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Multimodally assessed adaptive reactions to errors in primary school students and their relation to knowledge acquisition

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ABSTRACT

It has been widely recognized in educational research that, if addressed appropriately, errors can promote learning. Adaptive reactions to errors—including affective-motivational and action-related reactions—have been proposed to capture such adequate adjustments of affect and behavior to regulate learning processes. However, prior research addressing reactions to errors has left primary school students underrepresented. At the same time, findings from assessments beyond self-reported data are still sparse. Therefore, we multimodally assessed adaptive reactions to errors in an authentic learning situation within a digital mathematics learning environment. In a sample of 284 third-grade students, we found a positive relation between self-reported adaptive affective-motivational reactions to errors, as well as the corresponding behavioral indicator, and knowledge acquisition. For action-related reactions to errors, only the behavioral indicator was related to knowledge acquisition. These results highlight the relevance of adaptive reactions to error for primary school students while emphasizing the necessity of multimodal assessment.

Educational relevance statement: The results show that adaptive reactions to errors, including adaptive affective-motivational and action-related reactions to errors, positively relate to knowledge acquisition in primary school students. To fully understand their impact, multimodal assessment appears to be necessary. Therefore, teachers should take students' reports and behaviors into account while adopting a constructive approach to addressing errors in their classrooms.

1. Introduction

Self-regulated learning (SRL) is widely recognized as a critical contributor to academic success, with numerous studies highlighting the positive effects of SRL, particularly through metacognitive and motivational regulation (e.g., de Bruijn-Smolders et al., 2016; Jansen et al., 2019; Song et al., 2016; Wang & Sperling, 2020). The process of SRL is often described as cyclical, involving phases of planning (preactional), active engagement and monitoring (actional), and reflection and adjustment (postactional; Schmitz & Wiese, 2006), underlining the specific importance of how learners react and reflect on their learning, both in a behavioral but also in an emotional and motivational way (see e.g., Pintrich, 2000). This is especially the case when learners encounter challenges that require targeted responses (i.e., when errors, an inevitable part of any learning process, occur). Errors can be defined as behaviors that unintentionally deviate from a norm and prevent the achievement of a specific goal or meeting a certain criterion (Zhao & Olivera, 2006). Consequently, they are often perceived as negative or demotivating, even though they can play a crucial role in fostering learning processes when addressed appropriately (Metcalfe, 2017). Nevertheless, our understanding of the cognitive, motivational, and behavioral processes required for learners to benefit from the errors they make while learning is still at an elementary stage, and this knowledge gap appears to be particularly prevalent among young learners (see also Grassinger & Dresel, 2017).

Errors have the potential to reveal knowledge deficits or misconceptions (Zhang & Fiorella, 2023; Zhao, 2011) and thereby guide future learning and support self-evaluation and regulation of the

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learning process. From errors, learners not only gain insight into what they already know but also into what does not work (i.e., negative knowledge; Oser & Spychiger, 2005). How learners perceive their errors and whether they regard them as personal failure depends, among other things, on their level of aspiration. Given that failure can be described as the more global inability to reach personal goals (Zhao & Olivera, 2006), not all errors actually lead to failure. Drawing on that consideration, learners have to adaptively regulate their affective-motivational state as well as their concrete behavior following errors to be able to reach aspired knowledge gains.

1.1. Two components of adaptive reactions to errors

Adaptive reactions to errors—such as modifying one's strategy, focus, or motivation after committing an error—have been shown to be essential in learning from errors (Grassinger & Dresel, 2017; Grassinger et al., 2018). Adaptive reactions to errors allow learners to intentionally adjust their affect and behavior in response to errors, thus improving their understanding and performance. Based on theoretical considerations about the process of individual reactions to and learning from errors proposed by Tulis et al. (2016), research has highlighted that when learners adaptively react to (known) errors, two distinct types of reactions can be distinguished: adaptive affective-motivational reactions to errors and the adaptation of behavior and metacognitive activities (i.e., adaptive action-related reactions to errors; Dresel et al., 2013). While adaptive affective-motivational and adaptive action-related reactions to errors can be conceptualized as two separable factors, they remain intercorrelated at the same time (e.g., Grassinger & Dresel, 2017).

Adaptive affective-motivational reactions to errors refer to maintaining positive emotions (e.g., enjoyment) and motivation, as well as regulating negative emotions (e.g., shame) and motivationally relevant cognitions (e.g., self-doubt), once errors have occurred (Dresel et al., 2013). These emotional and motivational processes are triggered by an initial, most of the time rather vague, reaction to an error, followed by a deeper secondary appraisal process (Tulis et al., 2016). The quality of the reactions can be expected to depend on, among other things, learners' knowledge and expectations (Tulis et al., 2016) as well as the subjective interpretation of reasons for errors (see e.g., Stiensmeier-Pelster & Heckhausen, 2018; Weiner, 1985). Therefore, affective-motivational reactions to errors also reflect the learner's current level of motivation and, as a result, can influence and guide subsequent learning behavior (Tulis et al., 2016).

Adaptive action-related reactions to errors refer to intentional actions such as reflecting on one's own understanding, analyzing errors, and planning or executing specific strategies to improve learning, including additional practice. These responses represent purposeful efforts to learn from errors (Dresel et al., 2013). Such behaviors are characteristic of a highly self-regulated learner. They may occur during the actional phase of a learning task—through real-time adjustments, e.g., by repeating learning content after discovering a misconception—or in the postactional phase after the task has been completed, as part of a reflective process that informs future learning activities. Consequently, adaptive action-related reactions to errors can also be part of the preactional planning phase of the following learning cycle (see Schmitz & Wiese, 2006).

