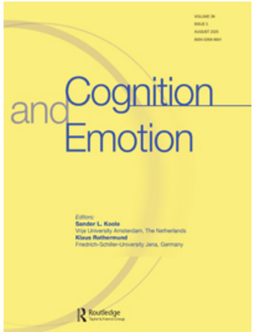

Cognition and Emotion

ISSN: 0269-9931 (Print) 1464-0600 (Online) Journal homepage: www.tandfonline.com/journals/pcem20

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COGNITION AND EMOTION
2025, VOL. 39, NO. 5, 1051–1063
https://doi.org/10.1080/02699931.2024.2427886

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Affect and executive function dynamics in primary school classrooms: an intensive longitudinal study

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ABSTRACT

This study investigates the temporal dynamics and affective associations related to executive function (EF) performance in primary school classrooms using an intensive longitudinal design. Data were collected from 35 students aged 8.9 to 11.4 years. Participants reported their affective experiences and completed EF measures three times daily following a fixed sampling schedule. The data collection spanned two consecutive school weeks across three primary school classrooms. Utilising Dynamic Structural Equation Modeling (DSEM), we examined 505 measurements of EF tasks and self-reported affective states over two weeks. The findings reveal significant within-person variability in EF, accounting for 52% of the observed variance, with performance declining later in the day and week. At the within-person level, positive affect was associated with improved EF performance, while negative affect was associated with poorer EF. No significant between-person relationships were found. These results underscore the importance of considering within-person processes and affective experiences in educational settings and highlight the need for further research employing intensive longitudinal methods to better understand the nuanced dynamics of affect and EF in real-world classroom environments.

ARTICLE HISTORY
Received 13 July 2024
Revised 30 October 2024
Accepted 4 November 2024

KEYWORDS
Executive functions; affective experiences; dynamic structural equation modelling (DSEM); intensive longitudinal design; primary school

1. Introduction

While affect is typically conceptualised as a transient, within-person, state construct, cognitive functioning, such as executive function (EF), is generally studied as a stable, between-person, trait variable. Research adopting such a nomothetic approach has enhanced our understanding of EF as group-level individual differences. However, it has also obscured the importance of individual variations that deviate from general trends and overlooked potentially meaningful changes in granular timescale (Dirk & Nett, 2022; Hamaker & Wichers, 2017; Pekrun et al., 2002; Schmitz & Skinner, 1993). Considering that classroom environments are inherently rich in affective and cognitive stimuli due to social interactions and learning activities, it is crucial to examine the relationship and temporal dynamics between affective experiences and cognitive performance. Understanding the antecedents of fluctuations in cognitive functioning within naturalistic classrooms can inform the development of school-based interventions by targeting these predictors.

1.1 Executive function and education

EF is a set of cognitive processes that regulate one's goal-directed activities in everyday life (Miyake et al., 2000), including (i) inhibitory control, which involves

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deliberately withholding automatic or ingrained impulses; (ii) cognitive flexibility, encompassing the ability to shift attentional focus or switch between tasks; and (iii) working memory, which involves retaining and manipulating information in mind. These three interrelated components can be integrated for goal maintenance and management and use those goals to bias ongoing processing, referred to as general EF (Friedman & Miyake, 2017; Gustavson et al., 2015; Miyake & Friedman, 2012).

Studies that have investigated EF as a stable between-person construct demonstrate that individual differences in EF significantly predict school readiness and academic achievement (Blair & McKinnon, 2016; García-Madruga et al., 2013; Huizinga et al., 2018; Zelazo, 2015) and show longitudinal associations with life success (Blair & Razza, 2007; Mann et al., 2017; Vandenbroucke et al., 2017). In the classroom, EFs play a dual role in learning, both indirectly and directly. They enable students to maintain focus, adhere to rules, adapt to new perspectives, and actively engage in classroom activities, thereby fostering reflective learning and a motivation to learn (Lyons & Zelazo, 2011; Marcovitch et al., 2010; Zimmerman, 2008). Conversely, students who struggle with EFs are more likely to disrupt their learning and that of others and are further associated with behavioural issues, suspensions, expulsions, or grade retention (McClelland et al., 2013).

In recent years, research using intensive longitudinal design has identified systematic fluctuations in EF performance at granular timescales. Evidence indicates that these fluctuations within individuals arise due to variables such as sleep patterns, physical activities, stress and affective and academic experiences (Dirk & Schmiedek, 2016; Neubauer et al., 2019; Trevillion et al., 2022; Wang et al., 2021; Yu et al., 2020, 2021). Understanding fluctuations in children's cognitive performance is essential, as these variations are linked to behavioural and academic outcomes (Dirk & Schmiedek, 2016), and potentially serve as early screening indicators for neurodevelopment disorders, such as attention deficit hyperactivity disorder (ADHD; Ali et al., 2019).

