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Trajectories of screen use during early childhood: Predictors and associated behavior and learning outcomes

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ABSTRACT

Little is known about the development of early screen use patterns. Using data from 1949 families in Calgary, Alberta, drawn from the All Our Families cohort, this study examined patterns of screen use across 3 time points (24, 36, 60 months) to identify trajectories of screen use, socio-demographic factors that predict trajectory membership, and whether high use trajectories relate to suboptimal child behavior and learning outcomes. Mothers reported on children's screen use (hours per day), children's behavior problems (Behavior Assessment System for Children) and developmental milestones (Ages and Stages Questionnaire). Using latent class growth modeling, two trajectories were identified: low to moderate screen use (90.5% of sample; 2.16, 3.28, and 1.34 h/day, respectively) and high-persistent screen use (9.5% of sample; 3.91, 5.26, and 3.31 h/day, respectively). A number of socio-demographic factors were associated with the high-persistent screen use trajectory. Additionally, the high-persistent screen use trajectory was associated with higher levels of externalizing behavior (e.g., inattention, aggression), poor adaptive skills (e.g., social, life skills), and less likelihood of achievement of developmental milestones (e.g., language, motor skills), at 60 months of age. Findings support that screen use patterns are formed early in childhood, emphasizing the need for prevention and early intervention.

1. Introduction

The American Academy of Pediatrics recommends no more than 1 hour of screen use per day for 2–5 year olds (i.e., time spent with a tablet, smartphone, TV, computer, video game or wearable technology). However, the majority of preschoolers are failing to meet screen use guidelines. A recent report suggests as many as 80% of 2 year olds and 95% of 3 year olds (Madigan, McArthur, Anhorn, Eirich, & Christakis, 2020) are exceeding the pediatric guidelines (American Academy of Pediatrics Council on Communications and Media, 2016; Tremblay et al., 2017; World Health Organization, 2019). While there is likely some high-quality programming that could be considered beneficial (Madigan, Racine, & Tough, 2020; Rice, Huston, Truglio, & Wright, 1990), according to the displacement hypothesis, when children are watching screens they spend less time practicing skill development via interactions with, and exploration of, their environment (Christakis, 2009). As such, there is growing concern among educators, researchers, health professionals, and parents about the impact of screen use on children's development (Rideout, 2017).

1.1. Trajectories of screen use

Only two studies (Chiu, Li, Wu, & Chiang, 2017; Trinh et al., 2020) have explicitly examined trajectories of screen use in preschool-aged children. One study focused solely on television (TV) viewing across 3 timepoints (18, 36, and 66 months) identifying three developmental trajectories among a representative Taiwanese sample (N = 18577): a consistently low trajectory (20% of sample), an increasing trajectory (46.5% of sample), and a consistently high trajectory (33.5% of sample; Chiu et al., 2017). The other study examined a composite of TV, movie and computer game use across 5 timepoints (12, 18, 24, 30, and 36 months), identifying two developmental trajectories of screen use among a representative US sample (N = 1045): a consistently low trajectory (73.3% of sample) and an increasing trajectory (26.7% of sample; Trinh et al., 2020). Both studies provide evidence that screen use patterns are forming early in development. Although these studies

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provide insight into early screen use trajectories for young children, an examination of whether trajectory membership is associated with children's behavior and learning outcomes has not been examined.

1.2. Behavior and learning outcomes of trajectory membership

Theoretically, children who are exposed to more persistent screen use may be missing out on learning opportunities, such as practicing language, communication, and literacy skills (Christakis, 2009; Tamis-LeMonda, Luo, McFadden, Bandel, & Vallotton, 2019), as well as parent and peer interactions that have been shown to build interpersonal skills and foster well-being (Radesky, Peacock-Chambers, Zuckeman, & Silverstein, 2016; Twenge & Campbell, 2018). Past research supports that children exposed to a higher duration of screen use tend to have associated behavior or social-emotional problems (Hinkley et al., 2014; Tamana et al., 2019), and are less likely to meet age appropriate developmental milestones (Madigan, Browne, Racine, Mori, & Tough, 2019). However, this research lacks a developmental perspective with most studies measuring children's screen use cross-sectionally (Browne, Thompson, & Madigan, 2020Odgers & Jensen, 2020). To our knowledge, the association between trajectories of screen use and children's behavior and learning outcomes has not been examined. Thus, studies examining the heterogeneous patterns of screen use development are needed to better understand the normative and persistent patterns of screen use that may emerge early in development, and how these patterns relate to child behavior and learning outcomes.

