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Tracing need for cognition in digital learning

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ABSTRACT

Need for Cognition (NFC) reflects individuals' tendencies to engage in and enjoy effortful cognitive activities and has been linked to positive academic outcomes (e.g., higher academic achievement). However, the extent to which NFC is expressed in actual learning behaviors remains unclear. Therefore, we investigated how NFC manifests in digital learning behaviors by analyzing behavioral trace data from undergraduate students in an online chemistry course across 4 periods (before Midterms 1 and 2, respectively, and before and after the final exam). Building on a comprehensive set of >600 behavioral indicators, ML models strongly predicted academic achievement (explained variance: 50.34%). Generally, self-testing behavior, lecture engagement, and greater overall activity were predictive of better performance. Based on these performance-relevant indicators, we applied hierarchical clustering to identify distinct patterns of learning behavior. Two learner profiles emerged: one characterized by timely, structured engagement with lectures and quizzes, and another characterized by high overall activity but more irregular behavior and limited use of core instructional materials. Contrary to theoretical assumptions and prior research relying on self-reported learning behaviors, students' NFC was not associated with membership in either behavioral digital trace profile. Taken together, these findings raise the possibility that, although NFC has been linked to academic success, this association may not be driven by differences in observable digital learning behaviors. Our study offers novel insights into NFC in digital learning and highlights the importance and challenges of adopting behavioral data to study individual differences.

1. Introduction

Need for Cognition (NFC) is a personality trait that reflects a person's tendency to seek out and engage in effortful cognitive activities (Cacioppo & Petty, 1982). NFC has received considerable attention in educational research, revealing robust links to student outcomes, such as academic performance (Liu & Nesbit, 2024) in both online (Chen & Wu, 2012; Jeske et al., 2014) and face-to-face educational settings (Elias & Loomis, 2002; Grass et al., 2017). The relationship between NFC and academic achievement is well established. A recent meta-analysis revealed a moderate effect size ($r = 0.20$) linking NFC to academic achievement (Liu & Nesbit, 2024). Other studies have demonstrated the effects of NFC on academic outcomes even beyond the influence of cognitive abilities (Lavrijsen et al., 2022; Preckel, 2014).

However, relatively little is known about the specific learning behaviors through which NFC may be expressed in educational settings, and existing studies have mostly relied on self-report measures of learning behaviors rather than direct behavioral indicators (Cazan & Indreica, 2014; Evans et al., 2003; Swafford et al., 2021; Xiao et al., 2024). As learning behaviors may explain why students high in NFC tend to perform better, identifying these behaviors could clarify how NFC manifests in behavior and thus refine our theoretical understanding of the construct. To date, the rise of digital learning platforms allows for the assessment of students' learning behaviors through log-based trace data (Arizmendi et al., 2023; Baker et al., 2020). Analyzing these digital traces therefore offers a promising approach for understanding how NFC is related to real learning behaviors that underpin students' academic success.

With the present study, we aim to examine how individual differences in NFC are reflected in students' learning behaviors in a real-world

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educational context. Using trace data from undergraduate students' activity on a learning management system over the course of a semester, we investigated whether students with different levels of NFC engage in systematically different patterns of learning behavior that are relevant for academic performance. By moving beyond self-reported learning strategies and focusing on observed behavior in digital learning environments, this study adds to our understanding of NFC and how it may be related to learning behaviors that contribute to students' academic success.

1.1. Need for cognition, learning behaviors, and academic achievement

NFC is part of a broader group of so-called investment traits, which reflect how much time and cognitive effort individuals are willing to invest in their intellect (Ackerman & Heggestad, 1997; von Stumm & Ackerman, 2013). Thus, NFC is conceptually close to cognitive abilities (Cacioppo et al., 1996; Fleischhauer et al., 2010). However, whereas cognitive abilities represent an individual's potential for performing well on cognitive tasks, NFC indicates their motivation to utilize that potential (Goff & Ackerman, 1992; von Stumm et al., 2011). Accordingly, individuals higher in NFC would be expected to engage more consistently in cognitively demanding activities within learning contexts.

Proposals for concrete behaviors associated with NFC can be drawn from studies on NFC in cognitive tasks and the literature on related traits (e.g., openness to experience or other intellectual investment traits such as intellectual curiosity). At the core of NFC is a willingness to exert effort (Kramer et al., 2021), along with engagement and persistence shown in cognitively demanding tasks (Cacioppo & Petty, 1982; Fleischhauer et al., 2015; Lavrijsen et al., 2023; Rigolizzo, 2019). People high in NFC consider cognitively demanding tasks to be enjoyable, and they favor complex tasks or activities over simple ones (See et al., 2009; Therriault et al., 2015; Zerna et al., 2024). Not only are people who are high in NFC drawn to intellectually challenging tasks, they also tend to process information more deeply and efficiently (Cacioppo et al., 1996; Enge et al., 2008; Mussel et al., 2016) and exhibit enhanced problem-solving skills (Coutinho, 2006; Nair & Ramnarayan, 2000; Rudolph et al., 2018).

Given that formal education involves cognitively demanding work, NFC may promote greater overall learning activity and engagement (von Stumm & Ackerman, 2013). Additionally, NFC has been found to be related to higher levels of self-control (Bertrams & Dickhäuser, 2012; Grass et al., 2019) and improved task focus (Levin et al., 2000; D. Li & Browne, 2006; Srivastava et al., 2010). These findings suggest that not only are individuals high in NFC more likely to engage in more effective learning behaviors, but they may also be more resistant to distractions. As a result, their learning may be more consistent and sustained over time, and they may be less prone to procrastination, which should also be positively reflected in their study results (Ferrari et al., 2018; Sarmany-Schuller, 1999; Wang & Mousavi, 2023).

This tendency toward effortful engagement and cognitively demanding strategies related to NFC should be particularly beneficial in learning contexts that require students to self-regulate their studying. Such demands increase with age and are especially pronounced in higher education, where a great deal of studying occurs outside the classroom. In higher education, students are expected to seek out additional resources independently when they struggle to understand course material. It has been theorized that individuals with higher levels of NFC are more inclined to actively seek out information themselves instead of relying on others (Cacioppo et al., 1996), an idea that has been supported by empirical findings that NFC is related to information-seeking behaviors (Coutinho et al., 2005; Curşeu, 2011; Fortier & Burkell, 2014; Mokhtari et al., 2013). For instance, in a study by Maur et al. (2024), when asked to conduct an unrestricted web search on a controversial topic, participants high in NFC showed more comprehensive and systematic search strategies and were more critical when they evaluated sources. Relatedly, other intellectual investment traits have been linked to revisiting and re-engaging with information (e.g., intellectual curiosity in Schumacher et al., 2025). Thus, in line with the idea that NFC fosters critical reflection, individuals high in NFC may also be more likely to revisit learning materials to consolidate their knowledge.

On a motivational-affective level, research has shown that NFC is associated with a positive attitude toward desirable difficulties—that is, study strategies that are mentally demanding and may feel counterproductive at first but may ultimately enhance long-term learning (De Bruin et al., 2023; Weissgerber et al., 2018). Among the desirable difficulties strategies, NFC was particularly strongly related to the self-reported use of generating learning materials, and, to a lesser extent, to self-testing and interleaved learning (Weissgerber et al., 2018). NFC has also been associated with higher levels of self-efficacy (Ajadi, 2022; Elias & Loomis, 2002; Fleischhauer et al., 2024) and mastery goal orientations (Day et al., 2007; Meier et al., 2014; Preckel, 2014), both of which make the use of desirable difficulties more likely (De Bruin et al., 2023; Weissgerber et al., 2016; Yan, 2018). In turn, these strategies are linked to improved learning outcomes (Hartwig & Dunlosky, 2012; Ifenthaler et al., 2023; Rodriguez et al., 2021).

To summarize, the comprehensive body of research on NFC suggests that NFC likely manifests in learning behaviors that support academic success. However, a major limitation that remains is the heavy reliance on self-reported measures of learning behaviors, which may be affected by social desirability or memory biases and the inability to verify whether students actually use the strategies they report (Q. Li et al., 2020; Parry et al., 2021; Roth et al., 2016). Additionally, most of the reported studies were cross-sectional and did not capture learning behaviors over extended periods, such as an entire semester or school year. Both limitations may be addressed by incorporating behavioral data to assess learning behaviors. The growing use of digital learning platforms enables the digital assessment of students' learning behaviors in the form of log-based trace data (Arizmendi et al., 2023; Baker et al., 2020). Analyzing these behavioral traces provides a promising avenue for understanding how NFC translates into actual learning behaviors, thus offering new ways to observe NFC in action.

1.2. Using trace data to capture learning behaviors

When students learn on a digital learning management platform, each interaction with the system (e.g., clicking on a lecture video, submitting a practice quiz, posting a comment in the discussion forum) is automatically recorded as a time-stamped log event. These log files offer rich, fine-grained, and time-sensitive documentation of students' behaviors on the platform. In this way, they can mitigate some limitations of self-reported learning behaviors, such as inaccuracies in students' recall or the lack of situational specificity in questionnaire measures (Roth et al., 2016).

However, to meaningfully interpret these raw trace data as indicators of learning behavior, the data must be contextualized by using information about the structure of the course (Arizmendi et al., 2023). For instance, the total number of clicks on lecture videos may serve as a basic measure of engagement; however, this measure can become even more informative when considered in relation to the total number of available videos because it indicates whether a student engaged with only a small portion of the content or watched all the lectures. Similarly, the timing of interactions can be critical for interpretation (von Keyserlingk et al., 2025). For example, submitting the first practice quiz in the second week of the semester likely reflects a different approach to learning than submitting it the night before the final exam.

Because behavioral trace data sets are often large and unstructured and involve large numbers of potentially meaningful predictors, one challenge is to identify the features most relevant to the prediction, and another is to ensure interpretability. ML approaches are commonly used to analyze this type of data because they can accommodate complex, nonlinear relationships and prioritize predictors according to their relevance for a given outcome (Hilbert et al., 2021), especially when combined with explainable AI methods (Chitti et al., 2020; Deininger et al., 2025). These aspects help reduce model complexity while preserving predictive accuracy (Yarkoni & Westfall, 2017).

Another approach to increase interpretability and summarize complex behavioral trace data at a higher level is to apply person-centered clustering methods to identify recurring patterns or profiles of learning behavior (Jang et al., 2017). Rather than focusing on isolated indicators, clustering allows for the integration of multiple learning behaviors into broader configurations that tend to co-occur within students. These configurations can be used to group students who exhibit similar patterns of learning behavior, making it possible to examine how these behavior patterns are associated with learning success and individual student characteristics (Jovanovic et al., 2024; Tempelaar et al., 2018; Xie et al., 2025).

1.3. Using trace data to examine students' NFC

Many researchers have used students' trace data to capture their learning behaviors, link these behaviors to learner characteristics, or predict learning outcomes across various online learning environments and age groups (Baker et al., 2020; Du et al., 2023; Ifenthaler & Yau, 2020). However, only a few studies have focused on personality traits and their relationship with learning behaviors in online courses (Matcha et al., 2020; Rüdian et al., 2019, pp. 8–15; Tlili et al., 2017, 2019; Wu & Lai, 2019). For example, Matcha et al. (2020) analyzed behavioral trace data from a MOOC and found that conscientiousness (i.e., being organized, responsible, and hardworking; Roberts et al., 2014) predicted the use of deep learning approaches, whereas more neurotic or emotionally unstable learners were more likely to use surface approaches to learning. Data-driven exploratory studies have demonstrated that algorithms can both predict behavior from self-report personality measures (Rüdian et al., 2019, pp. 8–15), as well as personality profiles from online learning behavior (Tlili et al., 2017, 2019).

