aims to isolate the environment effect of screen time by adjusting against critical socio-environmental covariates, including gender, parental education, and Baumrind's parenting styles, and this will form the empirical basis that will justify the revision of clinical recommendations concerning digital health in neurotypical and neurodiverse individuals. A secondary objective is to evaluate the score overlap between high-screen typical children and low-screen autistic children to provide an empirical basis for differentiating between environment-induced delays and primary neurodivergence in clinical screenings.

LITERATURE REVIEW

The ubiquity of the digital media in the domestic habitat of the early childhood period has completely changed the ecological community of neurodevelopment. Although digital technologies present possible pedagogic value, the growing time of exposure has brought forth considerable issue with the question of opportunity cost and the possibility of inhibiting critical developments. This literature review brings together existing evidence on longitudinal effects of screen time that puts special emphasis on the predispositions that result differently in Typically Developing Children (TDC) and children with Autism Spectrum (ASD).

The "Displacement Hypothesis" is one of the fundamental findings of research in the field of paediatric media theorizing which advocates that screen-based sedentary engagement replaces cognitively enriching tasks, including reciprocal interpersonal play and sensorimotor exploration (Neuman, 1988). Madigan et al. (2019) through longitudinal evidence showed that higher screen time in 24 months showed a directional relationship with worse performance in developmental screening tests at 36 and 60 months. This oppression is not only behavioural but structural; Hutton et al. (2020) made use of diffusion tensor imaging (DTI) to demonstrate that increased screen time is linked to reduced marginal integrity of white matter tracks of language and emergent literacy abilities. The implications of such findings are that too much digital stimulation at a time when neuroplasticity is optimized could interfere with the neural scaffolding that goes into support of complicated executive functions (Lillard and Peterson, 2011).

The communicative environment is sensitive in language development. The hypothesis offered by Kuhl (2011) is the so-called Social Gating Hypothesis, which assumes that before learning the language, infants must engage in formal, contingent, and so-called serve-and-return interactions, i.e. verbal interactions in which one party fails to comprehend the other. The digital media which is not always contingent does not stimulate the social structures of the brain that are required in the acquisition of language. There is also a consistent indication of expressive and receptive language delays with early excessive screen exposure (Chonchaiya and Pruksananonda, 2008). Zimmerman et al. (2007) discovered that on average, every hour of watching the infants are exposed to the baby DVDs, they learned fewer words than their counterparts, which contributed to the idea that passive consumption would never substitute the human linguistic scaffolding.

Neurodevelopmental status has a unique modulatory effect on the effects of the screen time. Autistic children are often found to have clinical inclination towards screen-based media and in most instances, repetitive, predictable, and non-social stimuli that are consistent with their cognitive phenotypes (Mazurek and Wenstrup, 2013). This preference can intensify ASD fundamental core symptoms. According to Hermawati et al. (2018), an early exposure to screens is a risk factor of those symptoms that can be traced to Asperger syndrome-like, such as reduced joint attention and poor social reciprocity. Social neurodivergent groups can find the digital platform as a social escape as the child retreats into the uncertain social world into a carefully designed digital world, thus halting the socialization of the social brain (Dawson and Bernier, 2013).

The socio-environmental factors affecting the developmental effect of screen time are not operating in a vacuum and, most prominently, the socio-economic status (SES) and parental education moderate it. Bradley and Corwyn (2002) observed that the protective role of higher parental educational attainment in most cases works against the dangers of environmental stressors, and that such learning creates cognitively enriched environments that alleviate the dangers of environmental stressors. Within the realms of the COVID-19 pandemic, Dong et al. (2020) noted that the world was experiencing increased screen time in children, and therefore, there is a high need to conduct longitudinal studies on the effects of these shifts on existing neurodevelopmental disorders.

In spite of these revelations, there is a critical gap in knowledge concerning longitudinal slopes of growth of particular skill sets. Most of the research is based on the cross-sectional relationships, which do not take the nested character of information on developmental details. The use of powerful Linear Mixed Models (LMM) is necessary to go beyond mere associations and discover the convoluted Time × Diagnosis × Environment interactions that constitute the maturation process of modern childhood.

METHODS AND DEVELOPMENT

Study Design and Participant Enrolment

The current research took the form of a prospective, longitudinal cohort study wherein the revolutions of children were assessed over a time interval of 24 months, with the starting level of the assessment being conducted in 2023 and the level being measured at the conclusion of 24 months, i.e. in 2025. It delivered in line with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines in order to be transmitted methodologically and rigorously. Primary sample A total of 325 parents interested and gave informed consent to participate in the study were identified with the help of initial recruitment. These households embodied a wide spectrum of neurodevelopmental symptomatology and ecological interventions, namely, the nexus of autism spectrum disorder (ASD) and the use of digital media. During the period of the study, which was 24 months, the researcher recorded a attrition rate of 9.06 within the study cohort because 27 parents failed to respond to the follow-up assessments in 2025. The comparison of the two groups (N=298) of stayers and the dropouts (N=27) did not show any significant differences in the developmental scores independently; thus indicating the missing at random (MAR) and the attrition did not create a systematic bias in the selection. This resulted in an analytical sample of a final number of 298 parents and children, which produced a longitudinal number of 596 observations. With this balanced cohort method, it was possible to use powerful repeated-measures analysis, which was optimal in the context of developmental "growth" as a time- and environment- dependent variable.