1.3. Predictors of trajectory membership

Individual, family, and environmental factors impact a child's screen use trajectory and offer avenues for additional prevention efforts. A number of socio-demographic factors have been associated with higher durations of screen use; including, household income (Hoyos Cillero & Jago, 2010; Rideout & Hamel, 2006), parental education level (Rideout & Hamel, 2006), the presence of an older sibling (Duch, Fisher, Ensari, & Harrington, 2013), ethnic minority status (Duch et al., 2013; Hoyos Cillero & Jago, 2010; Rideout & Hamel, 2006), child sex (Rideout & Hamel, 2006), maternal age (Duch et al., 2013), home-based versus center-based child care (Madigan, Racine, & Tough, 2020), maternal depression (Hoyos Cillero & Jago, 2010), and maternal screen use (Madigan, Racine, & Tough, 2020). Given the limited longitudinal studies for preschool aged children (Chiu et al., 2017; Trinh et al., 2020), to improve our ability to identify children at risk, research is needed to determine the socio-demographic factors that predict a child's screen use trajectory.

1.4. The current study

Several research gaps remain to adequately understand how screen use trajectories develop during the preschool years, the socio-demographic factors that may interrupt or expedite these patterns, and how these trajectories relate to child behavior and learning outcomes. The aims of this study were 3-fold. The first was to use a rigorous data analysis approach, Latent Class Growth Modeling (LCGM; Nagin, 2005), to identify homogeneous trajectories of screen use between the ages of 24 and 60 months, among a Canadian sample. The second was to identify the socio-demographic factors associated with trajectory membership. The third was to examine the association of patterns of screen use with child behavior and learning outcomes. This study is the first to validate the identified trajectories by examining the association between trajectory membership and behavior (i.e., internalizing, externalizing, and adaptive behavior) and learning (i.e., achievement of developmental milestones) outcomes at 60 months of age.

2. Methods

2.1. Study design and population

Participants included individuals recruited to participate in the All Our Families cohort, an ongoing pregnancy cohort of mothers and children from Calgary, Canada (Tough et al., 2017). Women were recruited between August 2008 and December 2010 through primary health care offices, community advertising, and laboratories. Inclusion criteria were: (1) $\geq$ 18 years, (2) fluent in English, (3) gestational age $<$ 25 weeks, and (4) receiving community-based prenatal care. Mothers and children have been followed for 5 years postpartum. A detailed description of the study sample can be found in Table 1. All procedures were approved by the institutional ethics board and informed consent was obtained from participants.

2.2. Exposure

2.2.1. Screen use

When children were 24, 36, and 60 months of age mothers self-reported the range of time their child spent using electronic devices (i.e., watching television programs; movies, videos, or stories on a VCR or DVD player; using a computer, gaming system, or other screen-based device) on a typical weekday and weekend day. A weighted average

Table 1
Sample demographics and study characteristics (n = 1949).

