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Investigating the impact of perceived mental fatigue on sustained attention performance: a latent growth curve analysis taking social desirability into account

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ABSTRACT

The relationships between perceived fatigue and changes in sustained attention performance during early stages of working on cognitively demanding tasks remain poorly understood. In addition, concerns have been raised that self-ratings of fatigue may be biased by socially desirable response tendencies, potentially confounding the relationship between perceived fatigue and attention performance. In this study, we assessed perceived fatigue briefly before tracking changes in concentration performance, processing speed, and error rates among $N = 110$ tenth graders, while they completed the d2-R test of sustained attention. By statistically controlling for social desirability, we examined relationships between perceived fatigue and the initial levels and slopes of three latent growth-curves capturing changes in the d2-R test's performance measures. Individuals with higher fatigue exhibited lower concentration performance, a weaker decline in processing speed, and a higher error rate over the course of testing. Post hoc power analyses supported the robustness of our results. Implications for mental fatigue research are discussed.

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KEYWORDS

Perceived mental fatigue; d2-R test of attention; vigilance; social desirability; latent growth curve modelling

Introduction

Gaining a deeper understanding of the relationship between the onset of perceived mental fatigue and sustained attention performance is crucial in psychological research, as it can inform the development of optimised learning and work schedules, breaks, and interventions to enhance performance in occupational and educational settings. Mental fatigue has been described as a psychobiological state of the human organism, which is induced by prolonged periods of effortful physical or cognitively demanding activities (Rubio-Morales et al., 2022; Van Cutsem et al., 2022). It can manifest physiologically through alterations in brain activity (e.g. Müller et al., 2021), behaviorally through cognitive performance declines (e.g. Lindner & Retelsdorf, 2019), and subjectively through the perception of negative affective states involving feelings such as effort and low energy (e.g. Hockey, 2013). It has been assumed that increasing fatigue during cognitively demanding tasks follows a temporal process closely related to declines in sustained attention performance (i.e. vigilance decrements; Boksem et al., 2005) and can be divided into an early (when starting to work after rest) and late (after hours of work) fatigue stage (Hockey, 2013) when attention shifts to the pursuit of alternative higher-value goals (e.g. Wiesner et al., 2021; Wiesner & Lindner, 2017).

In the present research, we focus exclusively on the early fatigue stage, for which there is a lack of studies that have investigated the relatively unknown relationship between individual differences in perceived fatigue and subsequent vigilance decrements during

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the first few minutes of task engagement. These rapid declines in vigilance were first described by Kraepelin (1897) and were observed in imposed, poorly controllable sustained attention tasks with high rates of successive events requiring rapid responses to target stimuli —conditions most likely to induce fatigue. In this regard, it was assumed that during action execution, the cognitive control system initially maintains attention, but attention quickly diminishes in response to lapses in monotonous tasks with low personal value. This decline in cognitive control, characterised by reduced neural response and effort, underlies the rapid onset of early fatigue symptoms such as reduced processing speed and high error rates (for an overview, see Hockey, 2013, pp. 62–85). Thus, the early fatigue stage was found to manifest physiologically and behaviorally, whereas the changes in speed and accuracy remain relatively poorly understood and therefore need to be further clarified.

Furthermore, it remains unclear whether interindividual differences in these early changes in sustained attention performance are related to differences in individual fatigue levels perceived prior to task execution. Since perceived fatigue was proposed to have a persistent component that accumulates throughout the day, individuals may remain fatigued to varying degrees even during recovery and cognitive rest periods (Bijleveld, 2023; Matthews et al., 2023). Furthermore, Boksem et al. (2005) found that changes in perceived fatigue were related to changes in attention performance with increasing time on task (i.e. over the course of 3 h). According to these findings, we speculated that individual differences in perceived fatigue at a given time point (i.e. prior to sustained attention task execution) should also be related to differences in sustained attention performance in the early fatigue stage, where processing speed decreases and error rates increase rapidly over the first minutes of testing (e.g. Hockey, 2013, pp. 62–85).

For our investigation, we considered a critical issue currently discussed in fatigue research: Of note, Kunasegaran et al. (2023) highlighted that fatigue ratings obtained through self-report questionnaires may be contaminated by socially desirable response tendencies, potentially biasing the effect size of the relationship between perceived fatigue and attention performance. Social desirability was assumed to be a personality trait encompassing impression management (presenting oneself favourably to influence others) and self-deception (an overly positive self-view; Holden & Passey, 2009). In clinical or laboratory settings, individuals with high social desirability may adjust their responses to align with social norms, often underreporting negative emotions such as perceived fatigue (e.g. Fastame & Penna, 2012). This bias can obscure true levels of fatigue, obscuring self-reported fatigue and its relationship to sustained attention performance.