However, most of the work on personality and trace data has primarily focused on the Big Five personality traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Digman, 1990). To our knowledge, NFC has not yet been assessed using behavioral trace data on learning behaviors in online learning courses. Nonetheless, as outlined in the previous section, there are several learning behaviors that could be theoretically linked to NFC and that can be modeled using trace data: overall engagement and consistency of engagement (Cicchinelli et al., 2018, pp. 191–200; Jovanović et al., 2021), procrastination behavior (Asarta & Schmidt, 2013; Paule Ruiz et al., 2015), information seeking (S. Li et al., 2022), and self-testing (Cicchinelli et al., 2018, pp. 191–200; T. C. Yang et al., 2018). Whereas these behaviors have previously been studied using trace data, they have not yet been connected to NFC. Importantly, such behaviors have also been used to predict learning outcomes such as final course grades (Chakrapani & Chitradevi, 2022). Examining these behaviors in relation to NFC may thus help shed light on the processes through which NFC can be beneficial for academic performance.

1.4. Study aims

The present study was designed to enrich previous research on the personality trait of NFC and its role in learning contexts by studying the real-world learning behavior of university students. Specifically, we addressed the question of whether individual differences in NFC are reflected in patterns of learning behavior by analyzing trace data from undergraduate students' activity on the Canvas learning platform over the course of a semester. From these traces, we first extracted behavioral indicators of learning and determined those that are most predictive of students' performance in the course. Next, we identified learning behavior profiles that students can be grouped into based on these performance-relevant behaviors. Finally, we tested whether these learning behavior profiles differ in students' levels of NFC.

Given our use of ML and clustering methods, the analyses were primarily exploratory, and we did not conduct traditional hypothesis testing. However, we have elaborated on plausible conceptual links between NFC and learning behaviors in the theoretical background sections. We formulated the following research questions (RQs).

- RQ1 Which learning behaviors are most strongly associated with academic performance?
- RQ2 What distinct learning behavior profiles can be identified among students based on these performance-relevant behaviors?
- RQ3 How do students' levels of NFC differ across the identified learning behavior profiles?

2. Method

2.1. Participants

Participants were recruited from a sample of undergraduate students who were attending a public university in the western United States in the fall term of 2020 and were part of an ongoing longitudinal multi-cohort study [details blinded for review]. Data collection for the overarching research project began in fall 2019, following ethics approval from the university's institutional review board (#HS: 2018-4646). The project received IRB approval to access administrative and digital trace data from these students for research purposes.

We used trace and administrative data from three parallel sections of students in a large introductory chemistry lecture ($N = 1185$). Final course grades were reported in the administrative data for 1168 students, forming the sample for RQ1 and RQ2. Additional survey data were collected from a subsample of students at the beginning of the semester. To test how students' NFC-levels were associated with their learning behaviors (RQ3), we relied on $N = 137$ students who had a valid NFC score from the core survey administered at the beginning of the school year. Table 1 provides information on descriptive statistics and demograhics.

2.2. The course

The chemistry course used for this study was a highly structured gateway course. As this term took place during the COVID-19 pandemic, teaching was exclusively conducted online using the university's online learning management system Canvas. Each week, multiple pre-recorded lecture videos were uploaded, accompanied by lecture notes and assigned readings. For every lecture, a self-assessment practice quiz was

Table 1
Descriptive statistics and demographics.

	n	%
Gender (female)	1165	64.46
Black	1145	3.06
Asian	1145	65.24
Hispanic	1145	20.87
White	1145	10.57
Other Ethnicity	1145	0.26
First Generation	1158	55.87
	n	*M (SD)*
Age	1168	18.18 (0.52)
High school GPA[a]	1167	4.02 (0.21)
Final grade[b]	1168	7.91 (2.68)
NFC[c]	137	3.62 (0.72)

Note. Percentages and missing values are reported for categorical variables. Means (*M*) and standard deviations (*SD*) are reported for continuous variables.
[a] Possible range: 0-5.
[b] Possible range: 0-12.
[c] Possible range: 1-5.

made available. In addition to these asynchronous materials, teaching assistants held problem-solving sessions via Zoom in which they discussed weekly problem sheets. These discussion sessions were highly recommended to the students, but attendance was not mandatory. Finally, students completed graded homework assignments on an external platform and thus, homework activities were not captured in the digital trace data used for this study.

2.3. Measures

2.3.1. Demographics

Data on gender, ethnicity, and first-generation college student status were collected via self-reports. High school GPA was retrieved from college record data and was recorded on a weighted 5.0 scale.

2.3.2. Need for cognition

NFC was assessed in the core survey at the beginning of the term with the Need for Cognition Scale-6 (NCS-6), which included six items (Lins De Holanda Coelho et al., 2020; sample item: "I really enjoy a task that involves coming up with new solutions to problems"). The internal consistency, computed as Cronbach's alpha, was good ($\alpha = .80$). The students responded to the items on a scale ranging from 1 (*extremely uncharacteristic*) to 5 (*extremely characteristic*).

2.3.3. Academic achievement

Academic achievement was assessed with the final course grade extracted from administrative data and could range from 0 to 12 points. Students failed the course if they had less than 5 points.

2.3.4. Behavioral indicators of learning

Behavioral indicators were computed on the basis of interaction events stored in the logfiles. These actions could be broadly grouped into eight categories: *quiz-related* (e.g., "Click on a quiz"; "Take a quiz"), *lecture-related* (e.g., "Visit page lecture video 1"), *discussion forum-related* (e.g., "Read a post in a discussion topic"; "Show the list of discussion topics"), *assignment-related* (e.g., "Click on an assignment"; "Visit assignments page"), *organizational* (e.g., "Visit the FAQs page"; "Show announcements"), *exam-related* ("View Midterm 1 quiz attempt"; "Visit grades page"), *overall activity* ("Visit the homepage of a course"; "Visit Modules page"), and *others* (e.g., "Click on a specific file"; "Click on a student"; see the Appendix for a list of all identified log events). To account for fluctuations in general activity across different periods of the semester (e.g., activities generally increased before exams), all behavioral indicators were calculated for four periods of the semester: Before Midterm 1, Before Midterm 2, Before final exam, and After final exam (see Fig. 1). For each identified interaction event, eight behavioral indicators were computed: the mean occurrence per day and the standard deviation (*SD*), both within each of the four periods of the semester (e.g., mean of "Take a quiz" before Midterm 1 and *SD* of "Take a quiz" before Midterm 1).

For each lecture video, a self-assessment quiz was provided. Using the syllabus, we identified the order of lecture videos and self-assessment quizzes during the semester. Using this information, we computed additional behavioral indicators that marked whether a student interacted with the lectures and quizzes "on time" (i.e., before the next lecture and quiz were uploaded). Similarly, we computed behavioral indicators that were based on how often students revisited lectures and quizzes, as well as during which period in the semester they did so (e.g., whether a student took a quiz from the period "Before Midterm 1" again in the period "Before final exam"). These indicators enriched the behavioral feature set by capturing aspects that indicated the pacing of activity (keeping up with the intended course schedule), and the completeness with which course materials were accessed (Asarta & Schmidt, 2013).

As many machine-learning algorithms and clustering approaches cannot handle missing data, we adopted the following strategy to address missingness (see Online Supplement G for the percentage of missing values prior to missing-data handling). For behavioral indicators, missing values reflect that a student did not show a certain behavior during a semester phase and therefore are not missing at random. Importantly, this missingness is informative, as it indicates low engagement. Accordingly, missing values for these indicators were set to 0. An exception was made for time-based variables (i.e., the mean and standard deviation of the time between when a lecture was scheduled and when it was first accessed). For these variables, substituting missing values with 0 would imply immediate access and thus be conceptually inappropriate. Instead, we applied k-nearest neighbors (k-nn) imputation, using all remaining behavioral indicators as predictors to impute missing values (Murti et al., 2019).

The final set consisted of $N = 649$ behavioral indicators. Although overall click patterns were very similar across course sections (see Online Supplement A), all behavioral indicators were centered within students in one section. See Online Supplement G for the full list of computed behavioral indicators.

2.4. Analyses

2.4.1. ML analysis pipeline for performance prediction

The feature set to address RQ1 included all behavioral features derived from the trace data, as well as the course code (which section the student was in) and high school GPA as a proxy for prior academic performance. Given the high dimensionality of this set, we applied

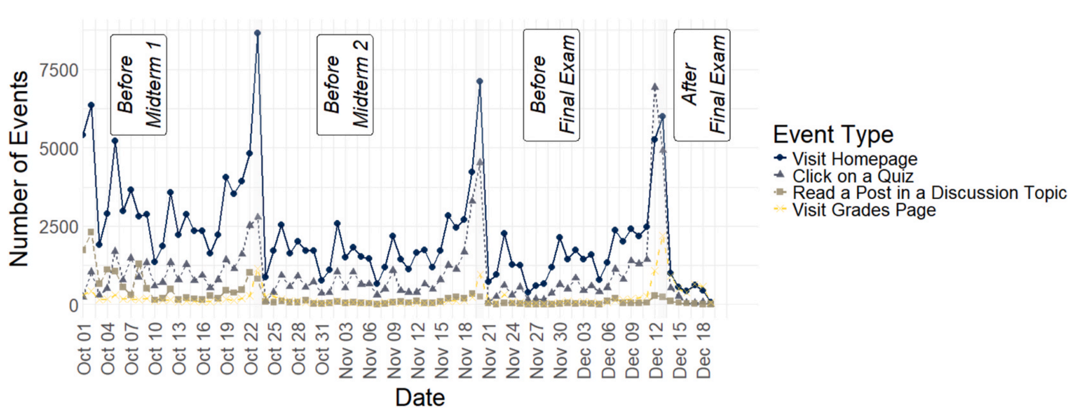

Fig. 1. Activity Patterns for All Students for Four Example Events Throughout the Semester
Note. Overview of the course structure across the semester, highlighting exam dates and the periods of the semester used to calculate behavioral indicators. The figure illustrates example interaction data for selected types of events: clicks on the homepage, clicks on a quiz, reads a post on a discussion topic, and clicks on the grades page. Shaded areas indicate the timing of Midterm 1, Midterm 2, and the final exam.

feature selection using LASSO regression (Least Absolute Shrinkage and Selection Operator) prior to model training. LASSO performs both regularization and variable selection by shrinking less informative coefficients to zero, thereby retaining only the most predictive features (Tibshirani, 1996).

We compared the performances of seven ML models that varied in complexity and were suitable for tabular data (Borisov et al., 2022): Linear Regression Model, Elastic Net Regression, Decision Tree, Support Vector Regression, Random Forest, Extreme Gradient Boosting (XGBoost), and Multilayer Perceptron. All models were built from scratch and did not rely on pre-trained parameters. Furthermore, all variables were scaled before training. Multicategorical features were one-hot encoded (i.e., converted into binary format). We trained all models using an 80:20 train-test split with 10-fold cross validation and grid search for hyperparameter tuning (see Online Supplement B for hyperparameter grids). We compared all models with a mean baseline. Given that our prediction tasks were regression problems due to the continuous outcome variable, we relied on explained variance and the root means square error (RMSE) as our primary evaluation criteria to compare the predictive power of all models and evaluate model performance. We selected the best-performing model on the basis of the highest explained variance, which evaluates the proportion of variance in the outcome captured by the model's predictions.

To identify the features that were most predictive of academic performance, we computed SHapley Additive exPlanations (SHAP) values to evaluate the contribution of each predictor to the model's prediction (i.e., feature importance; Lundberg & Lee, 2017). For each student, SHAP values quantify the contribution of each learning behavior indicator to the predicted outcome. The size of a SHAP value reflects the magnitude of a feature's impact on the prediction, while its sign indicates the direction of the effect: Positive values increase the prediction relative to the base value, negative values decrease it, and values near zero indicate a negligible influence. SHAP was selected as the explanation method due to its model-agnostic nature, enabling consistent interpretability across different ML algorithms. This ability was an essential requirement for our comparison of multiple predictive models. Moreover, SHAP provides explanations at the sample or group level, enabling an understanding of learning behaviors across student groups. Finally, SHAP accounts for multicollinearity by distributing the shared contribution of highly correlated features among them (Lundberg & Lee, 2017), a crucial advantage given the strong correlations between the features in our data set. The ML and SHAP analyses were conducted with Python version 3.11.11 using scikit-learn 1.3.2, xgboost 2.1.1, and shap 0.47.2.

