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Understanding Mean-Level and Intraindividual Variability in State Academic Self-Concept: The Role of Students' Trait Expectancies and Values

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The present study pursues a novel approach to examining how students' habitual trait expectancies (academic self-concept [ASC]) and trait values (academic interest and test anxiety) are related to their momentary state ASC. To this end, we drew on intensive longitudinal data obtained through 3 weeks of experience sampling in German secondary school students. We took a domain-general (school in general) and domain-specific (domain of mathematics) approach and differentiated the two test anxiety facets of worry and emotionality. We applied mixed-effects location scale models to analyze the relations between trait ASC, trait interest, and trait test anxiety on the one hand and mean-level and within-person variability in state ASC on the other (for school in general: $N = 289$, $N_{\text{obs}} = 6{,}211$; $M_{\text{lessons}} = 21.49$; for mathematics: $N = 243$, $N_{\text{obs}} = 2{,}075$; $M_{\text{lessons}} = 8.54$). After controlling for school grades, reasoning ability, and gender, we found that higher scores in trait interest and trait ASC were related to higher mean levels of state ASC for school in general and mathematics in particular. Further, higher scores in trait mathematics interest were related to less within-person variability in the state mathematics self-concept. We conclude by discussing the implications for the theory and practice of expectancy value research and more broadly for educational psychology.

Educational Impact and Implications Statement

In our study, we investigated how students' typical motivational–affective traits relate to their momentary perception of their own abilities in specific school lessons. Our results indicate that students who have a stronger interest in a particular subject tend to have more consistent daily perceptions of their abilities in that subject; students who have a weaker interest tend to have more fluctuating self-perceptions of their abilities.

Keywords: expectancy value, state academic self-concept, test anxiety, interest, experience sampling

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Academic self-concept (ASC), defined as the mental representation of one's academic abilities (Brunner et al., 2010; Marsh & Shavelson, 1985; Shavelson et al., 1976), is one of the oldest and most frequently investigated variables in educational psychology (Marsh et al., 2012). Research suggests that ASC is crucial for students' educational success and well-being (e.g., Marsh, Seaton et al., 2019; Trautwein & Möller, 2016). However, almost all previous research on ASC has relied on studies that have assessed ASC at the trait level on only one or very few time points bridging larger time gaps (e.g., Wu et al., 2021). Research that conceptualized ASC on a state level—focusing on students' momentary mental representation of their academic abilities—is very limited (for exceptions, see Hausen et al., 2022; Niepel et al., 2022). Consequently, our knowledge dwindles rapidly when it comes to state ASC, its within-person variability from one lesson to the next, and how the nomological network of motivational–affective characteristics relates to mean-level and within-person variability in state ASC.

The current study applied experience sampling (for an overview of this method, see, e.g., Zirkel et al., 2015) and studied students' mean-level and within-person variability in state ASC. Guided by previous motivation research in educational psychology (Eccles, 2009; Eccles & Wigfield, 2002; Wigfield et al., 2020), we aimed to understand how state ASC relates to students' typical expression in three key affective–motivational characteristics: test anxiety (TA), academic interest, and ASC at the trait level. In so doing, we examined German secondary school students across 3 weeks and took a general-school and domain-specific approach regarding all examined variables by focusing on students' learning experiences in school in general as well as specifically in the domain of mathematics.

Theoretical Background

To understand the specific modes of action and psychological processes by which TA, academic interest, and (trait) ASC constitute students' motivation, scholars regularly refer to the (situated) expectancy-value theory (e.g., Arens et al., 2011; Gogol et al., 2017). Positioned in the long tradition of expectancy-value theories in psychological motivation research (e.g., Atkinson, 1957; for an overview, see Heckhausen, 1991), Eccles et al. (1983) developed their expectancy-value theory, which was subsequently refined (Eccles & Wigfield, 2002; Wigfield & Eccles, 1992) and evolved into the situated expectancy-value theory (Eccles & Wigfield, 2020; Wigfield et al., 2020). The situated expectancy-value theory describes a variety of socialization and psychological factors that shape and control an individual's motivation and subsequent choices in different learning contexts.

In the situated expectancy-value theory, motivation can be divided into two broad components: (a) expectancy and (b) value. Both can be organized around two corresponding questions that students might ask themselves about their learning activities: "Can I do this activity?" and "Do I want to do this activity, and why?" The expectancy component includes two subcomponents. First, ability beliefs relate to one's overall competence in a specific domain, and second, one's expectancies of success with particular forthcoming tasks. Empirical studies have often revealed substantial correlations between these two subcomponents of expectancy, leading researchers to either combine them into a single construct or use them interchangeably (Eccles, 2009; Eccles & Wigfield, 2002). Therefore, students' ASC has frequently been used to operationalize the expectancy component (e.g., Guo et al., 2017; Niepel et al., 2019). The value component includes four subcomponents: intrinsic value (i.e., personal enjoyment deriving from an activity), attainment value (i.e., personal significance of achieving success in a task), utility value of the task (i.e., perceived benefits of engaging and succeeding in a particular domain), and cost (i.e., perceived drawbacks of participating in a task; Eccles & Wigfield, 2002). Students' academic interest can be considered an essential intrinsic value component and has been previously used to operationalize the subcomponent of intrinsic value (e.g., Eccles, 2009; van der Westhuizen et al., 2022). Students' TA can be considered as part of the cost aspect and TA has been previously used to measure cost (e.g., Eccles, 2009; Marsh, Van Zanden, et al., 2019; Weber et al., 2022; Wigfield et al., 2015).

To date, there is a lack of empirical studies that integrate and/or relate state variables to or into the situated expectancy-value theory (but see, e.g., Moeller et al., 2022; see also Malmberg & Martin, 2019). In particular, research on how students' habitual ASC, interest, and TA are linked to intraindividual processes or regulatory mechanisms that drive students' motivation in a given moment has yet to be conducted. Taking steps to bridge the gap, the current study employed experience sampling and analyzed how students' traits in TA, interest, and ASC relate to their mean-level state ASC and experienced variability in state ASC from one lesson to the next.

Trait and State ASC

Traits are conceptualized as stable interindividual differences, whereas states describe momentary personal conditions that can change in short periods (Rauthmann, 2021). ASC has often been conceived as a relatively stable trait in previous research (see Jansen et al., 2020), and the distinction between trait ASC and state ASC has rarely been applied, let alone investigated (for exceptions, see Hausen et al., 2022; Niepel et al., 2022).

We define trait and state ASC as follows: Trait ASC is the habitual mental representation of one's ability that a student typically experiences. State ASC is the momentary mental representation of one's ability experienced at a particular moment.

The idea of a state self-concept can be traced back to James (1890) and was already embedded in Shavelson et al.'s (1976) seminal work on self-concept. James (1890) already noted in his work on the self that our self-esteem and confidence can rise and fall from one day to another. In the original Shavelson et al. (1976) model, self-concept is conceptualized as a multidimensional (in terms of domain specificity) and hierarchical construct: At the apex of this hierarchy is the general self-concept, followed by the ASC and non-ASC. ASC (i.e., the general-school ASC [gASC]), in turn, was further differentiated into domain-specific ASCs, such as mathematics self-concept (MSC) or English self-concept. These self-concepts were further divided into more task-specific self-concepts. Finally, at the foundation of this hierarchy, the authors specified a situation-specific level, where self-concepts significantly change according to experienced situations (Shavelson et al., 1976).

Niepel et al. (2022) were the first to highlight that it is important to conceptually disentangle the domain specificity in ASC (e.g., gASC vs. MSC) from the temporal specificity in ASC (trait vs. state ASC). As such, both more domain-specific self-concepts (e.g., MSC) and more domain-general self-concepts (e.g., gASC) can be thought of as falling on a trait-to-state continuum, and both can be thus measured as traits and states (see Rauthmann, 2021).

Indeed, first empirical studies from an intraindividual perspective using experience sampling have shown that students' state ASC in terms of both gASC (Hausen et al., 2022) and MSC (Niepel et al., 2022) exhibits short-term variance from one school lesson to the next, thus indicating that ASC is a state in addition to its conventional conceptualization as a trait. For example, Niepel et al. (2022) found interindividual differences in how strongly students' current lesson-specific state MSC was related to their state MSC during the preceding lesson and how long it took to restore their typical trait-like level of MSC. Hence, it appears that students tend to perceive themselves as more competent during some lessons and less competent during others (Niepel et al., 2022).