To the best of our knowledge, this is the first study that aimed to control for participants' social desirability when examining relationships between perceived fatigue and subsequent changes in sustained attention performance during the initial minutes of task engagement. After assessing participants' social desirability and perceived fatigue at a time point when we assumed that they were mentally relaxed, we subsequently administered the d2-R test of sustained attention (Brickenkamp et al., 2010), which fulfilled two important prerequisites for our study: First, this test complied with the requirements for fatigue-inducing cognitive tasks in general (i.e. high successive event rates of targets; cf. Hockey, 2013, p. 70, p. 136). Second, the test allowed us to track early changes in sustained attention performance (i.e. concentration performance, processing speed, and error percentage) over time.

According to the literature (Hockey, 2013, pp. 62–85), we expected participants' concentration performance and processing speed to decline and error percentage to increase over the course of testing. Further, individuals with higher compared to lower levels of perceived fatigue were assumed to have lower initial levels and stronger declines in concentration performance and processing speed, as well as a higher initial level and a stronger increase in error rates over the course of testing.

Method

Participants

We used parts of an existing dataset from two studies (Lindner et al., 2017, 2019) carried out at the Leibniz Institute for Science and Mathematics Education at Kiel University. Participants were 129 tenth graders from various classes of six comprehensive schools in Germany. After participation, they were compensated with €20. We only included students with normal or corrected-to-normal vision in the dataset to ensure that the sustained attention performance results were unbiased due to effects of low vision. Hence, 19 students were excluded as they forgot their glasses. The final analysis sample ($N = 110$) comprised 45.5% female ($M_{age} = 15.56$, $SD = 0.76$) and 54.5%

male ($M_{age} = 15.70$, $SD = 0.67$) participants. 90.9% of the sample were right-handed participants, and 19.1% had worn glasses.

The study protocol was discussed at and ethically approved by the research colloquium of the Leibniz Institute for Science and Mathematics Education. Prior to participation, we obtained written informed consent from all participants and their parents. This study was carried out in accordance with the Declaration of Helsinki and the ethical guidelines for research with human participants, as proposed by the German Psychological Society (DGPs) and the American Psychological Association (APA).

Measures

Mental Fatigue We assessed perceived fatigue using three items (i.e. At the moment … "I feel mentally exhausted.", "It would take a lot of effort for me to concentrate on something.", "My mental energy is running low."; Cronbach's $\alpha = .93$) from the State Self-Control Capacity Scale (Bertrams et al., 2011), a widely used measure to assess perceived depletion, exhaustion, and mental fatigue (e.g. Graham et al., 2017; Wehrt & Sonnentag, 2024). Participants responded on a 7-point Likert scale anchored at 1 "*not true*" and 7 "*very* true". For our descriptive analysis, we calculated the mean score of perceived fatigue across the three items. In our main analyses, we further considered the three items as indicators of perceived fatigue and used them to specify a latent variable that was assumed to represent that construct.

Social Desirability To statistically control for socially desirable response tendencies in the mental fatigue ratings, we administered the Social Desirability Scale-17 (SES-17; Stöber, 1999), where participants responded with "yes" (= 1) or "no" (= 0) to 17 statements, such as "I occasionally gossip about others behind their backs" ($\alpha = .68$). Each individual's social desirability score was calculated by summing the "yes" responses across all 17 items, meaning that scores could potentially range from 0 (indicating no socially desirable responses) to 17 (indicating the maximum number of socially desirable responses). For our main analyses, we used the sum score of this scale as a manifest variable, which represented the degree of students' social desirability.

Sustained Attention Performance The paper-and-pencil version of the d2-R (Brickenkamp et al., 2010) was used to track changes in students' (visual) concentration performance (CP), processing speed (i.e. number of processed target objects; PT), and accuracy (error percentage; EP) over the course of testing. The test sheet contains 14 rows (rows 1 and 14 are not analyzed) with 57 stimuli each, including the letter "d" combined with two dashes placed above or below the letter as target stimuli and distractor stimuli, respectively. In total, the test contains 308 targets and 376 distractors for the rows 2–13. All students participated in group test sessions in which the standardised administration of the test required students to cross as many target items as possible while omitting any distractors. Working time per row was 20 s (4 min and 40 s total time-on-task), after which the test administrator called to continue with the next row. The d2-R allowed us to compute performance scores of four blocks including rows with identical symbols. More precisely, for each of the four blocks (i.e. block A (rows 2–4), block B (rows 5–7), block C (rows 8–10), and block D (rows 11–13)) we calculated the three main d2-R performance variables CP, PT, and EP. Blocks A to D represented the four measurement occasions, which allowed us to investigate performance changes across these occasions. CP is defined as the number of "hits" (i.e. PT minus the number of overlooked targets) minus the number of marked distractors (i.e. errors of commission; EC). For example, consider an individual i who worked for 20 s on the second row ($j = 2$) of the d2-R test processed 17 potential targets while overlooking 5 targets. Additionally, this participant accidentally marked 2 distractors, resulting in a CP score (CP_{i2}) for the second row of 17–5–2 = 10. If the same individual's CP scores were $CP_{i3} = 9$ for the third and $CP_{i4} = 8$ for the fourth row, then his or her total CP score for block A was $CP_{iA} = 10 + 9 + 8 = 27$. CP scores for blocks B to D were calculated in the same manner. In our main analyses, the scores of these four CP blocks ($\alpha_{CP\_A} = .84$, $\alpha_{CP\_B} = .83$, $\alpha_{CP\_C} = .78$, $\alpha_{CP\_D} = .84$) were indicators of processing speed adjusted for errors made. PT is defined as the number of all potentially processed target items per block, calculated as the sum of "hits" and overlooked targets (i.e. error overlooked, EO). For instance, individual i who worked for 20 s on the second row ($j = 2$) of the d2-R test had 9 hits and 8 overlooked targets, resulting in PT_{i2} score of 17. After calculating the PT_{i3} and PT_{i4} scores for rows three and four, the individual's total PT score for block A was $PT_{iA} = PT_{i2} + PT_{i3} + PT_{i4}$. The PT scores of blocks B to D were calculated similarly. In our main analyses, the scores of the four PT blocks ($\alpha_{PT\_A} = .87$, $\alpha_{PT\_B} = 84$, $\alpha_{PT\_C} = .81$,