1.2. Temporal dynamics of executive function performance

Variability in cognitive performance is commonly observed in everyday scenarios. Notably, Schmidt et al. (2007) examined how circadian rhythms impact cognitive abilities, finding that different times of the day can influence a range of cognitive tasks, including attention, EF, and memory. These performance fluctuations are closely linked to individual differences in peak circadian arousal times. This variability is also demonstrated in educational settings, as shown by Dirk and Schmiedek (2016), who used ambulatory assessments to identify significant, systematic variations in working memory performance among primary school children within classroom environments.

Despite widespread anecdotal recognition among educators, parents, and students of these fluctuations, empirical investigations into the temporal dynamics of EF performance remain sparse. Regarding existing literature, Van Der Heijden et al. (2010) assessed children aged 10–12 in a quasi-experimental setting, scheduling tests at 08:30, 10:00, or 13:00. Their findings indicated time-of-day effects on EF tasks, with improved working memory observed in the afternoon sessions compared to the morning. However, this study found no significant differences in inhibitory control or cognitive flexibility throughout the day. In contrast, Galeano-Keiner et al. (2022) conducted a longitudinal ambulatory study with 108 fifth graders, assessing working memory performance twice daily across four weeks. Their results consistently showed superior performance during morning sessions compared to the afternoon, across both spatial and numerical working memory tasks, independent of cognitive load. Additionally, Trevillion et al. (2022) noted an increase in working memory performance later in the week in a two-week intraindividual study involving 35 primary school children using digit recall tasks, with no significant time-of-day effects.

These studies underscore the importance of further research to understand the patterns and implications of these temporal fluctuations in EF performance, which could inform more effective educational strategies and assessments.

1.3. Impact of affective experiences on EF

Educational environments represent a critical source of affective experiences during the formative years of children and adolescents (Fiedler & Beier, 2014). However, the dynamics of how affective experiences within classroom settings impact children's cognitive functions remain underexplored. Of note, affect will be used as an umbrella term, to include emotions, which are relatively brief and with an object of appraisal, and moods, which last longer and without an object of appraisal (Fiedler & Beier, 2014; Pekrun & Linnenbrink-Garcia, 2014). Theoretical models provide varied perspectives on the relationship between affect and EF. Cognitive load theory, for instance, suggests that affective states universally compromise EF by overloading cognitive capacity (Ellis & Ashbrook, 1989; Seibert & Ellis, 1991). In contrast, Attention Control Theory posits that negative affect, specifically anxiety, undermines EF by reallocating attentional resources, diminishing the capacity for EF tasks (Eysenck et al., 2007). Additionally, Broaden-and-build theory (Fredrickson, 2001) argues that positive affect facilitates cognitive functions, fostering greater engagement in exploratory and integrative activities, which can enhance future cognitive resources but may impede performance in tasks requiring focussed attention.

Experimental research utilising emotion-induction paradigms generally supports the adverse impact of negative affect on EF in adult populations (Lindström & Bohlin, 2012; Mitchell & Phillips, 2007; Shields et al., 2016). However, findings regarding the influence of positive affect on EF are more ambiguous (Gabel & McAuley, 2020; Lautenbach, 2024). In studies with children, the effects of affect on EF vary. Fartoukh et al. (2014) found that a negative mood induction reduced performance in a task assessing working memory performance among children aged 9 to 12 years, while positive mood induction showed no significant effect compared to a neutral condition. Despite the significant finding, the effect size was modest (np^2 =.06). Similarly, Pnevmatikos and Trikkaliotis (2013) observed that anxiety inductions led to diminished inhibitory control in children within the same age range. These studies suggest that negative affect, particularly anxiety, consistently impairs EF in children, while the impact of positive affect remains to be better understood.

Intensive longitudinal studies conducted in naturalistic educational settings provide additional insights into these dynamics. For example, Neubauer et al. (2019) assessed the influence of affect on the working memory of primary school children through ambulatory assessments. Results demonstrated a general decrease in performance associated with higher levels of negative affect. Conversely, positive affect did not significantly impact working memory performance. Their analyses also highlighted substantial within-person variability, suggesting that the relationship between affect and working memory performance may differ significantly among individuals. Wang et al. (2021) further explored this phenomenon, examining daily EF over two weeks in a diverse adolescent cohort. Their findings indicated that intense negative moods were associated with reduced performance across all measured aspects of EF at the individual level, whereas positive moods showed no significant relationship with EF.

Together, these findings highlight the intricate and nuanced influence of affective experiences on EF, particularly during childhood development. Variability in results may arise from methodological differences in how affective experiences and EF are defined and measured across studies. Furthermore, substantial within-person variability likely contributes to these divergent outcomes. The contrasting impacts of positive and negative affect on cognitive capabilities observed both between and within individuals, underscore the necessity for further research to clarify these relationships across diverse developmental stages and naturalistic contexts.