In the present study, we used experience sampling (also known as ambulatory assessment, ecological momentary assessment, or daily dairies; Trull & Ebner-Priemer, 2014) to collect data on numerous measurement points over a relatively short period of time (i.e., intensive longitudinal data; Bolger & Laurenceau, 2013; Neubauer & Schmiedek, 2020). The experience sampling method allowed us to capture students' ASC as states in real time and real life, from lesson to lesson, as they occur in everyday school life. We examined between-person differences in mean-level and within-person variability in state ASC. The mean-level state ASC can be regarded as students' typical expression in their state ASC. If state ASC is aggregated over a longer period of time, it should conceptually approximate trait ASC (see Pekrun, 1988; Rauthmann et al., 2019). The variability in state ASC across time in intensive longitudinal data analyses refers to short-term ups and downs experienced by students during the examined time span. Previous research on within-person variability in self-esteem as a distinct yet related construct (Marsh, Seaton, et al., 2019) suggests that greater variability is rather indicative of a maladaptive psychological adjustment. Specifically, variability in self-esteem has been found to be associated with poorer mental health and lower academic adjustment (Gest et al., 2015; Geukes et al., 2017). A first study on the variability of state ASC, which originates from the same research project as the current study (see Method section below), points in a similar direction. Specifically, Hausen et al. (2022) examined how students' personality traits in terms of the Big Five, including their respective facets (Soto & John, 2017), were related to students' mean-level and within-person variability in state gASC. With regard to within-person variability in gASC, Hausen et al. (2022) found that students who reported higher scores in depression (i.e., facet of the Big Five trait negative emotionality/neuroticism) experienced more variability in their state gASC.

TA: Worry and Emotionality

TA refers to a set of phenomenological, physiological, and behavioral responses toward exam-related concerns about failure or negative consequences (Zeidner, 1998, 2020). Numerous trait-based research findings indicate that TA and ASC are interrelated. For instance, meta-analytical research has shown that greater TA and overall anxiety are significantly related to poorer ASC (Brumariu et al., 2023; von der Embse et al., 2018; see also Li et al., 2021). Specifically, Brumariu et al. (2023) found significant negative relations between anxiety and gASC ($r = -.25$) and MSC ($r = -.30$; see also Li et al., 2021). von der Embse et al. (2018) found a significant negative relation between TA and ASC (i.e., self-concept/academic confidence; $r = -.29$). However, most of the studies on TA and ASC are correlational, and it is, therefore, difficult to resolve the direction of causation (see Dowker et al., 2016). There is empirical evidence that trait-based measures of TA and ASC are reciprocally related, with TA and ASC negatively predicting each other over time (see Ahmed et al., 2012; Clem et al., 2021; Zhang, 2022). Hence, students who perceive themselves as more competent in school may typically be less afraid of failure, while, at the same time, students who are more anxious about failure in school may develop a less favorable ASC over time (see also Pekrun, 2006, 2023).

In the present study, we focus on the two widely acknowledged and empirically supported distinct, yet moderately correlated, TA facets of worry and emotionality, as proposed in the structural model of TA by Liebert and Morris (1967). The cognitive facet of worry comprises negative or intrusive thoughts about one's performance and the consequences of failure, whereas the affective facet, emotionality, refers to perceived physiological stress reactions (Liebert & Morris, 1967).

Findings on the relation between the two TA facets of worry and emotionality on the one hand and ASC on the other are more limited than for overall TA. The TA facets of worry and emotionality may have differing functional relations to students' ASC, indicating the need to study their relations to ASC separately. Students form their ASC through various sources, such as performance feedback and different comparison processes (Marsh, Seaton, et al., 2019; Trautwein & Möller, 2016). With respect to the relation between worry and ASC, having observed similar peers failing at school in the past potentially heightens students' worry about failure, leading them to question their competence (i.e., worry is negatively linked to ASC; see Schunk, 2023). Further, students can derive insights from their physiological and affective responses. Feeling a high level of emotionality prior to undertaking a task could indicate to the student that they may not possess the necessary ability to achieve success (i.e., emotionality is negatively linked to ASC; see Schunk, 2023). A lower level of emotionality could then be a sign of greater competence (see also Pekrun et al., 2007).

The findings on the relation between the two TA facets suggest that trait ASC significantly negatively relates to the affective facet emotionality, while inconsistent findings have been reported with regard to the cognitive facet worry (e.g., Arens et al., 2017; Raufelder & Ringeisen, 2016; Schneider et al., 2022; Zeidner & Schleyer, 1999). To explain the inconsistent findings regarding the cognitive facet of worry, Raufelder and Ringeisen (2016) discuss how increased worry among students with higher cognitive abilities can promote their ASC. When these students worry about upcoming tests, they can adjust their learning strategies (e.g., searching for new information, adapting a more structured learning approach) and thus perform better, strengthening their ASC. In contrast, higher emotionality (as an affective facet) would not show any such links with successful adaptation of learning strategies (see Raufelder & Ringeisen, 2016).

Academic Interest

Interest is often characterized as a long-lasting inclination toward a particular topic, such as an academic field (Krapp, 2002), involving feelings of personal importance and emotional value (Hidi &

Renninger, 2006; Krapp, 2002). As such, interest guides attention and enhances learning in various domains for learners of all ages (Renninger & Hidi, 2011). Previous trait-based research suggests that interest and ASC are reciprocally related over time (Marsh et al., 2005). Specifically, even though ASC was more strongly related to subsequent interest than vice versa, interest was also significantly linked to subsequent ASC. Marsh et al.'s (2005) findings suggest that students who believe they are good at a certain subject, such as mathematics, tend to develop more interest in it. Conversely, students who are more interested in mathematics also tend to devote more time and effort to it, which can increase their MSC.

Level of Domain Specificity

Previous trait-based research on the structure of TA, interest, and ASC revealed that not only ASC (as described earlier) but all three constructs can be considered multidimensional in terms of their domain specificity (e.g., Gogol et al., 2017; Schneider et al., 2022). Different hierarchical levels of specificity in TA, interest, and ASC have been assessed, typically about school in general and/or a specific school subject (e.g., the domain of mathematics; e.g., Gogol et al., 2017). When relations between constructs are investigated, it is crucial to consider matching the level of specificity for each construct examined (see, e.g., Goetz et al., 2010; Marsh, 2023). This concept is known as the specificity-matching principle (Brunswick, 1952; Swann et al., 2007; see also principle of correspondence; Ajzen & Fishbein, 1977). The specificity-matching principle accounts for the complexity of real-world situations, as dependent variables (or criteria) are likely to be influenced by numerous factors (Swann et al., 2007). Consequently, it recommends aligning the specificity of predictors and criterion: When the predictor is highly specific, selecting an equally specific criterion should minimize the influence of rival factors on the predictor–criterion relation (Swann et al., 2007). Consequently, the more specific a predictor is about its criterion, and the more the level of specificity between the examined variables matches, the more substantial the observed predictor–criterion relation should be.

In ASC theory and research, the focus has been on gASC and, in particular, on ASCs within specific academic domains (such as MSC), as the relations between ASC and relevant outcomes are known to be highly domain-specific (Marsh, 2023). In the present study, we focus on two levels of specificity: school in general and the domain of mathematics. Specifically, we examine how students' habitual general-school TA, interest, and ASC as traits, on the one hand, relate to their momentary state gASC on the other hand, and in addition, how students' trait mathematics-specific TA, interest, and ASC relate to their momentary state MSC.

The Present Study

The present study is the first to examine how students' habitual trait expectancies (trait ASC) and trait values (trait interest and trait TA) as key motivational–affective characteristics (as outlined in the situated expectancy-value theory; e.g., Eccles, 2009; Wigfield et al., 2020) relate to their lesson-to-lesson momentary (state) ASC in everyday school life. To this end, we drew on intensive longitudinal data obtained through 3 weeks of experience sampling in German secondary school students. We investigated how trait TA, trait interest, and trait ASC are linked to mean-level and within-person variability in state ASC. Regarding trait TA, we differentiated its two facets of trait worry and trait emotionality (Liebert & Morris, 1967). In our study, we furthermore took both a domain-general (i.e., TA, interest, ASC, and state ASC with regard to school in general) and domain-specific approach (i.e., TA, interest, ASC, and state ASC with regard to the domain of mathematics). In addition to school in general, we focused on the mathematics domain because mathematics was the subject with the most instructional time over the three weeks of data collection in our sample (see also Method section below) and is arguably the most researched in terms of domain-specific TA, interest, and ASC (e.g., Li et al., 2021; Wu et al., 2021).

On the basis of the situated expectancy-value theory (e.g., Eccles, 2009; Wigfield et al., 2020) and a careful synthesis of the existing literature, we addressed the following research questions (RQs) separately for state gASC and state MSC:

> *RQ1a:* How are traits in general-school worry, general-school emotionality, general-school interest, and gASC related to between-person differences in mean levels of state gASC?
>
> *RQ1b:* How are traits in mathematics-specific worry, mathematics-specific emotionality, mathematics-specific interest, and MSC related to between-person differences in mean levels of state MSC?