Characteristic	Value
Child sex, No. (%)	
Female	914 (46.9)
Male	996 (51.1)
Child screen use, h/day, mean (SD)	
24 months	2.33 (1.6)
36 months	3.47 (1.6)
60 months	1.53 (0.7)
Internalizing total score (BASC) at 60m, mean (SD)	50.46 (9.55)
Externalizing total score (BASC) at 60m, mean (SD)	49.21 (8.23)
Adaptive skills total score (BASC) at 60m, mean (SD)	52.91 (8.48)
Developmental milestones total score (ASQ-3) at 60m, mean (SD)	274.16 (28.36)
Maternal age, y, No. (%)	
Age >31	833 (42.7)
Age ≤31	1065 (54.6)
Maternal education, No. (%)	
High school education or less	142 (7.3)
Some or completed post-secondary	1807 (92.7)
Maternal race/ethnicity, No. (%)	
White	1592 (81.7)
Other	345 (17.7)
Missing	12 (0.6)
Maternal screen use at 24 m, No. (%)	
> 3 h per day	184 (9.4)
≤ 3 h per day	1412 (72.5)
Missing	353 (18.1)
Maternal depression (CES-D) at 24 m, No. (%)	
At risk score > 16	200 (10.3)
Low score <16	1396 (71.6)
Missing	353 (18.1)
Household income, No. (%), CAD$	
<60,000	343 (17.6)
≥ 60,000	1528 (78.4)
Missing	78 (4.0)
Older sibling, No. (%)	
Older sibling in the home	988 (50.7)
No older sibling	943 (48.4)
Missing	18 (0.9)
Child care at 24 m, No. (%)	
Center-based childcare	576 (29.5)
Home-based childcare	1009 (51.8)
Missing	364 (18.7)

Abbreviations: BASC, Behavior Assessment System for Children; ASQ-3, Ages and Stages Questionnaire, Third Edition; CES-D, Center for Epidemiological Studies Depression Scale; CAD$, Canadian Dollars.

across week and weekend days and electronic devices, was calculated to yield screen use in hours/day. At each timepoint, outliers greater than 4 SDs from the mean were treated as missing ($n = 8$ at 24 months, $n = 16$ at 36 months, $n = 7$ at 60 months). Although limited by reporter bias and recall, maternal-reported duration of child screen use is a widely used method to measure screen use (Hardy et al., 2013).

2.3. Outcomes

2.3.1. Child behavior

The Behavior Assessment System for Children (BASC-II; Kamphaus, 2015) was used at 60 months to gather a composite measure of: internalizing behavior, including anxiety, depression, somatization and withdrawal subscales; externalizing behavior, including aggression, attention issues, hyperactivity and atypicality subscales; and adaptive behavior, including activities of daily living, adaptability, functional communication and social skills subscales. Standardized T-scores were used with higher scores indicating greater problem or adaptive behavior. The BASC-II is a widely used tool to assess childhood behavior difficulties and has strong psychometric properties (Kamphaus, 2015).

2.3.2. Developmental Screener

At 60 months of age, mothers completed the Ages and Stages Questionnaire, Third Edition (ASQ-3; Squires & Bricker, 2009) The ASQ-3 is a parent-report screening measure used to evaluate children's developmental progress in 5 domains: communication, gross motor, fine motor, problem solving, and personal-social. Consistent with previous research (Madigan et al., 2019), a summed ASQ-3 score across all domains was used (lower raw scores indicate poorer development). The ASQ-3 has been shown to have good psychometric properties (Squires & Bricker, 2009).

2.4. Covariates

Child sex (1[female]; 0[male]), household income (bottom quartile split; 1[<60 000 CAD$];0 [≥60 000 CAD$]), maternal education (1 [high school education or less]; 0[some or completed postsecondary education]), older sibling (1[older sibling in the home]; 0[no older sibling]), ethnicity (1[other]; 0[White]), and maternal age (median split; 1 [>31 years]; 0[≤ 31 years]) were maternal self-report. When the child was 24 months of age mothers reported on childcare, maternal depression, and maternal screen use. Childcare was coded based on the primary method of care reported, with a minimum of 10 hours per week in this setting, (1[home-based childcare]; 0[center-based childcare]). Maternal depression was coded based on the at-risk cut-off for the Center for Epidemiological Studies Depression Scale (Lewinsohn, Seeley, Roberts, Allen, & 1997; CES-D; 1[at risk score, ≥ 16]; 0[low score, <16]). Maternal screen use was measured with a single self-report item asking the amount of time mothers spend watching television on a typical weekday (median split; 1[> 3 h per day];0[≤3 h per day]).