2.4.2. Clustering

To improve the interpretability of the resulting clusters, we reduced the feature set prior to clustering. Specifically, we retained only the most predictive features identified in the performance prediction model based on their mean absolute SHAP values. Mean absolute SHAP values quantify the average contribution of each feature to the model's predictive performance across observations. Features were ranked according to their SHAP importance, and the smallest subset accounting for 80% of the cumulative importance was selected for the clustering analysis. All features were standardized prior to clustering.

We used hierarchical agglomerative clustering with Ward linkage and Euclidean distance as our clustering approach (Nielsen, 2016). Solutions ranging from $k = 2$ to $k = 6$ clusters were considered. Cluster solutions were evaluated based on inspection of the dendrogram, average silhouette scores (Rousseeuw, 1987), and interpretability of the behavioral pattern. To characterize and compare the identified clusters, we computed cluster means of each behavioral indicator and identified those that showed the largest difference between clusters and were thus the most discriminatory. These differences were visualized using heatmaps to guide the labeling and interpretation of the clusters.

As a robustness check, k-means clustering solutions with $k = 2$–6 were additionally computed and compared to the hierarchical clustering results. Results of these analyses are reported in Online Supplement C.

2.4.3. Relationship between NFC and behavioral clusters

To examine whether students' NFC levels differed across the learning behavior clusters, we estimated linear models with NFC as the dependent variable and cluster membership as the main predictor, controlling for course section.

3. Results

3.1. Descriptives

General click activity decreased slightly over the course of the semester with clear peaks of activity on the days before the exams and the days of the exams (see Fig. 1). One hundred three students (9.49%) did not pass the course (i.e., achieved less than 5 points). Only three students (0.25%) achieved the best grade of 12 points.

Analysis of variance (ANOVA) indicated that the sections differed significantly in final course grade, $F(2, 296) = 21.40$, $p < .001$. Tukey's Honestly Significant Difference (HSD) post hoc comparisons revealed that students in course 40,020 had significantly better grades ($M = 8.58$, $SD = 2.38$) than students in courses 40,060 ($M = 7.40$, $SD = 2.74$; $p < .001$) and 40,080 ($M = 7.73$, $SD = 2.77$; $p < .001$). Hence, in the ML model, final grade was centered within each section to account for this issue.

For students with both measures available, we calculated correlations between NFC and academic achievement. NFC was not correlated with final course grade, $r(134) = 0.03$, $p = .765$. Highschool GPA was correlated with final course grade, $r(1165) = 0.27$, $p < .001$, but not with NFC, $r(136) = -0.07$, $p = .433$.

3.2. RQ1: learning behaviors predictive of final course grade

We used the full set of behavioral indicators ($N = 649$ behavioral indicators), along with course section and high school GPA to predict final course grade (centered within each section). In a first step, feature selection via LASSO regression reduced the predictor set to $N = 134$ features. The proportion of explained variance across the ML models ranged from 23.48% (RMSE = 2.28) for the Decision Tree model to 50.34% (RMSE = 0.50) for the XGBoost model (see Online Supplement D for full model results). These results indicate that behavioral indicators of learning were strong predictors of academic achievement.

Based on SHAP values, a total of 55 features accounted for over 80% of the model's predictive performance (see Online Supplement E for all mean absolute SHAP values). Fig. 2 shows a SHAP summary plot of the 15 most predictive features, ranked by their overall contribution to the model's predictive power. High school GPA emerged as a strong predictor of course grade. However, four behavioral indicators contributed even more to the model's predictions: Number of lectures watched before the final exam, average number of quiz retakes over the semester, variability in clicking on Lecture Video 25 before the final exam, and the number of quizzes taken before Midterm 1. In general, number of lectures watched before the final exam and number of quizzes taken before Midterm 1 were associated with better predicted grades. By contrast, a higher average number of quiz retakes was associated with lower predicted grades. The interpretation of variability in activity on lecture video 25 is less clear, though lower values appeared to correspond with lower predicted performance. As missing values on this variable indicated that a student did not engage in this behavior and were thus replaced with 0, this likely indicates that not interacting with lecture video 25 was associated with lower predicted grades.

In terms of behavioral categories, the majority of predictive features were quiz-related activities (30.91%), followed by lecture-related activities (29.09%) and indicators of overall activity (16.36%). The distribution of predictive features across the semester periods was

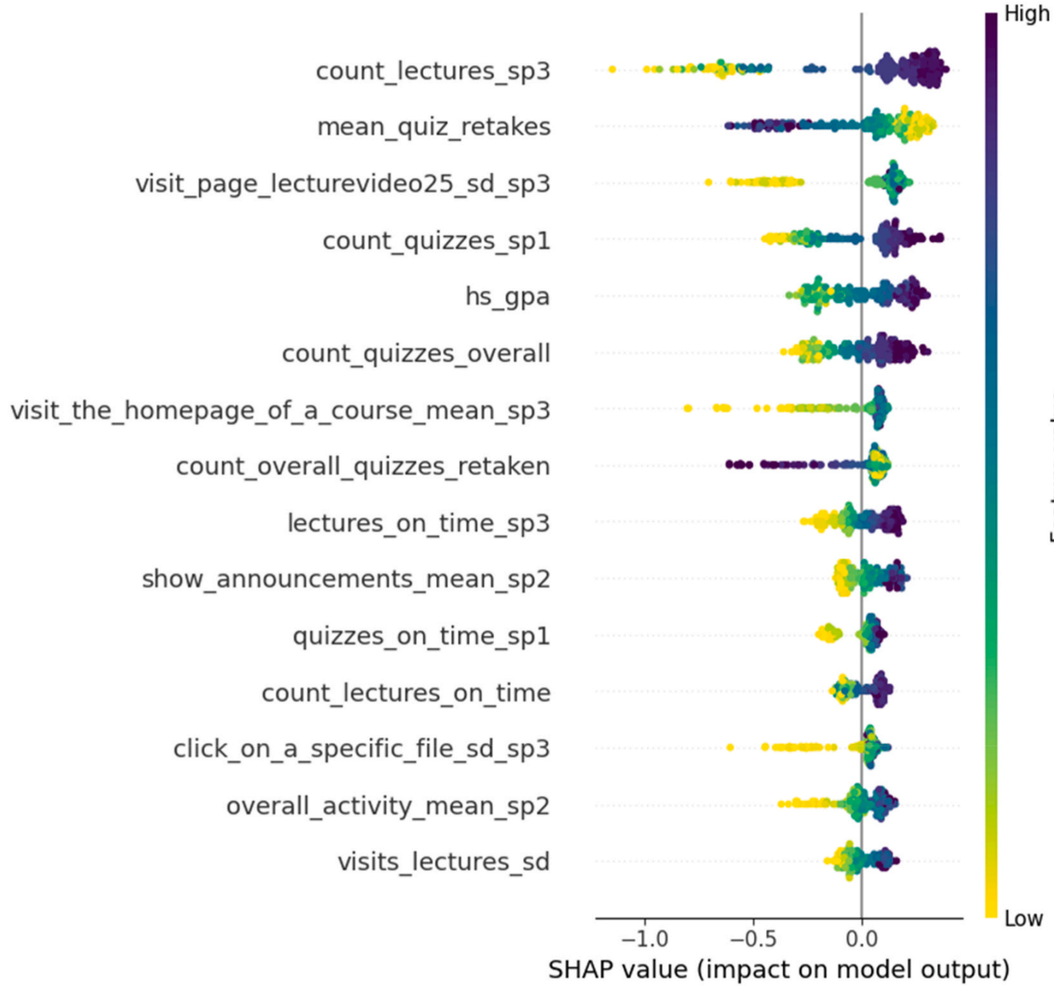

Fig. 2. SHAP Summary Plots for Predicting Final Course Grade
Note. SHAP summary plot of the 15 features most predictive of final course grade in the XGBoost model. Features are ranked by mean absolute SHAP value. Each point represents one student; the color shows the original feature value (from low in yellow to high in purple). The pattern of color gradients across the plot helps to visually infer whether a feature's effect is linear or more complex: a smooth left-to-right gradient suggests a monotonic effect, whereas more scattered patterns may reflect nonlinear or interaction effects. hs_gpa = high school grade point average. sd = standard deviation. sp = semester phase.

relatively balanced with 30.90% relating to the semester period before the final exam, 27.27% to the first semester period before Midterm 1, and 21.82% to the period preceding Midterm 2. Several of the most predictive indicators summarized behavior over the entire semester (12.73%), such as the total number of quizzes that were taken and the total number of quizzes that were retaken.

3.3. RQ2: clustering performance-related learning behaviors

We considered cluster solutions ranging from two to six clusters. For solutions with three or more clusters, a singleton cluster consistently emerged, indicating that one student represented a pronounced outlier in terms of their learning behavior and was repeatedly isolated into a separate cluster. This student was therefore excluded, and the clustering analysis was rerun on the reduced sample ($N = 1167$). After removal of the outlier, cluster solutions were more stable and interpretable across higher numbers of clusters, thus, all subsequent analyses were conducted on the reduced sample.

Inspection of the dendrogram suggested either a two- or three-cluster solution. The silhouette score was highest for the two-cluster solution (silhouette score = 0.602), although the three-cluster (silhouette score = 0.531) and four-cluster (silhouette score = 0.532) solutions also showed acceptable values. We therefore examined the two-, three-, and four-cluster solutions in greater detail. We found that in the three- and four-cluster solutions, some clusters were very small (i.e., comprising less than 10% of the total sample). Consequently, we retained the two-cluster solution for further analyses.

To characterize the identified clusters, we computed cluster means for all features and identified those that most strongly discriminated between the two clusters based on the magnitude of mean differences. For interpretation and labeling, we focused on the 15 most discriminatory features (see Fig. 3). These features primarily comprised count-based indicators of lecture and quiz engagement (e.g., total number of quizzes completed, number of lectures accessed on time) as well as indicators of behavioral consistency (e.g., the standard deviation of lecture visits across semester phases or the standard deviation of overall activity in the final semester phase).

Behavioral patterns of the two clusters were visualized using a heatmap (Fig. 3). The first cluster was characterized by overall high levels of lecture viewing and quiz completion. Students in this cluster seemed to consistently use the practice quizzes from beginning of the semester, as reflected by a high number of quizzes completed in the first semester phase. They also showed timely engagement following the course syllabus, with many quizzes and lectures completed or accessed before the next was uploaded. This cluster was labeled *Timely and Task-Focused Learners*.