Associations may differ at the trait and state levels (Wilson et al., 2017). Based on findings from the trait level (Raufelder & Ringeisen, 2016; Schneider et al., 2022), we tentatively expected to find a negative relation between trait emotionality and mean-level state ASC. Additionally, we expected to find a negative relation between trait worry and mean-level state ASC. Furthermore, we tentatively anticipated that trait interest would be significantly positively related to mean-level state ASC over a 3-week period of experience sampling (Marsh et al., 2005; van der Westhuizen et al., 2022). We expected trait ASC to be substantially related to mean-level state ASC.

> *RQ2a:* How are traits in general-school worry, general-school emotionality, general-school interest, and gASC related to between-person differences in within-person variability in state gASC?
>
> *RQ2b:* How are traits in mathematics-specific worry, mathematics-specific emotionality, mathematics-specific interest, and MSC related to between-person differences in within-person variability in state MSC?

RQ2 remains rather exploratory in nature due to the lack of experience-sampling research on the variability of state ASC in particular and state ASC in general. Based on the first finding that the Big Five facet depression was positively associated with variability in state ASC (Hausen et al., 2022), we tended to expect elevated variability in state ASC in students with higher TA (without making differentiated assumptions for worry and emotionality), lower interest, and lower trait ASC.

In addition, we aimed to examine whether the observed associations hold when controlling for students' school grades, reasoning ability, and gender. We controlled for school grades, reasoning ability, and gender in our final analyses as prior research has shown these factors to be associated with students' TA (e.g., Dowker et al., 2016;

von der Embse et al., 2018), interest (e.g., Schurtz et al., 2014; van der Westhuizen et al., 2022), and ASC (e.g., Brunner et al., 2008; Chen et al., 2012; Parker et al., 2018).

For both RQs, we expected to observe descriptively stronger relations when analyzing the mathematics-specific rather than the general-school measures, based on the specificity-matching principle (Brunswick, 1952; Swann et al., 2007). To address our RQs, we conducted mixed-effects location scale models (MELS; Hedeker & Nordgren, 2013).

Method

Participants and Procedure

We collected data as part of the larger "Dynamics of Academic Self-Concept in Everyday Life" project (Niepel et al., 2022), which focuses on everyday dynamics in state ASC and features three weeks of experience sampling. Within the project, we recruited a convenience sample of 18 classes (Grades 9 and 10) from six German secondary schools (i.e., Gymnasium) in four German federal states (Rhineland-Palatinate, North Rhine-Westphalia, Baden-Wuerttemberg, and Mecklenburg-Western Pomerania).[1] The data collection took place at the respective schools over a period of five weeks during the school year. In Week 1, students completed a preassessment (background inventory) in paper-pencil format. In Weeks 2–4, students participated in experience sampling by responding to brief electronic questionnaires on smartphones (e-diary). We examined a 3-week time span because such a duration is feasible for participants yet long enough to collect sufficient measurement points per student (see, e.g., Tsai et al., 2008, for a similar rationale). In Week 5, students completed a shorter postassessment (paper-pencil format). Participation was voluntary; written parental consent for participating students was obtained. The ethics review panel of the University of Luxembourg as well as the respective education authorities approved all procedures. Data from the larger research project have been used in other articles focusing on different RQs (e.g., Hausen et al., 2022, focused on the experience-sampling data on state gASC to examine relations between students' Big Five traits and state gASC; see also Transparency and Openness statement below).

In the present study, to address our RQs, we drew on data from the e-diary and background inventory phase. Specifically, we examined experience-sampling data on state gASC as assessed after every mathematics, physics, German, and English lesson and on state MSC data as assessed after every mathematics lesson. Further, the background inventory data provided information on students' general-school and mathematics-specific TA, interest, and ASC as traits, as well as on school grades, reasoning ability, and gender (see also Measures section below). Student characteristics for the present study in terms of data availability, as well as self-reported age and gender, are displayed in Table 1.

For experience sampling, students completed e-diaries on smartphones using the Android-based movisensXS application (Version 1.3.0-1.3.4; Movisens GmbH, 2017). Smartphones were all identical models and were given to the students for the project's duration. Depending on the occurrence of the four school subjects of mathematics, German, physics, and English, we programmed an event-contingent e-diary. Students received prompts through an auditory cue asking them to complete a short electronic questionnaire on the smartphone 3 min prior to the scheduled ending of the school lesson. Thus, the number of programmed prompts varied from class to class according to the respective class-specific timetable (i.e., between 16 and 42 lessons across all four subjects; between 3 and 16 mathematics lessons). Students were allowed to skip prompts or specific items during the e-diary data collection. As typical for intensive longitudinal designs, there are several reasons for missing data. Students were told to reject prompts when they did not attend a lesson or when the lesson did not take place (e.g., teacher's or student's illness). Further reasons for missing values occurred for exams, other obligations, and technical or logistical problems (e.g., students left smartphones at home, empty batteries). Of all the programmed prompts, students in our sample (see Table 1) replied, on average, to 21.49 prompts ($SD = 6.85$; range: 6–41) and to 8.54 prompts ($SD = 2.46$; range: 5–16) after mathematics lessons. Students provided 6,211 valid responses to 8,554 programmed prompts for state gASC, resulting in a compliance rate of 72.61%. Students provided 2,075 valid responses to 2,608 programmed prompts for state MSC, resulting in a compliance rate of 79.56%.

Measures

E-Diary

State ASC. State gASC and state MSC were assessed with three parallel-worded items each based on the short measure by Gogol et al. (2014) and the Self-Description Questionnaire (SDQ; Marsh et al., 1983). The SDQ is one of the best self-concept instruments available (Byrne, 2002), and Gogol et al. (2014) found that three-item short scales based on the SDQ are psychometrically sound for educational research purposes. Item phrasings (for gASC/MSC) were "Currently, I think that I am good at (most school subjects/mathematics)," "[…] work in (most school subjects/mathematics) is easy for me," and "[…] I learn things quickly in (most school subjects/mathematics)." Students responded to all items on a 6-point scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*), with higher scores implying higher state ASC. Available state gASC items assessed after all lessons were averaged to create a mean score per student and prompt for state gASC; available state MSC items assessed after mathematics lessons were averaged to create a mean score for state MSC. In the present study, level-specific reliabilities (Geldhof et al., 2014) revealed good reliability at each level (state gASC: $\omega = .995$ at Level 2, $\omega = .771$ at Level 1; state MSC: $\omega = .995$ at Level 2, $\omega = .866$ at Level 1) and the intraclass correlations (ICCs) for the three state gASC items ranged from .753 to .759 and for state MSC from .743 to .746, implying that around 25% of the variance (including measurement error) in the state ASC measures occurred within students.[2]

[1] The German school system comprises many different educational pathways, some of which differ from state to state. Depending on their performance level in primary school and their preferences, students are assigned to secondary schools. The Gymnasium leads to a higher education entrance qualification (the German "Abitur"), which, at the time of data collection, 44% of all students nationwide attended after primary school (Autorengruppe Bildungsberichterstattung, 2018).

[2] Reliabilities and ICCs were calculated using Mplus 8.3 (Muthén & Muthén, 1998–2019). Please note that these analyses should not be viewed as providing new results because reliability estimates and ICCs for gASC and MSC have already been reported by Hausen et al. (2022) and Niepel et al. (2022) drawing on the same research project data (albeit with slightly different sample sizes).