$\alpha_{PT\_D} = .82$) were used as indicators to specify a latent variable representing processing speed.

Finally, EP represents the relative error rate, which was calculated for each individual i and row j as $\frac{EO_{ij} + EC_{ij}}{PT_{ij}} \times 100$. The EP score for individual i in block A was computed as $\sum_{j=2}^{4} \frac{EO_{ij} + EC_{ij}}{PT_{ij}} \times 100$. The EP scores for blocks B to D were calculated in the same manner. In our main analyses, we used the scores of the four EP blocks as reliable indicators ($\alpha_{EP\_A} = .73$, $\alpha_{EP\_B} = .77$, $\alpha_{EP\_C} = .79$, $\alpha_{EP\_D} = .85$) of participants' accuracy on the d2-R test.

Procedure

As shown in Figure 1, during the group test sessions, all students answered questions about their socio-demographics, responded to the social desirability questionnaire, and rated their current state of mental fatigue immediately before the unannounced d2-R test was administered. The d2-R test administrator read the standardised instructions. Afterward, students worked on two example rows before the administrator said, "Start now!" while focusing on the stop watch to monitor the time. After every 20 seconds, the administrator said, "Stop! Next line!" until the test was completed. After completion, all test sheets were immediately collected.

Analysis

All preliminary analyses were carried out using SPSS version 29 (IBM Corp., 2021). To investigate students' levels and changes in concentration performance, processing speed, and accuracy, we applied latent growth curve modelling with Mplus 8.6 (Muthén & Muthén, 2017). In the latent growth curve model (i.e. M1) we used the scores calculated for the blocks A to D for each of the three performance measures (CP, PT, and EP) as indicators to specify latent intercepts and slopes to model the measures' initial levels and changes over time. The loadings on the three intercept factors were fixed to 1. The loadings of the slope factors were specified as follows: the loadings of the measures at the first measurement occasion (block A) were fixed to 0, whereas those at the last measurement occasion (block D) were fixed to 1. The loadings at the intermediate occasions were estimated freely to capture any shape of non-linear change (e.g. Bollen & Curran, 2006). The residual variances of CP, PT, and EP were set to be invariant over time (i.e. over blocks A to D; Horn, 1972), and correlations between their residuals at the same occasion (e.g. at block A) were allowed (e.g. Marsh & Hau, 1996).

To examine relations between students' levels of mental fatigue and subsequent levels and changes of concentration performance, processing speed, and accuracy, while controlling for social desirability and other covariates (i.e. age, gender, wearing glasses, and handedness), we specified a second model (i.e. M2). Model M2 comprised the three latent intercepts and slopes of CP, PT, and EP (as specified as in model M1) as outcome variables, and the three items of the mental fatigue measure as indicators of a latent fatigue predictor variable. Also, we included the manifest scale scores of all covariates.

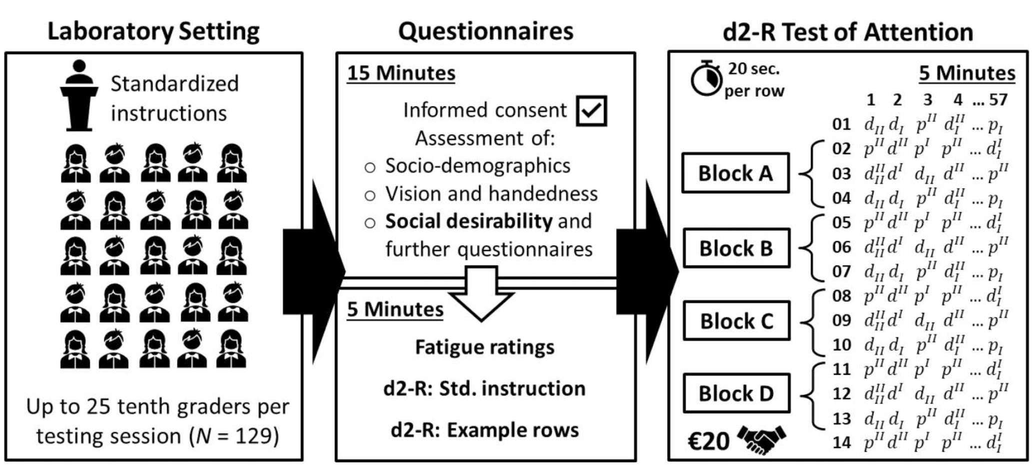

Figure 1. Visualization of the study protocol.