The second cluster showed high levels of overall activity and elevated values on SD-based features, indicating frequent but irregular

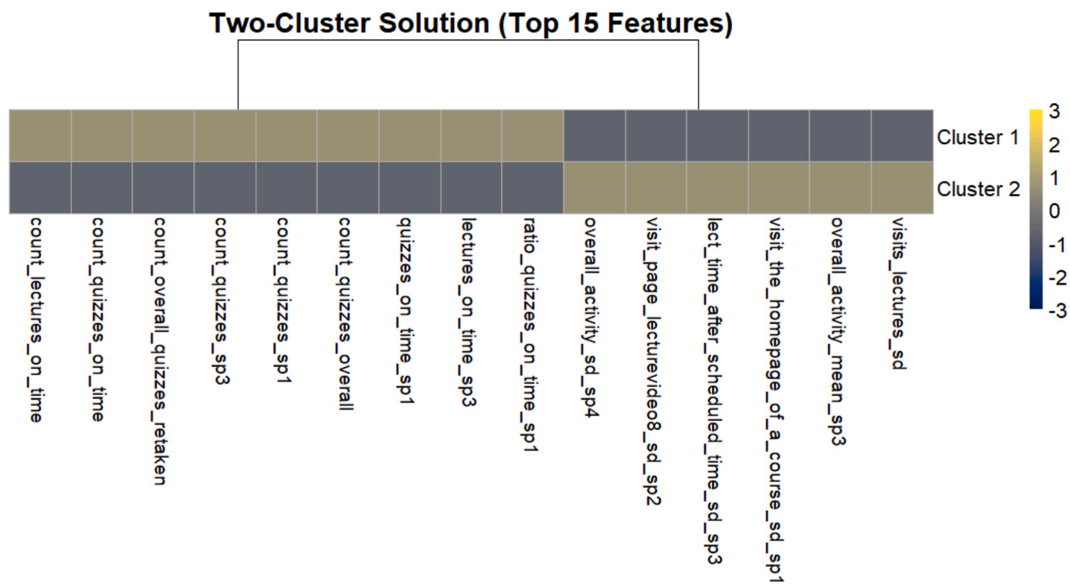

Fig. 3. Heatmap of the Two Behavioral Profiles Identified via Hierarchical Clustering
Note. The 15 features showing the largest mean differences between clusters are displayed. Values are standardized (z-scores) and represent relative differences between the two clusters. sd = standard deviation. sp = semester phase.

interaction with the learning management platform. Despite their high overall activity, students in this cluster showed comparatively low engagement with the practice quizzes and the lectures. This cluster was labeled *Inefficient and Irregular Learners*.

To assess the robustness of the clustering solution, we additionally conducted k-means clustering with $k = 2$ to $k = 6$ clusters. These analyses yielded highly comparable results and likewise favored a two-cluster solution based on silhouette width (silhouette score = 0.602). Further inspection confirmed that the two clusters were identical to those obtained using Ward's hierarchical clustering (see Online Supplement C), supporting the robustness of the identified behavioral profiles across clustering approaches.

3.4. RQ3: testing NFC levels across clusters

As sensitivity tests, we first checked whether the clusters systematically differ in their course section and their final grade. Chi^2 test showed that course sections differed significantly regarding their distribution across the two clusters, X^2 (2, $N = 1167$) = 6.34, $p = .042$. Descriptively, students from course 40,060 were less likely *inefficient and irregular learners* compared to the others. However, when conducting post-hoc pair-wise comparisons, these differences were not significant anymore when we applied alpha-corrections. We still included course section as a control variable in the following models.

A linear model with cluster membership and course section as predictors revealed that the two clusters differed significantly regarding their academic performance ($b = -0.88$), t (1163) = −4.60, $p < .001$). The *timely and task-focused learners* had significantly higher grades (M = 8.08, SD = 2.64) than the *inefficient and irregular learners* (M = 7.26, SD = 2.72).

Lastly, for the subsample that we had NFC measures for, we again computed linear models to predict NFC from cluster membership while controlling for course section. Results indicated no significant differences in NFC levels between the two clusters ($b = -0.04$), t (132) = −0.26, p = .793. Thus, cluster membership was not associated with systematic differences in students' NFC, suggesting that the behavioral digital trace profiles identified in the present study were largely independent of this dispositional characteristic.

4. Discussion

Previous research has shown that students' tendency to engage in and enjoy effortful cognitive activity, their NFC, is associated with more adaptive self-reported learning behaviors and academic performance. However, to date, studies have not used actual behavioral data to capture learning behaviors that could be associated with NFC. With the present study, we aimed to investigate whether students' NFC is associated with performance-related learning patterns by drawing on behavioral trace data from the digital learning platform Canvas. We tracked undergraduate students' learning activities across 1 semester and identified learning behaviors that are most predictive of their academic performance. Using these performance-related behavioral indicators, we clustered students who show similar distinct learning patterns. In contrast to theoretical conceptualizations and previous empirical findings, we did not find a relationship between students' NFC and their performance-related learning patterns. In the following, we discuss the major findings of our study in more detail.

4.1. Identifying performance-related learning behaviors from digital trace data

Learning management platforms like Canvas offer various features and tools that afford a wide range of possible student behaviors. However, not all of these behaviors are equally relevant for supporting learning progress and academic success. Therefore, as a first step, we identified those learning behaviors that are most informative for academic performance, as reflected in their predictive value for students' final course grades. To this end, we applied an ML approach to predict academic performance from a comprehensive set of behavioral learning indicators. An extensive body of research has shown that behavioral indicators of learning, derived from digital trace data, can meaningfully predict academic performance (Arizmendi et al., 2023). Consistent with this literature, our findings demonstrated that behavioral trace data explained a substantial portion of the variance in final course grades (50.34%). The most predictive indicators fell largely into three broad categories of learning activity: lecture viewing, quiz engagement, and overall platform activity.

The uploaded lectures constituted the core instructional component of this chemistry course and emerged as highly relevant for academic performance. Specifically, both a higher overall number of lectures visited and a higher number of lectures viewed on time (i.e., before the subsequent lecture was uploaded), particularly in the period leading up to the final exam, were predictive of better performance. These findings are in line with prior research showing that consistent engagement with core instructional materials supports academic success (Ye & Pennisi, 2022; Yoo et al., 2022). For each lecture, students were provided with optional self-assessment quizzes. Taking advantage of these quizzes was predictive of final course grade, further supporting the existing literature (van Halem et al., 2020; Ye & Pennisi, 2022). Both the number of quizzes completed early in the semester and consistently (i.e., before the next quiz was made available), as well as the total number completed across the semester, were positively associated with academic performance. This result is consistent with the literature showing that retrieval practice and self-assessment are powerful cognitive tools and effective active learning strategies (Adesope et al., 2017; Chi & Wylie, 2014). At the same time, a higher number of repeated quiz attempts was associated with lower performance. This pattern likely reflects difficulties in understanding the material, suggesting that frequent quiz retakes may serve as an early warning signal for students who could benefit from additional instructional support (e.g., Bernacki et al., 2020). Finally, overall activity indicators also contributed to performance prediction. In particular, fewer homepage visits before the second midterm and the final exam were predictive of lower final course grades. This aligns with previous studies suggesting that general activity on digital learning platforms tends to positively correlate with academic success, as it reflects greater engagement with the course (Cicchinelli et al., 2018, pp. 191–200; You, 2016; Yu et al., 2020).

Among the most predictive features, most were based on counts or mean values, which capture the completeness and frequency of students' engagement (e.g., Asarta & Schmidt, 2013). However, several variability-based indicators also emerged as relevant predictors. For these indicators, the relationships with course grade were not linear, however, particularly low values were usually predictive of lower course grades. Particularly low values on variability-based indicators suggest that students were not engaging in certain behaviors at all and, consequently, did not exhibit variability in these behaviors, which was detrimental to their learning progress.

In sum, our findings affirm the predictive validity of digital behavioral trace data for academic performance. We found that engagement with core instruction (i.e., lectures), and self-testing activities (i.e., quiz-taking), especially when carried out in a timely manner aligned with the course structure (i.e., working with materials from the current unit and not falling behind), were particularly beneficial for academic success. The alignment of our most predictive features with previous research and theoretical considerations (e.g., active engagement and retrieval practice) also lends support to the validity of the behavioral indicators we computed.

4.2. Performance-related learning patterns

In a next step, we examined how performance-relevant learning behaviors co-occur within individual students. Because we were subsequently interested in whether individual differences in terms of NFC were related to learning behavior, we adopted a person-centered approach to identify learning behavior patterns based on the behavioral activities most predictive of academic performance. By only focusing on behaviors that were relevant for academic performance, we reduced the potential feature space and ensured that the clustering was not driven by random or less-informative behaviors.

We found two groups of students in our sample: the *timely and task-focused learners* and the *inefficient and irregular learners.* Timely and task-focused learners made extensive use of lecture videos and practice quizzes, as reflected in high numbers of accessed lectures and completed quizzes. Moreover, their engagement closely followed the course structure, with many lectures and quizzes accessed within the intended unit and before the subsequent unit began. This type of timely interactions with lectures was likely particularly important but challenging in the context of this largely asynchronous chemistry course (Zeng & Xin, 2025). Because lecture videos were uploaded and remained available thereafter, students may have been tempted to postpone watching them. However, as course units build on one another, delaying engagement with earlier material can easily lead to accumulating learning gaps and making it more difficult to follow subsequent content. Furthermore, engaging with the practice quizzes early in the semester provides opportunities for spaced (or distributed) learning (i.e., studying over dispersed intervals of time), which is known to be a highly effective learning strategy (S. K. Carpenter et al., 2022; Latimier et al., 2021). Students who self-tested shortly after the lecture likely revisited the quizzes later during exam preparation, thereby benefiting from spaced practice rather than relying on massed practice ("cramming") immediately before the exam. All in all, this timely and structured interaction with core instructional activities from the beginning of the semester by the timely and task-focused learners aligns with prior research highlighting consistent engagement and self-testing as beneficial learning strategies (Adesope et al., 2017; Chi & Wylie, 2014; van Halem et al., 2020; Ye & Pennisi, 2022; Yoo et al., 2022). Consistent with this interpretation, timely and task-focused learners achieved higher course grades than inefficient and irregular learners.

Inefficient and irregular learners exhibited high levels of overall platform activity but comparatively lower engagement with lectures and quizzes. They also showed higher values on variability-based behavioral indicators, reflecting more irregular and inconsistent learning behavior. Higher but inconsistent engagement could signal difficulties with self-regulation or sustained commitment to learning (Alhazbi et al., 2024) which is typically detrimental to academic performance (Bourguet, 2024; Kim et al., 2018; H. Li et al., 2018). Despite their high overall activity, these students completed fewer quizzes and watched fewer lectures, suggesting that they did not use their time on the platform primarily to interact with core instructional content or engage in self-testing. This pattern underscores that overall activity alone is not a sufficiently fine-grained indicator of good learning behavior. Simply spending more time on the learning platform is unlikely to be beneficial if that time is not used strategically (e.g., Deininger et al., 2024). One possible explanation is that these students lacked effective learning strategies or the knowledge of how to prepare optimally for the course. Given that the sample consisted of undergraduate students at the beginning of their university studies, some may still be developing an understanding of which learning activities are most effective and how to implement them successfully, highlighting a potential need for additional instructional or strategic support at this time of one's academic career (Ainscough et al., 2018; McCabe, 2011).

4.3. The relationship between NFC and learning patterns

After identifying meaningful learner profiles, we examined whether students' levels of NFC were associated with the type of learning behavior pattern they exhibited. Contrary to our expectations, we found no relationship between NFC and learning pattern membership.

Based on theoretical assumptions and prior empirical research, we would have expected higher NFC to be associated with membership in the timely and task-focused learner group. NFC has consistently been linked to self-reported deep learning strategies (Cazan & Indreica, 2014; Evans et al., 2003; Swafford et al., 2021; Xiao et al., 2024), task focus (Levin et al., 2000; D. Li & Browne, 2006; Srivastava et al., 2010), and self-control (Bertrams & Dickhäuser, 2012; Grass et al., 2019). Moreover, NFC has been associated with meta-learning competencies, including intrinsic motivation and the self-regulatory ability to plan, monitor, and evaluate one's own learning (Uszyńska-Jarmoc et al., 2018), as well as with cognitive reflection and deliberation (Pennycook et al., 2016). Taken together, these characteristics would be expected to align with efficient and structured learning behavior rather than with irregular or inefficient patterns. In the following, we outline several theoretical and methodological factors that may help explain the absence of a relationship between NFC and learning behavior patterns in the present study.

The original theoretical conceptualizations of NFC encompass two components: individuals high in NFC tend to both *engage in* and *enjoy* effortful cognitive activity (Cacioppo et al., 1996; Cacioppo & Petty, 1982). Besides behavioral intentions, the self-report measures of learning behaviors that have been typically used in empirical studies often encompass a motivational component of learning approaches, such as the motive or learning orientation that fuels the use of certain learning behaviors (Cazan & Indreica, 2014; Evans et al., 2003). In contrast, learning behaviors captured through behavioral trace data may reflect qualitatively different aspects of learning, such as enacted actions, timing and sequencing of activities, and compliance with curricular structures (Arizmendi et al., 2023).