Table 1

Participant Availability and Characteristics for the Analyzed Samples of Each State ASC Measure

Outcome	Trait measures available[a]	State ASC available[b]	Total N	Participants: Age	Participants: Gender
State gASC	$N = 346$	$N = 352$, $N_{\text{obs}} = 7{,}620$	$N^{c} = 289$, $N_{\text{obs}} = 6{,}211$	$M = 15.32$ years, $SD = 0.69$, range: 13–17 years; based on $n = 279$	38.4% male students; based on $n = 282$
	Sample for main analyses[d]		$N = 248$, $N_{\text{obs}} = 5{,}293$	$M = 15.30$ years, $SD = 0.70$, range: 13–17 years; based on $n = 240$	36.3% male students; based on $n = 244$
	Sample for main analyses with no missing values on covariates[e]		$N = 238$, $N_{\text{obs}} = 5{,}051$	$M = 15.30$ years, $SD = 0.71$, range: 13–17 years; based on $n = 231$	36.6% male students; based on $n = 238$
State MSC	$N = 347$	$N = 353$, $N_{\text{obs}} = 2{,}660$	$N^{c} = 243$, $N_{\text{obs}} = 2{,}075$	$M = 15.35$ years, $SD = 0.66$, range: 13–17 years; based on $n = 235$	41.2% male students; based on $n = 238$
	Sample for main analyses[d]		$N = 215$, $N_{\text{obs}} = 1{,}827$	$M = 15.35$ years, $SD = 0.64$, range: 13–17 years; based on $n = 209$	38% male students; based on $n = 212$
	Sample for main analyses with no missing values on covariates[e]		$N = 199$, $N_{\text{obs}} = 1{,}693$	$M = 15.34$ years, $SD = 0.64$, range: 13–17 years; based on $n = 195$	38.9% male students; based on $n = 198$

Note. ASC = academic self-concept; gASC = general-school academic self-concept; MSC = mathematics self-concept.
[a] Response to at least one item for each of the examined traits was available. [b] Responses from at least five prompts (i.e., lessons; following suggestions by Asparouhov & Muthén, 2023) were available; students' responses after all lessons in the four domains (mathematics, physics, German, and English) were considered for gASC and responses after mathematics lessons were considered for state MSC. [c] Students who had values on the predictor variables as well as state gASC or MSC, respectively, were included in the analyses. Technical problems (i.e., an error in the e-diary phase that made it impossible to match the background data of the same student) caused most of the missing values here. [d] Students with no variance in state ASC were excluded from the main analyses (see Preliminary Analyses section). [e] Analyses including the covariates (i.e., school grades, reasoning ability, gender) were based on a reduced sample size due to missing data on the covariates.

Background Inventory

Trait TA. TA for school in general and mathematics was assessed with five items each for worry (e.g., "I think about what will happen if I don't do well") and emotionality (e.g., "My heart pounds") adapted from the German Test Anxiety Questionnaire (Hodapp, 1991). Items were displayed in a grid format with the item stems in the rows and the target domain in the columns (Rost & Sparfeldt, 2002). Students replied to all items on a 6-point scale ranging from 0 (*almost never*) to 5 (*almost always*), once when remembering classroom test situations for school in general and once for mathematics in particular ("In evaluative situations [e.g., tests, written or oral examinations] in [school/mathematics], …"). Higher values indicate higher levels of worry or emotionality. This adapted version of the German Test Anxiety Questionnaire has been found to be a valid instrument for measuring TA in German high school students (Schneider et al., 2022; Sparfeldt et al., 2005).

Trait Academic Interest. General-school interest and mathematics-specific interest were each assessed with five parallel-worded items (e.g., "I like [most school subjects/math]" and "[Most school subjects/math] is fun"); mathematics-specific interest was additionally assessed with a sixth item (i.e., "I wish we had more math lessons at school"). The interest items were adapted from Pohlmann et al. (2005). Students replied to all items on a 6-point scale ranging from 0 (*not true at all*) to 5 (*very true*). Higher values indicate higher levels of interest.

Trait ASC. Trait gASC and trait MSC were assessed with six parallel-worded items each (e.g., "I am good at [most school subjects/math]" and "Work in [most school subjects/math] is easy for me"), adapted from the German version of the SDQ (Marsh et al., 1983) and Gogol et al. (2014). Students replied to all items on a 6-point scale ranging from 0 (*not true at all*) to 5 (*very true*). Higher values indicate higher levels of trait gASC and trait MSC.

School Grades. Students reported their grades from the preceding school term as indicated on their report cards. We used students' mathematics grade and grade point average (GPA), which we determined by averaging students' grades in mathematics, physics, biology, chemistry, German, English, geography, and history. As German schools use a 6-point grading system, with higher numbers representing poorer achievement, we recoded the grades such that higher numbers indicated better achievement (1 = *insufficient* to 6 = *very good*).

Reasoning Ability. The German-language intelligence structure test-screening (Intelligenz-Struktur-Test-Screening [IST-screening]; Liepmann et al., 2012) was employed to capture students' reasoning ability. Students had 26 min to work on three 20-item subtests encompassing verbal, numerical, and figural material. The IST-screening builds upon the IST (Amthauer, 1970; Liepmann et al., 2007), an intelligence test that is widely applied in Germany (Schmidt-Atzert & Amelang, 2012). We administered Parallel Version A and used the reasoning ability raw composite scores in the present study.

Analytical Strategy

The statistics program R (Version 4.4.0; R Core Team, 2024) was used with packages dplyr (Wickham et al., 2023) and tidyr (Wickham et al., 2024) for data curation, psych (Revelle, 2024) for descriptive statistics, reliability, and correlation analysis, and car (Fox & Weisberg, 2019) for analysis of multicollinearity.

We conducted MELS (see Hedeker & Nordgren, 2013) using the statistics program MixWILD (Version 2.0; Dzubur et al., 2020) to examine the relations between students' trait TA (i.e., general-school and mathematics-specific worry and emotionality), academic interest (i.e., general-school interest and mathematics-specific interest), and trait ASC (i.e., trait gASC and trait MSC) on the one hand, and between-person differences in mean levels of and within-person variability in state ASC (i.e., state gASC and state MSC) on the other. MELS is an extension of multilevel models that allow for the estimation of between-person variance in random intercepts and slopes. Additionally, MELS allows for the specification of between-person variance in random variability (i.e., residual variance) by relaxing the assumption of homoscedasticity. A log-linear function is used to model the variability component. Consequently, MELS accounts for the interdependence among levels, temporal trends, and variability while simultaneously estimating how between- and/or within-person differences relate to the levels and variability in intensive longitudinal data with observations nested within individuals.

MELS offers several advantages over other approaches for modeling intraindividual variability (Geukes et al., 2017). First, by incorporating a time variable, MELS can account for potential temporal trends. Second, it allows for the estimation of the effects of predictors on both between-person differences in level and variability within a single model. Finally, MELS considers the covariance between each person's level and variability during model estimation, recognizing that level and variability are correlated random variables (see Baird et al., 2006, for an extensive discussion).

MixWILD includes complete data for any predictor and outcome variable at a specific measurement point in the analyses, providing valid inference for incomplete data under the missing at random assumption (Hedeker & Nordgren, 2013; see also Laird, 1988; Singer & Willett, 2003). MixWild handles missingness by using all the data available for analyses instead of listwise deletion (Hedeker & Nordgren, 2013; Singer & Willett, 2003).

In accordance with our RQs, level and variability were allowed to vary between participants in the main analyses. Thus, the specified MELS predict students' between-person differences in level and variability in state ASC in a single model and control for the statistical effects of students' levels of state ASC on variability and vice versa (for a similar methodology, see Križan & Hisler, 2019). To consider potential temporal trends in state ASC over the 3-week data collection period, we included a time variable in our models (Wang & Maxwell, 2015). This continuous time variable represents the time difference in hours between the current and the first programmed prompt within the e-diary based on the timetable of each class.

In our main analyses, we calculated null models with only the time variable predicting each outcome (i.e., state gASC and state MSC). Subsequently, we ran two sets of six models each with outcome-matching statistical predictors explaining between-person differences in level and variability, once for students' state gASC (RQ1a and RQ2a, resulting in Models gASC 1 to gASC 6) and once for their state MSC (RQ1b and RQ2b, resulting in Models MSC 1 to MSC 6): Models gASC 1 and MSC 1 were specified with only the worry component of TA as statistical predictor, Models gASC 2 and MSC 2 with only the emotionality component of TA as statistical predictor, Models gASC 3 and MSC 3 with interest as statistical predictor, and Models gASC 4 and MSC 4 with trait ASC as statistical predictor. In a second step, we specified Models gASC 5 and MSC 5 with all four predictor variables (i.e., worry, emotionality, interest, and trait ASC). Last, we added the covariates school grades, reasoning ability, and gender as statistical predictors in Models gASC 6 and MSC 6. In all models, we controlled for time (by including the time variable; described earlier). Further, we controlled for the class the students visited (students were nested in 18 classes) in all our analyses by including class indicators (i.e., 17 dummy variables representing 18 different classes).[3] All statistical predictors and outcome variables were z-standardized (except for gender; 0 = *male students*, 1 = *female students*; and dummy-coded class indicators). We set α at .05 (Cohen, 1988) and report effect sizes and their confidence intervals (CIs) (Cumming, 2014). Effect sizes are interpreted following Gignac and Szodorai (2016), who specified .10 as relatively small, .20 as typical, and .30 as relatively large.[4]

Transparency and Openness

We report how we determined our sample size and all data exclusions, and we adhered to the journal article reporting standards for quantitative research (Appelbaum et al., 2018). No manipulations were made in the study. Data cannot be made available because of data protection concerns. Readers interested in the data can contact Christoph Niepel. The main analyses were performed with MixWILD (Version 2.0; Dzubur et al., 2020). The analysis scripts are available on the Open Science Framework (OSF) platform (https://doi.org/10.17605/OSF.IO/PXA9S; Niepel et al., 2025). An overview of measures included in the larger research project as well as a list of other articles based on the project data is available on the OSF platform (https://doi.org/10.17605/OSF.IO/PXA9S; Niepel et al., 2025). The design and analysis of this study were not preregistered.

