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ORIGINAL RESEARCH

Investigating Learning Trajectories on Digital Attention Training Tasks in Primary School Children

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Abstract
Attention training programs have demonstrated potential for improving select cognitive skills and behaviors in children, but reported benefits are inconsistent. It is unclear whether variability in training benefits can be attributed to differences in children's learning trajectories on training tasks over the intervention period. This study examined the functional form of learning trajectories on adaptive attention training tasks in primary school children, and potential associations between these learning trajectories and (a) pre-training child characteristics (general cognitive ability, hyperactivity, inattention, age) and (b) outcomes on untrained tasks from pre- to post-training (attention, hyperactivity, inattention). A total of 38 children (5–9 years) completed a 5-week attention training program in class. The training sessions involved four tasks targeting selective attention, sustained attention, inhibition, or interference control. Assessments were conducted pre- and immediately post-training. Based on non-linear mixed-effects models, the learning trajectories were best described by asymptotic regression, where the largest rate of improvement occurred initially, followed by gradual flattening out as task difficulty approached the asymptote. For the sustained attention training task, lower asymptotes predicted larger reductions in hyperactive behaviour from pre- to post-training. For the sustained and selective attention training tasks, age was associated with the asymptotes of the learning trajectories. Collectively, these findings suggest that learning trajectories on certain attention training tasks are associated with select child characteristics and training outcomes. It is of interest for future cognitive training studies to examine the learning trajectories of tasks targeting different skills to contribute understanding of the processes associated with cognitive training outcomes.

Keywords Cognitive training · Learning trajectories · Attention · Adaptive training · Children

Introduction

Adaptive digital attention training programs have demonstrated promise for improving aspects of behavioral and cognitive attention for primary school children (Kirk et al., 2021a) and clinical childhood populations (Kollins et al., 2020; Kirk et al., 2016, 2017). Demonstrating the efficacy of cognitive training programs, such as those targeting attention, has been an important focus of child studies to date (Simons et al., 2016). Efficacy has generally been examined by comparing changes in scores on outcome measures collected pre- and post-intervention across training and control conditions (Kirk et al., 2016; Kirk et al. 2021a; Kollins et al., 2020; Scionti et al., 2020). Studies have consistently shown transfer of training to untrained tasks that are closely associated with the trained tasks, referred to as near transfer effects (Gathercole et al., 2019; Holmes et al., 2019; Kassai et al., 2019). However, evidence of gains on untrained tasks that are more distantly associated with the trained tasks referred to as far-transfer effects is inconsistent (Redick et al., 2013; Sala et al., 2019; Sala & Gobet, 2019). In recent years, contributing factors, such as individual pre-training abilities, have begun to be examined to help understand these inconsistencies in cognitive training outcomes (Gathercole et al., 2019; Dahlin, 2011; Tamm et al., 2013; van der Donk et al., 2020; van der Donk et al., 2017), including attention training outcomes in children (Kirk et al., 2021b; Kirk et al., 2022). Collectively, these studies suggest individual differences in

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pre-training attention abilities, age, and everyday functioning may influence training gains. Specifically, younger individuals with lower initial cognitive capacities tend to show greater benefits from training.

However, another potential contributor that has not previously been examined in relation to attention training is differences in learning trajectories (i.e., performance) on the training tasks across the intervention period. A few child studies have investigated learning trajectories on cognitive training interventions targeting working memory (Jaeggi et al., 2011; Loosli et al., 2012), inhibitory control (van der Donk et al., 2017), or executive functions (Minder et al., 2019). These studies predominantly suggest that children who show greater improvements on untrained near transfer measures also show greater improvements during training, i.e., steeper learning trajectories (van der Donk et al., 2017; Jaeggi et al., 2011; Loosli et al., 2012; Minder et al., 2019). Examining learning trajectories for attention training tasks and investigating their associations with outcome measures could provide important insight into why training gains are greater for some children as well as test the central assumption of cognitive training that repeated practice on a task results in improvements on that task which translates to improvements on untrained tasks.

Of the limited paediatric studies that have examined learning trajectories on cognitive training tasks, the majority report a non-linear trajectory; however, the data have only been modelled with linear terms (e.g., Minder 2019) or with the addition of non-linear terms (e.g., quadratic, van der Donk et al., 2017; Cleland et al., 2022). This approach although mathematically sound (i.e., a good fit for the data) is problematic because the inclusion of a quadratic term (for example van der Donk 2017) is not consistent with theories and known mechanisms of learning (Cochrane & Green, 2021). For instance, this approach would predict a peak in learning followed by a reversal in learning. In the fields of visual perceptual learning and skill learning, it is generally accepted that the functional form of learning is best described by an exponential function (Dosher & Lu 2007, Cochrane & Green 2021). Exponential functions, more specifically an asymptotic regression function, describe a pattern of learning where children learn new strategies to improve their performance on the task in initial training sessions, and subsequent use of the strategy may then only result in small performance increases and eventually reaching a plateau or asymptote (e.g., as proposed by Gathercole et al., 2019). In other words, asymptotic regression describes limited growth where learning approaches a plateau or horizontal asymptote over time and the rate of learning is proportional to the amount of training completed, i.e., is maximum at the beginning of training and decreases with time. It is therefore important to examine learning trajectories in relation to cognitive training tasks targeting skills such as attention, using exponential functions to accurately describe the functional form of learning. This understanding will provide information on the rate of learning on attention training tasks which may have impacts on the benefits transferred to untrained tasks and could therefore inform which skills are susceptible to training as well as guiding optimal training schedules.