Overall, adaptive action-related reactions to errors include analyzing potential reasons for errors, selecting suitable corrective methods, reassessing one's conceptual understanding, modifying present learning practices, and proactively designing future steps to resolve the issue (Dresel et al., 2013). However, it is important to note that students do not always engage with errors constructively. Reactions to errors can also be maladaptive in quality, often characterized by frustration, hopelessness, defensive insistence on incorrect answers, or a withdrawal from learning activities (Donaldson et al., 2025; Reindl et al., 2020). Whether students demonstrate such maladaptive patterns or react more adaptively to errors can depend on gender (Burmeister et al., 2024; Spear et al., 2025); hence, controlling for gender differences in studies investigating adaptive reactions to errors is advised.

1.2. Learning from adaptive reactions to errors

Despite growing interest, there remains limited research on how adaptive reactions to errors specifically impact the learning process and, subsequently, learning outcomes. Learning outcomes can include performance in specific learning tasks, academic performance overall, or, on a more general level, knowledge acquisition. Although theoretical models propose that adaptive reactions to errors can facilitate a more effective use of cognitive learning strategies (Chouvalova et al., 2024), enjoyment (Schrader & Grassinger, 2021), the willingness to work on errors (Tulis & Dresel, 2025), as well as knowledge acquisition directly (Tulis et al., 2016), empirical evidence still remains scarce. On a differentiated level, a longitudinal study by Grassinger et al. (2018), involving secondary school students in the subjects German, English (as a second language), and mathematics, showed that adaptive action-related reactions to errors were positively associated with academic performance. In contrast, adaptive affective-motivational reactions to errors only demonstrated indirect effects on academic performance via adaptive action-related reactions to errors. In a study with Italian secondary school students, these results were replicated; however, adaptive affective-motivational reactions to errors also revealed significant direct associations with academic performance (Soncini et al., 2022). Notably, in these studies, performance was measured via school grades, which can depend on many factors in addition to knowledge acquisition through adaptive reactions to errors. To explore more immediate effects on knowledge, a recent study (Spear et al., 2024) investigated how adaptive action-related reactions to errors can directly affect knowledge acquisition in a learning environment with psychological content. In contrast to the studies by Grassinger et al. (2018) and Soncini et al. (2022), the sample consisted of undergraduate university students. The findings revealed moderate improvements in knowledge after engaging in adaptive action-related reactions to errors.

While the aforementioned studies offer valuable insights, they largely center on secondary and post-secondary students, leaving primary school populations underrepresented in this area of research. Although adaptive affective-motivational and adaptive action-related reactions to errors are already distinguishable in this age group (see Spear et al., 2025), it remains to be empirically established whether they are similarly relevant for knowledge acquisition. This seems to be a particularly noticeable research gap, as it can be expected that children's self-regulatory behavior changes significantly during primary school. Research suggests that those changes in self-regulation are rather quantitative in nature (Zachariou & Whitebread, 2019), while also indicating big improvements in metacognitive abilities during this time period (Roebers & Spiess, 2017). Student motivation, on the other hand, frequently declines throughout primary school (Spinath & Spinath, 2005), which may also influence how primary school students react to errors. Lastly, it has to be stated that existing research has mostly focused on distal learning outcomes (e.g., Soncini et al., 2022), while only one study has investigated the immediate knowledge effects of adaptive reactions to errors, focusing specifically on adaptive action-related reactions, without including adaptive affective-motivational reactions in its study design (Spear et al., 2024; see also Dresel et al., 2013; Grassinger & Dresel, 2017).

1.3. Multimodal assessment of reactions to errors

A considerable amount of existing research on adaptive reactions to errors has relied on self-report indicators (e.g., Grassinger et al., 2018; Käfer et al., 2019), often including self-report questionnaires, instructing participants to rate their agreement to pre-formulated statements about potential reactions to errors on a Likert scale (e.g., Dresel et al., 2013).

While self-reports offer valuable access to learners' internal cognitive and emotional processes, they come with inherent limitations—especially when data is collected from children. Compared to adults, children are generally considered less capable of providing consistent, reliable, and valid self-assessments, partly due to their still-developing metacognitive and reflective abilities (Conijn et al., 2020), which could, for example, lead to overestimating their abilities (see Bouffard et al., 2011). Nevertheless, it is widely recognized that children's self-reports can still yield meaningful insights into their learning experiences and should not be dismissed outright (Sturgess et al., 2002). This is also the case for children's self-reports of their reactions to errors (Spear et al., 2025). To mitigate the methodological weaknesses of self-reports while retaining their benefits, researchers have increasingly emphasized the need for multimodal assessment strategies (Winne, 2010). These approaches can, for example, combine subjective perspectives with more objective behavioral indicators, allowing for a more comprehensive and nuanced understanding of learning processes (see e.g., Bernacki et al., 2025; D'Mello et al., 2009).

One particularly promising avenue involves the use of digital learning environments, which enable the collection of behavioral trace data—such as response times or interaction patterns—during digital learning tasks (Cleary & Russo, 2024). This enables researchers to collect a large amount of data that directly reflects learners' behavior as well as the quality of their performance in specific learning tasks. Potential examples include the number of completed learning tasks, task repetition, or correctly solved tasks. Given the above-mentioned limitations of self-report indicators (Conijn et al., 2020), behavioral trace data seems to offer an especially valid approach for measuring adaptive action-related reactions to errors in children. Adaptive action-related reactions to errors can, for example, be operationalized as the willingness to restudy a task in which the learner committed an error. Such a "restudy index" may be considered a potential direct indicator of constructive reactions to errors and has already been successfully implemented in another study, in which it was highly correlated with (university students') learning success and also closely related to self-reported adaptive action-related reactions to errors (Spear et al., 2024).