Results

Preliminary Analyses

Descriptive statistics, reliabilities (for all trait measures), and bivariate correlations between all examined variables are depicted in Tables 2 and 3. Moreover, we checked for multicollinearity in the data. Variance inflation factor was $<$10 for all variables, indicating that multicollinearity did not pose a threat to our analyses.

With regard to trait TA, we found that students' emotionality (general-school and mathematics-specific), but not worry (general-school or mathematics-specific), correlated negatively with aggregated mean levels of their state gASC. Both worry (general-school and mathematics-specific) and emotionality (general-school and

[3] The ICCs for each of the three state ASC items at the class level (i.e., students were nested into 18 classes) were rather small, with ICCs = .014 for state gASC, and ranging from ICC = .023 to ICC = .032 for state MSC. However, we incorporated class indicators into our main analyses to statistically control for possible classroom-level effects.

[4] Following the suggestion of an anonymous reviewer, we also tested the same series of models with TA as a composite score (without differentiating for the facets of worry and emotionality) to inform interested readers. The results are reported in Tables 3 and 4 in the online supplemental materials. While we found the same results for other relations, we found a statistically significant relation between the TA composite score and variability in state MSC. In the article, we kept the facets apart in line with the structural model of TA by Liebert and Morris (1967) and the TA instrument used (Hodapp, 1991; Schneider et al., 2022; Sparfeldt et al., 2005).

Table 2
Descriptive Statistics and Reliabilities

Variable	*n*	*M*	*SD*	Range	ω
1. State gASC (*M*)[a]	289	3.40	0.73	0–5	
2. State gASC (*SD*)[a]	289	0.33	0.28	0–2.11	
3. State MSC (*M*)[b]	243	3.16	1.15	0–5	
4. State MSC (*SD*)[b]	243	0.53	0.36	0–1.85	
5. $\text{Worry}_{\text{general}}$	289	4.24	1.20	0–5	.89
6. $\text{Emotionality}_{\text{general}}$	289	3.32	1.33	0–5	.91
7. $\text{Worry}_{\text{mathematics}}$	243	4.45	1.31	0–5	.93
8. $\text{Emotionality}_{\text{mathematics}}$	243	3.22	1.56	0–5	.94
9. Trait gASC	289	3.48	0.91	0–5	.95
10. Trait MSC	242	3.13	1.28	0–5	.96
11. General-school interest	214	2.62	0.86	0–5	.89
12. Math interest	213	2.32	1.14	0–5	.93
13. GPA	281	4.50	0.71	1–6	.91
14. Mathematics grade	231	4.42	1.08	1–6	
15. Reasoning ability	286	43.77	5.71	26–56	.79
16. Gender[c]	282				

Note. Reliabilities are depicted as McDonald's omega (ω). gASC = general-school academic self-concept; MSC = mathematics self-concept; GPA = grade point average.
[a] The state gASC variables refer to aggregated state ASC per student across time and the standard deviation thereof (i.e., calculated with R). [b] The state MSC variables refer to aggregated state MSC per student across time and the standard deviation thereof (i.e., calculated with R). [c] 0 = *male students*; 1 = *female students*.

mathematics-specific) were negatively associated with students' aggregated mean levels of state MSC. Students' general-school emotionality, but not worry (general-school or mathematics-specific), were positively associated with aggregated variability in state gASC (in terms of standard deviation). General-school and mathematics-specific emotionality were positively related to students' aggregated variability in state MSC. However, general-school and mathematics-specific worry were not related to students' aggregated variability in state MSC.

With regard to trait ASC and trait interest, we found that trait ASC (gASC and MSC) as well as trait interest (general-school and mathematics-specific) were positively related to students' aggregated mean levels of their state gASC, with correlations between mathematics-specific variables and state gASC being of descriptively similar size as correlations between general-school variables and state gASC. Similarly, both trait ASC (gASC and MSC) and interest (general-school and mathematics-specific) were positively correlated with state MSC. However, the correlations between mathematics-specific traits and state MSC were descriptively higher than the correlations between general-school traits and state MSC, which is in line with the specificity-matching principle (Brunswick, 1952; Swann et al., 2007).

Aggregated variability in state gASC was negatively correlated with trait ASC (gASC and MSC) and interest (general-school and mathematics-specific). Again, the correlations between general-school traits and variability in state gASC and mathematics-specific traits were descriptively of similar height. However, variability in state MSC correlated negatively with trait MSC and mathematics-specific interest, but not with trait gASC or general-school interest. Overall, although these findings allow us to grasp how the examined motivational–affective traits and levels of and variability in state ASC might be associated, they do not allow us to come to final conclusions.

In our sample, no variance in state gASC and state MSC over the three weeks of data collection was found for $N = 41$ and $N = 27$ students, respectively, and their data were removed from the MELS analyses (see Table 1). The subsample with no variance in state gASC had significantly lower means in general-school worry, $r(289) = -.12$, $p = .049$, and general-school emotionality, $r(289) = -.23$, $p < .001$, but not general-school interest and trait gASC, compared to students who exhibited variance in state gASC. The means of mathematics-specific worry, emotionality, and interest did not significantly differ between the subsample and analysis sample for state MSC. However, the subsample with no variance in state MSC showed significantly lower means in trait MSC, $r(245) = -.16$, $p = .01$, compared to students who exhibited variance in state MSC.

Main Analyses

Null Models

Students significantly varied in their level in state ASC (gASC: intercept = 0.540 on the log scale, $p < .001$; MSC: intercept = 1.284 on the log scale, $p < .001$). Moreover, students significantly varied in their degree of within-person variability (gASC: variability = 3.030 on the log scale, $p < .001$; MSC: variability = 1.326 on the log scale, $p < .001$) in state ASC. Higher state ASC levels were correlated with reduced variability (gASC: covariance = −.383 on the log scale, $p < .001$; MSC: covariance = −.460 on the log scale, $p < .001$). This finding suggests that students who have higher state ASC levels are more consistent, meaning their state ASC tends to fluctuate less.[5]

The Relations Between TA, Interest, and ASC as Traits and Between-Person Differences in Mean-Level State ASC (RQ1a and RQ1b)

Tables 4 and 5 show the results of the MELS separately for state gASC and state MSC, and Table 6 depicts the respective measures of model fit.

State gASC. We did not find any statistically significant association between students' levels of state gASC across three weeks and general-school worry, but we found that general-school emotionality was a statistically significant predictor, with a small-sized effect (Gignac & Szodorai, 2016; Table 4). Model gASC 2 (emotionality) showed that students with higher general-school emotionality reported lower levels of state gASC, $\beta = -.121$, $p = .034$. Moreover, both general-school interest (Model gASC 3) and trait gASC (Model gASC 4) were statistically significant predictors with large effect sizes. Students with higher general-school interest, $\beta = .311$, $p < .001$, and higher trait gASC, $\beta = .456$, $p < .001$, reported higher levels of state gASC. Both models also showed lower values in Akaike information criterion (AIC), Bayesian information criterion (BIC), and −2loglikelihood than the models including the anxiety components (Table 6), indicating that general-school

[5] Please note that the null model analysis for state gASC should not be viewed as providing new results because a MELS null model for gASC was already reported by Hausen et al. (2022) drawing on the research project data (albeit with slightly different sample sizes). For the sake of completeness, we nonetheless report the results obtained for the gASC null model.