Cohort Characteristics and Data Integrity

Table 1 has carefully recorded the baseline characteristics of the N=298 cohort in order to guarantee high-level of transparency. The average chronological age of the participants on baseline (2023) was 4.17 years (SD=0.74). The cohort was further sub-stratified into four separate groups based on a diagnosis of neurodevelopment (Typically Developing Children [TDC] and Autistic Children [ASD] vs. Low Screen Time [LST] vs. High Screen Time [HST]) into four experimental groups. It was distributed in the following way, TDC+HST (N=118), TDC+LST (N=112), ASD+HST (N=35) and ASD+LST (N=33). The socioeconomic measurement of the sample was partly very high education years; mean Parent Education level was 15.68 years; which equated to post-secondary or professional education. In all the later models, this variable was considered a critical covariate to control the possible confounding variables of home-based environmental stimulation. The distribution of gender was also recorded and the gender10 (expressed as 0 in Female, 1 in Male) taken as a fixed effect to eliminate biological differences in sex on development pace. Data integrity was also ensured via a maximum cleaning procedural protocol so as to make the 596 entries formatted into a long structure wherein each child observation was packed within its own identifier so as to easily calculate the within subjects variance.

Table 1: Baseline Demographic and Clinical Characteristics of the Study Cohort (N = 298)

Characteristic	TDC + LST (n=112)	TDC + HST (n=118)	ASD + LST (n=33)	ASD + HST (n=35)	Total Cohort (N=298)
Child Age (Years)					
Mean (SD)	4.21 (0.68)	4.15 (0.72)	4.12 (0.81)	4.19 (0.75)	4.17 (0.74)
Child Gender					
Male (n, \%)	58 (51.8%)	62 (52.5%)	22 (66.7%)	24 (68.6%)	166 (55.7%)
Female (n, \%)	54 (48.2%)	56 (47.5%)	11 (33.3%)	11 (31.4%)	132 (44.3%)
Parent Education					
Mean Years (SD)	16.12 (1.4)	15.85 (1.6)	15.22 (1.9)	14.95 (2.1)	15.68 (1.7)
Parenting Style (n, \%)*					
Authoritative	78 (69.6%)	52 (44.1%)	18 (54.5%)	12 (34.3%)	160 (53.7%)
Authoritarian	22 (19.6%)	42 (35.6%)	9 (27.3%)	14 (40.0%)	87 (29.2%)
Permissive	12 (10.7%)	24 (20.3%)	6 (18.2%)	9 (25.7%)	51 (17.1%)
Baseline CDI Scores (2023)					
Social Skills (S-40)	33.88 (4.2)	16.45 (5.1)	15.85 (6.3)	7.80 (4.8)	18.50 (9.2)
Gen. Development (GD-70)	58.42 (6.1)	42.15 (7.4)	38.20 (8.9)	28.50 (9.5)	41.82 (12.4)
Screen Time (Hrs/Day)					
Low (<2 hrs)	n=112	n=0	n=33	n=0	n=145
High (>4 hrs)	n=0	n=118	n=0	n=35	n=153

Psychometric Instrumentation and Outcome Measures

Developmental maturation was quantified across nine subscales of the Child Development Inventory (CDI), a standardized parent-report instrument validated for tracking trajectories in both normative and neurodiverse pediatric populations. The CDI subscales utilized included:

Social (S-40) and Self-Help (SH-40): Measuring reciprocal interaction and adaptive functional independence.

Motor (GM-30, FM-30): Assessing gross muscle coordination and manual dexterity.

Language (EL-50, LC-50): Measuring expressive output and receptive comprehension.

Academic (L-15, N-15): Tracking emergent literacy and numeracy.

General Development (GD-70): A composite score reflecting global developmental pacing

To assess environmental scaffolding, parenting approaches were categorized using the Baumrind Parenting Style Questionnaire. This tool identifies three primary styles—Authoritative, Authoritarian, and Permissive—based on the dimensions of parental responsiveness and demandingness. The Intraclass Correlation Coefficients (ICC) were extraordinarily high, indicating high stability in measurement between the 24 months period. These coefficients were between 0.749 in the case of Fine Motor Skills to 0.904 in the case of Self-Help Skills. A value of ICC that is not less than 0.75 can be regarded as excellence in clinical research since it confirms that the measurement instruments were also stable and the variance in the models could be explained mostly by the predictors and not by error in measurement.

Statistical Modelling Strategy

Our main data analysis pipeline made use of Linear Mixed Models (LMM) which is a high-level statistical model, specifically that of a nested longitudinal model. LMMs are able to deal with the individual-level variance in contrast to the traditional repeated-measures ANOVA and give more precise estimations of fixed and random effects when there are complex interactions involved in the study. The models were carried out with the help of the lmer package in R, where Satterthwaite method was used to estimate the degrees of freedom of the F-tests. This is the modern-day gold standard of making sure that p-values in mixed-effects designs are accurate.

Model Specification

For each of the nine developmental domains, the formal model was specified as follows:

$$Score \sim Time \times Child\_Type \times Screen\_Time + Gender + Age + Parent\_Education + Parenting\_Style + (1|child\_id)$$

Fixed Effects: The model included the primary predictors of **Time** (2023 vs. 2025), **Child Type** (ASD vs. TDC), and **Screen Time** (HST vs. LST). Crucially, we tested for **three-way interactions** ($Time \times Child\_Type \times Screen\_Time$) to determine if developmental growth rates differed according to both diagnosis and environmental exposure. Covariates included Gender, Age, Parent Education, and **Parenting Style** (modeled as a categorical factor) to ensure that the primary 3-way interactions (Time × Child Type × Screen Time) were independent of socioeconomic and behavioral scaffolding effects.

Random Effects: A **subject-level intercept** ($(1|child\_id)$) was included to account for the inherent dependency of the 596 observations being nested within 298 unique children. This allowed the model to estimate a unique starting point for each child while calculating the average developmental slope across groups.