2.5. Statistical analysis

The trajectories of screen use were examined using LCGM (Nagin, 2005). This method identifies homogenous subgroups of children following a distinct pattern of screen use over time. LCGM was performed estimating linear models with one through five trajectories followed by quadratic models. The model with the optimal number of trajectories based on the Bayesian information criteria (BIC), a significant parametric bootstrapped likelihood ratio test (BLRT), entropy, and interpretability was selected (Nylund, Asparouhov, & Muthén, 2007). Next, covariates were examined for differences across trajectories using chi-square tests.

Finally, to determine whether the trajectories differentially predicted child behavior and learning outcomes at 60 months of age, the manually implemented distal outcome method recommended by Asparouhov and Muthén, (2014) was used. This strategy permits testing for trajectory differences with covariates in a structural equation modeling (SEM) framework. Based on the preferred LCGA model, the measurement model is determined using the most likely class membership and incorporates probability weights to address imprecision of class membership. To constrain individuals to their most likely class, the logits for the classification probabilities for the most likely latent class membership obtained in the first stage of data analysis were entered as parameters for each class. Bolck, Croon, and Hagenarrs weights (BCH) were also used to control for the measurement error in each trajectory. To determine if the classes differentially predicted the outcomes (i.e., BASC and ASQ) the auxiliary model was constrained (i.e., null hypothesis) by setting the outcome intercept parameters for the trajectories to be equal when predicting the outcome. The freely estimated auxiliary model (i.e., alternative hypothesis) was computed by allowing the trajectories to vary independently while predicting the outcome. The two auxiliary models (i.e., constrained versus freely estimated) were compared by a chi-square difference test using loglikelihood values and scaling correction factors obtained from the maximum likelihood estimation with robust standard errors (MLR). This test statistic is comparable to an omnibus F-statistic in ANOVA. If the two models significantly differed, pairwise comparisons were conducted using post-hoc t-tests to identify class differences in the prediction of outcomes.

All covariates were controlled for in the final models examining associations between trajectory membership and child behavior and learning outcomes. Cohen's d was used to determine the effect size (0.2, small; 0.5, medium; 0.8, large; Cohen, 1988). All analyses were performed using Mplus 8.1(Muthén & Muthén, 2017). Findings were considered significant at the $p < .05$, 2-tailed level.

2.6. Missing data

From the initial pregnancy cohort (n = 3388), 95% (n = 3223) agreed to be contacted for follow-up research. Of those who agreed to follow-up and were eligible at the time of questionnaire completion, 76% completed the 24-month questionnaire (n = 1595), 69% completed the 36-month questionnaire (n = 1994), and 71% completed the 60-month questionnaire (n = 1992). Attrition rates observed in the current study are similar to other prospective birth cohorts (Browne, Wade, Prime, & Jenkins, 2018; Sontag-Padilla et al., 2015). Predictors of drop out are reported elsewhere (younger mothers; lower income; Madigan et al., 2019). The subsample used in this study (n = 1949) completed the screen use measure for at least 2 time points at either 24, 36, or 60 months. In order to estimate the effects of missing-data, models were run with Robust Maximum Likelihood (Graham, 2009).

3. Results

Based on screen use measured at 24, 36, and 60 months of age, the best fitting LCGM was the 2-trajectory quadratic model (Table 2, Fig. 1). The low to moderate screen use trajectory (n = 1764 [90.5%]) was composed of children who exhibited a lower level of screen use across all time points (2.14[1.37], 3.28[1.47], 1.35[0.43]; M[SD] hours/day, respectively). The high-persistent screen use trajectory (n = 185 [9.5%]) was composed of children who exhibited higher levels of screen use across all time points (3.90[2.10], 5.26[2.05], 3.31[0.43]; M[SD] hours/day, respectively).

Latent class growth modeling identified two trajectories of screen use across 24, 36, and 60 months of age (n = 1949): low to moderate screen use (90.5% of sample) and high-persistent screen use (9.5% of sample).