From this perspective, the absence of a relationship between NFC and observable learning behavior patterns in the present study raises the possibility that NFC may be more strongly related to how students *experience* learning (or report how they experience it) than to how they *behave* in formal learning environments. Specifically, NFC may be more closely tied to students' internal cognitive framing of learning experiences, that is, how they perceive, and mentally engage with learning, rather than their observable behaviors (Mussel, 2022; Silvia, 2005). This discrepancy may reflect a broader issue of construct misalignment, as self-report measures and behavioral trace data capture different layers of the learning process, including affective, regulatory, and cognitive components (Molenaar et al., 2023). At the same time, when both NFC and learning strategies are captured with self-reports, correlations may be inflated due to common method bias arising from shared method variance (Podsakoff et al., 2024). In addition, the two measurement approaches operate at different levels of granularity: while the self-report instrument assesses NFC at a global level, behavioral trace data captures highly specific learning activities (Rovers et al., 2019).

Taken together, although replications of the present findings are clearly needed before drawing more definitive conclusions, these considerations suggest that existing theories linking NFC to learning behavior may require refinement when applied to learning behaviors captured with behavioral data. In particular, theories developed and validated within self-report frameworks may not readily generalize to learning behaviors captured with behavioral trace data, highlighting the need to more carefully distinguish between subjective learning experiences and enacted learning behavior in future research.

Beyond these theoretical and measurement-related considerations, characteristics of the learning context and sample may also help explain the absence of a relationship between NFC and learning behavior patterns in the present study. Although Liu and Nesbit's (2024) meta-analysis demonstrated a positive relationship between NFC and academic achievement, we found no significant correlation between NFC and final course grade in our sample. This finding was particularly unexpected given that the relationship between NFC and achievement has been shown to grow stronger with age (Liu & Nesbit, 2024), and our sample consisted of undergraduate students. At the same time, the null findings of several studies included in the meta-analysis suggest that the effects of NFC on performance may be contingent on situational and sample characteristics (Diseth & Martinsen, 2003; Fellman et al., 2020; Furlan et al., 2016). The chemistry course analyzed here was a highly structured introductory course. As NFC encompasses a preference for cognitively engaging and meaningful tasks, such rigid structures may have limited opportunities for exploration or deeper thinking that students high in NFC typically value. In addition, the fully online learning environment during the COVID-19 pandemic may have been perceived as intellectually unstimulating by students high in NFC. Passive learning formats, such as prerecorded lectures and limited interaction, may have dampened their motivation and engagement. Alternatively, students may have experienced substantial external pressure, as the course was a gateway course and highly relevant for their subsequent academic progress. In such high-stakes situations, effects of NFC may be less pronounced, because cognitive engagement is driven primarily by situational demands rather than individual differences (Cacioppo et al., 1996). This idea aligns with research showing that individuals' perceptions of a situation can shape whether and how their personality traits are expressed (e.g., Jach et al., 2022; Rauthmann et al., 2014). However, it should be acknowledged that these potential mechanisms are post hoc explanations that cannot be directly tested within the present study and therefore require further empirical examination.

4.4. Limitations and future directions

As a first attempt to explore how NFC may manifest in learning behaviors using behavioral trace data, this study provides an important step toward understanding the role of NFC in online educational contexts. Whereas the findings offer valuable insights, several limitations must be acknowledged.

Behavioral traces of learning are inherently context-specific (Arizmendi et al., 2023). The indicators identified in this study may reflect learning behaviors that are unique to the chemistry course examined, as the design and structure of a specific online course determine which kind of log events can be identified and what kinds of behavioral indicators can be computed (Nkomo et al., 2021). Whereas many of the behaviors considered here are quite common in online courses (e.g., self-assessment quiz taking, lecture engagement), others might not generalize as easily to different subjects or classes. For instance, in language classes, assignments like (collaborative) writing tasks can be a central part of instruction (Peeters et al., 2020; Rakovic et al., 2022), while they are less common in STEM classes. Even within the same discipline, instructors may structure their courses differently and make use of different combinations of learning resources within the learning management system. Consequently, the behavioral traces captured vary depending on whether features such as feedback tools, chat functions, or external textbooks are incorporated (Gašević et al., 2016). Accordingly, the structure of a course may also shape the learning behaviors and strategies that students adopt. Thus, although we identified distinct groups of students based on their learning behavior patterns, this does not imply that students will consistently adopt the same strategies across different courses or even across topics within the same course. Rather, prior research suggests that effective learning involves flexibly adapting one's strategies to the specific demands of a given learning context (Brunner et al., 2025; Donche et al., 2013).

Moreover, learning also takes place outside of the learning management system, introducing the challenge that the behavioral trace data cannot capture all relevant learning behaviors. For instance, in this chemistry course, homework assignments were hosted on an external platform, limiting the behavioral data we could access. That said, because the semester occurred during the COVID-19 pandemic with fully remote instruction, the trace data from Canvas likely captured more of the students' total learning activity than it might have in a traditional, in-person semester. Still, future research is needed to examine whether the observed behavioral patterns generalize across disciplines, instructional contexts, and learning environments, as this generalizability would also be essential for informing educational practice (Mathrani et al., 2021).

Furthermore, whereas log-file data provide rich, time-sensitive records of overt learning behaviors, their construct validity must be critically examined (Bernacki et al., 2025; Goldhammer et al., 2021). Inferences about cognitive and motivational processes are based on activity patterns and are therefore indirect. For instance, students may engage with practice quizzes for a variety of reasons: to identify knowledge gaps and guide subsequent study, to gauge their current level of performance, or to reduce uncertainty about the format of the final exam (T. S. Carpenter & Hodges, 2024; C. Yang et al., 2023). A promising direction for strengthening construct validity is to use multimodal learning analytics, which integrates additional data sources, such as videos, think-aloud protocols, and physiological measures to more comprehensively capture cognitive, metacognitive, affective, and motivational processes of learning (Bernacki et al., 2025; Molenaar et al., 2023).

Another potentially fruitful direction for future research is the inclusion of more fine-grained behavioral indicators and temporal patterns. Students with high NFC may participate in similar activities as their peers overall but may approach them with greater focus or deliberation, as suggested by research linking NFC to increased task focus and cognitive engagement (Levin et al., 2000; D. Li & Browne, 2006). As discussed earlier, the lower variability observed in some behaviors could also indicate more deliberate planning, possibly pointing to more structured and well-managed study sessions among students with high NFC. Additionally, including information on the temporal sequence of learning activities can add a more detailed understanding of students' learning behaviors (Colling et al., 2025; Jovanovic et al., 2024; Xie et al., 2025). For instance, sequential analyses would allow us to capture whether students who exhibit beneficial learning behaviors, such as taking practice quizzes early in the semester, continue to do so throughout the course (Sher et al., 2020). Unfortunately, our data did not include login and logout events, and we were thus unable to examine learning behaviors on a learning session level. Future research could build on these findings by breaking behavioral traces into smaller units, such as session-based indicators, to better capture patterns of cognitive engagement (Bühler et al., 2024; Kuhlmann et al., 2024).

4.5. Conclusion

Whereas NFC has consistently been linked to academic success, this study is the first to examine how it manifests in undergraduate students' actual learning behaviors using trace data on a learning management platform. While we identified learning behavior patterns that were meaningfully related to academic performance, NFC itself was not related to these behavioral patterns. Our findings suggest that the links between NFC and learning behavior, which have been previously established through self-report measures, may not readily translate to observable learning behavior, highlighting the need for further research on NFC from a behavioral perspective.

CRediT authorship contribution statement

Aki Schumacher: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Luise von Keyserlingk:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Hannah Deininger:** Writing – review & editing, Methodology, Formal analysis. **Renzhe Yu:** Methodology, Data curation. **Nia Nixon:** Writing – review & editing. **Lisa Bardach:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT, developed by OpenAI, for language editing. The entire manuscript was checked with ChatGPT for grammar, spelling, and improvements in readability. All conceptual and substantive content was written entirely by the authors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2026.109021.

Appendix

	Identified log actions	Category
1	Click a page in a course	Overall activity
2	Click an external tool	Other
3	Click on a quiz	Quiz-related activity
4	Click on a specific file	Other
5	Click on a student	Other
6	Click on an assignment	Assignment-related activity
7	Click on Assignment Info	Assignment-related activity
8	Click on final exam	Exam-related activity
9	Click on Midterm 1	Exam-related activity
10	Click on Midterm 2	Exam-related activity
11	Click on Zoom page	Other
12	Collapse all modules on the Module page	Other
13	Collapse or Expand a Module	Other
14	Post a reply to a discussion topic	Discussion-related activity

(*continued on next page*)

(*continued*)

	Identified log actions	Category
15	Read a post in a discussion topic	Discussion-related activity
16	Reply to a specific discussion reply	Discussion-related activity
17	Search for announcements	Organizational
18	Show Announcements	Organizational
19	Show the list of discussion topics	Discussion-related activity
20	Submit a quiz	Quiz-related activity
21	Submit edits on a specific discussion reply	Discussion-related activity
22	Subscribe to a discussion topic	Discussion-related activity
23	Take a quiz	Quiz-related activity
24	Take final exam	Exam-related activity
25	Take Midterm 1	Exam-related activity
26	Take Midterm 2	Exam-related activity
27	Unsubscribe from a discussion topic	Discussion-related activity
28	View a file (inline view)	Other
29	View a specific quiz attempt	Quiz-related activity
30	View final exam quiz attempt	Exam-related activity
31	View Midterm 1 quiz attempt	Exam-related activity
32	View Midterm 2 quiz attempt	Exam-related activity
33	View Previous Attempts on a quiz	Quiz-related activity
34	Visit a discussion topic	Discussion-related activity
35	Visit a quiz (Canvas mobile app)	Quiz-related activity
36	Visit a quiz by submission details	Quiz-related activity
37	Visit a quiz submission	Quiz-related activity
38	Visit an assignment (Canvas mobile app)	Assignment-related activity
39	Visit an assignment quiz from Grades	Assignment-related activity
40	Visit an assignment submission	Assignment-related activity
41	Visit Assignments page	Assignment-related activity
42	Visit final exam quiz (Canvas mobile app)	Exam-related activity
43	Visit final exam quiz by submission details	Exam-related activity
44	Visit final exam quiz submission	Exam-related activity
45	Visit Grades page	Exam-related activity
46	Visit Midterm 1 quiz (Canvas mobile app)	Exam-related activity
47	Visit Midterm 1 quiz by submission details	Exam-related activity
48	Visit Midterm 1 quiz submission	Exam-related activity
49	Visit Midterm 2 quiz (Canvas mobile app)	Exam-related activity
50	Visit Midterm 2 quiz by submission details	Exam-related activity
51	Visit Midterm 2 quiz submission	Exam-related activity
52	Visit Modules page	Overall activity
53	Visit page 'Course Assignments'	Assignment-related activity
54	Visit page 'Course Requirements'	Organizational
55	Visit page 'Exam Information and Respondus'	Organizational
56	Visit page 'FAQ Wileyplus Homework'	Organizational
57	Visit page 'FAQs'	Organizational
58	Visit page 'Lecture Video 1'	Lecture-related activity
59	Visit page 'Lecture Video 2'	Lecture-related activity
60	Visit page 'Lecture Video 3'	Lecture-related activity
61	Visit page 'Lecture Video 4'	Lecture-related activity
62	Visit page 'Lecture Video 5'	Lecture-related activity
63	Visit page 'Lecture Video 6'	Lecture-related activity
64	Visit page 'Lecture Video 7'	Lecture-related activity
65	Visit page 'Lecture Video 8'	Lecture-related activity
66	Visit page 'Lecture Video 9'	Lecture-related activity
67	Visit page 'Lecture Video 10'	Lecture-related activity
68	Visit page 'Lecture Video 11'	Lecture-related activity
69	Visit page 'Lecture Video 12'	Lecture-related activity
70	Visit page 'Lecture Video 13'	Lecture-related activity
71	Visit page 'Lecture Video 14'	Lecture-related activity
72	Visit page 'Lecture Video 15'	Lecture-related activity
73	Visit page 'Lecture Video 16'	Lecture-related activity
74	Visit page 'Lecture Video 17'	Lecture-related activity
75	Visit page 'Lecture Video 18'	Lecture-related activity
76	Visit page 'Lecture Video 19'	Lecture-related activity
77	Visit page 'Lecture Video 20'	Lecture-related activity
78	Visit page 'Lecture Video 21'	Lecture-related activity
79	Visit page 'Lecture Video 22'	Lecture-related activity
80	Visit page 'Lecture Video 23'	Lecture-related activity
81	Visit page 'Lecture Video 24'	Lecture-related activity
82	Visit page 'Lecture Video 25'	Lecture-related activity
83	Visit page 'Lecture Video 26'	Lecture-related activity
84	Visit page 'Lecture Video 27'	Lecture-related activity
85	Visit page 'Syllabus and Weekly Reading Assignments'	Organizational
86	Visit page 'Wileyplus Online Homework'	Other
87	Visit Quizzes page	Quiz-related activity
88	Visit the homepage of a course	Overall activity

Data availability

Data will be made available on request.