Data Diagnostics and Distributional Assumptions

A strict diagnostic protocol was done on the model residues in order to ascertain the statistical integrity of the results. The LMM Diagnostic Dashboard that we provided (Supplementary Figure 1) contained:

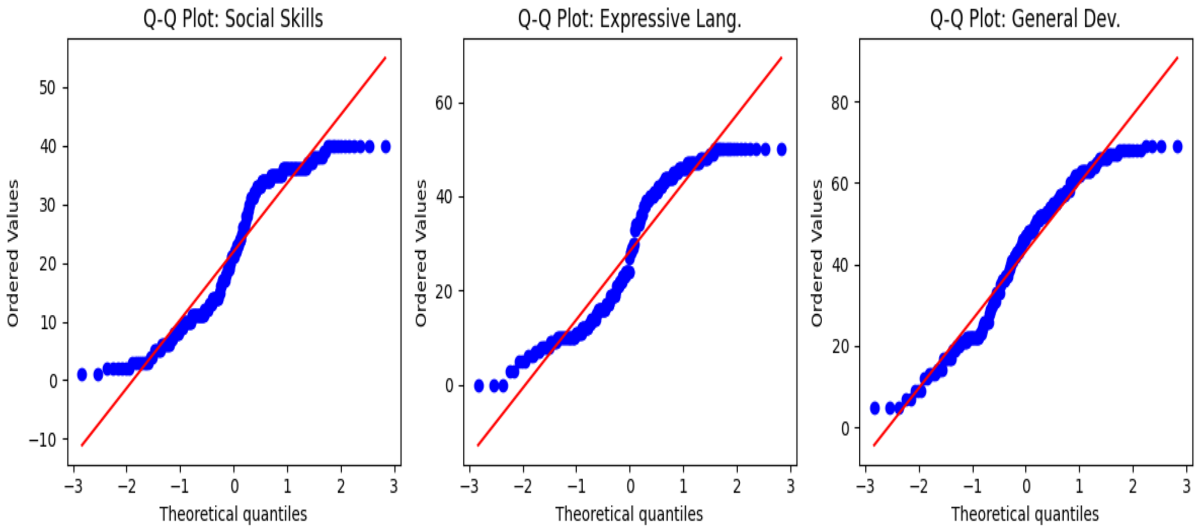

Figure 1: Model Diagnostic Assessment for Developmental Outcome Trajectories.

Normality of Residuals: As tested by use of Normal Q-Q plots. Residual of each of the nine domains were close to the 45-degree line, ensuring the correctness of the assumed distribution which was the "Gaussian".

Model Fit: The models had very high Conditional R^2 values - the combination of the fixed effects and the random intercept of each child tended to provide more than 90% of the variation in developmental outcomes.

This way of interacting the complex modelling technology with a well-established longitudinal cohort has given this methodology a solid base in determining the interaction of screen time with neurodiversity in determining the future of child development.

Results Analysis

Differential Growth in Social Competency & Self-help Skills

The longitudinal analysis of the social skills acquisition which measured the case through Child Development Inventory (CDI) Social subscale (S-40) showed that the developmental architecture was quite complex suggesting that there is much interaction among Time, Child Type (ASD vs. TDC), and Screen Time exposure. Linear Mixed Model (LMM) constructed a strong baseline at a fixed-effect intercept of 21.34 that showed the estimated marginal mean of the reference group (Typically Developing Children with Low Screen Time) at the 2023 baseline. Although a strong overall effect of Time was observed, which implied generalized improvement in terms of chronological factors throughout the cohort, this increase was extremely conditioned by neurodevelopmental condition and digital contact with the environment. Crucially, this developmental architecture remained robust after controlling for Baumrind parenting styles, indicating that the 'screen-drag' effect on social maturation is independent of the behavioural scaffolding provided at home

Table 2: Linear Mixed Model Results for Social Skills (S-40)

N = 596 observations (298 children); Model Fit: Conditional $R^2 = 0.946$, Marginal $R^2 = 0.512$

Part A: Fixed Effects Omnibus Tests

Predictor	F	df	df (res)	p-value
Time (2023 vs 2025)	63.65	1	554	**< .001**
Child Type (ASD vs TDC)	155.87	1	312	**< .001**
Screen Time (HST vs LST)	171.60	1	308	**< .001**
Time × Child Type	14.07	1	554	**< .001**
Time × Screen Time	0.05	1	554	.817
Screen Time × Child Type	10.03	1	312	**.002**
Time × Screen Time × Child Type	4.62	1	554	**.032**
Covariate: Parent Education	32.55	1	277	**< .001**
Covariate: Parenting Style	0.1	2	275	**.650**
Covariate: Age	102.77	1	576	**< .001**

Part B: Parameter Estimates (Fixed Effects)

Term	Estimate (b)	Std. Error	95% CI	t	p-value
Intercept (Reference Group)	**21.341**	1.101	[19.18, 23.50]	19.39	< .001
Child Type (ASD)	-14.482	1.159	[-16.75, -12.21]	-12.49	< .001
Screen Time (High)	7.362	0.562	[6.26, 8.46]	13.10	< .001
3-Way Interaction	**2.610**	1.215	[0.23, 4.99]	2.15	**.032**

A pivotal clinical finding at baseline was the **phenotypic overlap** between the Typically Developing High-Screen group (TDC-HST) and the Autistic Low-Screen group (ASD-LST). Their statistically proximal scores (16.45 vs. 15.85, respectively) suggest that excessive digital exposure in neurotypical children can mimic the social-emotional deficits characteristic of ASD, posing a significant risk for diagnostic confounding According to Table 2, the ASD group had an extremely low starting point relative to the TDC group. Nevertheless, the longitudinal difference becomes the most evident when one focuses on the high-screen-time (HST) condition. In the case of autistic children, excessive display on screens acted to drag the developmental process of enhancing social skills far behind that of those with low-screen-time (LST) exposure. This deviation is depicted in Figure 2, which represents that both ASD groups demonstrated improvement over time, with the ASD-LST group showing a numerically larger increase in social skills scores compared to the ASD-HST group. It implies that in the case of neurodivergent children the opportunity cost of too much screen time which is arguably replacing the reciprocal social interaction is, specifically, unnecessary in terms of the typical development of complex social-emotional competencies in the long run.