1.4. Present study

Building on the premise that EF performance can be differentiated into within-person and between-person variations, we conducted an intensive longitudinal study to investigate the temporal dynamics of EF and its associations with affective experiences in naturalistic classroom settings. The study spanned two weeks and was conducted in three state primary school classrooms in Oxfordshire, UK. The data set included repeated measures of EF task performance, self-reported affective states, precise timestamps of data collection, and individual-specific details such as gender and age. This study utilised a subsample from the [masked for review] dataset, comprising 505 measurements nested within 35 children, each providing valid data on affect and EF measures. We employed Dynamic Structural Equation Modeling (DSEM) (Asparouhov et al., 2018) to dissect the within- and between-person variances and the moment-to-moment fluctuations in EF. This multilevel approach will allow us to better comprehend the dynamics of EF in educational settings. The hypothesised model is depicted in Figure 1, leading to the formulation of the following research questions:

RQ (1): does children's EF vary in classroom settings?

We differentiate the proportion of variance attributed to differences between individuals (between-person level) as opposed to variations within the same individual (within-person level), aiming to determine the overall stability of EF performance. Moreover, we

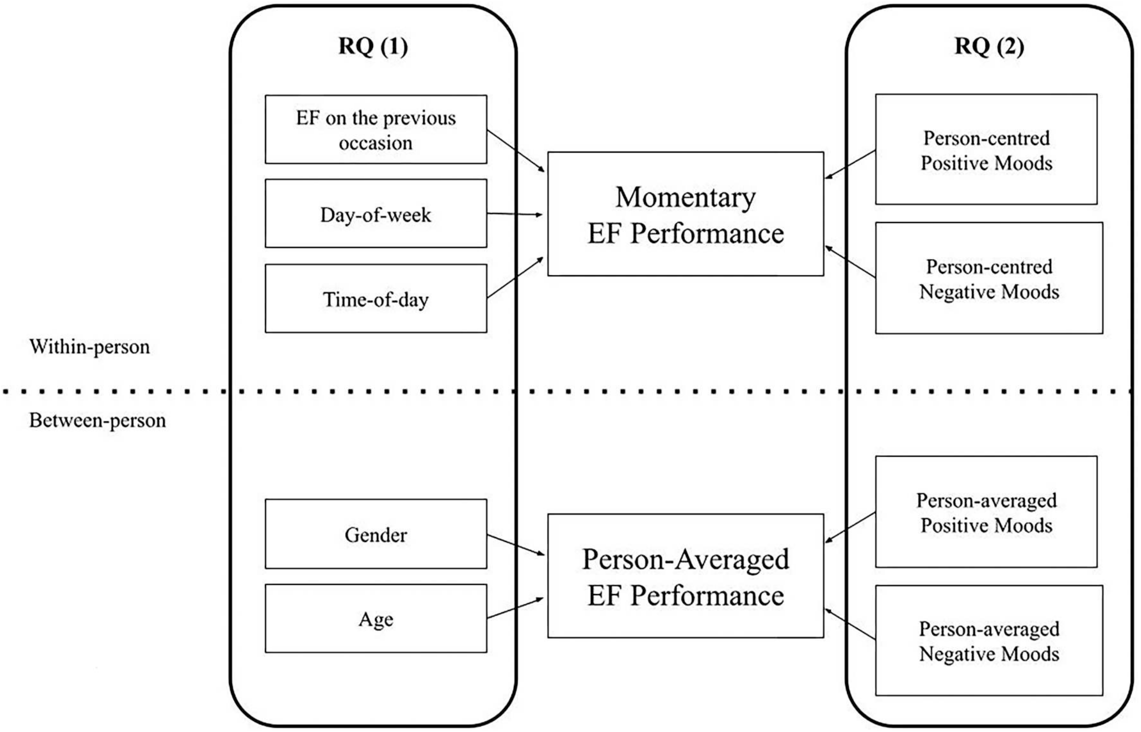

Figure 1. Hypothesised Theoretical Model in Within-person and Between-person Level.
Directions of predictions are represented by arrows.

assess the temporal stability of EF by analysing the autoregressive effects and investigating the predictive value of time-of-day and day-of-week on EF performance. Personal characteristics (i.e. gender and age) will also be examined to account for between-person differences in EF performance in the current sample.

RQ(2): how are affective experiences in classrooms associated with variations in EF?

At the within-person level, we centre the analysis on individuals, assessing whether their current affective states, positive and negative, predict concurrent EF performance. At the between-person level, we utilise averages of positive and negative affect across individuals to determine if they predict overall EF performance throughout the two-week data collection period. Credible predictors identified in RQ(1) will be retained as covariates.

2. Method

2.1. Sample and procedure

The [masked for review] received ethical approval from the [first and last authors' institution]. All participants in this study provided informed opt-in parental or guardian consent. Students' participation was voluntary and could be withdrawn anytime. This study leverages a subsample from the [masked for review] project, initially established to explore dynamics among physical activity, student engagement, and cognitive functioning in three primary school classrooms within the same school. Only procedures related to variables of our current research interest (i.e. affective experiences and EF performance) will be discussed.