Table 3
Intercorrelations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. gASC (*M*)[a]	—														
2. gASC (*SD*)[a]	−.23***	—													
3. State MSC (*M*)[b]	.63***	−.23***	—												
4. State MSC (*SD*)[b]	−.21***	.50***	−.35***	—											
5. $\text{Worry}_{\text{general}}$	.01	.04	−.16**	.08	—										
6. $\text{Emotionality}_{\text{general}}$	−.17**	.12*	−.28***	.13*	.52***	—									
7. $\text{Worry}_{\text{mathematics}}$	−.04	.05	−.20***	.10	.85***	.45***	—								
8. $\text{Emotionality}_{\text{mathematics}}$	−.24***	.11	−.43***	.20***	.51***	.82***	.57***	—							
9. Trait gASC	.57***	−.20***	.46***	−.06	−.05	−.13*	−.13*	−.23***	—						
10. Trait MSC	.50***	−.17**	.77***	−.22***	−.18**	−.25***	−.26***	−.45***	.62***	—					
11. General-school interest	.44***	−.15*	.29***	−.03	.15*	.01	.11	−.03	.46***	.30***	—				
12. Math interest	.38***	−.18**	.68***	−.29***	−.04	−.12*	−.12	−.31***	.38***	.71***	.47***	—			
13. GPA	.43***	−.13*	.36***	−.06	−.03	−.07	−.14*	−.23***	.76***	.55***	.33***	.34***	—		
14. Mathematics grade	.37***	−.13*	.53***	−.17**	−.15*	−.12*	−.27***	−.33***	.60***	.72***	.22***	.50***	.79***	—	
15. Reasoning ability	.17**	−.05	.30***	.14*	−.07	−.10	−.13*	−.22***	.26***	.37***	.03	.25***	.36***	.39***	—
16. Gender[c]	−.12*	.09	−.27***	.12*	.19**	.21***	.19**	.29***	.01	−.25***	.10	−.21***	.08	−.08	−.11

Note. Values printed in bold type were statistically significant ($p < .05$). Based on $N = 289$ students. gASC = general-school academic self-concept; MSC = mathematics self-concept; GPA = grade point average.
[a] The state gASC variables refer to aggregated state gASC per student across time and the standard deviation thereof (i.e., calculated with R). [b] The state MSC variables refer to aggregated state MSC per student across time and the standard deviation thereof (i.e., calculated with R). [c] 0 = *male students*; 1 = *female students*.
* $p < .05$. ** $p < .01$. *** $p < .001$.

interest and trait gASC are stronger predictors of state gASC than TA. Moreover, the model with all four predictors showed similar relations with gASC (Model gASC 5), except for the relation with emotionality, which became statistically nonsignificant ($p > .05$). Model gASC 5 with all four predictors showed similar AIC, BIC, and −2loglikelihood values compared to the model with trait gASC only (Model gASC 4), indicating that trait gASC is a strong predictor of state gASC. These relations held when controlling for students' GPA, reasoning ability, and gender (Model gASC 6). We found differences in state gASC in favor of male students, suggesting that they have a higher state gASC than female students.

State MSC. For students' levels of state MSC across three weeks, both mathematics-specific TA components were statistically significant predictors, with small-to-large effect sizes (Gignac & Szodorai, 2016; Table 5). Students higher in worry ($\beta = -.154$, $p = .003$; Model MSC 1) and higher in emotionality ($\beta = -.341$, $p < .001$; Model MSC 2) reported lower levels of state MSC across mathematics lessons. Moreover, both mathematics-specific interest (Model MSC 3) and trait MSC (Model MSC 4) were statistically significant predictors with large effect sizes. Students with higher mathematics-specific interest, $\beta = .601$, $p < .001$, and higher trait MSC, $\beta = .654$, $p < .001$, reported higher levels of state MSC. Again, these two models showed lower AICs, BICs, and −2loglikelihoods than the models with the anxiety components (Table 6), indicating that mathematics-specific interest and trait MSC are stronger predictors of state MSC than TA. The model with all four predictors showed similar relations with state MSC for mathematics-specific interest and trait MSC (Model MSC 5), except for the relation between mathematics-specific worry and emotionality with MSC, which became statistically nonsignificant ($p > .05$). Model MSC 5 with all four predictors showed lower AIC, BIC, and −2loglikelihood values than the model with trait MSC only (Model MSC 4), indicating that a model with all four predictors explained more variance than the model with only trait MSC. These associations remained after controlling for mathematics grade, reasoning ability, and gender (Model MSC 6). We found gender differences in state MSC in favor of male students, suggesting that they have a higher state MSC than female students.

The Relations Between TA, Interest, and ASC as Traits and Between-Person Differences in Within-Person Variability in State ASC (RQ2a and RQ2b)

State gASC. Neither TA component or general-school interest emerged as a statistically significant predictor of variability in state gASC (Table 4), but significant associations were found between students' trait gASC and variability in their state gASC, with a negative effect ($\tau = -.333$ $p = .003$; Model gASC 4). Thus, students with higher trait gASC reported less variability in their state gASC. These relations held in Model gASC 5 with all four predictors, but the negative relation between trait gASC and variability in state gASC vanished when GPA, reasoning ability, and gender were introduced into the model (Model gASC 6). We found no gender differences in variability in state gASC, but reasoning ability was negatively associated with variability in state gASC ($\tau = -.249$, $p = .047$).

Model gASC 5 (all four predictors) showed that students with higher trait gASC ($\tau = -.301$, $p = .012$) still reported more

Table 4

Mixed-Effects Location Scale Model With General-School Variables Statistically Predicting Mean Levels of and Within-Person Variability in State gASC

		State general-school academic self-concept									
		Level					Variability				
				95% CI					95% CI		
Model	Variable	β	*SE*	*LL*	*UL*	*p*	τ	*SE*	*LL*	*UL*	*p*
gASC 1	$\text{Worry}_{\text{general}}$	.013	.056	−.097	.123	.819	.108	.110	−.108	.324	.331
gASC 2	$\text{Emotionality}_{\text{general}}$	**−.121**	**.057**	**−.233**	**−.009**	**.034**	.099	.115	−.126	.324	.309
gASC 3	$\text{Interest}_{\text{general}}$	**.311**	**.052**	**.209**	**.413**	**<.001**	−.141	.109	−.355	.073	.196
gASC 4	Trait gASC	**.456**	**.050**	**.358**	**.554**	**<.001**	**−.333**	**.110**	**−.549**	**−.117**	**.003**
gASC 5	$\text{Worry}_{\text{general}}$	.062	.057	−.050	.174	.276	.098	.130	−.157	.353	.449
	$\text{Emotionality}_{\text{general}}$	−.104	.058	−.218	.010	.073	.015	.133	−.246	.276	.907
	$\text{Interest}_{\text{general}}$	**.160**	**.052**	**.058**	**.262**	**.001**	−.045	.119	−.278	.188	.706
	Trait gASC	**.388**	**.053**	**.284**	**.492**	**<.001**	**−.301**	**.120**	**−.536**	**−.066**	**.012**
gASC 6	$\text{Worry}_{\text{general}}$	.085	.057	−.027	.197	.134	.110	.130	−.145	.365	.397
	$\text{Emotionality}_{\text{general}}$	−.058	.060	−.176	.060	.336	−.050	.137	−.319	.219	.714
	$\text{Interest}_{\text{general}}$	**.182**	**.054**	**.076**	**.288**	**<.001**	−.033	.124	−.276	.210	.789
	Trait gASC	**.379**	**.078**	**.226**	**.532**	**<.001**	−.295	.178	−.644	.054	.098
	GPA	.058	.082	−.103	.219	.478	.113	.186	−.252	.478	.544
	Reasoning ability	−.023	.055	−.131	.085	.678	**−.249**	**.125**	**−.494**	**−.004**	**.047**
	Gender[a]	**−.384**	**.107**	**−.594**	**−.174**	**<.001**	.149	.246	−.333	.631	.544

Note. Coefficient estimates are standardized betas (β) for the level and taus (τ) for the variability. Values in bold type were statistically significant ($p < .05$) with a CI not including zero. gASC = general-school academic self-concept; CI = confidence interval; *LL* = lower limit; *UL* = upper limit; GPA = grade point average.

[a] Gender is not *z*-standardized and therefore shows the group difference between male and female students in state gASC (0 = *male students*; 1 = *female students*).

variability in state gASC. A 1-*SD* increase in students' trait gASC (variance ratio: .740; 95% CI: [.50, .94]) was related to a 26% less variable state gASC (for detailed methodology, see Huisingh-Scheetz et al., 2021). This negative relation between trait gASC and variability in state gASC vanished when covariates were added to the analyses. Moreover, in Model gASC6, a 1-*SD* increase in students' reasoning ability score (variance ratio: .780; 95% CI: [.61, 1.00]) was related to a 22% less variable state gASC.

State MSC. Students' mathematics-specific TA and variability in their state MSC across three weeks (Table 5) were positively related, while mathematics interest and trait MSC were negatively related to variability in state MSC. More worried ($\tau = .201$, $p = .017$; Model MSC 1) and more emotional ($\tau = .287$, $p = .001$; Model MSC 2) students indicated more variability in state MSC across mathematics lessons, while students who were interested in mathematics ($\tau = -.287$, $p < .001$; Model MSC 3) and had a higher trait MSC ($\tau = -.238$, $p = .005$; Model MSC 4) reported less variability in state MSC.