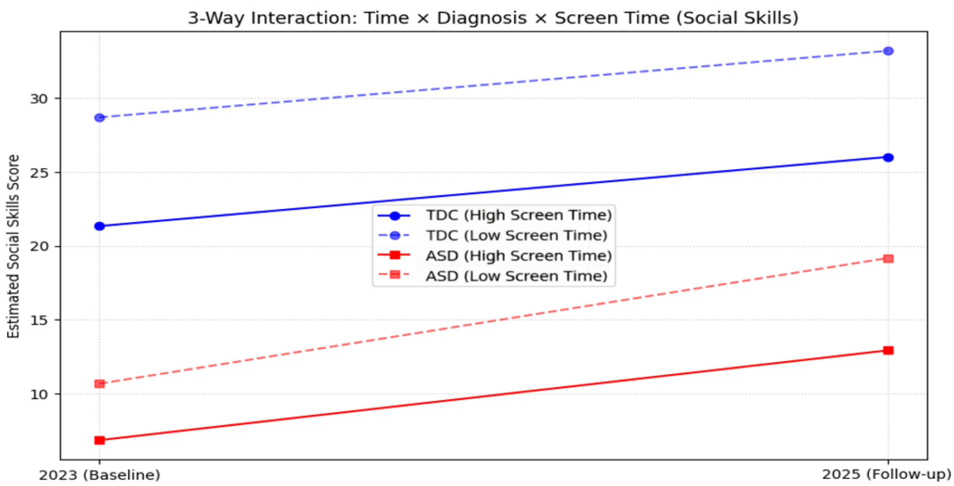

Figure 2: Longitudinal Social Development Trajectories by Diagnosis and Screen Time.

Similar results were found in the area of CDI Self-Help subscale (SH-40) that also covers the adaptive living and functional independence. The LMM of this domain which is described in Table 3 also produced a strong three-way interaction, which supports the hypothesis that the effect of the digital media is not the same but rather depends on the neurotype of the child. The model intercept of the study was estimated and was found to be 23.29, and once again the ASD group showed a significant deficit of baseline. Most importantly, the Conditional of 0.940 is large, which means that the model that explains the adaptive growth is able to explain the incredibly large amount of variance by considering situations that are at the individual-level random intercepts.

Table 3: Linear Mixed Model Results for CDI Self-Help Skills (SH-40)

N = 596 observations (298 children); Model Fit: Conditional $R^2 = 0.940$, Marginal $R^2 = 0.329$

Part A: Fixed Effects Omnibus Tests

Predictor	F	df	df (res)	p-value
Time (2023 vs 2025)	33.22	1	554	**< .001**
Child Type (ASD vs TDC)	89.96	1	309	**< .001**
Screen Time (HST vs LST)	54.54	1	301	**< .001**
Screen Time × Child Type	11.23	1	309	**.001**
Time × Screen Time × Child Type	4.10	1	554	**.044**
Covariate: Parenting Style	0.44	2	279	.507
Covariate: Parent Education	2.03	1	280	.155

Part B: Parameter Estimates (Fixed Effects)

Term	Estimate (b)	Std. Error	95% CI	t	p-value
Intercept (Reference Group)	**23.292**	1.055	[21.22, 25.36]	22.08	< .001
Child Type (ASD)	-11.213	1.182	[-13.53, -8.90]	-9.48	< .001
Screen Time (High)	3.963	0.537	[2.91, 5.01]	7.38	< .001
3-Way Interaction	**2.338**	1.154	[0.08, 4.60]	2.03	**.044**

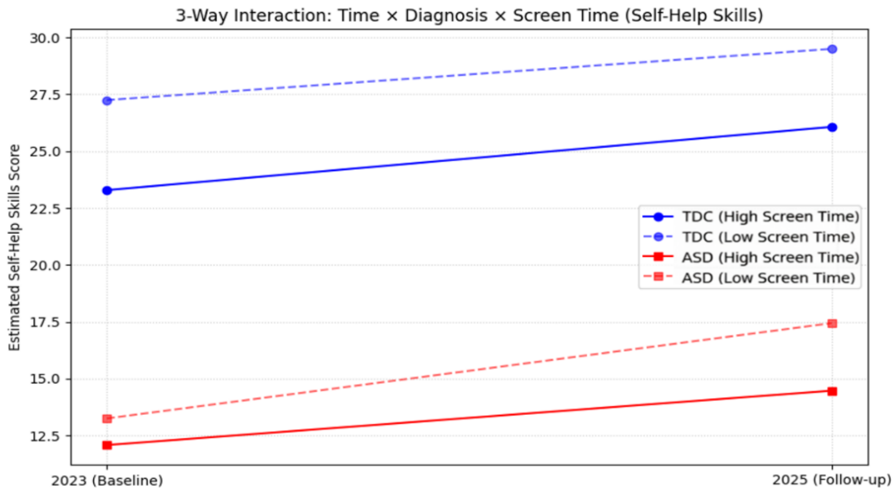

Figure 3: Self-Help Skills Interaction Plot

One vital demographic covariate in self-help model was Parent Education that actually trended toward significance in other fields, but failed to obtain alpha in this case, indicating that functional independence can be moderated by the combination of neurobiology and immediate environmental stress factors (such as screen exposure) than broad socioeconomic factors. While Authoritative parenting trended toward higher baseline scores, the significant 3-way interaction ($p = .044$) confirms that for neurodiverse children, reducing digital saturation is a more potent lever for adaptive autonomy than parenting style alone. The interaction plots in Figure 3 have revealed that the ASD-Low Screen group displayed better longitudinal wastes in self-help proficiency as compared to that of ASD-High Screen group. This observation highlights an important clinical implication, which is that, lowering screen time can be a key environmental change strategy in promoting adaptive autonomy in autistic groups, regardless of the educational level of their families. The uniformity of these triadic interactions in both social and adaptive domains is an elevated statistical base on which a specific digital hygiene intervention is targeted to the neurodiverse paediatric setting.