References

Ackerman, P. L., & Heggestad, E. D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin, 121*(2), 219–245.

Adesope, O. O., Trevisan, D. A., & Sundararajan, N. (2017). Rethinking the use of tests: A meta-analysis of practice testing. *Review of Educational Research, 87*(3), 659–701. https://doi.org/10.3102/0034654316689306

Ainscough, L., Stewart, E., Colthorpe, K., & Zimbardi, K. (2018). Learning hindrances and self-regulated learning strategies reported by undergraduate students: Identifying characteristics of resilient students. *Studies in Higher Education, 43*(12), 2194–2209. https://doi.org/10.1080/03075079.2017.1315085

Ajadi, T. A. (2022). Academic self-efficacy as a determinant of the need for cognition, parental involvement and extraversion among secondary school students in Oyo state, Nigeria. *Papers in Education and Development, 40*(2), 87–98.

Alhazbi, S., Al-ali, A., Tabassum, A., Al-Ali, A., Al-Emadi, A., Khattab, T., & Hasan, M. A. (2024). Using learning analytics to measure self-regulated learning: A systematic review of empirical studies in higher education. *Journal of Computer Assisted Learning, 40*(4), 1658–1674. https://doi.org/10.1111/jcal.12982

Arizmendi, C. J., Bernacki, M. L., Raković, M., Plumley, R. D., Urban, C. J., Panter, A. T., Greene, J. A., & Gates, K. M. (2023). Predicting student outcomes using digital logs of learning behaviors: Review, current standards, and suggestions for future work. *Behavior Research Methods, 55*(6), 3026–3054. https://doi.org/10.3758/s13428-022-01939-9

Asarta, C. J., & Schmidt, J. R. (2013). Access patterns of online materials in a blended course. *Decision Sciences Journal of Innovative Education, 11*(1), 107–123. https://doi.org/10.1111/j.1540-4609.2012.00366.x

Baker, R., Di, X., Park, J., Yu, R., Li, Q., Cung, B., Fischer, C., Rodriguez, F., Warschauer, M., & Smyth, P. (2020). The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: Opening the black box of learning processes. *International Journal of Educational Technology in Higher Education, 17*(1), 219. https://doi.org/10.1186/s41239-020-00187-1

Bernacki, M. L., Chavez, M. M., & Uesbeck, P. M. (2020). Predicting achievement and providing support before STEM majors begin to fail. *Computers & Education, 158*, Article 103999. https://doi.org/10.1016/j.compedu.2020.103999

Bernacki, M. L., Yu, L., Kuhlmann, S. L., Plumley, R. D., Greene, J. A., Duke, R. F., Freed, R., Hollander-Blackmon, C., & Hogan, K. A. (2025). Using multimodal learning analytics to validate digital traces of self-regulated learning in a laboratory study and predict performance in undergraduate courses. *Journal of Educational Psychology, 117*(2), 176–205. https://doi.org/10.1037/edu0000890

Bertrams, A., & Dickhäuser, O. (2012). Passionate thinkers feel better: Self-control capacity as mediator of the relationship between need for cognition and affective adjustment. *Journal of Individual Differences, 33*(2), 69–75. https://doi.org/10.1027/1614-0001/a000081

Borisov, V., Leemann, T., Seßler, K., Haug, J., Pawelczyk, M., & Kasneci, G. (2022). Deep neural networks and tabular data: A survey. *IEEE Transactions on Neural Networks and Learning Systems, 35*(6), 7499–7519. https://doi.org/10.1109/TNNLS.2022.3229161

Bourguet, M.-L. (2024). Demonstrating the impact of study regularity on academic success using learning analytics. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 736–741). https://doi.org/10.1145/3636555.3636845

Brunner, S. N., Bäuerlein, K., Conti, M., & Karlen, Y. (2025). Measuring individual differences in students' knowledge about self-regulated learning strategies with a digital tool. *Learning and Individual Differences, 119*, 102656. https://doi.org/10.1016/j.lindif.2025.102656

Bühler, B., Bozkir, E., Deininger, H., Gerjets, P., Trautwein, U., & Kasneci, E. (2024). On task and in sync: Examining the relationship between gaze synchrony and self-reported attention during video lecture learning. *Proceedings of the ACM on Human-Computer Interaction, 8*, 1–18. https://doi.org/10.1145/3655604

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology, 42*(1), 116–131. https://doi.org/10.1037/0022-3514.42.1.116

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin, 119*(2), 197–253. https://doi.org/10.1037/0033-2909.119.2.197

Carpenter, T. S., & Hodges, L. C. (2024). Student responses to spaced practice in two large gateway chemistry courses. *Journal of Chemical Education, 101*(2), 429–437. https://doi.org/10.1021/acs.jchemed.3c00773

Carpenter, S. K., Pan, S. C., & Butler, A. C. (2022). The science of effective learning with spacing and retrieval practice. *Nature Reviews Psychology, 1*(9), 496–511. https://doi.org/10.1038/s44159-022-00089-1

Cazan, A.-M., & Indreica, S. E. (2014). Need for cognition and approaches to learning among university students. *Procedia - Social and Behavioral Sciences, 127*(1), 134–138. https://doi.org/10.1016/j.sbspro.2014.03.227

Chakrapani, P., & Chitradevi, D. (2022). Academic performance prediction using machine learning: A comprehensive & systematic review. In *Proceedings of the 2022 international conference on electronic systems and intelligent computing (ICESIC)* (pp. 335–340). https://doi.org/10.1109/ICESIC53714.2022.9783512

Chen, C.-H., & Wu, I.-C. (2012). The interplay between cognitive and motivational variables in a supportive online learning system for secondary physical education. *Computers & Education, 58*(1), 542–550. https://doi.org/10.1016/j.compedu.2011.09.012

Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist, 49*(4), 219–243. https://doi.org/10.1080/00461520.2014.965823

Chitti, M., Chitti, P., & Jayabalan, M. (2020). Need for interpretable student performance prediction. In *2020 13th international conference on developments in eSystems engineering (DeSE)* (pp. 269–272). https://doi.org/10.1109/DeSE51703.2020.9450735

Cicchinelli, A., Veas, E., Pardo, A., Pammer-Schindler, V., Fessl, A., Barreiros, C., & Lindstädt, S. (2018). Finding traces of self-regulated learning in activity streams. *Proceedings of the 8th international conference on learning analytics and knowledge (LAK '18)*. https://doi.org/10.1145/3170358.3170381

Colling, L., Deininger, H., Parrisius, C., Von Keyserlingk, L., Bodnar, S., Holz, H., Kasneci, G., Nagengast, B., Trautwein, U., & Meurers, D. (2025). How do learners practice? – theory-informed sequence analyses to investigate self-regulated learning processes and their link to achievement. *Educational Psychology*, 1–24. https://doi.org/10.1080/01443410.2025.2599786

Coutinho, S. (2006). The relationship between the need for cognition, metacognition, and intellectual task performance. *Educational Research and Reviews, 1*(5), 162–164. https://doi.org/10.5897/ERR.9000373

Coutinho, S., Wiemer-Hastings, K., Skowronski, J. J., & Britt, M. A. (2005). Metacognition, need for cognition and use of explanations during ongoing learning and problem solving. *Learning and Individual Differences, 15*(4), 321–337. https://doi.org/10.1016/j.lindif.2005.06.001

Curşeu, P. L. (2011). Need for cognition and active information search in small student groups. *Learning and Individual Differences, 21*(4), 415–418. https://doi.org/10.1016/j.lindif.2011.02.005

Day, E. A., Espejo, J., Kowollik, V., Boatman, P. R., & McEntire, L. E. (2007). Modeling the links between need for cognition and the acquisition of a complex skill. *Personality and Individual Differences, 42*(2), 201–212. https://doi.org/10.1016/j.paid.2006.06.012

De Bruin, A. B. H., Biwer, F., Hui, L., Onan, E., David, L., & Wiradhany, W. (2023). Worth the effort: The start and stick to desirable difficulties (S2D2) framework. *Educational Psychology Review, 35*(2), 41. https://doi.org/10.1007/s10648-023-09766-w

De Holanda, L., Coelho, G., Hanel, H. P., P, Wolf, J., & L. (2020). The very efficient assessment of need for cognition: Developing a six-item version. *Assessment, 27*(8), 1870–1885. https://doi.org/10.1177/1073191118793208

Deininger, H., Parrisius, C., Lavelle-Hill, R., Meurers, D., Trautwein, U., Nagengast, B., & Kasneci, G. (2025). Who did what to succeed? Individual differences in which learning behaviors are linked to achievement. In *Proceedings of the 15th international learning analytics and knowledge conference* (pp. 771–782). https://doi.org/10.1145/3706468.3706571

Deininger, H., Pieronczyk, I., Parrisius, C., Plumley, R. D., Meurers, D., Kasneci, G., Nagengast, B., Trautwein, U., Greene, J. A., & Bernacki, M. L. (2024). Using theory-informed learning analytics to understand how homework behavior predicts achievement. *Journal of Educational Psychology, 117*(1), 12–37. https://doi.org/10.1037/edu0000906

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology, 41*(1), 417–440. https://doi.org/10.1146/annurev.ps.41.020190.002221

Diseth, Å., & Martinsen, Ø. (2003). Approaches to learning, cognitive style, and motives as predictors of academic achievement. *Educational Psychology, 23*(2), 195–207. https://doi.org/10.1080/01443410303225

Donche, V., De Maeyer, S., Coertjens, L., Van Daal, T., & Van Petegem, P. (2013). Differential use of learning strategies in first-year higher education: The impact of personality, academic motivation, and teaching strategies. *British Journal of Educational Psychology, 83*(2), 238–251. https://doi.org/10.1111/bjep.12016

Du, J., Hew, K. F., & Liu, L. (2023). What can online traces tell us about students' self-regulated learning? A systematic review of online trace data analysis. *Computers & Education, 201*, Article 104828. https://doi.org/10.1016/j.compedu.2023.104828

Elias, S. M., & Loomis, R. J. (2002). Utilizing need for cognition and perceived self-efficacy to predict academic performance. *Journal of Applied Social Psychology, 32*(8), 1687–1702. https://doi.org/10.1111/j.1559-1816.2002.tb02770.x

Enge, S., Fleischhauer, M., Brocke, B., & Strobel, A. (2008). Neurophysiological measures of involuntary and voluntary attention allocation and dispositional differences in need for cognition. *Personality and Social Psychology Bulletin, 34*(6), 862–874. https://doi.org/10.1177/0146167208315556

Evans, C. J., Kirby, J. R., & Fabrigar, L. R. (2003). Approaches to learning, need for cognition, and strategic flexibility among university students. *British Journal of Educational Psychology, 73*(Pt 4), 507–528. https://doi.org/10.1348/000709903322591217