The [masked for review] started with a one-hour training session on the initial school visiting day by two qualified researchers to guide students on reporting their affective experiences and carrying out the EF task using tablets. Within a school day, participants were instructed to report their affective experiences and complete the EF task three times per day after the first morning lesson (at 10:30 a.m.), before lunch (at 12:00 p.m.) and after their afternoon lesson (at 14:30 p.m.). The implementation of time-based sampling at three distinct intervals each day was informed by both empirical and practical considerations. The specific times (morning, pre-lunch, and afternoon) were selected to correspond with distinct periods of the school day, thereby facilitating the investigation of diurnal patterns and the differential impacts of various school activities on the variables of interest. Furthermore, this sampling strategy was designed to integrate with the existing classroom schedules, minimising disruptions to the routine operations of both teachers and students. To enhance compliance and participation, teachers were instructed to prompt participants to complete the assessments at the designated times. Students were guided to complete the EF assessment after reporting their affective experiences to ensure the experience of the EF assessment did not alter their affective experiences. The data collection lasted for ten school days across two weeks (Monday to Friday of each week).

The present subsample comprising 505 measurements nested in 35 students (17 females, 18 males; mean age = 9.98 years; age range = 8.9–11.4 years) drawn from three classrooms in consecutive grades (Grade 4: $n = 12$; Grade 5: $n = 14$; Grade 6: $n = 9$), each providing valid data on concurrent affective experiences and EF measures. The mean number of measurements completed by the participants was 14.4 (SD = 4.21), with a range of 5 to 20. As the [masked for review] was originally designed for different research questions, priori statistical power analyses were not determined based on the purpose of the current study. Post-hoc Monte Carlo simulations in Mplus 8.7 were conducted to inspect whether the models were adequately powered to detect empirically meaningful effects. We examined the 95 % coverage measure, which indicates the proportion of replications for which the confidence interval (CI) covered the population value. All significant results reported in the current study fell within the 95% coverage range of 0.92 to 0.98, which is considered good coverage (Schultzberg & Muthén, 2018).

2.2. Materials and measures

Students were guided to report their affective experiences and EF assessment using tablet computers (Hudl 2; screen size: 8.3″ IPS panel, HD 1920 × 1200, Pixel density of 273 PPI). All tablets were programmed only to be able to operate two applications (Qualtrics for reporting affective experiences and OpenSesame for EF assessment). All other applications on the tablets were disabled.

2.2.1. Affective experiences

Participants' affective experiences were assessed through the modified version of the Learning Experience Questionnaire (LEQ; Malmberg et al., 2013). 10 question items were included to understand the intensity of students' affective experiences ("*Right now, I feel …*") according to valences (positive and negative). Five items were designed to measure positive affect (PA; active, calm, cheerful, excited and relaxed), and the remaining five were designed to measure negative affect (NA; angry, annoyed, bored, frustrated and sad) on five-point scales (1 = *not at all*, 5 = *very much*). We created composite scores for positive and negative affect for each measurement point, with higher scores indicating more intense affective experiences.

Estimated reliabilities of the two scales were obtained using multilevel confirmatory factor analysis (Geldhof et al., 2014). The respective estimates suggested good internal consistency at the between-person level, $\omega = .875$ (PA) and $\omega = .975$ (NA), and the within-person level, $\omega = .768$ (PA) and $\omega = .875$ (NA). The intraclass correlation (ICC) of PA and NA, which represents the proportion of between-person variance relative to the total variance, was .46 and .54, respectively. This indicates that the overall variance of PA was predominantly driven by within-person fluctuations, while NA was predominantly driven by between-person differences.

2.2.2. Executive function

The Hearts and Flowers (HF) task, a gamified EF assessment (Davidson et al., 2006) was utilised to measure EF, with visual stimuli scaled to the consistent screen size of all devices used. Participants received pre-recorded instructions through headphones. On the first two days of data collection, participants completed the task with more training trials and longer instructions. From the third day onwards, the HF task was changed to a version with fewer training trials and briefer instructions.

The HF task included three blocks of trials. Children started with 12 congruent heart trials (6 left, 6 right), during which they were instructed to press the button on the same side as the presented heart stimuli. This was followed by 28 incongruent flower trials (14 left, 14 right), where students were instructed to press the button on the opposite side of the flower stimuli. The HF task concluded with 60 mixed trials, in which both heart and flower stimuli appeared (congruent left = 22, congruent right = 26, incongruent left = 8, incongruent right = 4).

All stimulus presentation times were 600 ms. Anticipatory responses (RT $<$ 250 ms) and responses that took longer than 2000 ms were excluded (Camerota et al., 2020). Responses ±3 *SD* from the individual mean response time per block were excluded as outliers. A block that recorded at least 60% valid responses was treated as a valid block. In addition, any block with accuracy scores below chance ($<$ 50%) was treated as an invalid.

The mean accuracy of the mixed blocks was chosen as a proxy for general EF performance (the unity component of EF in the unity and diversity model; Miyake et al., 2000), since performing well in these blocks requires simultaneous use of three components of EF (Camerota et al., 2020; Diamond, 2012). Furthermore, successful goal maintenance would manifest as prioritising accuracy, as students were instructed to complete the task "*as fast as you can, but not so fast that you make a mistake.*" Mean accuracy scores for each mixed block were calculated as the proportion of correct responses.