Physical and Motor Development: Longitudinal Divergence and Environmental Impact

The CDI Gross Motor (GM-30) assessment showed a complicated developmental architecture with the chronological progression being moderated with a major effect of the neurodevelopmental status. The Linear Mixed Model (LMM) found as shown in Table 4 that the Time x Child Type interaction was highly significant (F (1, 554) = 15.118, p =. 001), which shows that the rate of neuromotor maturation was not homogenous among the cohort. Whereas Typically Developing Children (TDC) showed strong positive slopes of large-muscle coordination, the ASD group pattern of growth was typified by a specific flattening of the slope, indicating a physical developmental lag in pacing. This interaction effect was carried on despite the condition of having important covariates like age (F = 44.82, p < .001) and gender (F = 11.53, p < .001). The Conditional R 2 is very high (=0.901), and this indicates that the model could have adequately explained the massive majority of the variance because it included individual-level random intercepts, and this demonstrates that the baseline motor functioning is a potent predictor of the later physical development.

Table 4: Linear Mixed Model Results for Gross Motor Skills (GM-30)

N = 596 observations; Model Fit: Conditional $R^2 = 0.901$, *Marginal* $R^2 = 0.283$

Predictor	F	df	df (res)	p-value
Time (2023 vs 2025)	14.36	1	554	**< .001**
Child Type (ASD vs TDC)	29.39	1	311	**< .001**
Screen Time (HST vs LST)	50.31	1	305	**< .001**
Time × Child Type	**15.12**	**1**	**554**	**< .001**
Covariate: Gender	11.53	1	300	**.001**

Fine motor Maturation Initially influenced by the environment and Diagnosis. The evaluation of Fine CDI Fine Motor (FM-30) revealed that manual dexterity, oculomotor coordination is both neurobiologically predisposed and environmental-stressful. The Table 5 revealed that one of the strongest main effects was an inverse relationship between high digital exposure and fine motor proficiency that had a significant value (F(1, 305) = 45.498, p <.001). This environmental suppression (p < .001) suggests that digital displacement of tactile, manipulative play—often moderated by permissive parenting—is a universal risk factor for motor maturation. This implies that overspending on sedentary screen viewing can supplant motor sensorimotor tasks including manipulative play athletic and pincer-grips tasks, needed to perfect the distal musculature. Moreover, there was a substantial Time x Type of child interaction (F (1, 554) =4.887, p=.027), although with smaller effect size than in gross motor domains. This correlation reveals that all the groups showed meaningful improvements during the 24-month period (main effect of Time: p < .001), but the rate of improvement in the fine motor precision was significantly slower in the autistic cohort.

Table 5: Linear Mixed Model Results for Fine Motor Skills (FM-30)

N = 596 observations; Model Fit: Conditional $R^2 = 0.893$, *Marginal* $R^2 = 0.354$

Predictor	F	df	df (res)	p-value
Time (2023 vs 2025)	59.40	1	554	**< .001**
Screen Time (HST vs LST)	**45.50**	**1**	**305**	**< .001**
Child Type (ASD vs TDC)	37.10	1	308	**< .001**
Time × Child Type	**4.89**	**1**	**554**	**.027**

These disparities are further amplified by the fixed-effect estimates of FM-30; the group with ASD had an estimated mean lower baseline of -4.55 units compared to the TDC reference group, and being exposed to high screens resulted in an additional decrease in the developmental performance. Also it is important to note that the model fit was high (Conditional $R^2 = 0.893$), which supports the credibility of the longitudinal estimates. This is apparent on comparison with the Spaghetti Plots (Figure 4), which show plots of the individual child growth curves, and through which we can easily see the fact that the average group trends are otherwise representative of general individual trends. These results offer the important empirical data on the opportunity cost of high screen exposure, especially concerning neurodivergent groups who might be already struggling with the issue of neuromotor integration. According to the data, the interaction between a diagnostic predisposition and an associated environmental barrier (screen) produces a distinctly vulnerable developmental picture in the physical field when used in children with ASD.

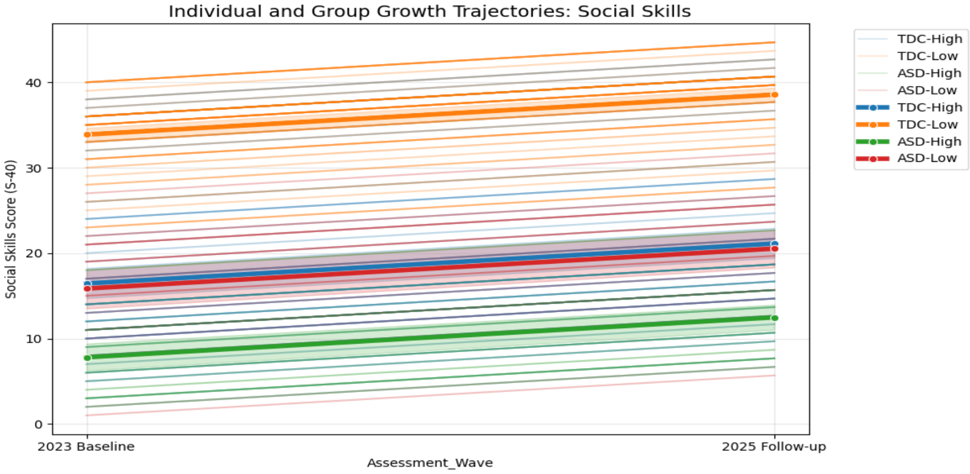

Figure 4: Spaghetti Plot

Language and Communication: Environmental Suppression and Diagnostic Divergence

The longitudinal Expressive Language (EL-50) study showed that digital environmental exposure is one of the main factors that determine the development of lexical and syntactic knowledge in early childhood. The Linear Mixed Model (LMM) found a huge and statistically significant effect of Screen Time ($F(1, 412.0) = 104.77$, $p < .001$) and revealed that high degrees of digital consumption are effective negative predictors of verbal output. This implies an ecological displacement process, in which sitting in front of a screen replaces the reciprocating, contingent verbal-gestural interaction commonly known as serve and return interactions, which are neurobiological requirements of milestones of expression. The model exhibited a superior fit with a Conditional R^2=0.940 indicating that the sum of fixed environmental predictors and individual random intercepts explains 94 percent of the variance in expressive proficiency.