Fellman, D., Lincke, A., & Jonsson, B. (2020). Do individual differences in cognition and personality predict retrieval practice activities on MOOCs? *Frontiers in Psychology, 11*, 2076. https://doi.org/10.3389/fpsyg.2020.02076

Ferrari, J. R., Crum, K. P., & Pardo, M. A. (2018). Decisional procrastination: Assessing characterological and contextual variables around indecision. *Current Psychology, 37*(2), 436–440. https://doi.org/10.1007/s12144-017-9681-x

Fleischhauer, M., Enge, S., Brocke, B., Ullrich, J., Strobel, A., & Strobel, A. (2010). Same or different? Clarifying the relationship of need for cognition to personality and intelligence. *Personality and Social Psychology Bulletin, 36*(1), 82–96. https://doi.org/10.1177/0146167209351886

Fleischhauer, M., Schweitzer, F. M., & Enge, S. (2024). Yes, I can: The interplay of need for cognition and task confidence in cognitive task performance. *Journal of Intelligence, 12*(12), 128. https://doi.org/10.3390/jintelligence12120128

Fleischhauer, M., Strobel, A., & Strobel, A. (2015). Directly and indirectly assessed need for cognition differentially predict spontaneous and reflective information processing behavior. *Journal of Individual Differences, 36*(2), 101–109. https://doi.org/10.1027/1614-0001/a000161

Fortier, A., & Burkell, J. (2014). Influence of need for cognition and need for cognitive closure on three information behavior orientations. *Proceedings of the American Society for Information Science and Technology, 51*(1), 1–8. https://doi.org/10.1002/meet.2014.14505101066

Furlan, S., Agnoli, F., & Reyna, V. F. (2016). Intuition and analytic processes in probabilistic reasoning: The role of time pressure. *Learning and Individual Differences, 45*, 1–10. https://doi.org/10.1016/j.lindif.2015.11.006

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education, 28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002

Goff, M., & Ackerman, P. L. (1992). Personality-intelligence relations: Assessment of typical intellectual engagement. *Journal of Educational Psychology, 84*(4), 537–552.

Goldhammer, F., Hahnel, C., Kroehne, U., & Zehner, F. (2021). From byproduct to design factor: On validating the interpretation of process indicators based on log data. *Large-Scale Assessments in Education, 9*(1), 20. https://doi.org/10.1186/s40536-021-00113-5

Grass, J., Krieger, F., Paulus, P., Greiff, S., Strobel, A., & Strobel, A. (2019). Thinking in action: Need for cognition predicts self-control together with action orientation. *PLoS One, 14*(8). https://doi.org/10.17605/OSF.IO/WN8XM

Grass, J., Strobel, A., & Strobel, A. (2017). Cognitive investments in academic success: The role of need for cognition at university. *Frontiers in Psychology, 8*, 790. https://doi.org/10.3389/fpsyg.2017.00790

Hartwig, M. K., & Dunlosky, J. (2012). Study strategies of college students: Are self-testing and scheduling related to achievement? *Psychonomic Bulletin & Review, 19*(1), 126–134. https://doi.org/10.3758/s13423-011-0181-y

Hilbert, S., Coors, S., Kraus, E., Bischl, B., Lindl, A., Frei, M., Wild, J., Krauss, S., Goretzko, D., & Stachl, C. (2021). Machine learning for the educational sciences. *The Review of Education, 9*(3). https://doi.org/10.1002/rev3.3310

Ifenthaler, D., Schumacher, C., & Kuzilek, J. (2023). Investigating students' use of self-assessments in higher education using learning analytics. *Journal of Computer Assisted Learning, 39*(1), 255–268. https://doi.org/10.1111/jcal.12744

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research & Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Jach, H. K., DeYoung, C. G., & Smillie, L. D. (2022). Why do people seek information? The role of personality traits and situation perception. *Journal of Experimental Psychology: General, 151*(4), 934–959. https://doi.org/10.1037/xge0001109

Jang, E. E., Lajoie, S. P., Wagner, M., Xu, Z., Poitras, E., & Naismith, L. (2017). Person-oriented approaches to profiling learners in technology-rich learning environments for ecological learner modeling. *Journal of Educational Computing Research, 55*(4), 552–597. https://doi.org/10.1177/0735633116678995

Jeske, D., Stamov-Roßnagel, C., & Backhaus, J. (2014). Learner characteristics predict performance and confidence in e-Learning: An analysis of user behaviour and self-evaluation. *Journal of Interactive Learning Research, 25*(4), 509–529.

Jovanovic, J., Gašević, D., Yan, L., Baker, G., Murray, A., & Gasevic, D. (2024). Explaining trace-based learner profiles with self-reports: The added value of psychological networks. *Journal of Computer Assisted Learning, 40*(4), 1481–1499. https://doi.org/10.1111/jcal.12968

Jovanović, J., Saqr, M., Joksimović, S., & Gašević, D. (2021). Students matter the most in learning analytics: The effects of internal and instructional conditions in predicting academic success. *Computers & Education, 172*, Article 104251. https://doi.org/10.1016/j.compedu.2021.104251

Kim, D., Yoon, M., Jo, I.-H., & Branch, R. M. (2018). Learning analytics to support self-regulated learning in asynchronous online courses: A case study at a women's university in South Korea. *Computers & Education, 127*, 233–251. https://doi.org/10.1016/j.compedu.2018.08.023

Kramer, A.-W., Van Duijvenvoorde, A. C. K., Krabbendam, L., & Huizenga, H. M. (2021). Individual differences in adolescents' willingness to invest cognitive effort: Relation to need for cognition, motivation and cognitive capacity. *Cognitive Development, 57*, 100978. https://doi.org/10.1016/j.cogdev.2020.100978

Kuhlmann, S. L., Plumley, R., Evans, Z., Bernacki, M. L., Greene, J. A., Hogan, K. A., Berro, M., Gates, K., & Panter, A. (2024). Students' active cognitive engagement with instructional videos predicts STEM learning. *Computers & Education, 216*, Article 105050. https://doi.org/10.1016/j.compedu.2024.105050

Latimier, A., Peyre, H., & Ramus, F. (2021). A meta-analytic review of the benefit of spacing out retrieval practice episodes on retention. *Educational Psychology Review, 33*(3), 959–987. https://doi.org/10.1007/s10648-020-09572-8

Lavrijsen, J., Preckel, F., & Verschueren, K. (2023). Seeking, mastering, and enjoying cognitive effort: Scrutinizing the role of need for cognition in academic achievement. *Learning and Individual Differences, 107*, Article 102363. https://doi.org/10.1016/j.lindif.2023.102363

Lavrijsen, J., Vansteenkiste, M., Boncquet, M., & Verschueren, K. (2022). Does motivation predict changes in academic achievement beyond intelligence and personality? A multitheoretical perspective. *Journal of Educational Psychology, 114*(4), 772–790. https://doi.org/10.1037/edu0000666

Levin, I. P., Huneke, M. E., & Jasper, J. D. (2000). Information processing at successive stages of decision making: Need for cognition and inclusion–exclusion effects. *Organizational Behavior and Human Decision Processes, 82*(2), 171–193. https://doi.org/10.1006/obhd.2000.2881

Li, Q., Baker, R., & Warschauer, M. (2020). Using clickstream data to measure, understand, and support self-regulated learning in online courses. *The Internet and Higher Education, 45*, Article 100727. https://doi.org/10.1016/j.iheduc.2020.100727

Li, D., & Browne, G. J. (2006). The role of need for cognition and mood in online flow experience. *Journal of Computer Information Systems, 46*(3), 11–17. https://doi.org/10.1080/08874417.2006.11645894

Li, H., Flanagan, B., Konomi, S., & Ogata, H. (2018). Measuring behaviors and identifying indicators of self-regulation in computer-assisted language learning courses. *Research and Practice in Technology Enhanced Learning, 13*(1), 19. https://doi.org/10.1186/s41039-018-0087-7

Li, S., Zheng, J., & Lajoie, S. P. (2022). Temporal structures and sequential patterns of self-regulated learning behaviors in problem solving with an intelligent tutoring system. *Educational Technology & Society, 25*(4), 1–14.

Liu, Q., & Nesbit, J. C. (2024). The relation between need for cognition and academic achievement: A meta-analysis. *Review of Educational Research, 94*(2), 155–192. https://doi.org/10.3102/00346543231160474

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Proceedings of the 31st international conference on neural information processing. 31st international conference on neural information processing systems (NIPS 2017)*.

Matcha, W., Gašević, D., Jovanović, J., Uzir, N. A., Oliver, C. W., Murray, A., & Gasevic, D. (2020). Analytics of learning strategies: The association with the personality traits. In *Proceedings of the tenth international conference on learning analytics & knowledge (LAK '20)* (pp. 151–160). https://doi.org/10.1145/3375462.3375534

Mathrani, A., Susnjak, T., Ramaswami, G., & Barczak, A. (2021). Perspectives on the challenges of generalizability, transparency and ethics in predictive learning analytics. *Computers and Education Open, 2*, Article 100060. https://doi.org/10.1016/j.caeo.2021.100060

Maur, A., Zlatkin-Troitschanskaia, O., Martin de los Santos Kleinz, L., Schmidt, S., & Shenavai, K. (2024). Latent profiles of generic critical online reasoning: Examining young professionals in law, medicine, and teaching using process and performance data. In O. Zlatkin-Troitschanskaia, M.-T. Nagel, V. Klose, & A. Mehler (Eds.), *Students', graduates', and young professional critical use of online information* (pp. 23–46). Springer. https://doi.org/10.1007/978-3-031-69510-0_2.

McCabe, J. (2011). Metacognitive awareness of learning strategies in undergraduates. *Memory & Cognition, 39*(3), 462–476. https://doi.org/10.3758/s13421-010-0035-2

Meier, E., Vogl, K., & Preckel, F. (2014). Motivational characteristics of students in gifted classes: The pivotal role of need for cognition. *Learning and Individual Differences, 33*, 39–46. https://doi.org/10.1016/j.lindif.2014.04.006

Mokhtari, H., Davarpanah, M.-R., Dayyani, M.-H., & Ahanchian, M.-R. (2013). Students' need for cognition affects their information seeking behavior. *New Library World, 114*(11/12), 542–549. https://doi.org/10.1108/NLW-07-2013-0060

Molenaar, I., Mooij, S. D., Azevedo, R., Bannert, M., Järvelä, S., & Gašević, D. (2023). Measuring self-regulated learning and the role of AI: Five years of research using multimodal multichannel data. *Computers in Human Behavior, 139*, Article 107540. https://doi.org/10.1016/j.chb.2022.107540

Murti, D. M. P., Pujianto, U., Wibawa, A. P., & Akbar, M. I. (2019). *K-nearest neighbor (k-nn) based missing data imputation.* https://doi.org/10.1109/ICSITech46713.2019.8987530, 83–88.

Mussel, P. (2022). Processes underlying the relation between cognitive ability and curiosity with academic performance: A mediation analysis for epistemic behavior in a five-year longitudinal study. *Journal of Intelligence, 10*(2), 23. https://doi.org/10.3390/jintelligence10020023

Mussel, P., Ulrich, N., Allen, J. J. B., Osinsky, R., & Hewig, J. (2016). Patterns of theta oscillation reflect the neural basis of individual differences in epistemic motivation. *Scientific Reports, 6*(1), Article 29245. https://doi.org/10.1038/srep29245

Nair, K. U., & Ramnarayan, S. (2000). Individual differences in need for cognition and complex problem solving. *Journal of Research in Personality, 34*(3), 305–328. https://doi.org/10.1006/jrpe.1999.2274

Nielsen, F. (2016). Hierarchical clustering. In *Introduction to HPC with MPI for data science*. Cham: Springer. https://doi.org/10.1007/978-3-319-21903-5_8. Undergraduate topics in computer science.