Model MSC 5 (all four predictors) showed that students with higher mathematics-specific interest ($\tau = -.265$, $p = .036$) still reported more variability in state MSC. A 1-*SD* increase in students' mathematics-specific interest score (variance ratio:.77; 95% CI: [.60, .98]) was related to a 23% less variable state MSC. This negative relation between mathematics-specific interest and variability in state MSC remained stable when covariates were added to the analyses ($\tau = -.281$, $p = .033$; Model MSC 6). Again, we found no gender differences in variability in state MSC. Each additional point (i.e., 1-*SD* increase) in mathematics-specific interest (variance ratio:.76; 95% CI: [.58, .98]) was significantly associated with 24% less variability in students' state MSC. The relation between mathematics-specific worry, mathematics-specific emotionality, trait MSC, and variability in state MSC became nonsignificant in Models MSC 5 and MSC 6.[6,7]

Discussion

Guided by the situated expectancy-value theory (e.g., Eccles, 2009; Wigfield et al., 2020), the present experience-sampling study was the first to explore how mean-level and within-person variability in state ASC relates to students' habitual motivational–affective characteristics in trait TA, trait interest (both reflecting aspects of the value component), and trait ASC (reflecting expectancy). Hereby, we differentiated TA's two facets worry and emotionality (Liebert & Morris, 1967). Using MELS (Hedeker & Nordgren, 2013), we controlled for the statistical effects of students' state ASC level on state ASC variability and vice versa, while controlling for potential temporal trends in our analyses. Our results overall suggest that students' habitual characteristics in both expectancy-value components (i.e., trait interest reflecting the intrinsic value aspect of value and trait ASC reflecting expectancy) appear to play a crucial role in the unfolding of students' state ASC, which was assessed in a highly ecological manner from one lesson to the next.

[6] We additionally controlled for the school subject after which state gASC was collected by adding three dummy variables (i.e., representing the respective four school subjects) into our analyses. We obtained the same pattern of results for these analyses as we did in our main analyses.

[7] An anonymous reviewer suggested reporting the results for the models using general-school traits as statistical predictors of (domain-specific) state MSC and mathematics-specific traits as statistical predictors of (general-school) state gASC to test further the specificity-matching principle (Swann et al., 2007). The corresponding models had convergence problems, so we decided not to report them.

Table 5

Mixed-Effects Location Scale Model With Mathematics-Specific Variables Statistically Predicting Mean Levels of and Within-Person Variability in State MSC

		State mathematics self-concept									
		Level					Variability				
				95% CI					95% CI		
Model	Variable	β	*SE*	*LL*	*UL*	*p*	τ	*SE*	*LL*	*UL*	*p*
MSC 1	$\text{Worry}_{\text{mathematics}}$	**−.154**	**.051**	**−.254**	**−.054**	**.003**	**.201**	**.087**	**.030**	**.372**	**.017**
MSC 2	$\text{Emotionality}_{\text{mathematics}}$	**−.341**	**.050**	**−.439**	**−.243**	**<.001**	**.287**	**.088**	**.115**	**.459**	**.001**
MSC 3	$\text{Interest}_{\text{mathematics}}$	**.601**	**.040**	**.523**	**.679**	**<.001**	**−.287**	**.086**	**−.456**	**−.118**	**< .001**
MSC 4	Trait MSC	**.654**	**.036**	**.583**	**.725**	**<.001**	**−.238**	**.084**	**−.403**	**−.073**	**.005**
MSC 5	$\text{Worry}_{\text{mathematics}}$	−.009	.046	−.099	.081	.842	.143	.106	−.065	.351	.179
	$\text{Emotionality}_{\text{mathematics}}$	−.083	.048	−.177	.011	.087	.131	.113	−.090	.352	.246
	$\text{Interest}_{\text{mathematics}}$	**.234**	**.054**	**.128**	**.340**	**<.001**	**−.265**	**.127**	**−.514**	**−.016**	**.036**
	Trait MSC	**.455**	**.054**	**.349**	**.561**	**<.001**	.026	.125	−.219	.271	.833
MSC 6	$\text{Worry}_{\text{mathematics}}$	−.017	.049	−.113	.079	.726	.159	.115	−.066	.384	.166
	$\text{Emotionality}_{\text{mathematics}}$	−.058	.051	−.158	.042	.262	.159	.124	−.084	.402	.198
	$\text{Interest}_{\text{mathematics}}$	**.249**	**.055**	**.141**	**.357**	**.001**	**−.281**	**.132**	**−.540**	**−.022**	**.033**
	Trait MSC	**.444**	**.072**	**.303**	**.585**	**.001**	.074	.171	−.261	.409	.664
	Mathematics grade	−.023	.061	−.143	.097	.711	−.060	.141	−.336	.216	.669
	Reasoning ability	.056	.043	−.028	.140	.186	−.018	.104	−.222	.186	.863
	Gender[a]	**−.212**	**.079**	**−.367**	**−.057**	**.008**	.224	.189	−.146	.594	.235

Note. Coefficient estimates are standardized betas (β) for the level and taus (τ) for the variability. Values in bold type were statistically significant ($p < .05$) with a CI not including zero. MSC = mathematics self-concept; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.
[a] Gender is not *z*-standardized and therefore shows the group difference between male and female students in state MSC (0 = *male students*; 1 = *female students*).

Trait Interest Is Related to Mean Level and Variability in State ASC

Our results suggest that independently of their trait TA (i.e., worry and emotionality), trait ASC, school grades, reasoning ability, and gender, students with higher trait interest seem to perceive themselves as more competent in daily school life. This finding held across both examined levels of domain specificity, that is, for school in general as well as for the mathematics-specific variables. In addition, with regard to the domain of mathematics, our results suggest that independently of students' trait TA (i.e., worry and emotionality), trait MSC, school grades, reasoning ability, and gender, students who are more interested in mathematics tend to perceive their academic competencies as more stable from one mathematics lesson to another.

The question arises as to why students who are more interested in mathematics should perceive fewer ups and downs in their daily state ASC. Past research on intraindividual variability in trait self-representations in adolescents (Gest et al., 2015) suggests that an increased variability reflects a form of vulnerability and is indicative of maladaptive psychological functioning. This trait-based evidence is in line with previous state-based research on self-esteem (indicating that higher variability in self-esteem is associated with poorer mental health; Geukes et al., 2017) and recent research on the association between students' traits in terms of their Big Five personality traits and variability in state ASC (Hausen et al., 2022). Hausen et al. (2022) found greater variability in state gASC among students reporting higher depression (as a facet of Big Five's negative emotionality). In accordance with these previous findings, we suggest that higher short-term stability in state ASC among students with higher trait domain-specific interest reflects a form of resilience and is indicative of more adaptive psychological functioning. Students who are more interested in a subject (i.e., mathematics) are likely to engage more consistently with the material taught at school. This can lead to a more stable self-concept as they regularly validate their understanding of this subject. Further, as academic interest has been shown to be associated with positive emotions toward the subject, higher interest in a subject could promote positive emotions (see, e.g., Pekrun, 2023), which facilitates more positive performance feedback (while buffering negative feedback), for instance, through social, temporal, or dimensional comparison processes (see Möller et al., 2011; Niepel et al., 2014; Wolff et al., 2021). Finally, students who are intrinsically motivated in a subject are arguably more resilient to external factors that may fluctuate from lesson to lesson, promoting a more stable state self-concept. Future experience-sampling research is indicated here to examine such intraindividual mechanisms.

Trait ASC Is Related to Mean-Level State ASC

Our study has shown that ASC and aggregated state ASC correlate significantly (and thus provide evidence for convergent validity), but this correlation is far from perfect.[8] If state ASC is aggregated over a longer period of time, it should conceptually approximate trait ASC (Pekrun, 1988; Rauthmann et al., 2019). However, the time period examined here is far too short to reasonably assume that the aggregated state ASC corresponds to the trait ASC.

Our findings indicate that students with a stronger habitual perception of their own ability also perceive themselves as more competent on a situational level in daily school life, regardless of their levels of trait TA, trait interest, school grades, reasoning ability, or gender.

[8] Please note that the correlation between trait gASC and aggregated state gASC was already reported in Hausen et al. (2022) albeit based on a slightly different sample size. The results for trait MSC and aggregated state MSC have not been previously reported in any article.

Table 6
Mixed-Effects Location Scale Models: Model Fit

Model	State general-school ASC			Model	State mathematics self-concept		
	AIC	BIC	−2loglikelihood		AIC	BIC	−2loglikelihood
Null model	4,056	4,081	4,042	Null model	2,708	2,732	2,694
gASC 1	4,087	4,238	4,001	MSC 1	2,862	2,724	2,642
gASC 2	4,084	4,235	3,998	MSC 2	2,698	2,837	2,616
gASC 3	4,057	4,208	3,971	MSC 3	2,600	2,738	2,518
gASC 4	4,018	4,169	3,932	MSC 4	2,552	2,690	2,470
gASC 5	4,016	4,188	3,918	MSC 5	2,302	2,470	2,200
gASC 6	3,590	3,781	3,480	MSC 6	2,533	2,684	2,443

Note. ASC = academic self-concept; AIC = Akaike information criterion; BIC = Bayesian information criterion; gASC = general-school ASC; MSC = mathematics self-concept.