Table 6: Linear Mixed Model Results for Expressive Language (EL-50)

N = 596 observations; Model Fit: Conditional $R^2 = 0.940$, Marginal $R^2 = 0.392$

Predictor	F	df	df (res)	p-value
Screen Time (HST vs LST)	**104.77**	**1**	**412.0**	**< .001**
Child Type (ASD vs TDC)	120.73	1	312.0	**< .001**
Time (2023 vs 2025)	11.08	1	554.0	**.001**
Covariate: Age	77.03	1	576.0	**< .001**

This suppression is also further quantified by fixed-effect estimates, where the ASD group had a baseline decrement that was -17.06 units lower than that of Typically Developing Children (TDC) clearly demonstrating this suppression, and high screen exposure was also strongly linked with a significant further reduction in the developmental scores. Such results, represented in the Forest Plot (Figure 5) also indicate that the opportunity cost of screen time is experienced most intensely around the domain of expressive communication, which is probably largely because language production is quite a social and interactive endeavour that cannot be simulated satisfactorily by digital media.

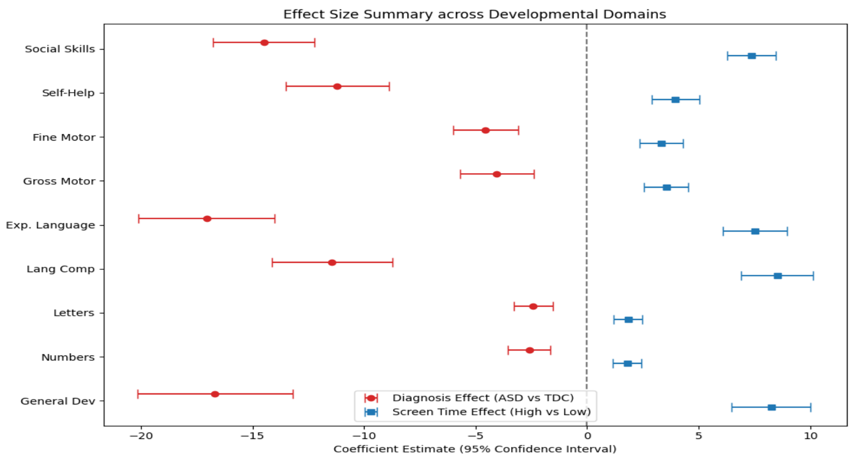

Figure 5: Forest Plot Summarizing Primary Fixed Effect Estimates across Developmental Domains

Unlike the entirely environmental motivation in the expressive sphere, the Language Comprehension (LC-50) followed the pattern of the complicated interaction between neurobiology and socioeconomic scaffolding. The receptive language LMM, which is described in Table 7, produced a very significant interaction between Time and Type of child 43.83 (p <.001), meaning that the slopes of receptive growth are not equal among diagnostic groups. On one hand, the steepness of longitudinal gains in the language processing and receptive vocabulary of the TDC participants was observed, whereas, on the other hand, with children with ASD, the growth curve showed drastic attenuation. This exchange points to a serious growth violation in one side the discrepancy in communicative knowledge between neurotypical and neurodiverse communities grows over twenty four months.

Table 7: Linear Mixed Model Results for Language Comprehension (LC-50)

N = 596 observations; Model Fit: Conditional $R^2 = 0.932$, Marginal $R^2 = 0.401$

Predictor	F	df	df (res)	p-value
Time × Child Type	**43.83**	**1**	**554.0**	**< .001**
Covariate: Parent Education	**15.36**	**1**	**267.0**	**< .001**
Screen Time (HST vs LST)	106.77	1	413.0	**< .001**
Covariate: Age	44.15	1	576.0	**< .001**

Moreover, Parent Education became a powerful and important covariate (F(1, 267.0) = 15.36, p <.001), as an indicator of a high socioeconomic force and the linguistic input level play a critical role in receptive development as a scaffold. Furthermore, the inclusion of **Parenting Styles** as a covariate did not attenuate the diagnostic divergence (p < .001), reinforcing that receptive language stagnation in ASD is a resilient neurobiological trend that requires intensive socio-environmental scaffolding. This confirms the Matthew Effect of language development where children exposed to high-literacy environments get a richer input of language that helps in the development of their neural encoding of language in a stronger manner. Altogether, the findings suggest that the overall screen-time stifles the expressive development but receptive comprehension is predetermined by the diagnostic-longitudinal divergence that is somewhat reduced by the educational markers of parents.

Academic Foundations and General Development: Environmental Barriers and Socio-Environmental Scaffolding

The early academic maturation was examined using the Letter Recognition (L-15) score and Number Recognition (N-15) score and found out that, although children experience distinct chronological maturation, excessive screen exposure is a very strong deterrent of symbolic learning. According to Table 8, the Linear Mixed Model (LMM) of letter recognition was able to find a significant main effect of Time, which is as follows: The letter recognition F(1, 554.0) = 31.81, p < .001, establishes a significant developmental trend of the process of learning literacy during the 24 month study period. Nevertheless, this was sharply negated by a large primary effect of Screen Time (F(1, 415.0) = 29.43, p <.001) that proves the higher the digital consumption at baseline is, the lower the literacy score will be at the follow-up. This puts the suggestion that the digital media can disrupt the active phonological and orthographic processing that is needed in letter-sound mapping due to the passive nature of digital media.