Related to this, it is of interest to understand whether specific child characteristics are associated with these learning trajectories to help clarify why some children perform better than others on attention training tasks and whether certain subgroups of children may benefit from different training schedules. To date, only a limited number of cognitive training studies have examined the potential influence of pre-training child characteristics on learning trajectories. These studies of working memory or inhibition training tasks have found that neither pre-training child cognitive abilities (Loosli et al., 2012; Minder et al., 2019; van der Donk et al., 2017) nor age (van der Donk et al., 2017) was associated with learning trajectories. It is of interest to determine whether these findings extend to learning trajectories on attention training tasks, especially given children's pre-training attention (i.e., higher inattention and hyperactivity) and age (i.e., younger age) have been found to influence training outcomes (i.e., greater improvements in attention skills; Kirk et al., 2022).

This study aimed to examine learning trajectories on attention training tasks by describing (a) the functional form of learning trajectories on adaptive attention training tasks, (b) whether learning trajectories on attention training tasks are associated with near (i.e., attention skills) and far (i.e., inattention and hyperactivity) training outcomes in children, and (c) whether pre-training child characteristics (i.e., pre-training general cognitive ability, inattention, hyperactivity, and age) influence learning trajectories. We expected learning trajectories to show a non-linear pattern best described by asymptotic regression. Furthermore, we expected a positive association between the rate of learning on the learning trajectories and change in the near outcome measures (i.e., attention skills). To address the study aims, we used data from a previously conducted trial in 38 primary school children (5–9 years) evaluating the effectiveness of an adaptive digital attention training program delivered in the classroom over 5 weeks compared with a placebo or usual teaching control conditions (Kirk et al., 2021a). Children who received attention training showed greater reductions in inattention and hyperactivity in the classroom at post-training than children who were assigned to the control conditions and greater improvements in sustained attention and reductions in hyperactivity at 6-month follow-up compared to children in the usual teaching condition.

Materials and Methods

Participants

The current study used data from 38 primary school children (aged 5 to 9 years) who completed a 5-week digital attention training program as part of a previously conducted trial (Kirk et al., 2021a). Children were recruited from three primary schools within metropolitan Melbourne. Children eligible for the trial were (a) enrolled in participating Preparatory, Grade 1, or Grade 2 class; (b) fluent in English; and (c) did not have an intellectual disability based on parent report at pre-training and confirmed by an IQ Composite score >70 (KBIT-2; Kaufman & Kaufman, 2004). Children were excluded if they had any visual, auditory, or motor impairments based on parent report that would prevent them from participating in the assessments or the training program.

The trial was prospectively registered with the Australian New Zealand Clinical Trials Registry (ACTRN12616001111460) and performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Monash University Human Research Ethics Committee and the Catholic Education Office Melbourne. Parents provided written consent.

Intervention

Tali Train is a game-based digital attention training program designed for children with intellectual and developmental delay (Kirk et al., 2016). The program is delivered on a touch screen tablet and comprises 25 training sessions, of 20-min duration, over a 5-week period. Tali Train is visually engaging and includes verbal reinforcement and a reward system to encourage motivation. Teachers delivered the program in class as part of the typical school day via 7-in. touchscreen tablets, with all children in class participating in the sessions concurrently. Each session involved training on four adaptive training tasks each targeting a different attention process. All children started each training task at level 1 and progressed to subsequent levels depending on their performance. If children failed to successfully meet the pass criteria for a given level, they would repeat the same level. If children failed to successfully meet the pass criteria for a given level twice in a row, then the level would be reduced, and children would complete the previous difficulty level. Manipulations of task difficulty were guided by past literature on each of the training tasks (Lindqvist & Thorell, 2009).

Training Task 1 | Selective Attention Children are required to locate predefined targets among a series of distractors that differ from the target in size, color, pattern, and orientation. Difficulty was increased by changing the following variables: decreasing the number of targets, increasing the number of distractors, increasing the total number of items, changing the distractor type, moving the features of the distractors, moving the distractors and the targets, and increasing the number of background distractors (see Table S1). Each level was a unique combination of these variables to form 340 levels. A level was successfully completed when (a) all the targets had been located, (b) there were no more than 20 non-target touches in the level, and (c) less than 40% of the distractors were touched.

Training Task 2 | Sustained Attention Children are required to monitor a moving target and to indicate when the target stops moving as quickly as they can. Difficulty was increased by changing the following variables: increasing the number of targets, increasing the number of background distractors, increasing the time before the target(s) stopped, and decreasing the time the target(s) remained stationary (see Table S2). Each level was a unique combination of these variables to form 524 levels. A level was successfully completed when (a) all the targets had been touched, (b) there were no more than 20 non-target touches in the level, and (c) there were no missed targets.