For both models, estimations were carried out in a structural equation modelling (SEM) framework, using the robust maximum likelihood estimator (MLR), which is robust against many violations of the normality assumption (e.g. Marsh et al., 2022). We had no missing data.

The goodness of fit was assessed by means of the chi-square statistic (χ^2), the Tucker–Lewis index (TLI; Tucker & Lewis, 1973), the comparative fit index (CFI; Bentler, 1990), the root mean square error of approximation (RMSEA; Browne & Cudeck, 1993), and the standardised root mean squared residual (SRMR; Jöreskog & Sörbom, 1993). As the chi-square statistic is known to be very sensitive to sample size and to small deviations from perfect fit, we focused on the other fit measures and followed Browne and Cudeck (1993) and Marsh et al. (2004), who recommended that the TLI and CFI values should be .90 or greater, RMSEA values should be .08 or smaller, and SRMR values should be below .08. To evaluate the statistical power of our results, we conducted post hoc power analyses using Monte Carlo simulations as implemented in Mplus 8.6 (Muthén & Muthén, 2017). All data and syntaxes required to reproduce the analyses presented in this article can be retrieved from: https://osf.io/gxues/?view_only = 779e3594fdba49b485962f45dff2fc74.

Results

In a first step, we plotted students' mean changes in concentration performance ($M_{CP\_A} = 37.49$ ($SD = 6.97$); $M_{CP\_B} = 37.81$ ($SD = 7.63$); $M_{CP\_C} = 36.01$ ($SD = 6.67$); $M_{CP\_D} = 34.70$ ($SD = 7.03$)), processing speed ($M_{PT\_A} = 44.10$ ($SD = 8.46$); $M_{PT\_B} = 43.52$ ($SD = 7.92$); $M_{PT\_C} = 42.05$ ($SD = 7.88$); $M_{PT\_D} = 41.24$ ($SD = 8.31$)), and error percentage ($M_{EP\_A} = 14.24$ ($SD = 11.62$); $M_{EP\_B} = 12.74$ ($SD = 11.43$); $M_{EP\_C} = 13.46$ ($SD = 12.23$); $M_{EP\_D} = 14.63$ ($SD = 13.68$)) that occurred over the course of the d2-R test blocks A to D (see Figure 2). Also, we visualised a descriptive extreme group comparison, plotting changes in performance measures for average fatigue ($N = 110$, $M = 2.84$, $SD = 1.55$), high fatigue ($\geq +1$ SD; $N = 21$, $M_{\text{high fatigue}} = 5.42$, $SD = 0.69$), and low fatigue (≤ -1 SD; $N = 11$, $M_{\text{low fatigue}} = 1.00$, $SD = 0.00$) groups. As evident from the figure, the mean trajectories of concentration performance and processing speed indicated the expected decrease over time, whereas the visual inspection did not reveal the expected increase in error percentage. Compared to the low fatigue group, individuals with high levels of mental fatigue showed a lower concentration performance and processing speed, and a higher error rate throughout the whole test.

In the second step, we focused on the results from the SEM analyses. Unless mentioned otherwise, estimated model parameters were statistically significant at $p \leq .001$. All tests were two-tailed.

Model M1 fitted reasonably well: χ^2 (42) = 72.604, TLI = .964, CFI = .977, RMSEA = .081 and, SRMR = .066. The estimates of the intercepts were $\mu_{I\_CP} = 37.81$ for concentration performance, $\mu_{I\_PT} = 43.94$ for processing speed, and $\mu_{I\_EP} = 13.35$ for error percentage, each with significant variances ($\sigma^2_{I\_CP} = 44.76$; $\sigma^2_{I\_PT} = 52.94$; $\sigma^2_{I\_EP} = 100.33$). We also found a negative slope for concentration performance ($\mu_{S\_CP} = -3.02$), indicating a decrease in this measure over the course of the four testing blocks. However, there was significant heterogeneity across participants as indicated by a significant slope variance ($\sigma^2_{S\_CP} = 9.11$). The same held true for the slope for processing speed ($\mu_{S\_PT} = -2.93$, $\sigma^2_{S\_PT} = 18.64$), while the slight increase ($\mu_{S\_EP} = 0.76$, $\sigma^2_{S\_EP} = 25.77$) of the error rates was not significantly different from zero ($p = .438$). Taken together, we found mean level decreases of concentration performance and processing speed over the course of working on blocks A to D, while accuracy did not change significantly over time.