Table 3 shows the odds of membership in the high-persistent screen use trajectory based on the socio-demographic covariates. Results from the chi-square difference tests show that ethnic minority status (Odds Ratio [OR], 2.43; 95% CI, 1.70–3.47), high school education or less (OR, 3.20; 95% CI, 2.04–5.02), lower income (OR, 2.78; 95% CI, 1.91–4.07), home-based childcare (OR, 1.55; 95% CI, 1.04–2.32), and higher levels

Table 2
Fit indices for latent growth model solutions.

Trajectory	Log likelihood	BIC	BLRT	Entropy
Linear Models				
1	−8480.62	16999.11	N/A[a]	1
2	−7981.74	16024.09	.000	0.95
3	−7877.37	15838.06	.000	0.85
4	−7653.77	15335.53	.000	0.92
5	−7486.63	15007.25	.000	0.91
6	Would not converge			
Quadratic Models				
1	−8091.74	16228.93	N/A[a]	1
2	−7543.91	15163.57	.000	0.95
3	−7349.15	14759.86	.000	0.77
4	Would not converge			

AbbreviationsBIC, Bayesian Information Criterion; BLRT, Bootstrap. Likelihood Ratio Test.
[a] BLRT is not available for the one-class model.

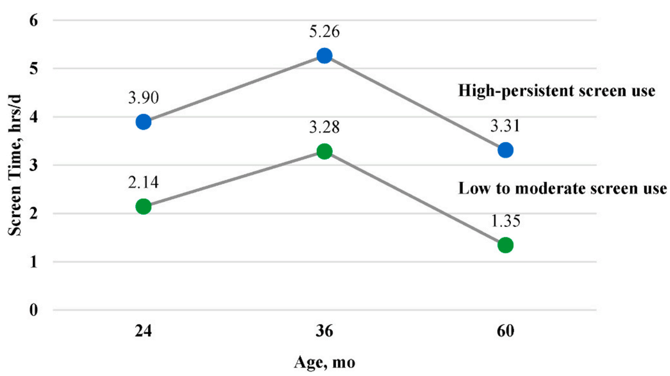

Fig. 1. Mean screen use by trajectory.

Table 3
Odds Ratio for the High-Persistent Screen use Trajectory as a Function of the Socio-demographic Covariates.

Covariate	High-Persistent Trajectory	
	OR (95%CI)	*p*
Ethnic minority status	2.43 (1.70–3.47)	.000
High school education or less	3.20 (2.04–5.02)	.000
Maternal screen use >3 h/d	5.68 (3.45–9.36)	.000
Income ≤60,000 CAD$	2.78 (1.91–4.07)	.000
Home-based childcare	1.55 (1.04–2.32)	.023
Female child	0.92 (0.66–1.28)	.617
Maternal at-risk depression	1.55 (0.92–2.61)	.143
Older sibling	0.78 (0.57–1.07)	.123
Maternal age >31y	1.12 (0.81–1.55)	.495

Abbreviations: OR, odds ratio; CI, confidence interval.

of maternal screen use (OR, 5.68; 95% CI, 3.45–9.36), was associated with greater risk of classification in the high-persistent screen use trajectory. The trajectories did not significantly differ by child sex [$\chi2(1, N = 1798) = 0.25, p = .617$], maternal age [$\chi2(1, N = 1898) = 0.47, p = .495$], older sibling status [$\chi2(1, N = 1933) = 2.38, p = .123$], or maternal depression [$\chi2(1, N = 1435) = 2.14, p = .143$].

3.1. Trajectory membership predicting behavior outcomes at 60 months

When examining externalizing behavior (BASC Externalizing Composite) at 60 months of age, the constrained auxiliary model and the freely estimated auxiliary model significantly differed [$X^2(1, N = 1949) = 5.11, p = .024$]. Pairwise comparisons revealed that the high-persistent screen use trajectory predicted significantly higher levels of externalizing symptoms (M, 51.05; SD, 8.18) at 60 months of age compared to the low to moderate screen use trajectory (M, 48.99; SD, 8.21; $t(1947) = 1.78, p = .013$), with a small effect size ($d = 0.25$; Fig. 2a).