Training Task 3 | Inhibition Children are required to press the screen when a target appears but to withhold responding when a non-target appears. Difficulty was increased by changing the following variables: increasing the proportion of Go trials, decreasing item display time, decreasing time between items, increasing the number of items presented, and disguising non-target items as target items (see Table S3). Each level was a unique combination of these variables to form 368 levels. A level was successfully completed when (a) the target had been touched, and (b) there were no more than 20 non-target touches in the level, or (c) a response to the non-target was withheld.

Training Task 4 | Interference Control This task presents a target that is flanked by non-targets facing in either the same (congruent) or opposite (incongruent) direction to the target. Children are required to make a response (left or right) depending on the direction the target is facing. Level of difficulty was increased by changing the following variables: changing the orientation of the target, decreasing the size of the target, moving the location of the target, increasing the number of non-targets, modifying the location of the non-targets, and decreasing the spacing between the non-targets (see Table S4). Each level was a unique combination of these variables to form 388 levels. A level was successfully completed when (a) a correct response was made (left or right) and (b) there were no more than 20 non-target touches in the level.

Measures

General Cognitive Ability

The Kaufman Brief Intelligence Test – Second Edition (KBIT-2; Kaufman & Kaufman, 2004) was conducted at pre-training to assess general cognitive functioning. The KBIT-2 is suitable for individuals aged 4 to 90 years and has three subscales: Verbal Knowledge, Matrices, and Riddles. The full-scale intelligence composite score, calculated based on the three subscales, was used in analyses (M=100; SD=15; range 40–160).

Inattention and Hyperactivity

The Strengths and Weaknesses of ADHD symptoms and Normal behavior scale (SWAN; Swanson et al., 2012) was used to assess inattention and hyperactivity at pre-training. The SWAN consists of 18 items and has been used in children aged 4 to 18 years. Teachers rated children's behavior on each item over the last week on a 7-point scale, ranging from 3 "far below average" to –3 "far above average." The first 9 items relate to inattention and the last 9 items relate to hyperactivity. A raw score for each domain was generated by totalling responses in each section, with higher scores indicating greater symptoms of either inattention or hyperactivity (maximum of 54).

Attention

Subtests from the Test of Everyday Attention for Children Second Edition, junior version (TEACh-2; Manly, Anderson, Crawford, George, & Robertson, 2017), designed for children aged 5 to 7 years, were used to measure change in attention from pre-training to immediately post-training. (1) Selective attention was measured by the *Balloon Hunt* subtest which involved four trials where children had to locate as many balloons as they could on a piece of paper in 15 s. The mean number of balloons located across trials was reported, with higher scores reflecting better performance (maximum 48). (2) Sustained attention was measured by the computerized *Simple Reaction Time* (SRT), which required children to press the keyboard spacebar as quickly as possible when a blue blob appeared on the screen. The blue blob appeared at infrequent intervals and the task typically took 6 min to complete. The mean response time in milliseconds was recorded, with lower scores reflecting better performance. (3) Inhibition was measured by the *Sustained Attention to Response Task* (SART) which involved the random presentation of shapes on a computer screen. Children pressed the spacebar as quickly as possible when a shape appeared on the screen (go trial) but were instructed to withhold a response if the shape was a triangle (no-go trial). The total number of responses to no-go trials was recorded (commission), with lower scores indicating better performance. No outcome measure for interference control was included.

Data Analysis

All data analyses were implemented in R version 3.5.2 (R Core Team, 2021) using the "nlme" package (Linear and NonLinear Mixed Effect Models, version 3.1-153; Pinheiro, Bates, DebRoy & Sarkar, 2019). To examine the learning trajectories of each of the four adaptive attention training tasks across the 5-week intervention period, mixed effects models were used (functions "lme" and "nlme" within the "nlme" package; Pinheiro, Bates, DebRoy & Sarkar, 2019). Two models were compared to analyze each learning trajectory, i.e., the relationship between the number of training sessions and the difficulty level attained on the attention training task: (a) linear model; and (b) non-linear, asymptotic regression model (function "SSasymp"). In the linear model, the y-intercept term denoted the difficulty level on the training task at the beginning of the intervention period and the slope, the change in difficulty level on the training task over the intervention period (time variable). In the asymptotic regression model, the equation was $y = a + (b–a) \times \exp(-c \times \text{training session})$, where y was the difficulty level, a was the asymptote of difficulty level, b was the y-intercept (as above for the linear model), and c the rate constant (the rate at which difficulty level approaches the asymptote and referred to as "rate" from this point). In both models, observations over time (i.e., difficulty level attained in each training session), nested within children, were included as random factors. Best fitting random effects structure and changes in model fit (relative model fit) were evaluated using the maximum likelihood ratio test; using −2 times the change in log-likelihood ($-2LL$), distributed as chi-square (χ^2) with degrees of freedom equal to the number of parameters added. As per "nlme" recommendations, confidence intervals were used to evaluate the statistical significance of model coefficients (Pinheiro, Bates, DebRoy & Sarkar, 2019). Effect sizes were estimated using marginal r^2, the proportion of total variance explained through the fixed effects (Nakagawa & Schielzeth, 2013).