The fit of main model M2 was good as well: χ^2 (112) = 166.898, TLI = .961, CFI = .975, RMSEA = .067 and, SRMR = .050. As shown in Figure 3, while controlling for students' social desirability (also for age, gender, forgotten glasses, and handedness), perceived mental fatigue was negatively related to the intercept of concentration performance ($\beta_{MF \rightarrow I\_CP} = -.357$, $p = .001$, 95% CI [-.563, −.152]), and positively related to the slope of processing speed ($\beta_{MF \rightarrow S\_PT} = .326$, $p = .031$, 95% CI [.030, .623]). This means that both the initial concentration performance and its decline were on a lower level throughout testing for individuals who felt stronger fatigued. Furthermore, the decline in processing speed over time was weaker for higher fatigued students. The positive relation between perceived fatigue and the intercept of error percentage ($\beta_{MF \rightarrow I\_EP} = .383$, $p < .001$, 95% CI [.200, .567]) indicated that higher fatigued students showed consistently less accuracy over the course of testing than lower fatigued students did. The positive relation between perceived fatigue and the slope of concentration performance as well as the negative associations between perceived fatigue, the intercept of processing speed, and the slope of error

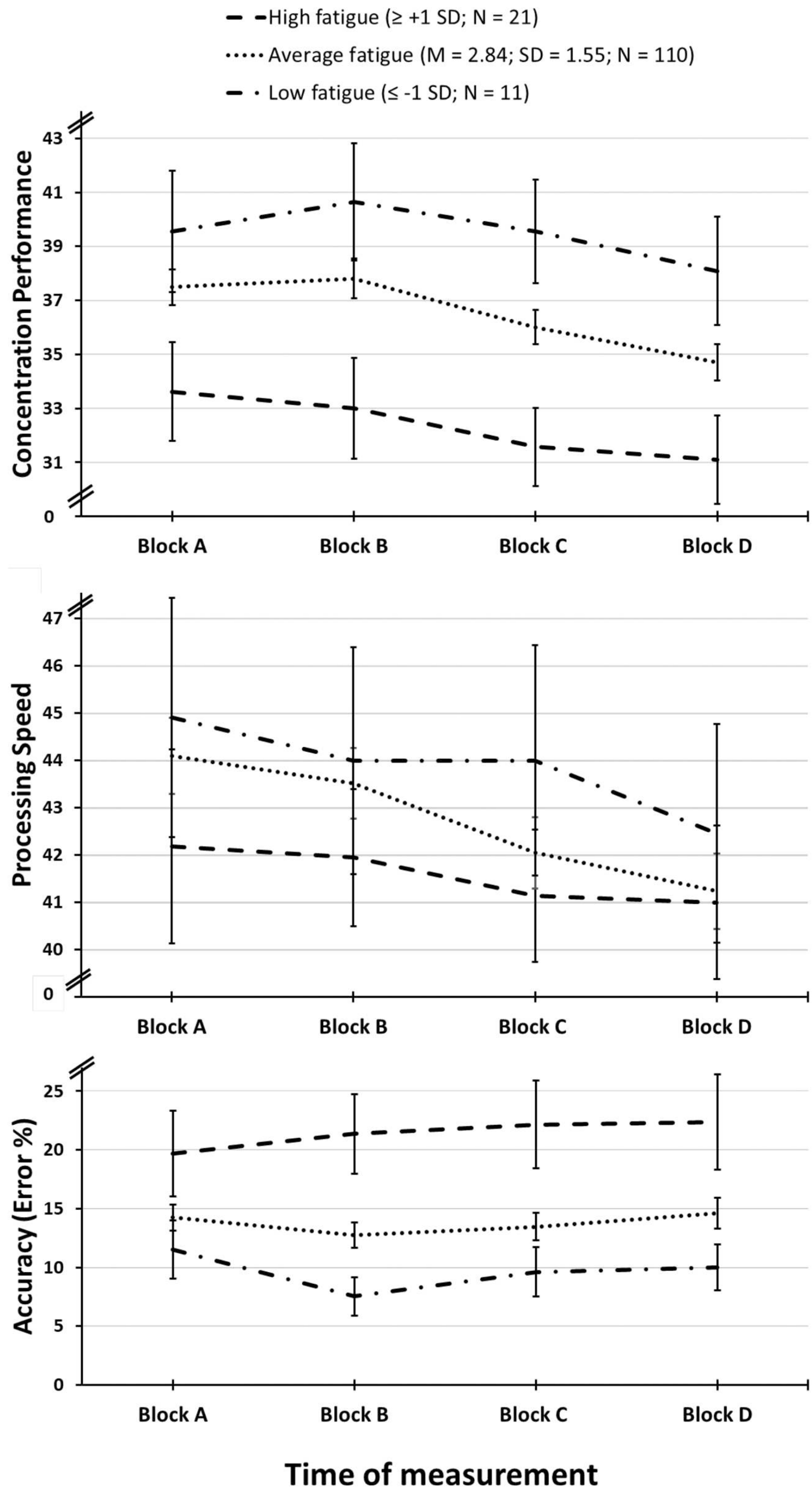

Figure 2. Changes in concentration performance, processing speed, and accuracy (y-axis represents mean scores across participants of the corresponding variables) over the course of testing (i.e. blocks A to D; x-axis) as a function of students' level of perceived mental fatigue. Bars represent standard errors.