In addition, facial readers (see e.g., Lewinski et al., 2014) or other methods for recording and coding learners' facial expressions or behavioral (body) reactions in general can be considered a valid indicator of learners' emotional states (see D'Mello et al., 2009). Different facial expressions can be detected and distinguished from one another (e.g., Ekman & Friesen, 1978) and are presumed to reflect the learner's affect, especially in younger children (e.g., Berhenke et al., 2011). When considering adaptive affective-motivational reactions to errors, some prior studies have indicated that positive emotions positively affect learning achievement by strengthening motivation and improving learning processes (Pekrun et al., 2002; Pekrun et al., 2017). In contrast, negative emotions can negatively affect accuracy in problem solving tasks (Merrick & Fyfe, 2023). Nevertheless, there are also indications that the relation between positive emotions and learning achievement might in fact be a little more complicated and that positive emotions can, in some cases, also be negative for learning outcomes (Merrick & Fyfe, 2023). In addition, such counterintuitive effects might also be possible for negative emotions, as one might argue that, when it comes to reactions to errors, negative emotions may be the more "natural" reaction and could even lead to a motivational boost. What seems clear is that an initial negative affective reaction to an error that quickly neutralizes or turns positive, either through intentional emotion regulation or other more passive processes, would be considered adaptive (see e.g., Tulis et al., 2016). On the other hand, a sustained or long-lasting negative reaction may reflect deficient emotion regulation, while a positive reaction to an error could reflect a lack of motivation in terms of task value, among other possibilities (see e.g., Reindl et al., 2020). Overall, integrating such different data sources can help triangulate findings, enhance validity, and provide deeper insights into how learners adapt to errors.

Despite the multiple advantages of multimodal and behavioral measurement, especially in young respondents, research using such data in the context of adaptive reactions to errors remains scarce. While automatically assessed facial expressions have been brought into relation with general academic achievement in university students (Miao et al., 2026), to our knowledge, only one study to date measured primary school students' human-coded affective reactions to errors (or, more precisely, corrective feedback) using their facial expressions, as well as tone of voice and verbal statements, showing higher negative affect to be associated with less favourable learning behavior (Merrick & Fyfe, 2023). It should also be noted that both adaptive affective-motivational as well as adaptive action-related reactions to errors represent rather comprehensive constructs and therefore are unlikely to be fully captured by a single behavioral measure. While self-report measures generally aim at encompassing the full range of adaptive reactions to errors, behavioral indicators tend to provide more fine-grained assessments of specific aspects. Therefore, different behavioral operationalizations often only capture some specific aspects of respective reactions to errors and, therefore, have to be chosen theoretically grounded and only interpreted within their intended scope.

1.4. The present study

The present study adds to existing research in two key ways. First, by taking a closer look at primary school students' reactions to errors. This is a still largely neglected population group in this area of research that needs to be further studied because of significant metacognitive and motivational changes during this period. Second, by applying informative yet rarely used multimodal data that can deepen our understanding of adaptive reactions to errors (e.g., in terms of the relationship between affect and behavior) and provide guidance for future studies on measurement options.

Addressing the aforementioned research gaps, the present study applies and extends a paradigm originally developed with undergraduates (Spear et al., 2024) to an authentic classroom setting with younger primary school students, while also adapting the digital learning environment and content to the needs of these students. As a result, both action-related and affective-motivational reactions to errors were assessed multimodally, via self-reports as well as behavioral indicators. The measures for the behavioral indicators were derived from the digital learning environment, including video data (measuring adaptive affective-motivational reactions to errors) as well as trace data (measuring adaptive action-related reactions to errors). Taking advantage of this multimodal approach, it is analyzed whether primary school students' self-reports relate to their knowledge acquisition, whether behavioral indicators (i.e., measured through video and trace data) relate to their knowledge acquisition, and whether the inclusion of behavioral indicators can add to the informative value of self-reports. Consequently, we tested the following hypotheses:

Hypothesis 1. Primary school students' self-reports of their affective-motivational and action-related reactions to errors positively relate to their knowledge acquisition.

Hypothesis 2. Primary school students' behaviorally assessed affective-motivational and action-related reactions to errors positively relate to their knowledge acquisition.

Hypothesis 3. Behavioral indicators of affective-motivational and action-related reactions to errors add to the informative value of self-reports of affective-motivational and action-related reactions to errors when predicting knowledge acquisition.

2. Methods

2.1. Procedure

Primary schools were recruited by sending invitation letters and information sheets to the principals of regional schools, who then forwarded these materials to teachers interested in the study. Teachers of third-grade classrooms could freely decide whether or not to participate. Student participation was voluntary, and parental permission was required. The study was approved by the ethics committee of the University of Education Weingarten and the regional government. Data collection was carried out in a group setting directly in primary school classrooms. The students began the assessment with a prior knowledge test. Upon completing the test, students independently worked in a digital learning environment. Afterward, students responded to a questionnaire in which they retrospectively reported their approach to handling errors during the digital learning environment and completed a knowledge test. The entire study was situated in mathematics as this subject offers the advantage of a clear and objective criterion for the (in) correctness of responses in contrast to subjects that are typically tested via more open-ended text format questions, such as reading comprehension, and is therefore particularly well-suited for error research.