The HF Mixed block demonstrated good between-person reliability (0.93). Within-person reliability was assessed to determine whether within-person differences in cognitive performance from one occasion to the next reflected systematic variance. This assessment involved decomposing within-person variation into two sources: across occasions and within occasions. The HF Mixed block demonstrated a within-person reliability of 0.40, which is consistent with other empirical studies that have reported within-person reliability of ambulatory cognitive tests using the same calculation (0.15–0.36, Brose et al., 2012; 0.41–0.53, Sliwinski et al., 2018).

2.3. Analytic procedures

R version 4.4.0 was used in data preparation and descriptive analyses. Mplus Version 8.7 (Muthén & Muthén, 1998–2017) software was used to carry out Dynamic Structural Equation Models (DSEM; Asparouhov et al. (2018); Hamaker et al. (2018)).

To accommodate naturalistic classroom timetables, the measurement occasions in the current [Mask for Review] dataset were unevenly spaced in three ways: an 18-h gap between consecutive school days, a 66-h gap over the two-weekend days of data collection, and instances of absence or non-response on either instrument. We used the Mplus "*tinterval*" option to address this uneven spacing and segmented our 2-week data collection period into 1.5-h intervals. Therefore, the first data point is indicated as tinterval = 1 (on the first day of data collection at 10:30 a.m.) and the last data point is indicated as tinterval = 180 (on the last day of data collection at 14:30 p.m.). This method effectively handles missing data (e.g. over 80%) with a fine grid of time segments (Asparouhov et al., 2018).

In our main analysis, we decomposed EF and affect into within-person and between-person components as is customary in multilevel modelling in DSEM. The between-person component represents stable trait-like means, whereas the within-person component represents situational state-like deviations from these stable means. All estimates in the primary analyses were treated as fixed effects.

To address **RQ (1) "Does children's EF vary in classroom settings?"**, the autoregressive effect, temporal dynamics and personal characteristics are tested in three consecutive steps. Model 1.1, the "autoregressive model," regressed EF at Time t (concurrent time-point) on Time t-1 at the within-person level. In Model 1.2, the "temporal effect" model, we incorporated time-of-day (−1 = approximately 10:30 a.m., 0 = approximately 12:00 p.m., 1 = approximately 2:30 p.m.) and day-of-week (−2 = Monday, −1 = Tuesday, 0 = Wednesday, 1 = Thursday, 2 = Friday) as temporal predictors at the within-person level. Model 1.3, the "personal characteristics" model, featured grand-mean-centred child characteristics (age, gender) at the between-person level. To address "**RQ (2) How are affective experiences in classrooms associated with variations in EF?**", Model 2, the "affective experience" model, included NA and PA at both levels. At the within-person level, PA and NA were person-centred to interpret them as deviations from individual means. At the between-person level, PA and NA were person-averaged. Credible predictors identified in RQ 1 were retained as covariates. A detailed model illustration can be found in Figure 2.

Due to the complexity of the current analysis, traditional frequentist methods like maximum likelihood (ML) often encounter convergence issues or are intractable (Muthén & Asparouhov, 2012). Therefore, the Bayesian Markov Chain Monte Carlo (MCMC) is used for estimation instead. Results are based on two MCMC chains with 3000 iterations after keeping only every 50th iteration (thin = 50) to reduce autocorrelation between the MCMC draws. We kept the Mplus defaults of diffuse priors and a burn-in period of 50%.