To examine whether each learning trajectory was associated with training outcomes, Pearson correlation coefficients were determined between learning trajectory mixed model parameters for an attention training task and change in target outcome measure from pre- to post-training, e.g., the asymptote of the selective attention learning trajectory and change in performance on the selective attention outcome measure. Correlations between the model parameters and changes in inattention and hyperactivity outcome measures from pre- to post-training were also calculated. Note that there was no outcome measure assessing interference control so the learning trajectory on the interference control training task could not be examined. Effect sizes were estimated from the Pearson correlation coefficient (Cohen, 1988). False discovery rate (FDR) correction was applied to adjust for multiple comparisons (FDR = 5%; Benjamini & Hochberg, 1995).

To examine whether pre-training child characteristics predicted the learning trajectories, general cognitive ability, inattention, hyperactivity, and age were mean centered and entered as fixed effects into each of the models. All predictors were entered into the models as continuous variables. Interaction terms were entered into the models for all fixed effects and investigated in terms of the model parameters. As above, confidence intervals were used to evaluate the statistical significance of model coefficients (Pinheiro, Bates, DebRoy & Sarkar, 2019).

Power estimations were simulated post hoc using the "simr" package in R (version 1.0.5) for linear mixed models (Brysbaert & Stevens, 2018; Green & MacLeod, 2016). "simr" can estimate the power to detect a specific effect in a model. The power to detect the interaction terms for general cognitive ability, inattention, hyperactivity, and age was estimated for each of the four adaptive attention training tasks using linear mixed models. The effect was assessed by comparing the models to an alternative model that only included main effects for general cognitive ability, inattention, hyperactivity, and age. All random effects were assumed to be the same in both models. The power to detect the interactions was greater than 89% for the four adaptive attention training tasks. Power estimations were based on 1000 simulations and an alpha level of .05. The modelling technique implemented utilized the high number of observations, and based on the power estimations, the current study was sufficiently powered for an investigation of learning trajectories. Power analyses were not conducted for the correlations.

Results

Characteristics of the 38 children (M_{age} = 7.29 years) in this study who completed the attention training program are summarized in Table 1. For the study sample, the mean standardized IQ was in the *average range*. One participant had a parent-reported diagnosis of autism spectrum disorder. The majority of parents were university educated. Across all four attention training tasks, the average number of sessions completed by the children was 19.16 (*SD* = 2.65) out of a total of 25 sessions. Figure 1 shows individual and average progression on each of the four attention training tasks.

Table 1 Child characteristics of the study participants, pre-training

Measure	*n*	*M (SD)*
Age in months	38	87.47 (13.04)
General cognitive ability[a]	38	104.97 (13.44)
Total ADHD symptoms[b]	37	0.65 (22.7)
Selective attention[c] (mean targets)	37	15.08 (3.61)
Sustained attention[c] (mean response)	35	676.34 (218.62)
Inhibition[c] (number of no-go trials)	37	10.86 (5.91)
	n	%
Male sex	21	55
Parental level of education		
Secondary education or below	3	9.4
Partial university/TAFE	3	9.4
University degree	18	56.3
Postgraduate degree	8	25.0

[a]KBIT-2 standard score *M* 100 (*SD* 15)
[b]Total SWAN raw score (range –54 to 54)
[c]TEACh-2 raw scores.

Learning Trajectories for the Attention Training Tasks

For the selective attention training task, over half of the children (*n* = 23, 60.52%) reached the maximum difficulty level (i.e., level 340) between training sessions 16 and 20. The average number of levels completed was 306.21 (*SD* = 49.18) and children completed an average of 16 levels per session (*SD* = 1.69). For the sustained attention training task, none of the children reached the maximum difficulty level (i.e., level 524). The average number of levels completed was 219.84 (*SD* = 55.68) and children completed an average of 11.41 levels per session (*SD* = 2.17). For the inhibition training task, all children reached the maximum difficulty level (i.e., level 368) between sessions 8 and 12. On average, children completed 19.65 levels per session (*SD* = 3.41). For the interference control training task, all children reached the maximum difficulty level (i.e., level 388) between sessions 6 and 10. On average, children completed 20.72 levels per session (SD = 3.59). The ceiling effect observed on the inhibition and interference control training tasks limited accurate interpretation of the learning trajectories and for this reason no further examination was included for these training tasks. For indicative results, see Table S6.

For each of the selective and sustained attention training tasks, initially, the "simplest" versions of the linear and asymptotic regression models were compared for each learning trajectory (see Table S5 for model details). Both models included random effects for the difficulty level reached on the task over time: the linear model included random intercepts and slopes and the asymptotic model random asymptotes. The model fit for each learning trajectory was significantly better for the asymptotic model