2.2. Materials and measures

2.2.1. Digital learning environment

The digital learning environment consisting of mathematical learning content was programmed using PsychoPy (Version: 2024.2.4; Peirce, 2019) and hosted online via www.pavlovia.org (Bridges et al., 2020). The students accessed this digital learning environment with tablet computers (Microsoft Surface Pro 4) and headphones (TIMIO children's headphones). The digital learning environment included four chapters, each consisting of an audio-visually presented learning phase with instructions and exemplary calculations (dealing with measurement units, addition, subtraction, and division) and five chapter-specific test items (the items and their item difficulties are available in the Supplementary Materials). The learning content and test items were developed in consultation with primary school teachers to warrant correct and appropriate presentation and difficulty. We aimed at providing test items of various difficulties in order to ensure a high likelihood of errors while still representing a realistic learning scenario with easily solvable items in between. After each test item, students received immediate feedback indicating solely whether their response was correct or incorrect without any additional information (“Your answer was correct/wrong”). During this item feedback, short videos of the child's reaction were recorded via the tablet computer's integrated video camera. Videos were only recorded for those whose parents expressly consented to this. At the end of each chapter, students additionally received a summarizing feedback regarding all test items of the previous chapter. Here, each test item was listed again with a statement indicating the (in)correctness of each answer. Thereupon, students could decide whether they wanted to move on to the next chapter or if they would like to repeat the previous chapter. When repeating a chapter, students had the opportunity to revise the learning content as well as reattempt the test items they had previously answered incorrectly. Previously correctly answered test items reappeared with the correct answer already presented and the instruction that no further response was required. A visual illustration of the digital learning environment's structure, including the presentation of the feedback, can be found in Fig. 1. In order to carry out this investigation as a field study directly in classrooms, it was necessary to adhere to a fixed time schedule. Therefore, all students worked for 30 minutes in the digital learning environment. As learning pace and performance levels are particularly heterogeneous in primary school classrooms, it was not feasible for all students to complete the digital learning environment. Therefore, students were explicitly instructed that completing the digital learning environment within the given timeframe was not required; instead, they were encouraged to prioritize effective learning. On average, students completed 2.85 chapters (Range: 1–4 chapters) and received 5.04 error feedbacks (Range: 1–18).

2.2.2. Knowledge tests

Prior mathematics knowledge was assessed using subscales of the DEMAT 2+ (Krajewski et al., 2020). These subscales were chosen with a total of 26 items to cover the four aforementioned topics of the subsequent learning environment and demonstrated very good internal consistency with α = .92. The prior knowledge score represents the sum of correct responses. The mathematics knowledge test at the end of the assessment consisted of 12 researcher-developed items covering the learning content of the digital learning environment, with 3 items related to each chapter (all items can be found in the Supplementary Materials). To ensure validity (utilizing validity evidence based on test content), the items were structured similarly to those used in the digital learning environment but were not identical. This enabled us to assess conceptual learning during the digital learning phase rather than mere memorization of item content. All students were administered the whole test; however, we calculated an individual knowledge score for each child in which only a subset of items, based on each student's number of completed chapters, was included. This procedure accounts for the varying number of completed chapters between the students within the given timeframe. Items that comprised the content of a completed chapter were weighted with 1, and items representing the content of uncompleted chapters were weighted with 0. The scores represent the proportion of correctly solved items to ensure comparability between students. The mathematics knowledge test's validity is also evidenced based on relations to other variables, namely a sufficient association of *r*

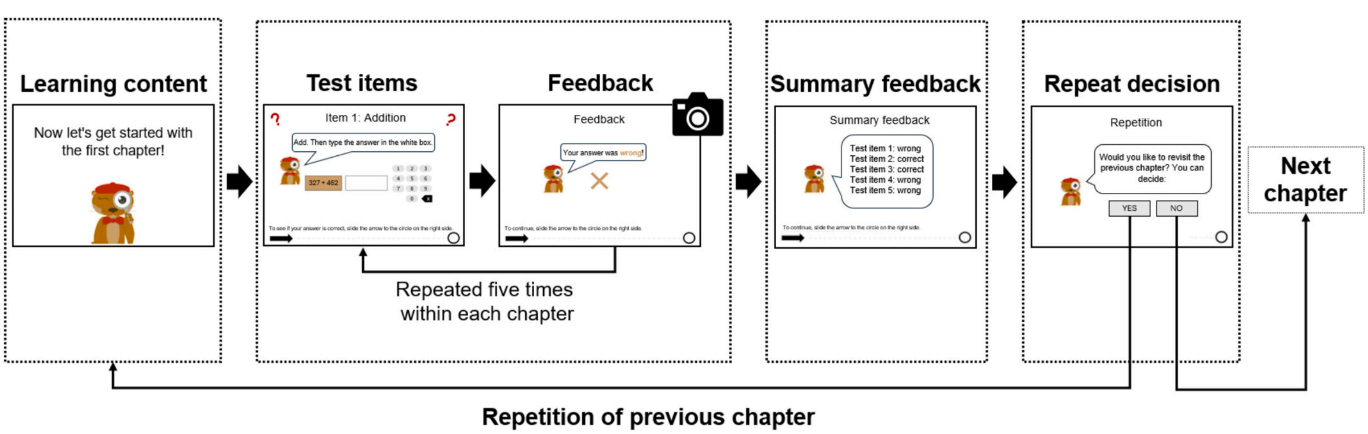

Fig. 1. Illustration of the structure of each chapter of the digital learning environment.