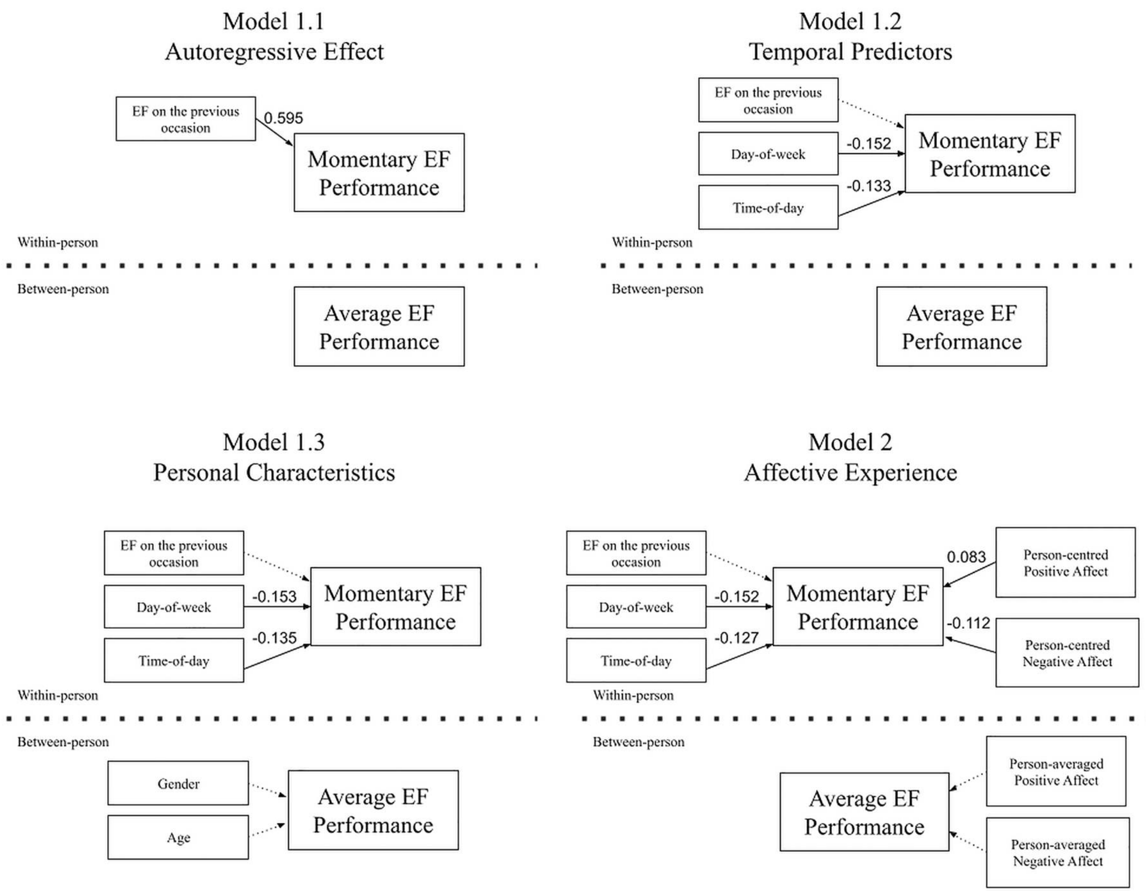

Figure 2. Dynamic Structural Equation Models (DSEM) of associations between Executive Function temporal, personal and affective predictors. Standardised parameter estimates from posterior distribution are from Mplus 8.7. 90% credible intervals are presented in the text. Significant paths are drawn in solid lines.

Reported estimates are the medians of the resulting posterior parameter distributions with their associated 90% credible intervals (Gelman et al., 2013). Parameters whose 90% credible interval does not contain zero were considered credibly different from zero, analogously to the two-tailed 10% α-level used for all analyses reported in this work (Austin, 2009).

A 90% credible interval is often used in Bayesian analysis as an alternative to a 95% interval for several key reasons. A 90% credible interval indicates that, given the observed data and the assumed model, there is a 90% probability that the true parameter lies within this range. This interpretation is specific to Bayesian inference, where probabilities are assigned directly to the parameter (Gelman et al., 2013). Compared to a 95% credible interval, a 90% interval offers a narrower range of plausible values. This narrower interval reflects a willingness to accept a 10% chance that the true value lies outside the range (5% in each tail), trading a minor reduction in confidence for a clearer focus on the most likely values (Gelman & Carlin, 2014; Gelman et al., 2013). Additionally, 90% intervals can reduce the impact of uncertain extremes in small samples, providing a more interpretable summary of the posterior distribution in cases where very wide intervals could obscure meaningful patterns (Gelman & Carlin, 2014; Gelman et al., 2013). For a detailed introduction to Bayesian statistics used in the DSEM framework, see Asparouhov et al. (2018) and Hamaker et al. (2018).

3. Results

3.1. Descriptive statistics

Descriptive statistics are presented in Table 1. On the within-person level, NA exhibited a negative correlation with accuracy in the mixed block, suggesting that when a child experienced a higher intensity of NA, he or she also tended to perform less accurately in the mixed block concurrently. Moreover, time-of-day negatively correlated with accuracy in the mixed block, indicating that children tended to perform less accurately on HF mixed trials later in the day. None of the between-person variables showed credible correlations. The ICC of EF performance, was .48, indicating that the overall variance was predominantly driven by within-person fluctuations.

3.2. Dynamic structural equation models

The quality of convergence and model fit was assessed through autocorrelation plots, trace plots, and posterior distribution plots. Additionally, the maximum potential scale reduction values of all models were ≤ 1.05, indicating appropriate convergence (Asparouhov et al., 2018; Gelman et al., 2013).

To address **RQ (1)**, Model 1.1 (see top-left in Figure 2), the autoregressive effect of EF (i.e. EF_t on EF_{t-1}) was credible (β = 0.595, C.I. [0.448, 0.684]), indicating EF performance in the current session was predicted by the previous session. In Model 1.2 (see top-right in Figure 2), later day in the week predicted lower EF ($\beta = -0.152$, C.I. [−0.224, −0.070]), and later time in the day also predicted lower EF ($\beta = -0.133$, C.I. [−0.206, −0.058]) at the within-person level. Note that the autoregressive effect drops out of credibility (C.I. [−0.024, 0.061]). In Model 1.3 (see bottom-left in Figure 2), neither gender (CI [−0.488, 0.042]) nor age (CI [−0.149, 0.372]) credibly predicts the between-person differences in EF performance. Therefore, no personal characteristics were included in the subsequent model.