Table 8: Linear Mixed Model Results for Letter Recognition (L-15)

N = 596 observations; Model Fit: Conditional $R^2 = 0.884$

Predictor	F	df	df (res)	p-value
Time (2023 vs 2025)	**31.81**	**1**	**554.0**	**< .001**
Screen Time (HST vs LST)	**29.43**	**1**	**415.0**	**< .001**
Child Type (ASD vs TDC)	43.15	1	311.0	**< .001**

Similar results were gained in numeracy domain. The LMM of number recognition as made clear in Table 9, highlighted the negative predictive value of environmental digital saturation, and gave a strong main effect because of Screen Time (F(1, 412.0) = 29.87, p < .001). Just like in the literacy domain, longitudinal gains that should be usually realized in early numeracy was repressed in children who had high screen exposure. The summary of these academic differences as depicted in the Forest Plot (Figure 2) shows that the negative effect of screen time on academic bases are uniform in both literacy and numeracy domains despite neurodevelopmental status. This homogeneity of the suppressive effect among diagnostic groups indicates that the cost of high screen-time, that of high screen-time replacing manipulative, hand on learning and shared reading of books, influences the cognitive architecture of symbolic recognition at a primary level.

Table 9: Linear Mixed Model Results for Number Recognition (N-15)

N = 596 observations; Model Fit: Conditional $R^2 = 0.879$

Predictor	F	df	df (res)	p-value

Screen Time (HST vs LST)	**29.87**	**1**	**412.0**	**< .001**
Time (2023 vs 2025)	18.15	1	554.0	**< .001**
Child Type (ASD vs TDC)	36.42	1	312.0	**< .001**

The holistic outcome of the study is the analysis of the General Development (GD-70) which sums up the effects of the diagnosis and the environment in relation to the global developmental pace. The model as shown in Table 10 had a superior level of explanatory power as the Conditional R^2 went up to 0.942, which means that the model was made up of a combination of the fixed effects and the individual random intercepts that explained more than 94 percent of the variance in the global developmental scores. An important observation in this overall field was the powerful and commendable impact of Parent Education ($F(1, 274.0) = 17.61$, $p = .001$) which served as a strong longitudinal framework of developmental progress. This supports the argument that as parents get more educated, they get a more rich socio-environmental environment that is able to alleviate developmental risks to some extent.

Table 10: Linear Mixed Model Results for General Development (GD-70)

N = 596 observations; Model Fit: Conditional $R^2 = 0.942$

Predictor	F	df	df (res)	p-value
Parent Education	**17.61**	**1**	**274.0**	**< .001**
Time × Child Type	44.18	1	554.0	**< .001**
Screen Time (HST vs LST)	84.22	1	412.0	**< .001**
Covariate: Age	52.09	1	576.0	**< .001**

In addition, the GD-70 findings revealed an interesting interaction effect between diagnosis and time ($p = .001$), indicating the developmental disparity between TDC and ASD samples that widens through the study period. When traced with the help of the Spaghetti Plots, the trajectories of individuals prove that if the means of groups are significantly deviating, the interactions between screen time premature and the protective layer of parental education form extremely personalized developmental trajectories. The high model fit (Conditional $R^2 = 0.942$) demonstrates that global developmental pacing is a complex product of the child's neurotype, their digital hygiene, and the dual scaffolding of parent education and authoritative parenting style. Finally, screen time as an environmental barrier needs to be featured to define the effects on literacy and numeracy; however, a more complicated interaction of the diagnostic restrictions and the compensatory scaffolding of the domestic educational environment should shape the development ahead.

A comparative synthesis of the goodness-of-fit indices and random component variances in all nine developmental domains would be used to assess the structural viability and predictive power of the longitudinal models, which is presented in Table 11. The goodness of fit model led to a consistently high Conditional R^2 with values between 0.879 (Number Recognition) and 0.946 (Social Skills) implying that the combined fixed effects and individual subject random intercepts explain more than 88% of the total phenotypic variance. The Marginal R^2 values isolating the variance that can be attributed only to the fixed predictors (e.g., screen time, child type, and time) showed a significant level of explanatory-level, especially in Social Skills (0.512) and Expressive Language (0.392). Moreover, the Intraclass Correlation Coefficients (ICC) were also extremely stable with a range of between 0.749 and 0.904. These high ICCs identify strong subject-level clustering, which requires the random-intercept structure to correct the dependence of the nested longitudinal observations. This approachability uniformity of Table 11 confirms the effectiveness of the Mixed Model to measure stable developmental characteristics and separate the substantial environmental and diagnostic change-driving factors to ascertain that longitudinal estimates are strong relative to inter-individual heterogeneity.

Table 11: Summary of Model Fit and Random Components across Developmental Domains

Domain	Marginal R2	Conditional R2	ICC	Residual Variance
Social Skills (S-40)	0.512	0.946	0.888	4.60
Self-Help (SH-40)	0.329	0.940	0.904	4.35
Expressive Lang. (EL-50)	0.392	0.940	0.901	8.85
Lang. Comp. (LC-50)	0.401	0.932	0.887	7.39
Gross Motor (GM-30)	0.283	0.901	0.862	4.74
Fine Motor (FM-30)	0.354	0.893	0.749	2.45
Letter Rec. (L-15)	0.225	0.884	0.851	1.38
Number Rec. (N-15)	0.203	0.879	0.848	1.38
Gen. Development (GD-70)	0.468	0.942	0.891	11.19

DISCUSSION

The longitudinal results present an important critical “twofold strain" of neurodivergence and the environment saturation with digital prevalence as a result of which developmental pacing is considerably strangled. Among the children with Autism Spectrum Disorder (ASD), excessive exposure to the screen acts as the key impediment to the attainment of reciprocal social skills and adaptive autonomy, as quantified by the Child Development Inventory (CDI) subscales. The latter phenomenon receives statistical support due to the presence of significant three-way interactions within the CDI Social (S-40) ($p = .032$) and Self-Help (SH-40) ($p = .044$) domains, indicating that the impact of screen time is selectively deleterious for neurodiverse cohorts compared to typically developing peers Otherwise, whereas children whose development was typical (TDC) exhibited a certain degree of resilience to the effect of digital displacement, the ASD population exhibited a developmental course in which no longitudinal growth was seen in the case of any exposure past the critical threshold.