Nkomo, L. M., Daniel, B. K., & Butson, R. J. (2021). Synthesis of student engagement with digital technologies: A systematic review of the literature. *International Journal of Educational Technology in Higher Education, 18*, 1–26.

Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2021). A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. *Nature Human Behaviour, 5*(11), 1535–1547. https://doi.org/10.1038/s41562-021-01117-5

Paule Ruiz, M. P., Riestra González, M., Sánchez Santillán, M., & Pérez Pérez, J. R. (2015). The procrastination related indicators in e-learning platforms. *Journal of Universal Computer Science, 21*(1), 7–22.

Peeters, W., Saqr, M., & Viberg, O. (2020). Applying learning analytics to map students' self-regulated learning tactics in an academic writing course. *International Conference on Computers in Education*, 245–254.

Pennycook, G., Cheyne, J. A., Koehler, D. J., & Fugelsang, J. A. (2016). Is the cognitive reflection test a measure of both reflection and intuition? *Behavior Research Methods, 48*(1), 341–348. https://doi.org/10.3758/s13428-015-0576-1

Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior, 11*, 17–61. https://doi.org/10.1146/annurev-orgpsych-110721-040030

Preckel, F. (2014). Assessing need for cognition in early adolescence: Validation of a German adaption of the cacioppo/petty scale. *European Journal of Psychological Assessment, 30*(1), 65–72. https://doi.org/10.1027/1015-5759/a000170

Rakovic, M., Fan, Y., Van Der Graaf, J., Singh, S., Kilgour, J., Lim, L., Bannert, M., Jarvela, S., & Gasevic, D. (2022). Using learner trace data to understand metacognitive processes in writing from multiple sources. In *12th international learning analytics and knowledge conference* (pp. 130–141). https://doi.org/10.1145/3506860.3506876

Rauthmann, J. F., Gallardo-Pujol, D., Guillaume, E. M., Todd, E., Nave, C. S., Sherman, R. A., Ziegler, M., Jones, A. B., & Funder, D. C. (2014). The situational eight DIAMONDS: A taxonomy of major dimensions of situation characteristics. *Journal of Personality and Social Psychology, 107*(4), 677–718. https://doi.org/10.1037/a0037250

Rigolizzo, M. (2019). Ready and willing to learn: Exploring personal antecedents to taking on learning challenges. *Journal of Workplace Learning, 31*(4), 289–304. https://doi.org/10.1108/JWL-08-2018-0101

Roberts, B. W., Lejuez, C., Krueger, R. F., Richards, J. M., & Hill, P. L. (2014). What is conscientiousness and how can it be assessed? *Developmental Psychology, 50*(5), 1315–1330. https://doi.org/10.1037/a0031109

Rodriguez, F., Kataoka, S., Janet Rivas, M., Kadandale, P., Nili, A., & Warschauer, M. (2021). Do spacing and self-testing predict learning outcomes? *Active Learning in Higher Education, 22*(1), 77–91. https://doi.org/10.1177/1469787418774185

Roth, A., Ogrin, S., & Schmitz, B. (2016). Assessing self-regulated learning in higher education: A systematic literature review of self-report instruments. *Educational Assessment, Evaluation and Accountability, 28*(3), 225–250. https://doi.org/10.1007/s11092-015-9229-2

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7

Rovers, S. F. E., Clarebout, G., Savelberg, H. H. C. M., De Bruin, A. B. H., & Van Merriënboer, J. J. G. (2019). Granularity matters: Comparing different ways of measuring self-regulatedlearning. *Metacognition and Learning, 14*(1), 1–19. https://doi.org/10.1007/s11409-019-09188-6

Rüdian, S., Vladowa, G., Gundlach, J., Kazimzade, G., & Pinkwart, N. (2019). Predicting culture and personality in online courses. *Proceedings of the first international workshop on supporting lifelong learning Co-Located with the 20th international conference on artificial intelligence*.

Rudolph, J., Greiff, S., Strobel, A., & Preckel, F. (2018). Understanding the link between need for cognition and complex problem solving. *Contemporary Educational Psychology, 55*, 53–62. https://doi.org/10.1016/j.cedpsych.2018.08.001

Sarmany-Schuller, I. (1999). Procrastination, need for cognition and sensation seeking. *Studia Psychologica, 41*(1), 73–85.

Schumacher, A., Kammerer, Y., Scharinger, C., Gottschling, S., Hübner, N., Tibus, M., Kasneci, E., Appel, T., Gerjets, P., & Bardach, L. (2025). How do intellectually curious and interested people learn and attain knowledge? A focus on behavioral traces of information seeking. *European Journal of Personality*. , Article 08902070241309124. https://doi.org/10.1177/08902070241309124

See, Y. H. M., Petty, R. E., & Evans, L. M. (2009). The impact of perceived message complexity and need for cognition on information processing and attitudes. *Journal of Research in Personality, 43*(5), 880–889. https://doi.org/10.1016/j.jrp.2009.04.006

Sher, V., Hatala, M., & Gašević, D. (2020). Analyzing the consistency in within-activity learning patterns in blended learning. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 1–10). https://doi.org/10.1145/3375462.3375470

Silvia, P. J. (2005). What is interesting? Exploring the appraisal structure of interest. *Emotion, 5*(1), 89–102. https://doi.org/10.1037/1528-3542.5.1.89

Srivastava, K., Shukla, A., & Sharma, N. K. (2010). Online flow experiences: The role of need for cognition, self-efficacy, and sensation seeking tendency. *International Journal of Business and Information Technology, 3*(2), 93–100.

Swafford, M., Anderson, R., & Wilson, M. (2021). The need for cognition and self-regulated learning in online environments. *The CTE Journal, 9*(2), 1–7.

Tempelaar, D., Rienties, B., Mittelmeier, J., & Nguyen, Q. (2018). Student profiling in a dispositional learning analytics application using formative assessment. *Computers in Human Behavior, 78*, 408–420. https://doi.org/10.1016/j.chb.2017.08.010

Therriault, D. J., Redifer, J. L., Lee, C. S., & Wang, Y. (2015). On cognition, need, and action: How working memory and need for cognition influence leisure activities. *Applied Cognitive Psychology, 29*(1), 81–90. https://doi.org/10.1002/acp.3078

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society - Series B: Statistical Methodology, 58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Tlili, A., Denden, M., Essalmi, F., Jemni, M., Kinshuk, Chen, N.-S., & Huang, R. (2019). Does providing a personalized educational game based on personality matter? A case study. *IEEE Access, 7*, 119566–119575. https://doi.org/10.1109/ACCESS.2019.2936384

Tlili, A., Essalmi, F., Ayed, L. J. B., Jemni, M., & Kinshuk. (2017). A smart educational game to model personality using learning analytics. In *2017 IEEE 17th international conference on advanced learning technologies (ICALT)* (pp. 131–135). IEEE. https://doi.org/10.1109/ICALT.2017.65.

Uszyńska-Jarmoc, J., University of Bialystok, P., Żak-Skalimowska, M., & University of Bialystok, P. (2018). The need for cognition and meta-learning competence among students of teacher education at the university level. *Kultura i Edukacja, 122*(4), 40–62. https://doi.org/10.15804/kie.2018.04.02

van Halem, N., van Klaveren, C., Drachsler, H., Schmitz, M., & Cornelisz, I. (2020). Tracking patterns in self-regulated learning using students' self-reports and online trace data. *Frontline Learning Research, 8*(3), 140–163. https://doi.org/10.14786/flr.v8i3.497

von Keyserlingk, L., Lauermann, F., Li, Q., Yu, R., Rubach, C., Arum, R., & Heckhausen, J. (2025). Students' study activities before and after exam deadlines as predictors of performance in STEM courses: A multi-source data analysis. *Learning and Individual Differences, 117*, Article 102598. https://doi.org/10.1016/j.lindif.2024.102598

von Stumm, S., & Ackerman, P. L. (2013). Investment and intellect: A review and meta-analysis. *Psychological Bulletin, 139*(4), 841–869. https://doi.org/10.1037/a0030746

von Stumm, S., Hell, B., & Chamorro-Premuzic, T. (2011). The hungry mind: Intellectual curiosity is the third pillar of academic performance. *Perspectives on Psychological Science, 6*(6), 574–588. https://doi.org/10.1177/1745691611421204

Wang, Q., & Mousavi, A. (2023). Which log variables significantly predict academic achievement? A systematic review and meta-analysis. *British Journal of Educational Technology, 54*(1), 142–191. https://doi.org/10.1111/bjet.13282

Weissgerber, S. C., Reinhard, M.-A., & Schindler, S. (2016). Study harder? The relationship of achievement goals to attitudes and self-reported use of desirable difficulties in self-regulated learning. *Journal of Psychological & Educational Research, 24*(1).

Weissgerber, S. C., Reinhard, M.-A., & Schindler, S. (2018). Learning the hard way: Need for cognition influences attitudes toward and self-reported use of desirable difficulties. *Educational Psychology, 38*(2), 176–202. https://doi.org/10.1080/01443410.2017.1387644

Wu, F., & Lai, S. (2019). Linking prediction with personality traits: A learning analytics approach. *Distance Education, 40*(3), 330–349. https://doi.org/10.1080/01587919.2019.1632170

Xiao, Q., Dai, Q., Ma, J., & Yuan, F. (2024). Effective deep learning requires a "balance" between need for cognition, flow experience, and positive academic emotions. *Studia Psychologica, 66*(4), 237–252. https://doi.org/10.31577/sp.2024.04.903

Xie, K., Jiang, Z., Men, Q., Pan, Z., & He, J. (2025). Profiles of students' behavioral engagement and their associations to academic motivation in online learning. *Journal of Computing in Higher Education*. https://doi.org/10.1007/s12528-025-09465-1

Yan, Z. (2018). Student self-assessment practices: The role of gender, school level and goal orientation. *Assessment in Education: Principles, Policy & Practice, 25*(2), 183–199. https://doi.org/10.1080/0969594X.2016.1218324

Yang, T. C., Chen, M. C., & Chen, S. Y. (2018). The influences of self-regulated learning support and prior knowledge on improving learning performance. *Computers & Education, 126*, 37–52. https://doi.org/10.1016/j.compedu.2018.06.025

Yang, C., Li, J., Zhao, W., Luo, L., & Shanks, D. R. (2023). Do practice tests (quizzes) reduce or provoke test anxiety? A meta-analytic review. *Educational Psychology Review, 35*(3), 87. https://doi.org/10.1007/s10648-023-09801-w

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science, 12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393

Ye, D., & Pennisi, S. (2022). Using trace data to enhance students' self-regulation: A learning analytics perspective. *The Internet and Higher Education, 54*, Article 100855. https://doi.org/10.1016/j.iheduc.2022.100855

Yoo, J. E., Rho, M., & Lee, Y. (2022). Online students' learning behaviors and academic success: An analysis of LMS log data from flipped classrooms via regularization. *IEEE Access, 10*, 10740–10753. https://doi.org/10.1109/ACCESS.2022.3144625

You, J. W. (2016). Identifying significant indicators using LMS data to predict course achievement in online learning. *The Internet and Higher Education, 29*, 23–30. https://doi.org/10.1016/j.iheduc.2015.11.003

Yu, R., Li, Q., Fischer, C., Doroudi, S., & Xu, D. (2020). Toward accurate and fair prediction of college success: Evaluating different sources of student data. *Proceedings of the International Conference on Educational Data Mining (EDM 2000)* (pp. 292–301). International Educational Data Mining Society.

Zeng, H., & Xin, Y. (2025). Comparing learning persistence and engagement in asynchronous and synchronous online learning, the role of autonomous academic motivation and time management. *Interactive Learning Environments, 33*(1), 276–295. https://doi.org/10.1080/10494820.2024.2344033

Zerna, J., Strobel, A., & Strobel, A. (2024). The role of need for cognition in well-being: Review and meta-analyses of associations and potentially underlying mechanisms. *Collabra: Psychology, 10*(1), Article 92885. https://doi.org/10.1525/collabra.92885