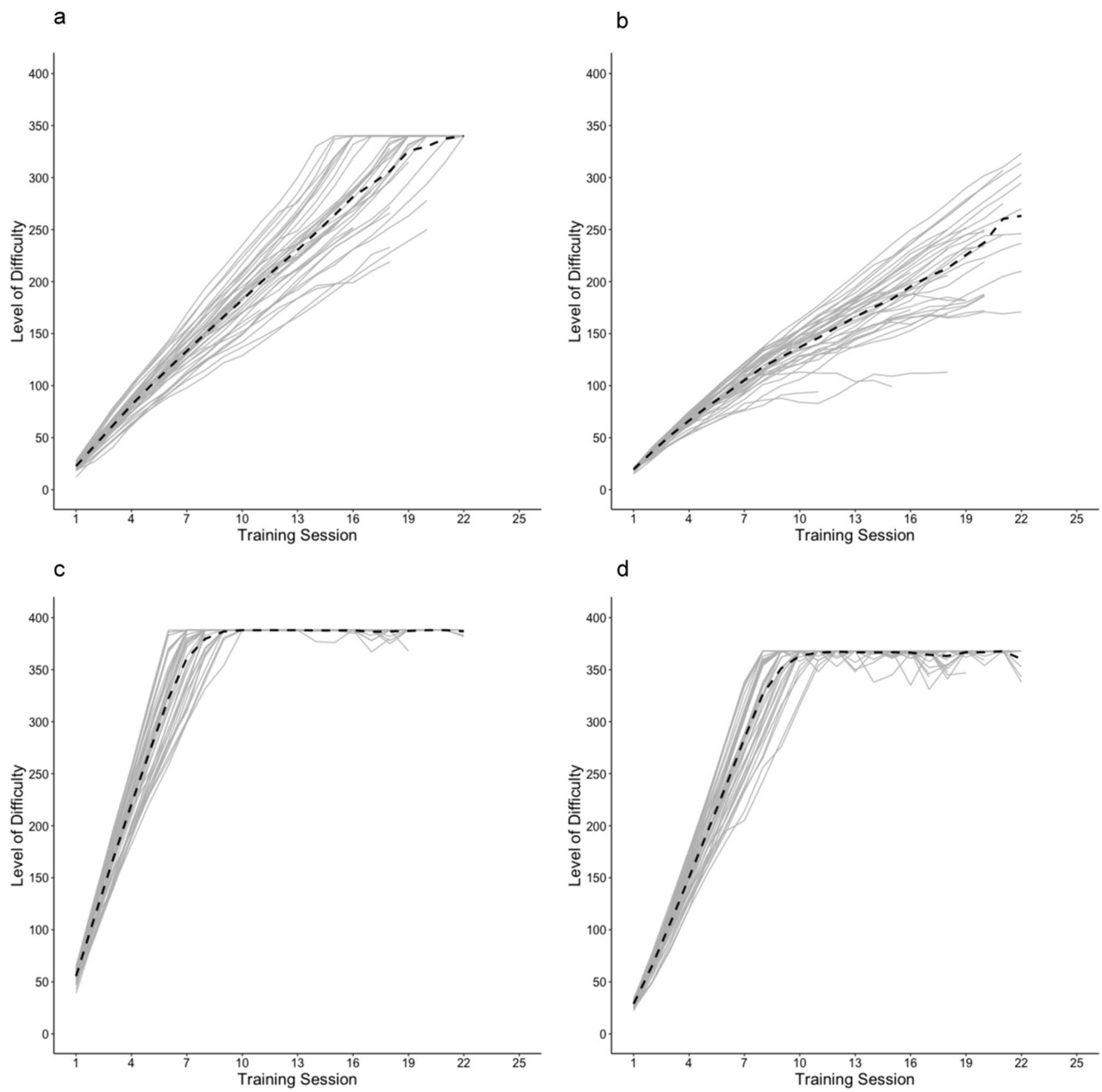

Fig. 1 Development of individual (light grey lines) and mean (bold dashed black line) learning trajectories over the training period for **a** the selective attention training task; **b** the sustained attention training task; **c** the interference control training task; **b** the inhibition training task

compared to the linear model (selective attention AIC = 5731.08; $\Delta\chi^2$ (1) = 295.40, $p < .001$; sustained attention AIC = 5152.11; $\Delta\chi^2$ (1) = 230.94, $p < .001$). Next, model complexity was increased to analyze the contribution of the asymptote, *y*-intercept, and rate as random effects to model fit. For the selective attention learning trajectory, the best model fit for the asymptotic model was found when the asymptote and rate were modelled as random effects (AIC = 5089.08; for 3 parameters compared to two, $\Delta\chi^2$ (3) = 0.01, $p > .05$). For the final selective attention model, the asymptote was 675.82 (SE 20.80; 95% CI 635.04–716.59) difficulty levels, the rate was 0.032 (ln(0.032) = −3.44; SE 0.05; 95% CI −3.53 to −3.33) difficulty levels and the *y*-intercept was not statistically significant (−2.37, SE 1.29; 95% CI −4.91 to 0.17). The correlation coefficient between the fixed effects for the asymptote and rate was −.86. For the sustained attention learning trajectory, the best model fit for the asymptotic model was found when the asymptote, rate, and y-intercept were modelled as random effects (AIC = 4484.35; for 3 parameters compared to two, $\Delta\chi^2$ (3) = 54.25, $p < .001$). For the final sustained attention model, the asymptote was 468 (SE 45.17; 95% CI 380.28– 557.31) difficulty levels, the rate to reach the asymptote was 0.044 (ln (0.044) = −3.13; SE 0.12; 95% CI −3.36 to −2.90) and the y-intercept was 3.86 (SE 0.98; 95% CI 1.95–5.78) difficulty levels. The correlation coefficient between the fixed effects for the asymptote and rate was −.94.