= .40 ($p < .001$) with the well-validated prior knowledge mathematics test and a correlation of $r = -.44$ ($p < .001$) with previous mathematics grades (higher numbers represent worse performance in German school grades). We calculated the internal consistencies for this test separately for each possible combination of included items (i.e., 1, 2, 3, or 4 chapters), which were all in an acceptable range (α = .79–.82).

2.2.3. Self-reported indicators

Adaptive reactions to errors were assessed via a self-report measure specifically developed to capture adaptive reactions to errors in primary school students (Spear et al., 2025). The wording of the items was set in a way to always refer to errors in the digital learning environment completed previously. The scale includes two subscales, one assessing adaptive affective-motivational reactions to errors with 5 items (e.g., "When I made an error during the digital learning program, I enjoyed learning just as much") and one assessing adaptive action-related reactions to errors with 7 items (e.g., "When I did something wrong during the digital learning environment, I tried to understand why I made the error"). All items were answered on a 6-point Likert scale ranging from 1 ("I strongly disagree") to 6 ("I strongly agree"). All items can be found in the Supplementary Materials. Both subscales demonstrated very good internal consistencies with α = .94 for adaptive affective-motivational and α = .91 for adaptive action-related reactions to errors.

Evidence for the validity of the self-reported reactions to errors stems from analyzing their internal structure. The found correlation of $r = .51$ between the two subscales is in the range of earlier findings and underscores the conceptualization as separable although positively associated dimensions (an additionally conducted confirmatory factor analysis revealed a significantly better model fit for a two-factor model in comparison to a one-factor model; details can be obtained from the Supplementary Materials).

2.2.4. Behavioral indicators

To add to the self-reported indicators, adaptive reactions to errors were also assessed via behavioral indicators that were chosen as approximations of complex behavior, always focusing on a central aspect of the construct to be measured. This multimodal approach allows for a deeper understanding, while compensating for some deficiencies of single indicators.

2.2.4.1. Emotion regulation index. As a behavioral indicator of adaptive affective-motivational reactions to errors, we derived a variable from the children's immediate affective reactions to error feedback recorded via short videos. Videos were excluded from the analysis if the child's face—from forehead to bottom lip—was not clearly visible, if the eyes or mouth were obscured (e.g., by the child's hands), if poor lighting prevented clear visibility, or if the child was not working independently during the video (e.g., interacting with a research assistant). In total, 1154 videos of error feedback situations were recorded, of which 778 videos passed the exclusion criteria and were therefore coded as well as included in the analysis. Video data were explored using NOVA (Baur et al., 2020) and features were extracted using DISCOVER (Hallmen et al., 2025). Together, they form a multimodal analysis framework that supports the synchronized annotation and automated analysis of social and affective signals in audio-visual data. DISCOVER integrates state-of-the-art machine learning models to extract behavioral cues such as facial expressions, gaze, and vocal characteristics, and is widely used in affective computing and psychotherapy research (Terhürne et al., 2022). In the present study, automatic facial expression analysis was used to derive continuous estimates of valence. Specifically, valence was computed using EmoNet (Toisoul et al., 2021), a deep neural network trained on the large-scale in-the-wild dataset AffectNet (Mollahosseini et al., 2019), which provides frame-level valence scores enabling temporal analyses of affective dynamics.

For each video, individual frames (25 frames per second) were analyzed as still images to obtain corresponding valence values from −1 to 1. In order to reduce the influence of random extreme deviations from frame to frame, these values were smoothed (using the R package *modelbased*; Makowski et al., 2025) before further analysis. For our emotion regulation index, we aimed to identify videos that contained evidence of positive regulation. This is operationalized as a positive cumulative change in valence of more than 0.25 within the video. It is important to note that this does not guarantee that the valence changed from negative to positive; it could denote a change from negative to neutral, or from neutral to positive. Further, a positive change in facially expressed valence does not necessarily reflect intentional or conscious emotion regulation strategies being enacted; this could also be the result of the emotion passively fading. Nevertheless, we selected the label emotion regulation index because it most intuitively reflects one possible interpretation of the index. The value of 0.25 was determined based on visual inspection of a subset of 50 randomly selected videos (see Supplementary Materials for more details on how this variable was calculated), and each video was labeled as showing evidence of emotion regulation (1) or not (0). We averaged the emotion regulation index across all error feedback videos of each participant.

2.2.4.2. Restudy index. Based on a study from Spear et al. (2024), we utilized the students' decision to restudy a chapter of the digital learning environment as a behavioral indicator of adaptive action-related reactions to errors. This behavioral indicator was selected because revisiting previously studied content after making an error reflects an intentional and adaptive regulation of the learning process. Engaging in such revision and repeated practice constitutes an essential component of adaptive action-related reactions to errors. For this index, we assigned the following values: If a student voluntarily restudied the previous chapter after having made at least one error in the test items, it was coded with 1. In contrast, it was coded with 0 if a student did not restudy the previous chapter after at least one error. This value was assigned for each chapter separately and then averaged across all completed chapters of each student, in which at least one error occurred. Consequently, the restudy index ranged from 0, indicating no adaptive action-related reactions to errors at all, to 1, indicating perfect action-related error adaptivity as every occasion of an error was followed by a repeated processing of previous learning material.