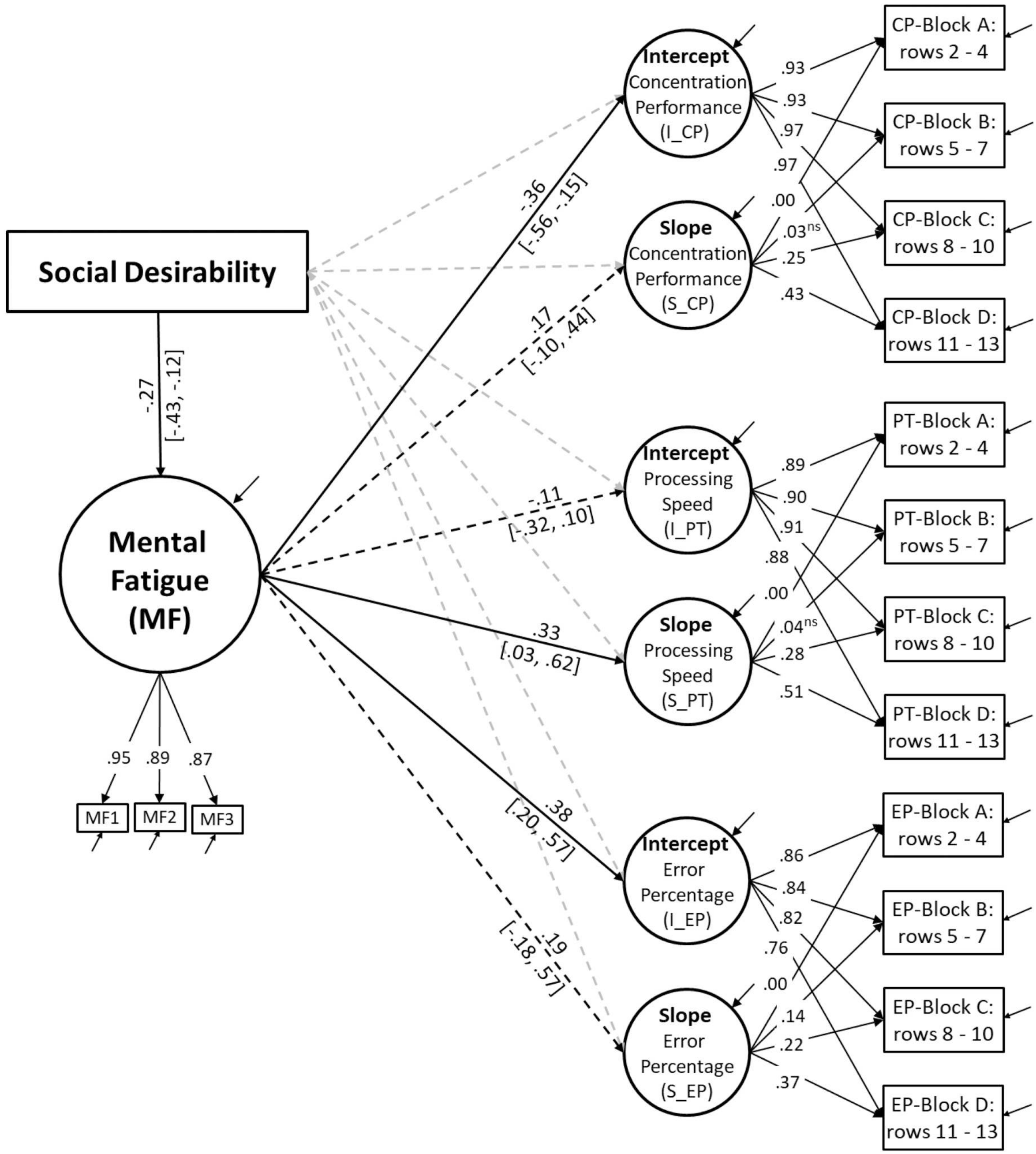

Figure 3. Results of model M2 including perceived mental fatigue, the three latent growth curves with intercepts and slopes of the factors concentration performance, processing speed, and accuracy, and the covariate social desirability. MF1, MF2, and MF3 represent the item scores used as indicators of the fatigue ratings at the group level. Not displayed are the covariates age, gender, corrected-to-normal vision (wearing glasses), and handedness. All parameter estimates are standardised estimates. Dashed lines indicate nonsignificant (ns) effects. Residual variances and correlations were omitted to increase readability.

percentage, were not significant (cf. dashed lines in Figure 3). This suggests that variations in mental fatigue were not systematically related to variations in changes of these outcome variables over time. As expected, students with higher tendencies toward social desirability showed lower fatigue ratings, whereas social desirability was not significantly related to any of the sustained attention performance outcomes.