Association Between Learning Trajectories and Outcome Measures

For the selective attention learning trajectory, the correlations between the asymptotes and rates, and each of the study outcome measures were all non-significant with small effect sizes ($p > .05$; asymptotes: selective attention $r = -.26$, inattention $r = -.35$, and hyperactivity $r = -.23$; rates: selective attention $r = -.02$; inattention $r = .12$ and hyperactivity $r = .29$). For the sustained attention learning trajectory, the correlations were statistically significant between the asymptotes and hyperactivity ($r = .60$; $p = .002$; FDR corrected $p = .013$) and between rates and hyperactivity; however, this correlation did not persist after correction for multiple comparisons ($r = -.38$; $p = .077$; FDR corrected $p = .231$). Correlations were not statistically significant for the other study outcome measures ($p > .05$; asymptotes: sustained attention $r = -.04$, inattention $r = .28$; rates: sustained attention $r = .20$, inattention $r = -.02$).

Associations between Child Characteristics and Learning Trajectories

For the selective and sustained attention training tasks, age (but not general cognitive ability, inattention, or hyperactivity) predicted each learning trajectory (Table 2). For the selective attention learning trajectories, older children had lower asymptotes compared to younger children. For the sustained attention learning trajectories, older children had higher asymptotes compared to younger children (Fig. 2).

Discussion

The aim of the study was to investigate, for the first time, the functional form of learning trajectories on attention training tasks using exponential functions and to assess whether individual differences in learning trajectories were associated with training outcomes in primary school children. In addition, the impact of pre-training child characteristics on individual learning trajectories was examined. This study showed that in primary school children learning trajectories on selective and sustained attention training tasks were characterized by an initial large increase in improved performance before the rate of improvement subsequently slowed and eventually reached a plateau or asymptote. There was some evidence that these learning trajectories were associated with changes on the studied outcome measures. Specifically, for the sustained attention training task, the learning trajectories with lower asymptotes (i.e., plateaus at lower

Table 2 Model coefficients for learning trajectories on selective attention and sustained attention training tasks

	Selective attention *Est, SE* *[95% CI]*	Sustained attention *Est, SE* *[95% CI]*
Asymptote	629.03, 22.26 [585.54, 672.53]]	471.47, 19.05 [434.24, 508.71]
ln(Rate)	−3.32, 0.06 [−0.23, −0.01]	−3.43, 0.05 [−3.53, −3.34]
y-Intercept	−3.78, 1.45 [−0.20, −0.03]	9.83, 0.05 [8.02, 11.65]
Asymptote × age	3.04, 0.73 [1.61, 4.47]	3.04, 0.77 [1.53, 4.54]
Asymptote × general cognitive ability [a]	0.43, 0.72 [−0.97, 1.84]	−0.49, 0.76 [−1.97, 1.00]
Asymptote × hyperactivity[b]	−0.90, 1.48 [−3.80, 1.99]	−2.92, 1.56 [−5.97, 0.14]
Asymptote × inattention[c]	−0.44, 1.15 [−2.69, 1.81]	0.43, 1.21 [−1.94, 2.80]

EST, estimate; *SE*, standard error; *CI*, confidence interval

[a]KBIT-2 standard score *M* 100 (*SD* 15)