To address **RQ (2)**, time-of-day and day-of-week were retained in Model 2 as covariates. In Model 2 (see bottom-right in Figure 2), PA predicted better concurrent EF ($\beta = 0.083$, C.I. [0.008, 0.159]) and NA predicted lower concurrent EF ($\beta = -0.112$, C.I. [−0.187, −0.038]) at the within-person level. Neither of the between-person relationships was credible (PA: C.I. [−0.368, 0.231]; NA: C.I. [−0.466, 0.120]).

4. Discussion

Educational settings, particularly classrooms, are inherently characterised by intricate affective and cognitive dynamics. Given the pivotal role of EF in academic success and classroom behaviour, this study aims to address a gap in the literature by investigating how affective experiences impact cognitive performance at the within-person level in naturalistic classrooms. Our current intensive longitudinal study identifies reliable within-person variations in EF performance in classrooms. We observed systematic temporal fluctuations in EF, with better performance earlier in the week and the day. Our findings also reveal distinct patterns in how affective experiences associated with EF differently at the within-person level compared to the between-person level. At the within-person level, participants demonstrated improved EF performance when they reported experiencing more intense positive affect. Conversely, poorer EF performance was observed when participants reported experiencing more intense negative affect. At the between-person level, neither the average levels of positive nor negative affect experienced by children during this two-week data collection period accounted for differences in EF performance between individuals.

4.1. Executive function fluctuation in primary school classrooms

Although the extant literature has investigated EF as a stable, between-person construct, the current study adds to the growing evidence suggesting that cognitive performance fluctuates at granular timescales. Specifically, 52% of the variation in EF performance can be attributed to within-person variability, rather than between-person differences. Our findings align with the within-person fluctuation in EF found in prior intensive longitudinal studies with children and adolescents (48%, Neubauer et al., 2019; 40%–55%, Wang et al., 2021; 42%, Trevillion et al., 2022).

Furthermore, current findings indicate that EF exhibits systematic temporal fluctuations, with performance being better earlier in the week and in the morning compared to the afternoon throughout the two-week testing period. Note that after accounting for the effects of time-of-day and day-of-week, the autoregressive effect of EF performance was no longer credible. This indicates that the observed fluctuations in EF performance are predominantly driven by these time-related variables, rather than by an inherent autoregressive trend. Our findings contrast with those of Trevillion et al. (2022), who investigated working memory in isolation and found credible autoregressive effects suggesting that working memory performances of primary school

Table 1. Descriptive statistics at within-person and between-person levels.

Within-person Variable	1.	2.	3.	4.	*n*	M/%	SD	Min	Max
1. HF Mixed Block Accuracy					508	0.92	0.07	0.57	1.00
2. Positive affect	.02				508	3.20	1.23	1	5
3. Negative Affect	**−.12**	.05			508	1.56	0.99	1	5
4. Time of day[a]	**−.10**	−.05	−.00		508	−0.10	1.38	−1	1
5. Day of week[b]	−.05	−.03	.00	−.05	508	0.12	0.91	−2	2
Between-person Variable	**6.**	**7.**	**8.**	**9.**	***n***	**M/%**	**SD**	**Min**	**Max**
6. HF Mixed Block Accuracy					35	0.92	0.05	0.74	0.99
7. Positive affect	−.09				35	3.26	0.96	1.62	5.00
8. Negative Affect	.20	.13			35	1.56	0.69	1.00	4.31
9. Gender[c]	−.24	.10	.10		35	51%			
10. Age	.06	−.12	−.02	.16	35	9.98	0.75	8.90	11.35

Note: [a] −1 = approx 10:30 a.m., 0 = approx 12:00 p.m., 1 = approx 14.30 p.m.;[b] −2 = Monday, −1 = Tuesday, 0 = Wednesday, 1 = Thursday, 2 = Friday;
[c] 0 = girl, 1 = boy.
Pairwise correlation coefficients in bold indicate that the credible interval did not contain zero.

students are statistically stable over time, with a temporal dependency that carries over from morning to afternoon and from afternoon to the following morning. Additionally, they observed that working memory was higher later in the week, with no differences between morning and afternoon.

Overall, while existing evidence suggests systematic temporal fluctuations in cognitive performance in primary school classrooms, empirical investigations remain scarce, and the observed directionalities are mixed. The current findings contribute to the literature by elucidating the cyclic fluctuations associated with time-of-day and day-of-week. Future studies would benefit from comparing the temporal fluctuations of EF across different testing paradigms, targeted EF components, measurement intervals, and scoring methods. Such comparisons could help determine whether the temporal patterns of various EF components diverge or if observed disparities result from methodological differences.