When examining internalizing behavior (BASC Internalizing Composite) at 60 months of age, the constrained auxiliary model and the freely estimated auxiliary model did not significantly differ [$X^2(1, N = 1949) = 0.75, p = .385$]. Thus, the trajectories did not differentially predict internalizing problem behavior at 60 months of age.

When examining adaptive behavior (BASC Adaptive Composite) at 60 months of age, the constrained auxiliary model and the freely estimated auxiliary model significantly differed [$X^2(1, N = 1949) = 19.76, p < .001$]. Pairwise comparisons revealed that the high-persistent screen use trajectory predicted significantly lower levels of adaptive behavior

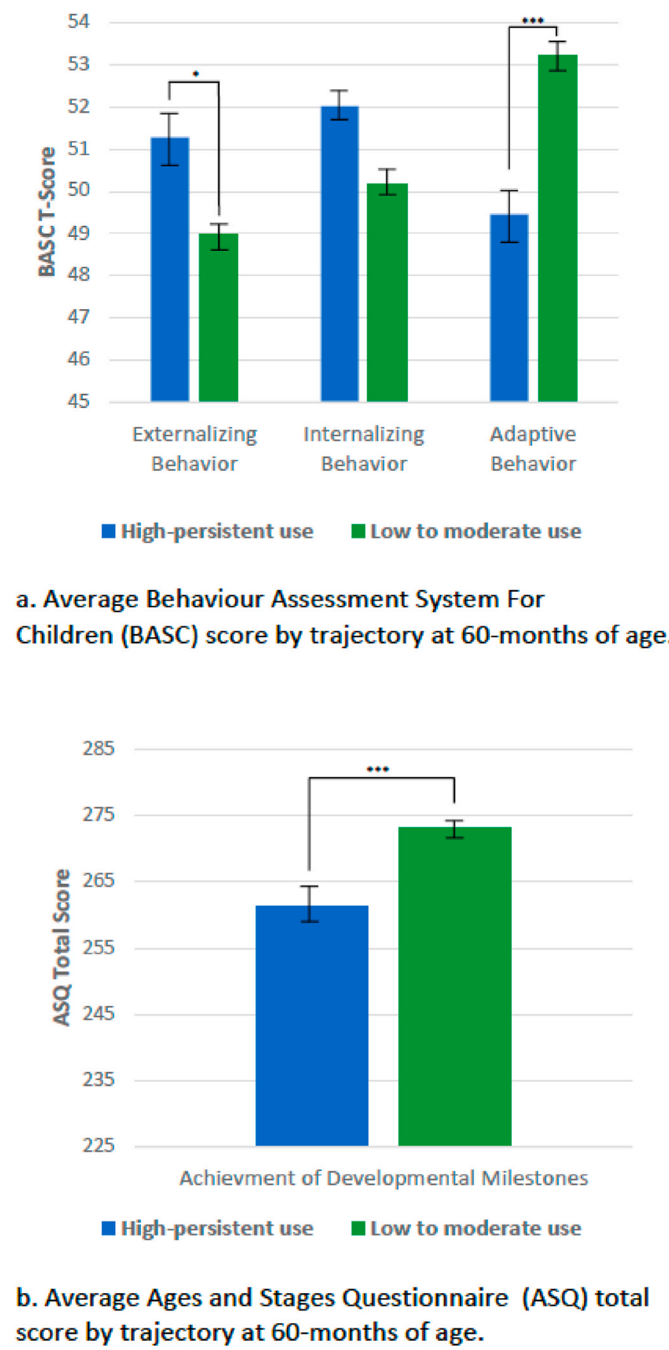

Fig. 2. Child Behaviour (a) and Developmental Screener (b) Outcomes at 60 months of age by Trajectory. *Notes.* *$p < .05$, **$p < .01$, ***$p < .001$. Error bars represent standard error.