2.3. Participants

To determine an adequate sample size for detecting the hypothesized effects, a Monte Carlo simulation was carried out using the *lavaan* package (Rosseel, 2012). For each considered sample size (200−300), 1000 simulated datasets were generated and re-estimated at α = .05, revealing a sufficient sample size of approximately 250 students to provide at least 80% power for the most complex planned analysis (Multimodal Model; see 2.4 Data analysis for more details) and to detect small-to-medium effects (β = .35) for the predictors of interest, while also including prior knowledge as control. Data was collected from 360 students, of whom only 318 were considered for this study (42 students made no errors in the digital learning environment and are therefore not meaningful in analyzing reactions to errors). However, several students had to be excluded for various other reasons. Two children were excluded because they did not finish at least one chapter of the digital learning environment, and 4 students were excluded because they were not able to engage with the digital learning environment without external support from teachers. An additional 20 students were excluded because of signs of non-compliance indicated by high item non-response during the digital learning phase. Given that the study was conducted in an authentic classroom setting without strict laboratory conditions, students had the opportunity to leave test items unanswered during the digital learning environment. However, to ensure that findings reflect genuine engagement with the learning environment, we consider this exclusion criterion necessary. Following the standard boxplot rule (values exceeding Q3 + 1.5 × IQR), students with more than 25% non-response to test items in the digital learning environment were considered statistical outliers in our sample and therefore excluded. Another 8 students were not included in the analysis because either the data from the digital learning environment could not be matched to the questionnaire data (because of participant code errors) or due to technical errors during the data saving process of the digital learning environment. Therefore, the final sample consisted of 284 students (68% of whom additionally consented to video recordings) from 21 third-grade classrooms from 6 primary schools in Bavaria, Germany, which slightly exceeded our targeted sample size. The average age was 10.0 years ($SD = 0.74$), with girls comprising 51% of the sample. The average mathematics grade in the last school report was 2.2, which is classified as "Good to Satisfactory" in the German school system. A migration background, defined as having at least one parent born outside Germany, was reported by 49% of the sample, which is above the regional average of approximately 26%.

2.4. Data analysis

For all analyses, we used R Studio (Version 4.4.1; R Core team, 2024).[1] Missing data occurred quite seldom for the self-reported indicators (no more than 3.5% on the item level). For prior knowledge, less than 1% of students had missing values. Missing data for the emotion regulation index was higher (37.7% of the students), as not all children had additional parental consent for video recordings (32%), and for some students, none of the recorded videos were codable according to the outlined criteria (5.7%). To rule out systematic bias between students with and without video consent, we checked for differences in demographic characteristics and all variables included in this study: prior knowledge ($p = .621$), knowledge ($p = .843$), adaptive affective-motivational reactions to errors ($p = .296$), adaptive action-related reactions to errors ($p = .783$), restudy index ($p = .203$), age ($p = .997$), migration background ($p = .208$), and previous mathematics grades ($p = .383$). Hence, no group differences between the two groups were found. There was no missing data for the restudy index or knowledge score. Missing values were imputed using the Full Information Maximum Likelihood estimation in all analyses (Peugh & Enders, 2004). We performed structural equation modeling using the *lavaan* package and its corresponding *sem*()-function with Maximum Likelihood estimation (Rosseel, 2012). However, in order to account for the nested data structure of students in classrooms, a cluster-robust estimation process was applied. This procedure ensures that standard errors and fit indices are corrected for the non-independence of observations. Confidence intervals were calculated using a bootstrapping procedure with 1000 resamples. Three separate models were calculated: a model including self-reported indicators of adaptive reactions to errors (Self-report Model), a model including behavioral indicators (Behavioral Model), and an integrative model combining both self-reported and behavioral indicators (Multimodal Model). Each model predicted post-test performance (referred to as knowledge) while controlling for pretest performance (referred to as prior knowledge). This relative consideration of knowledge to prior knowledge allows for the interpretation of the effect of different independent variables on knowledge acquisition. Prior knowledge, knowledge, and the behavioral indicators were included as manifest variables while the self-reported indicators were modeled as latent factors—each indicated by two parcels using the Item-to-Construct Balance approach (Little et al., 2002). In order to determine the factor loadings for this parceling approach, we used the *lavaan* package (Rosseel, 2012) with its *cfa*() function. In response to literature demonstrating gender differences in adaptive reactions to errors, we also included gender as an additional control variable in all models, allowing us to derive general statements.

3. Results

3.1. Descriptive results and bivariate correlations

Descriptive results and bivariate correlations can be found in Table 1. As typically observed in young respondents, self-reported adaptive affective-motivational and adaptive action-related reactions to errors were slightly left-skewed. In comparison, both behavioral indicators were slightly right-skewed, suggesting that actual behavior was less positive than indicated by the children's self-reports. Consistent with these descriptive differences, the self-reported and behavioral indicators of adaptive affective-motivational reactions to errors were not correlated. In contrast, the self-reported and behavioral indicators of adaptive action-related reactions to errors demonstrated a small positive correlation.

3.2. Relation of adaptive reactions to errors to knowledge acquisition

The results of estimating the Self-report Model are displayed in Table 2 and Fig. 2. Here, adaptive affective-motivational reactions to errors were significantly related to knowledge acquisition. In contrast, adaptive action-related reactions to errors did not exhibit a relation to knowledge after taking prior knowledge into consideration. In total, 22% of the variance in knowledge could be explained. These findings indicate that students who retrospectively reported having experienced joy and motivation even after the occurrence of an error during the digital learning environment demonstrated greater knowledge gains. This did not apply to students who reported that they had adjusted their learning behavior specifically to address the present error during the digital learning environment. Consequently, the Self-report Model partly supported Hypothesis 1 with adaptive affective-motivational reactions to errors significantly relating to knowledge acquisition, but not adaptive action-related reactions to errors.