Finally, to evaluate the statistical power of detecting the significant estimates in our model M2, we conducted post hoc power analyses, where we used the parameter estimates from our real data analyses as population values. The sample size was fixed at $N = 110$. We chose 10,000 replications with a seed value of 10,000 for the random population draws. The statistical power of our analyses was demonstrated by the percentage of replications that led to the rejection of the null hypothesis that the parameter is zero ($\alpha = 5\%$, two-sided). In the simulation study, the number of draws that were rejected due to nonpositive definite covariance matrices of the latent variables were 186 and thus, negligibly small. The statistical power for the relationships between perceived fatigue, the intercepts of concentration performance and error percentage, as well as the slope of processing speed was 92.8%, 95.2%, and 64.3%, respectively. The coverage rates for these parameters were 93.7%, 94.2%, and 91.6%, respectively. Except for the statistical power of the relationship between fatigue and the changes in processing speed, these results underline the high power and accuracy of our analysis to detect the significant relationships between perceived fatigue and sustained attention performance.

Discussion

In the present study, we focused on the early stage of the mental fatigue process, where sustained attention performance was assumed to drop rapidly over the course of the first few minutes of working on imposed, poorly controllable tasks with high successive event rates (Hockey, 2013). Furthermore, we aimed to investigate relationships between individual differences in perceived fatigue briefly before task execution and subsequent changes in concentration performance, processing speed, and error rates over time, while controlling for social desirability.

As hypothesised, the results of model M1 revealed that students' concentration performance and processing speed declined, whereas, somewhat unexpectedly, their error rates did not change significantly over the course of sustained attention testing. The simultaneous reduction in concentration performance (i.e. processing speed adjusted for errors) and processing speed (i.e. without accounting for accuracy) over time suggested a cumulative fatigue effect at the behavioral level that was rapidly induced, diminishing participants' attentional capacity and slowing down their pace, while their accuracy remained stable over time. Thus, participants may have prioritised avoiding errors over maintaining their initial speed. The stability in accuracy alongside reduced speed and processing efficiency indicated a shift from a high-speed, accuracy-balanced approach to a more conservative, accuracy-preserving approach as work on the d2-R test progressed (Bates & Lemay, 2004; Steinborn et al., 2018). Our results provide evidence for the early onset of decrements in sustained attention performance during the short-lasting d2-R test. The concentration performance and processing speed decreases may have partly resulted from habituation, where repeated similar stimuli lead to decreased responsiveness, while individuals might still maintain accuracy by exerting compensatory effort (e.g. Hockey, 2010). This effect has been studied in vigilance tasks, where stable accuracy is maintained alongside declines in response speed (Hockey, 2013).

For answering our main research question, we investigated tenth graders who were assumed to be relatively cognitively relaxed when they rated their levels of mental fatigue immediately before starting to work on the subsequent d2-R test of sustained attention. Whereas students' mean level of perceived fatigue was relatively low ($M = 2.84$), their variabilities in fatigue ($Var = 2.39$) indicated that these differences might have been due to accumulations of nonrecoverable fatigue levels over the course of varying daily activities before participating in our study (see also Bijleveld, 2023; Hockey, 2013; Matthews et al., 2023). As shown in Figure 3, students with higher tendencies toward social desirability reported lower levels of perceived fatigue, while their sustained attention performance outcomes were not significantly related to social desirability. As already suggested by Kunasegaran et al. (2023), this result underscores the importance of controlling for participants' social desirability levels when investigating self-reported fatigue, even though relationships between perceived fatigue and objectively measured outcomes are hardly affected by social desirability.

As expected, the results of our main analysis (i.e. model M2) revealed that the initial state of the generally declining concentration performance was on a lower level for individuals who felt stronger fatigued, while their error rates were on a consistently higher level throughout testing. These statistically high-powered effects were medium sized. Against our expectation, the decline in processing speed over time was weaker for more fatigued students, indicating that they tended to work faster but less precisely compared to less fatigued students (speed-accuracy trade-off). However, the results pattern in model M2 appeared to illustrate a compensatory mechanism in response to perceived fatigue, aligning closely with Hockey's (2013) speculations. Our findings indicate that highly fatigued individuals managed a lower initial level of concentration but demonstrated similar (i.e. parallel) concentration declines similar to individuals with lower fatigue levels. This pattern suggests that participants who felt fatigued may have faced stronger baseline limitations in attention rather than a more pronounced progressive fatigue-related decline in attention. Additionally, fatigued participants appeared to maintain or even slightly increase their processing speed as a compensatory response, resulting in a speed-accuracy trade-off where accuracy may have been strategically managed to stabilise the error rate despite fatigue. This adaptive response suggested a prioritization of speed over precision in fatigued individuals, aligning with compensatory control models (e.g. Hockey, 2010) and emphasising how perceived fatigue influences the initial level of concentration and the subsequent trade-off strategies used to allocate effort selectively to manage key aspects of cognitive performance (see also Kok, 2022; Kurzban et al., 2013).