[b]Total SWAN Hyperactivity raw score

[c]Total SWAN Inattention raw score

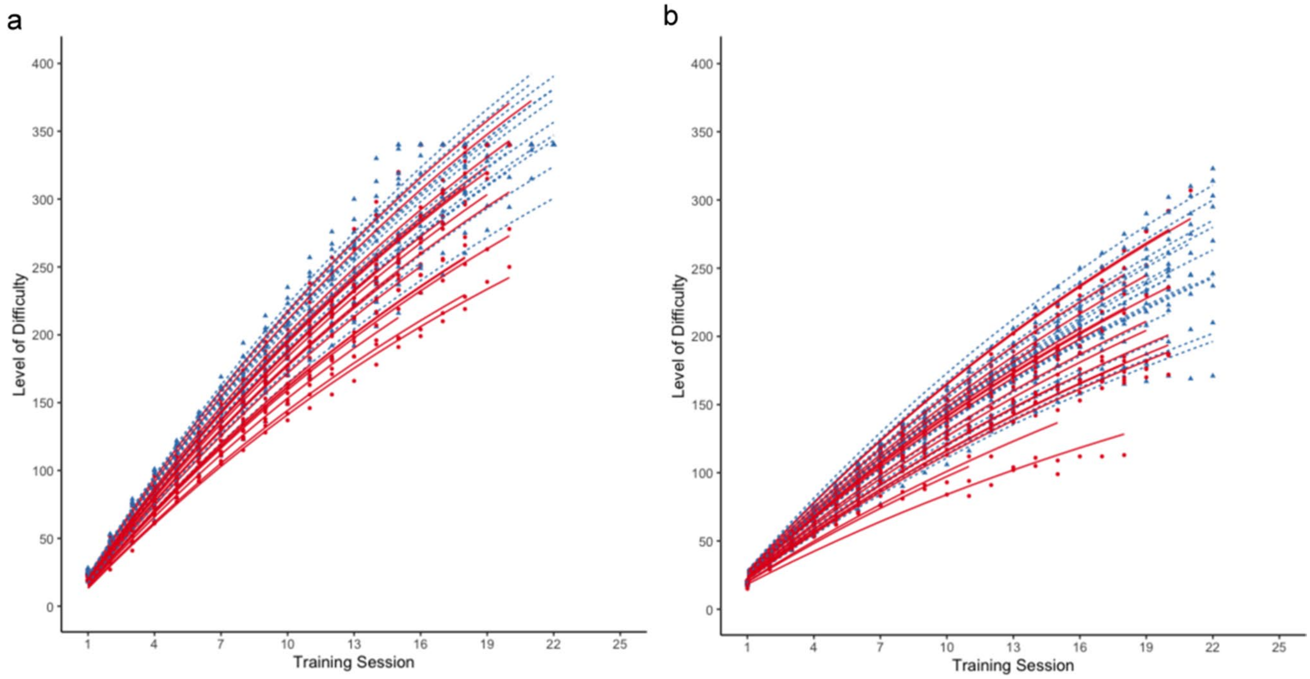

Fig. 2 Predictors for the attention learning trajectories: **a** selective attention—training sessions × age: **b** sustained attention—training sessions × age. For visualization, the data is presented as two groups. Younger age: circles = observed data and solid line = fitted data. Older age: triangles = observed data and dashed line = fitted data

difficulty levels) were associated with greater reductions in hyperactivity from pre- to post-training. Select child characteristics were associated with learning trajectories on the selective and sustained training tasks: specifically, for the selective attention training task older children's performance levelled off at a lower difficulty level whereas for the sustained attention training task older children's performance levelled off at a higher difficulty level. Neither general cognitive ability nor pre-training inattention or hyperactivity was associated with the learning trajectories on any of the training tasks.

Consistent with past studies, we found that the largest increase in learning on adaptive attention training tasks occurred during the first few training sessions, and that the rate of increase in performance then progressively decreased over the course of the 25-session intervention period, i.e., a flattening of the learning trajectory (Jolles & Crone, 2012; van der Donk et al., 2017). It is likely that at the beginning of training, when the training task is new and/or the difficulty level is low, children learn new strategies that rapidly improve their performance (Gathercole et al., 2019). However, as training progresses, continual practice of the acquired strategies only conveys small incremental gains (Gathercole et al., 2019; van der Donk et al., 2017). Our findings raise the question of whether the complexity of the attention training tasks in the initial levels was too basic for our sample of primary school children, and therefore rapid initial progression through the task's may reflect at least in part the reduced cognitive load required in the initial levels of the attention training tasks. Importantly, we found little evidence of deterioration over the course of the 5-week intervention period on the selective and sustained attention training tasks, indicating children were still progressing through the levels of these tasks in the later training sessions, albeit at a slower rate. Our findings contrast a previous investigation of digital working memory training in children which reported an inverted-U learning trajectory whereby children showed large increases in learning, followed by relatively stability in learning and some deterioration thereafter (Orylska et al., 2019). Our novel findings thus highlight that the functional form of learning trajectories may differ depending on the cognitive skill that is being trained.

In our study, learning trajectories for the interference control and inhibition training tasks could not be conducted as children reached the maximum difficulty level (i.e., ceiling) before the end of the intervention period (at approximately session 14 of the 25 allocated training sessions). These findings indicate that these training tasks did not have sufficient levels for the study population and consequently were not adaptive towards the end of the training period. The ceiling effects observed on these tasks may help to explain why improvements in interference control and inhibition outcome measures were not observed in our evaluation of the efficacy of the attention training program used in the current study

(Kirk et al., 2021a). Despite the ceiling effects, the findings provide preliminary support for asymptotic performance and predict the difficulty level a child may have reached with additional training. Higher levels of difficulty could be incorporated into the interference control and inhibition training tasks to sufficiently train primary school children. The current study highlights that examining learning trajectories on each training task of a cognitive training program provides important insight for understanding why changes in outcome measures may or may not occur following training. These findings also underscore the importance of investigating learning trajectories early in the design and development of new training tasks to ensure the suitability of the programs for their intended population.

The current study showed that children with lower asymptotes (i.e., plateaus at lower difficulty levels) on the sustained attention training task had greater reductions in parent-rated hyperactivity from pre- to post-training. No further significant associations between learning trajectories on the sustained or selective attention training tasks and studied outcome measures of attention were observed. Although these findings are inconsistent with past training studies in children with ADHD, which indicate steeper learning trajectories are associated with larger benefits for working memory (van der Donk et al., 2017) and behavioral outcomes (Minder et al., 2019), the outcomes of our cluster-randomized controlled trial which evaluated the attention training program used in this study only demonstrated benefits in reducing inattention and hyperactivity, but not in promoting improvements in attention (i.e., selective attention, sustained attention or inhibition; Kirk et al., 2021a). Therefore, the lack of an observed association between the learning trajectories on attention training tasks and some of the study outcome measures could be related to a lack of sensitivity of the outcome measures employed to detect change over a 5-week period. Recent reviews suggest that although attention tasks may appear to be functionally overlapping, our understanding of the underlying processes related to these attention tasks may be incorrect (von Bastian et al., 2022). Evidence from working memory training studies show that even when there is a strong overlap in the cognitive skill trained and the outcome measure, transfer is often absent (De Simoni & von Bastian, 2018). Greater models of cognition are therefore required to understand if and how improvements in outcome measures can be expected via cognitive training.