(M, 49.54; SD, 9.28) at 60 months of age compared to the low to moderate screen use trajectory (M, 53.15; SD, 8.35; $t(1947) = -3.23$, $p < .001$), with a small effect size ($d = 0.41$; Fig. 2a).

3.2. Trajectory membership predicting developmental milestone achievement at 60 months

When examining achievement of developmental milestones (ASQ Total) at 60 months of age, the constrained auxiliary model and the freely estimated auxiliary model significantly differed [$X^2(1, N = 1949) = 8.88$, $p = .002$]. Pairwise comparisons revealed that the high-persistent screen use trajectory predicted a significantly lower total score for achievement of developmental milestones (M, 261.34; SD, 43.91) at 60 months of age compared to the low to moderate screen use trajectory (M, 273.15; SD, 29.21; $t(1947) = -9.41$, $p = .007$), with a small effect size ($d = 0.32$; Fig. 2b).

4. Discussion

The emerging media options now available to young children has resulted in increased screen use among this demographic (Rideout, 2017). Indeed, screen use is now considered ubiquitous in the lives of young children, with approximately 98% of children under age 8 living in a home with an internet-connected device, and, on average 5 devices per household (Common Sense Media, 2018). However, currently, little empirically supported information can be provided to practitioners and parents about the onset and developmental course of early screen use patterns and factors that may put children at risk for membership in a high screen use trajectory group. Using a robust method for examining trajectories known as Latent Growth Curve Modeling, the current study identified two trajectories of screen use across 3 time points (24, 36, and 60 months) for a Canadian sample of preschoolers: a high-persistent screen use trajectory (9.5% of sample) and a low to moderate screen use trajectory (90.5% of sample). These identified trajectories are similar to past research using a comparable composite of screen use (i.e., tv, computer, video game), over a similar developmental time frame (Trinh et al., 2020).

The current study is unique in that it included children from 24 to 60 months of age, an age span specific to the screen use guidelines for children ages 2–5 years. Trajectories identified in the current study suggest that screen use patterns (i.e., duration of screen use) may be formed early in development. Specifically, the high-persistent trajectory group (9.5% of the sample) had high levels of screen use at 24 months (~4 h per day) and maintained high levels of screen use across the early childhood period. For both trajectories, duration of screen use peaked at 36 months: on average the high-persistent screen use trajectory group and the low to moderate screen use trajectory group engaged in 5.26 and 3.28 hours of screen use per day, respectively. These durations are not only well above the pediatric screen use guidelines (1 hour per day), but they also make up a large portion of children's waking hours and suggest that screen use is likely interfering with important learning opportunities and interactions with caregivers, as well as other adaptive health behaviors such as sleep and physical activity (Tremblay et al., 2017). A decrease in screen use was observed from 36 to 60 months, which may be on account of school entry and associated environmental changes in terms of reduced accessibility to media devices.

This is the first study to validate the predictive ability of screen use trajectories on preschoolers' behavior and learning outcomes. The high-persistent screen use trajectory predicted higher levels of externalizing symptoms (e.g., inattention, aggression), lower levels of adaptive behavior (e.g., age appropriate life skills, leadership), and poor performance on a screening measure assessing children's achievement of developmental milestones (e.g., age appropriate language, social skills, fine and gross motor skills) at 60 months of age. These findings are consistent with previous variable-centered studies (i.e., correlational studies) looking at the association between screen use exposure and preschoolers' developmental outcomes (Hinkley et al., 2014; Madigan et al., 2019; Tamana et al., 2019). The current person-centered analysis examining individual differences via trajectory analyses suggests that children in the high-persistent screen use group (9.5% of the sample) may largely be driving the association between screen use and problematic child behavior and learning outcomes. Along with other important factors in a child's early life, screen use influences child behavior and learning outcomes. That said, effect sizes for these findings are small; however, small effect sizes can have large public health implications (Madigan, McArthur, Anhorn, Eirich, & Christakis, 2020).