4.2. Association between affective experiences and executive function

At the within-person level, poorer EF performance was observed when participants reported more intense negative affect than their average. The negative association between affect and EF is consistent with the cognitive load theory and attentional control theory, both suggesting that negative affective experiences tax cognitive resources, thereby impairing EF performance (Ellis & Ashbrook, 1989; Eysenck et al., 2007; Seibert & Ellis, 1991). Our findings are consistent with the greatest portion of prior research that has reported a negative effect of negative affective experiences on EF performance using experimental approaches (Fartoukh et al., 2014; Pnevmatikos & Trikkaliotis, 2013), as well as intensive longitudinal studies with children (Neubauer et al., 2019) and adolescents (Wang et al., 2021). Conversely, participants demonstrated improved EF performance when they reported more intense positive affect. Such findings do not align with prior intensive longitudinal studies, which generally showed no significant coupling of positive affective states with EF performance (Neubauer et al., 2019; Wang et al., 2021). Our findings align more closely with the broaden-and-build theory (Fredrickson, 2001), which proposes that positive emotions enhance cognitive function, rather than with the cognitive load theory, which suggests that heightened positive emotions disrupt cognitive functioning. Nevertheless, the negative impact of positive affect on EF suggested by cognitive load theory should not be dismissed.

Individuals vary in their capacity to process external stimuli, resulting in differing susceptibilities to environmental influences, as articulated in the Environmental Sensitivity Framework (Pluess, 2015). This framework is further substantiated in research examining the relationship between affect and cognitive performance. For instance, Neubauer et al. (2019) found substantial interindividual differences in intraindividual affect-working memory coupling, which can be categorised into four latent profiles: (1) children who exhibited relatively weaker effects of affect on affect-working memory coupling; (2) children with significantly stronger negative effects of negative affect and deactivation; (3) children experiencing significantly stronger positive effects of activation; and (4) children with both stronger negative effects of negative affect and deactivation, and stronger positive effects of positive affect and activation. Future research with larger and more diverse samples should incorporate random effects models to better understand these interindividual differences in intraindividual fluctuation patterns.

At the between-person level, neither positive nor negative affect accounted for variations in EF performance in our sample, demonstrating divergent patterns compared to the within-person level. This contributes to accumulating evidence across multiple fields showing that between-person findings may not generalise to within-person relationships or may even be contradictory (e.g. Dirk & Nett, 2022; Hamaker & Wichers, 2017; Hoffman, 2015; Pekrun et al., 2002; Schmitz & Skinner, 1993.

4.3. Future direction & limitations

The modest sample size of this study, influenced by disruptions from the COVID-19 pandemic, underscores the necessity for future research to expand methodological frameworks that can more effectively capture individual variances. Future research should utilise larger and more diverse samples and employ random effects models to determine whether meaningful heterogeneity exists in the associations between affect and cognitive performance. Additionally, readers should note that no directionality in the relationship between affect and EF should be inferred from the current findings, as this study focussed on their concurrent associations. Future studies would benefit from employing experimental and intervention approaches to clarify the directionality between affective experiences and EF performance.

Regarding affective measurements, the current study only categorised affective experiences according to valence (positive vs. negative). While this is the most intuitive and widely used categorisation of affect, investigating affect according to other dimensions may yield different results. Specifically, Leonhardt et al. (2016) demonstrated that a six-factor model describing three affect dimensions–valence, energetic arousal, and tense arousal–best captured the affective experiences reported in a sample of primary school students. Notably, the PA and NA scales used in the current study include items representing both high and low activation states. This may pose a risk of different aspects of PA/NA partially cancelling each other out (e.g. high levels of "excited" might not align with high levels of "calm"), potentially obscuring nuances in affective experiences. Future research should, therefore, explore how the arousal level of affect covaries with the negative effects of negative affective states assessed in the present study.

4.4. Empirical & practical implication

This study contributes to an evolving trend in educational research that shifts focus from group-based analyses towards investigating within-person processes. It highlights the distinct differences in between-person and within-person variances, which is particularly pertinent in understanding how affective experiences impact EF in educational settings. We hope our study can prompt future educational studies to employ intensive longitudinal methods to gather real-time data within naturalistic settings. Moreover, enhancing traditional longitudinal designs by integrating these methods could transform conventional single-timepoint assessments into comprehensive, intensive longitudinal data collection phases. Such advancements would facilitate deeper insights into the causal dynamics and the continuity of within-person changes over time.

We hope the findings of our study will extend into educational practice. Cognitive performance is increasingly recognised as a dynamic construct that fluctuates systematically over time. This understanding supports the development of personalised education strategies tailored to the unique needs of individual students by adjusting learning timetables and interventions. Such an approach has the potential to optimise EF and enhance overall learning outcomes, making education more effective and responsive to each student. Moreover, students' affective experiences are intricately connected not only to their social and emotional well-being but also to their cognitive functioning. Therefore, teachers should be encouraged to place greater emphasis on creating a positive affective climate in the classroom and fostering effective social-emotional regulation skills among students.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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