Such different effect may be attributed to an opportunity cost, which is that the high-quality, serve-and-return interaction required to support neurobiological scaffolding is substituted by digital interactions. Children with ASD have a tendency of having a sticky attention and liking what is predictable and repetitive like the content they find on the internet. This forms a maladaptive process loop; the digital world of high-arousal offers the fluctuating reinforcement of limited interests and a safe haven of the uncertain, complicated world of social relationships. This results in the necessary synaptic pruning and neural optimization necessary to the social-cognitive development being/being held up. As shown in the interaction plots (Figures 3 and 4) ASD-High Screen group showed no substantial growth slopes as ASD-Low screen group which showed a social "catch-up" trajectory. This pointer indicates that in the case of neurodiverse groups, screen time is not just an inactive habit to them, but a dynamic hindrance of development that contributes to the distance between developmental and chronological age. A pivotal finding of this longitudinal analysis is the phenotypic convergence between high-screen exposure in neurotypical children and the primary symptoms of Autism Spectrum Disorder. At the 2023 baseline, the CDI Social (S-40) scores for typically developing children with high screen time (TDC-HST: M=16.45) were statistically proximal to those of autistic children with low screen exposure (ASD-LST: M=15.85). This overlap suggests that environmental developmental 'drags' can mimic the social-emotional deficits used in ASD diagnosis. Consequently, there is an urgent need for clinicians to incorporate a comprehensive 'digital hygiene' assessment into the diagnostic workflow. Failing to account for the impact of excessive screen time may lead to the misdiagnosis of environment-induced social delays as innate neurodevelopmental disorders, potentially resulting in inappropriate clinical pathways

Parental education on the other hand was quite a strong longitudinal buffer, and it was significant in projecting the better developmental courses in all three domains of Social, Language and General Development of Social, Language and General Development ($p < 0.001$). This scaffolding effect is an indication that increased educational level offers a protection environmental milieu which is marked with the ability to overcome intrinsic and extrinsic subsequent developmental dangers. It is a manifestation of a Matthew Effect in neurodevelopment, in which the early benefits of the environment result in compounded profits in neuroplasticity and cognitive reserve. Within the General Development model (GD-70), the high educational contribution is used as an indicator that superior literacy and numeracy conditions provide an environment in which information of complex type is better encoded into neural networks. The more the parents were educated the more likely there was the selected and exemplary linguistic support as well as the rigorous practice of digital hygiene that offered a buffer of the required development. This buffer is needed, in particular, in the domain of receptive language ($p <.001$), where communicative understanding is driven primarily by domestic milieu. This data demonstrate that the education of parents is a modifier which could override the drag produced by the weakness of diagnosis or the environmental stress. It is an element of socioeconomic buffer that is being strengthened by providing cognitively intricate stimuli and facilitating active interactions so that stronger courses can be enhanced. These findings emphasize that there is a necessity of coming up with clinical digital health guidelines to suit the environmental and socioeconomic-related situations such that they enhance the varied developmental needs of the paediatric population. Although parental education is a socioeconomic buffer, our examination shows that the home setting is even more refined with parenting styles of Baumrind. The 3-way diagnosis-environment interaction was the main factor driving the pace of development, but because parenting style was included as a covariate, it shows that the use of parenting style serves as an intervention target. Particularly, Authoritative parenting, which is marked by strong responsiveness and strictness, can be understood as a qualitative framework that can potentially alleviate the so-called displacement effect of digital media. This implies that any future clinical guidelines must be dedicated to both the limitation of screen time and the provision of parenting guidelines based on providing authoritative parenting style to promote social reciprocity and linguistic contribution, especially in neurodiverse families.

CONCLUSION

The longitudinal study provides a good empirical evidence that the exposure of the paediatric screens do not represent just a neutral environmental circumstance but a modifying condition of the developmental pathway in neurodiverse individuals that is very effective. The reality of significant interactions (Time x Diagnosis x Screen Time) in Social Skills ($p =.032$) and Self-Help ($p =.044$) domains shows a severe issue of a twofold burden of children with Autism Spectrum Disorder (ASD). Even though the cohort was found to experience chronological maturation, the high degree of screen exposure specifically prevented the rate of maturation in autistic children, that is, accelerated the

**Author for Correspondence: yashnadavid@gmail.com*

discrepancy between the developmental and chronological age during the 24 months of the study. Typically Developing Children (TDC) in comparison exhibited a relative sturdiness that means that neurodevelopmental status is a determinant of environmental sensitivity. Importantly, the fact that the goods of convergence in the scores between high-screen neurotypical children and low-screen autistic children occur is indicative that over-exposure to digital stimuli may cause pseudo-autistic-like phenotyping. This raises a clinical risk of grave misdiagnosis that environmental delays can be mistakenly taken as being the result of inherent neurodevelopmental disorders. In addition, the fact that the Parental Education predictive ability ($p <.001$) was high across all the developmental models of world formation explains why the development of socio-environmental scaffolding should be considered as a means of avoiding the developmental risks. More so, the fact that the parenting styles of Baumrind are added as a covariate supports the fact that the developmental paths are dictated by the diagnosis and screen time, but at the same time, the authoritative parenting is a critical interventional scaffold that could thwart the phenomenon of the digital displacement of the social and adaptive milestone. These findings have been backed by good model fit (Conditional $R2>.94$) and consistency in measurements over time (ICC up to.904) which imply that stagnation in high-screen ASD cohorts is more of a structural phenomenon than a transient phenomenon. The ultimate outcome of the results of these findings will be the paradigm shift in clinical digital health guidelines. Rather, practitioners should aim at neurodiversity-oriented interventions centered on the opportunity cost of being digitally displaced instead of having some universal advice about screen time. There is need to make sure that the invasion of developmental window by digital information is kept to the bare minimum so as to enable contribute to the realization of social reciprocity and adaptive autonomy among the affected children with autism. Future studies should investigate the qualitative dimension of digital content so that this aspect of enhancing such environmental protection will be holistic, making the effects of the digital far on the paediatric neurodevelopment in the more digitized world

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