Similar to the previous trajectory studies, lower maternal education and home-based childcare were factors associated with the high-persistent screen use trajectory (Chiu et al., 2017; Trinh et al., 2020). The current study also adds to this literature via findings suggesting that ethnic minority status, lower income, and high levels of maternal screen use, were associated with the high-persistent screen use trajectory. These findings are in line with the growing evidence that the family environment can play an important role on children's screen use (Duch et al., 2013; Hoyos Cillero & Jago, 2010) and that socio-demographically disadvantaged children may experience more screen use because of limited caregiver ability to provide alternative activities (Browne et al., 2018). This study also highlights home-based care and maternal screen use patterns as additional environmental factors to consider. Alternatively, maternal age, child sex, having an older sibling, and maternal depression were not significantly associated with trajectory membership in this study. Although past cross-sectional research has highlighted these factors as significant predictors of screen use duration at a single time-point (Duch et al., 2013; Hoyos Cillero & Jago, 2010; Rideout & Hamel, 2006), the current study suggests that when examining trajectories of screen use, maternal age, child sex, having an older sibling, and maternal depression may not be key socio-demographic factors impacting trajectory group membership.

This study highlights that patterns of screen use are forming in the early years of life. The findings therefore support the need for family-level intervention to encourage engagement with technology in an age-appropriate way, with particular attention to at-risk populations and parents as the agents of change. Practitioners can review and emphasize the importance of using a Family Media Plan (American Academy of Pediatrics, 2019) to help manage and monitor how, when, and where screens are used in the home. Additionally, because parent media use is a strong predictor of child media use (Madigan, Racine, & Tough, 2020), it may be particularly helpful to target parent screen use viewing while providing education about the impact of parent media use on child use.

5. Limitations

Using a large longitudinal cohort, this study sheds light on important factors that may be useful in identifying children at risk for patterns of high screen use exposure. However, the findings must be interpreted with the following limitations in mind. First, this study would be strengthened if replicated with objective measures of child behavior, learning outcomes, and screen use. Second, the current sample was socio-demographically homogeneous. While this is representative of the region of data collection, it can limit the generalizability of the study findings. Lastly, we examined duration of child screen use on a "typical day", but did not examine how time was spent (content) and with whom it was spent (context), which may be important considerations for understanding associations between screen use and child outcomes (Christakis, 2009; Madigan, McArthur et al., 2020). Collecting more information about the content and media devices used, as well as the shared screen environment between parents and children, would illuminate the mechanisms contributing to the relation between screen use duration and poor developmental outcomes.

6. Conclusions

In response to the evolving digital landscape and rapid increase in accessibility and exposure to screen media, there is a need for longitudinal approaches to better understand the long-term impact of screen use for young children (Browne et al., 2020). In the current study, we identified two unique patterns of screen use – a high-persistent screen use trajectory and a low to moderate screen use trajectory, suggesting that early screen use patterns may persist over time. Moreover, a number of socio-demographic factors (i.e., lower maternal education, home-based childcare, ethnic minority status, lower income, and high levels of maternal screen use) are associated with the high-persistent screen use trajectory, providing insight into at-risk populations. Further, building from previous research, the results show that the unique trajectories identified are related to child behavior and learning outcomes at 60 months of age, with high screen use users reporting higher levels of externalizing symptoms, poorer adaptive skills, and poorer achievement of developmental milestones. The findings from this study support the need for practitioners and educators to encourage families to engage with technology in an age-appropriate way during a sensitive period of child development.

Declaration of competing interest

None.

CRediT authorship contribution statement

Brae Anne McArthur: Conceptualization, Formal analysis, Writing - original draft. **Dillon Browne:** Formal analysis, Writing - review & editing. **Suzanne Tough:** Data curation, Methodology, Funding acquisition, Writing - review & editing. **Sheri Madigan:** Conceptualization, Formal analysis, Writing - original draft, Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2020.106501.

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