In the Behavioral Model (see Table 2 and Fig. 3), in contrast, both indicators contributed to explaining knowledge acquisition. The emotion regulation index, as a behavioral indicator of adaptive affective-motivational reactions to errors, as well as the restudy index, as a behavioral indicator of adaptive action-related reactions to errors, were significantly related to knowledge, even when taking individual prior knowledge and gender into account. In this model, a similar amount of variance in knowledge (25%) was explained as in the Self-report Model. These findings indicate that both effective emotion regulation and the adaptive adjustment of the learning process in terms of repeatedly processing prior learning material significantly relate to knowledge acquisition. Consequently, Hypothesis 2 was fully supported. Since all variables were allowed to covary freely, the model was fully saturated, resulting in zero degrees of freedom. As the observed and model-implied covariance matrices are identical in such cases, global fit indices are not informative and therefore not reported.

The results of simultaneously including self-reported and behavioral indicators of adaptive reactions to errors in the Multimodal Model can be found in Table 2 and Fig. 4. The result pattern remained the same as in the models investigating self-reported and behavioral indicators separately. Self-reported adaptive affective-motivational reactions to errors were significantly related to knowledge acquisition, as well as the corresponding behavioral indicator. For adaptive action-related reactions to errors, only the behavioral indicator was significantly related to knowledge acquisition, while self-reported adaptive action-related reactions to errors were not. With this integrated model, 29% of the variance in knowledge could be explained, which was slightly more than the variance that was explained by the models only including either self-reported or behavioral indicators. Consequently, Hypothesis 3 was supported as the inclusion of behavioral indicators led to an increased

[1] Data and analytic code can be found in the Open Science Foundation (OSF) repository: https://osf.io/gq73j/

Table 1
Descriptive results and bivariate correlations.

		M (SD)	Range		Skew		(1)	(2)	(3)	(4)	(5)
			Potential	Actual		ICC					
(1)	Self-reported adaptive affective-motivational reactions to errors	4.94 (1.20)	1–6	1–6	−1.39	.06					
(2)	Self-reported adaptive action-related reactions to errors	4.78 (1.10)	1–6	1–6	−1.12	.02	.51**				
(3)	Emotion regulation index	0.19 (0.26)	0–1	0–1	1.54	.00	.05	−.02			
(4)	Restudy index	0.34 (0.42)	0–1	0–1	0.68	.00	–.01	.11*	.02		
(5)	Prior knowledge	20.39 (5.53)	0–26	2–26	−1.46	.09	.27**	.19**	−.08	.04	
(6)	Knowledge	0.64 (0.26)	0–1	0–1	−0.39	.00	.27**	.20**	.17**	.16**	.40**
(7)	Knowledge acquisition						.22**	.14*	.23**	.20**	

Note. $N = 284$. * $p < .050$. ** $p < .010$. ICC = proportion of between-classroom variance on total variance. (7) Knowledge acquisition shows partial correlations of respective variables with knowledge, controlling for prior knowledge.

Table 2
Direct effects, standard errors, and 95% confidence intervals (Bootstrap) for all structural equation models.

	β	*SE*	*p*	CI (95%)
Self-report Model				
Self-reported adaptive affective-motivational reactions to errors	.23	0.018	.003	[.08, ∞]*
Self-reported adaptive action-related reactions to errors	−.02	0.018	.402	[−.18, .14]
Prior knowledge	.39	0.004	<.001	[.27, .51]
Female	.20	0.023	<.001	[−.31, −.10]
Behavioral Model				
Emotion regulation index	.19	0.059	<.001	[.09, ∞]*
Restudy index	.17	0.030	<.001	[.08, ∞]*
Prior knowledge	.44	0.003	<.001	[.32, .55]
Female	.19	0.020	<.001	[−0.29, −.09]
Multimodal Model				
Self-reported adaptive affective-motivational reactions to errors	.23	0.019	.004	[.09, ∞]*
Emotion regulation index	.17	0.057	.001	[.08, ∞]*
Self-reported adaptive action-related reactions to errors	−.03	0.017	.353	[−.18, .13]
Restudy index	.19	0.028	<.001	[.10, ∞]*
Prior knowledge	.39	0.004	<.001	[.27, .52]
Female	.19	0.020	<.001	[−.29, −.08]

Note. Female was coded as 1 = girls and 0 = boys. One-sided 95% confidence intervals and *p*-values are presented for variables demonstrating hypothesized effects (*); otherwise, two-sided 95% confidence intervals and *p*-values are presented.

informative value compared to solely considering self-reported indicators.

4. Discussion

Given SRL's significant role in predicting students' academic success (e.g., de Bruijn-Smolders et al., 2016; Jansen et al., 2019; Song et al., 2016; Wang & Sperling, 2020), this study highlights the importance of reacting adaptively to and learning from errors, a key component of SRL. As a first result, descriptive and correlational results indicated relatively large differences between self-reported and behavioral indicators. This is especially true for adaptive affective-motivational reactions to errors but also holds for adaptive action-related reactions to errors, despite the small association between the self-report and the behavioral indicator. In a second step, structural equation models revealed that both adaptive affective-motivational and action-related reactions to errors related to students' respective mathematics knowledge, even when controlling for prior knowledge. Interestingly, though, while for adaptive affective-motivational reactions to errors, the self-reported as well as the behavioral indicator (i.e., the emotion regulation index) were significantly related to knowledge acquisition, for action-related reactions to errors, only the behavioral indicator (i.e., the restudy index) was significantly related.