We found that children's pre-training age predicted the learning trajectory of the selective and sustained attention training tasks. Specifically, for the sustained attention training task, older children's performance levelled off at a higher difficulty level. These findings suggest that older children may be better equipped to progress through sustained attention tasks, which is consistent with the maturation of this attention skill, which undergoes rapid development in middle childhood and continues to mature into late childhood (Scerif, 2010). In contrast, our results indicate that for the selective attention training task older children's performance levelled off at a lower difficulty level. Although these findings were unexpected, there are two potential explanations. Firstly, selective attention is one of the earliest aspects of attention to develop, with the orienting reflex being present at birth and remaining stable across the life span (Plude, Enns & Brodeur, 1994). As such, older children in the current sample may have found this task too simplistic and therefore disengaged with the task resulting in lower levels of difficulty being reached. Secondly, the selective attention training task included in the current intervention required children to focus their attention on a specified area and to locate targets with the same characteristics among distractors which differed from the targets on various dimensions. Past research indicates that younger children have a narrower visual field (Enns & Girgus, 1985) and pay less attention to changing dimensions in selective attention tasks (Hanania & Smith, 2010). Therefore, younger children may have been less susceptible to the effects of increased frequency and variation of distractors (i.e., increased difficulty) over the course of the intervention on this particular training task.

Interestingly, we found little evidence that pre-training general cognitive ability, inattention, or hyperactivity was associated with learning trajectories on the attention training tasks. While many of our correlation effect sizes were moderate, they did not reach statistical significance with our sample size. It is plausible, given this is a new study that these effect sizes are larger than typically found and provide explanatory use for future work (Funder & Ozer, 2019). Although very few studies have investigated the impact of general cognitive ability on learning trajectories during cognitive training, several studies have shown that children with higher pre-training cognitive ability are more likely to experience greater gains on outcome measures following training (Gathercole et al., 2019; Minder et al., 2019). In contrast, other studies indicate that those with lower abilities and poorer pre-training behaviors tend to experience greater benefits from training (e.g., Spencer-Smith et al., 2020; Kirk et al., 2016; 2017). These previous findings suggest that a certain level of cognitive capacity may be required to benefit from cognitive training (Lövdén et al., 2012); however, our results indicate that this level of cognitive capacity may not be required to engage in cognitive training, at least attention training.

The current study has important limitations to consider. We aimed to examine the learning trajectories of four adaptive training tasks; however, the inhibition and interference control training tasks had ceiling effects. Given the current attention training program was designed for young children with intellectual and developmental disabilities, future trials for primary school children could consider additional difficulty levels for the interference control and inhibition training tasks to avoid ceiling effects. Although the ceiling effects can be viewed as a study limitation, they also highlight the importance of studying learning trajectories of training programs in specific populations during program development. The sensitivity of the cognitive outcome measures as well as the lack of change across these measures over the training period may have also influenced the results for the hypothesis that there would be associations between the learning trajectories and attention outcomes. Furthermore, the fit of the data was only evaluated for linear or asymptotic regression functions. Although this approach is more advantageous than fitting the data using quadratic terms or higher order polynomials, which is common in the cognitive training field, future studies should endeavor to include a broader range of functions that may facilitate a more detailed understanding of learning trajectories.

The current study highlights the need for future cognitive training studies to examine learning trajectories in addition to changes on outcomes measures between pre-training and post-training to fully understand outcomes observed following training. The learning trajectories of the selective and sustained attention training tasks revealed that primary school children were able to progress through the tasks, with the rate of improvement on the training tasks being rapid initially, followed by a steady decrease in the rate of improvement, and eventual plateau or asymptote. The study suggests that child age can influence attention training learning trajectories, with older children's performance flattening off at a higher difficulty level on the sustained attention training task, and a lower difficulty level on the selective attention training task. However, the rate of learning on select attention training tasks (i.e., sustained attention) only influenced change in performance on select outcome measures (hyperactivity). This study highlights the need for future studies to examine the rate of learning on various cognitive training tasks in order to understand the mechanisms that drive gains in untrained skills after the intervention period. These studies are crucial in determining which cognitive skills are susceptible to training. Finally, this study indicates that attention training in its current form may not be adequate in challenging attention capacities within this population of primary school children and may therefore not be sufficient to enhance attention abilities.

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Author Contribution HK conceived the research idea, created the research design, applied for and received funding, selected the measures to be included, recruited participants, collected data, entered the data, provided feedback, and drafted sections of the manuscript. SR determined the statistical tests, performed the statistical analyses, and drafted sections of the manuscript. KC provided feedback on this manuscript. MSS was involved in the creation of the research design, measure selection, and provided feedback on this manuscript.

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Data Availability The data that support the findings of this study are available from the corresponding author upon request.

Declarations

Ethics Approval and Consent to Participate The trial was prospectively registered with the Australian New Zealand Clinical Trials Registry (ACTRN12616001111460) and performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Monash University Human Research Ethics Committee and the Catholic Education Office Melbourne. Informed written consent was obtained for each child from their parents.

Consent for Publication Informed written consent was obtained for each child from their parents.

Conflict of Interest The authors have no conflict of interest to declare and have no financial or personal relationship that may be considered a conflict of interest. HK and KC are listed co-inventors on an international patent for the attention training program used in the current study.

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