This holds true for both the general-school and mathematics-specific level of analysis. We did not find trait ASC to be related to between-person differences in within-person variability in state ASC, when controlling for shared variances with GPA, reasoning ability, and gender at the between-level, and mean-level state ASC at the within-level. An observed link between trait gASC and state gASC variability disappeared after the analyses included the control variables. On the intraindividual level, however, we found that within-person variability in state ASC was negatively related to mean-level state ASC. This suggests that students with a higher mean level in situation-specific perceptions of their own abilities tend to perceive less short-term variability in their state ASC. However, at the same time (controlling for this within-person relation), students with stronger habitual perceptions of their own abilities (trait ASC) are not more likely to exhibit (more or) less variability in their daily ability perceptions (state ASC) than their peers with comparably weaker trait ASC. Accordingly, students seem to rate their academic abilities as higher (or lower) from lesson to lesson, regardless of whether they habitually report higher or lower levels in trait ASC. This aligns with our observation that students' school grades (school grades are typically closely linked to ASC; Möller et al., 2020) do not appear to be associated with lower (or higher) short-term variability in state ASC.

TA and State ASC

TA (i.e., worry and emotionality), which reflects the value aspect of costs in the situated expectancy-value theory (Eccles, 2009; Wigfield et al., 2015), seems to play a comparably less important role than interest (reflecting the value aspect of intrinsic value) and trait ASC (reflecting expectancy) when it comes to everyday state ASC formation. Trait TA was not statistically significantly related to the level of state ASC beyond trait interest and trait ASC. Trait ASC interacts with specific situations, directly affecting state self-concepts. These trait manifestations in states (Asendorpf & Rauthmann, 2020) create continuity between who we think we are overall and how we see ourselves at any given time. Trait interest draws students' attention to specific tasks (Renninger & Hidi, 2011). For example, suppose students are interested in a topic. In that case, they will likely feel more connected to the activity of learning about it, reinforcing their state self-concept as a competent person in that situation. In contrast, high levels of trait TA might divert students' attention from the momentary learning activity in class; students think less about their competence in that specific situation than about their past failures in other situations. Our results suggest that trait ASC and trait interest help build a coherent state self-concept, while trait TA tends to disrupt this daily integration.

We know from previous educational–psychological research that it is important to note that investigations of mathematics anxiety as a trait versus as a state can yield diverging results (Goetz et al., 2013). Accordingly, future research should examine the dynamic interplay between self-concept, interest, and TA simultaneously at the trait and state levels.

In solely focusing on the relations between the TA facets of worry and emotionality on the one hand and state ASC on the other, we found some interesting findings that can add to TA theory and research. Specifically, we found emotionality to be descriptively stronger related to state ASC than worry (across both levels of specificity, i.e., for state gASC and state MSC). This result joins previous research findings focusing on the relation between TA and ASC as traits that point in a similar direction (Schneider et al., 2022; see also Raufelder & Ringeisen, 2016). Hence, the present study suggests that the TA facets of worry and emotionality have differing functional relations to students' state ASC, which underscores the importance of differentiating the two TA facets in future research on TA and/or the relation between TA and (state) ASC (see also Dowker et al., 2016). As Raufelder and Ringeisen (2016) highlighted, the relation between the TA facet worry and ASC may be moderated by students' cognitive ability and mediated by their academic achievement. When students worry about upcoming tests, those with higher cognitive ability might adjust their learning strategies and ultimately perform better, leading to a higher ASC (see the introductory part). However, further research is needed to test this assumption.

Level of Domain Specificity: General-School Versus Mathematics-Specific

In previous research, TA, interest, and ASC have been operationalized on different levels of domain specificity—typically at the level of school in general (e.g., "I am good at school") and at the domain-specific level (e.g., "I am good at math"). We focused on school in general as well as on the domain of mathematics. Overall, we observed our findings to be more pronounced (more statistically significant results with descriptively stronger effect sizes) when analyzing the mathematics-specific rather than general-school measures. This finding is in line with the specificity-matching principle (Brunswick, 1952; Swann et al., 2007), which states that the better the match between the predictor variables and the criterion is in terms of breadth and generality, and the more specific the level of analysis is, the more substantial the observed predictor–criterion relations should be (see, e.g., Marsh, 2023).

Further Findings

We found female students to report comparably lower levels of state ASC (i.e., gASC and MSC) than male students. For state MSC, this finding is in line with trait-based research (e.g., Niepel et al., 2019). For state gASC, the statistical effect for gender was descriptively stronger than for state MSC in our main analyses. On a bivariate level, however, we found a descriptively stronger correlation between gender and MSC than between gender and gASC. Thus, this finding can probably be attributed to shared variances between the included predictors.

Regarding the observed between-person differences in the within-person variability in state ASC, we had not formulated any expectations regarding our covariates due to the novelty of our approach. Surprisingly, we found that reasoning ability was significantly associated with short-term variability in gASC. However, this pattern only emerged in our general-school analyses and was not significantly different from zero in our mathematics-specific analyses. Since this pattern did not emerge at the bivariate level, we had not formulated a priori expectations, and this pattern was not consistent across both levels of domain specificity, we are reluctant to elaborate on this finding further. Further investigations are required to determine whether this result can be confirmed in replication studies.

Limitations

We examined trait measures that were assessed prior to the experience-sampling data collection and analyzed them as statistical predictors of state measures' mean level and variability. However, causal inferences regarding the examined variables cannot be drawn based on the presented findings, and implicit causal interpretations should be made with appropriate caution (Grosz et al., 2020). Future research should examine interest, TA, and ASC at the state level (see Moeller et al., 2022) to gain a more comprehensive picture of intraindividual and short-term mechanisms and potential reciprocal relations from one lesson to another (as trait-based research has found reciprocal relations between TA and ASC as well as between interest and ASC; see, e.g., Ahmed et al., 2012; Marsh et al., 2005).

Our study was among the first to examine intraindividual variability in state ASC, and we found interest to be significantly related to variability in ASC when focusing on a specific domain rather than on school in general only (as discussed earlier). As our study on the variability of state ASC was exploratory due to its novelty, the present study lays only the groundwork, and further replication studies are indicated here.

Female students were slightly overrepresented in our examined sample (in comparison to data from the Federal Statistical Office of Germany; Statistisches Bundesamt, 2021). However, we controlled for potential gender effects in our main analyses and accordingly reported and discussed statistical associations among the examined variables that were statistically independent of gender. Future research is needed to independently replicate our findings and test their generalizability to different student populations in different educational systems, school types, and age groups (to name a few).

Implications and Conclusion

By adding a state and short-term perspective, we extended existing expectancy-value theory and research, and, in particular, existing ASC theory and research that have been extensively focusing on ASC on a trait level (for an overview, see Eccles & Wigfield, 2020; Marsh, Seaton, et al., 2019) while neglecting students' momentary state ASC. Our study suggests that future research should consider the known debilitating effects of lower levels of ASC (e.g., Marsh, Seaton, et al., 2019) while also focusing on the potential vulnerability that goes along with greater short-term variability in state ASC. Previous research provided initial evidence (Hausen et al., 2022) that a more stable self-concept over a short period of time might be regarded as an indicator of adaptive psychological functioning. As such, a more stable short-term state self-concept could be linked to greater resilience to everyday school difficulties, enabling students to successfully navigate their school careers. As an important and novel finding, our results indicate that fostering academic interest in a particular subject tends to enable not only a higher but also a more stable short-term state ASC with regard to the same subject. The present study highlights the importance of promoting students' interests. We know from previous research that practitioners can promote learners' interest through stimulating teaching methods, real-life applications of the material covered, and novel and challenging activities and tasks (e.g., Belland et al., 2013; Renninger & Hidi, 2011; Wigfield et al., 2014). In terms of research, as has frequently been found in trait-based research on motivational–affective variables, especially in trait-based ASC research (Marsh, 2023), researchers should ideally match the breadth and specificity of the predictor and outcome variable to gain a more accurate picture of the interrelations and potential causal pathways of the variables of interest. Furthermore, the present research findings emphasize the need for future studies using experience sampling to investigate intraindividual, short-term adaptive mechanisms, such as those derived from the situated expectancy-value theory (Eccles, 2009; Wigfield et al., 2020) and other frameworks (e.g., Pekrun, 2006), to augment our understanding of academic motivation and self-regulation in everyday school life.

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