We speculate that the patterns observed in the present study regarding early fatigue may also influence test-taking behavior and performance levels during prolonged engagement in cognitively demanding tasks (i.e. later fatigue stages). For instance, a higher tendency to feel fatigued before starting to work on 140-minutes lasting achievement tests was associated with poorer performances in the corresponding mathematics and science tests (Lindner et al., 2024), while participants' self-control capacity and effort investment consistently decreased throughout the testing period (Lindner et al., 2018). However, further research is required to deepen our understanding of the psychological mechanisms underlying the interrelations between early fatigue, changes in sustained attention, and behaviors associated with varying performance trajectories in later fatigue stages.

Practical implications

Our study's findings on the relations between perceived fatigue and sustained attention performance have practical implications for both educational and workplace settings. As already shown, structured breaks during cognitive tasks seem essential in educational and work contexts to reduce fatigue effects, helping individuals sustain attention and accuracy (Kim et al., 2018; Sievertsen et al., 2016). Research provided evidence that short, strategically placed rest intervals, as well as specific brain training techniques, can improve cognitive endurance and resilience to mental fatigue, which may help individuals optimise both productivity and accuracy in learning and working environments (Díaz-García et al., 2025; Rees et al., 2017). In the workplace, planned rest seemed to promote engagement and consistent performance across the workday, balancing speed with accuracy, and maintaining overall efficiency (Kim et al., 2018). In high-stakes fields such as surgery, aviation, and driving, fatigue management is critical to safety and performance. Recent research showed that wearable biosensors for monitoring stress and fatigue in these areas enable early recognition of fatigue cues, allowing personnel to take timely breaks to maintain precision and prevent critical errors (Ma et al., 2024). As shown by Al-Shargie et al. (2019), interventions such as specific video gaming or transcranial direct current stimulation (tDCS) demonstrated the strongest improvements of vigilance, indicating that such enhancement techniques might also be promising to reduce fatigue proneness. Taken together, integrating fatigue-management into daily work, learning and performance routines may support safer operations and improve performance efficiency in cognitively demanding tasks.

Strengths and limitations

A major strength of our study is the use of structural equation modelling (SEM) and growth curve analysis, which enabled us to test our hypothesised associations between perceived fatigue and trajectories in sustained attention performance by integrating all assumed relationships between variables within a single model and using latent variables. SEM provides measurement error-free estimates and reduces alpha inflation, thereby enhancing the rigour of our findings. Additionally, growth curve modelling allowed us to examine the temporal changes in sustained attention over time, providing a more comprehensive understanding of how performance unfolds under different levels of perceived fatigue. Another strength of the present study was that in our main analyses, we controlled for participants' social desirability and additional covariates to minimise potential confounding effects on the associations between perceived fatigue and performance outcomes. Finally, we conducted a post-hoc power analysis to assess the robustness of the results, adding further confidence in our study's findings.

Our results and interpretations of the relationships between perceived fatigue and changes in sustained attention performances are limited to adolescents (i.e. tenth graders), and the statistical power to detect effects of fatigue on changes in processing speed was not optimal (i.e. 64.3%). However, power analyses themselves may not be optimal (Zitzmann et al., 2024). Therefore, we recommend replicating our study while drawing on a larger sample of approximately one hundred additional participants, preferably also including adults. One seeming shortcoming of the present study concerns the low internal consistency of the social desirability scale (SDS-17). However, we wish to emphasise that the reported coefficient (Cronbach's α) is just an estimate of internal consistency. Because our sample size is limited, and thus, there is considerable uncertainty inherent in this estimate, it is difficult to conclude how high the SDS-17's internal consistency actually is. A larger sample size could help to address this limitation in future studies. Increasing the sample size may not only reduce uncertainty by narrowing the credible interval around the estimate but also yield an estimate that is closer to the actual, possibly higher internal consistency in the studied population. Our hope that internal consistency could be acceptable is motivated by Tran et al. (2012), who noted that Cronbach's α values vary between .59 and .76 across studies, indicating that an acceptably high value of > .70 is possible.

Conclusion

While controlling for social desirability, our study demonstrates that individual differences in perceived fatigue are significantly associated with variations in subsequent sustained attention performance decrements. Applying the d2-R test of sustained attention, we found that more fatigued participants initially exhibited lower concentration performance, which declined at a similar rate to less fatigued individuals. They also maintained or slightly increased their processing speed, indicating a compensatory strategy that prioritised speed over accuracy, helping to stabilise error rates over time. These findings highlight the impact of perceived fatigue on cognitive performance, emphasising the importance of structured breaks and fatigue management in educational, workplace, and safety-critical settings, while encouraging further research into the underlying mechanisms of perceived fatigue and sustained attention performance.

Consent to participate

Informed consent was collected from all participants.

Disclosure statement

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

Data availability statement

Data and syntaxes can be accessed at https://osf.io/gxues/?view_only = 779e3594fdba49b485962f45dff2fc74.

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