In line with assumptions about the still-developing metacognitive

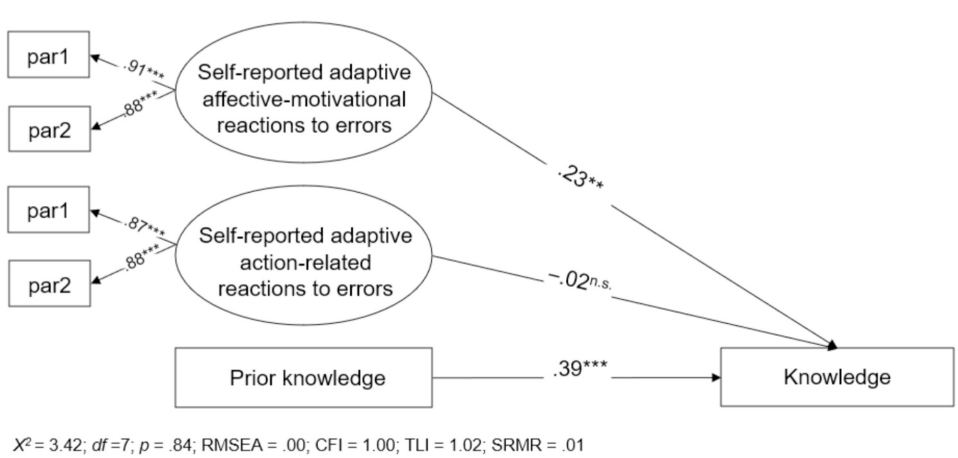

Fig. 2. Self-report Model (*** $p < .001$, n.s. = not significant).

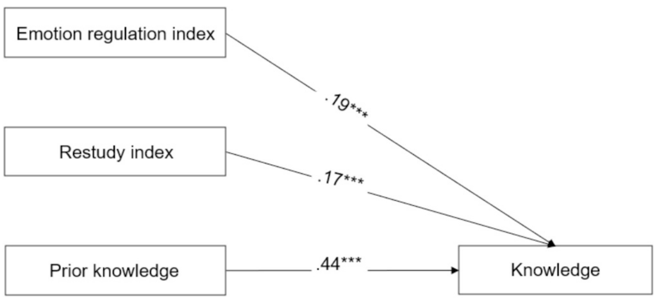

Fig. 3. Behavioral Model (*** $p < .001$).

and reflective abilities of children (e.g., Conijn et al., 2020), it can be argued that these to some extent diverging results between self-report and behavioral measures reflect primary school students' partly limited abilities in accurately self-reporting their adaptive reactions to errors and their tendency to overestimate themselves (see e.g., Bouffard et al., 2011). This may be attributable, at least in part, to a still relatively high assessment of one's own self-competence, which deteriorates over the course of one's school career, as has been repeatedly shown (e.g., Jacobs et al., 2002). When recognizing this potential overestimation, our results can also provide further insights into the process by which self-reported adaptive affective-motivational and action-related reactions to errors differentially relate to knowledge acquisition.

4.1. Relevance of adaptive reactions to errors for knowledge acquisition

On a theoretical level, the presented results add to a better understanding of adaptive reactions to errors, by, once again, showing some indication for two distinct types of reactions—despite the strong intercorrelation between the factors (see also Dresel et al., 2013). Our results are also in line with previous findings suggesting indirect (Grassinger et al., 2018; Soncini et al., 2022) and direct (Soncini et al., 2022) effects of adaptive affective-motivational reactions to errors on more distal academic performance measures, as we also found self-reported and behaviorally assessed adaptive affective-motivational reactions to errors to be related to immediate knowledge acquisition. Consequently, these results suggest that, as both variables demonstrate independent positive relations even when included simultaneously in one model, the perception of primary school students as having a more adaptive affective-motivational reaction to errors is important in addition to actually regulating negative affective states, which also emphasizes that affective-motivational reactions to errors reflect learners' motivation and, subsequently, can influence and guide learning (see e.g., Tulis et al., 2016). In contrast to these findings, we only found a significant relation for the behavioral indicator—but not the self-report measure—of adaptive action-related reactions to errors (i.e., restudy index) to students' knowledge acquisition. These results are not in line with the findings of previous studies revealing direct effects of self-reported indicators of adaptive action-related reactions to errors on knowledge acquisition for older students (Grassinger et al., 2018; Soncini et al., 2022; Spear et al., 2024). However, this may be due to the differences in the participants' ages. While all other mentioned studies focused on secondary school or university students, who can be considered more capable of accurately evaluating their own adaptive action-related reactions to errors, the current study focuses on primary school students, who may tend to overestimate themselves (see Bouffard et al., 2011). Such an overestimation of the adaptivity may have differential consequences for affective-motivational and action-related reactions to errors. In this sense, an overestimation of the adaptivity of one's own affective-motivational reactions to errors, even without actual effective emotional or motivational regulation, could act as a protective shield against the potentially negative effects of maladaptive affective-motivational reactions. In contrast, this does not seem to be the case for adaptive action-related reactions to errors. On an action level, the actual reaction to errors appears crucial, while just thinking (and consequently stating in the self-reports) to have reacted to errors adaptively is not sufficient; hence, only the behavioral indicator demonstrated a positive relation to knowledge acquisition.

On a more practical level of explicit implications for educators, our results underscore the relevance of teachers supporting students in the process of adaptively reacting to errors. This seems particularly important, as teachers often report not knowing how to respond when students make errors (Breternitz & Tulis, 2024) or how to set a positive error climate in the classroom, leading to a strong necessity for support (Dresel et al., 2025). This could, for example, be established through instructions on how to implement tasks with a productive failure instructional design (see e.g., Kapur, 2010) or on how to provide supportive feedback (Soncini et al., 2025). The latter seems especially important, as supportive feedback has been shown to increase adaptive responses to errors (Soncini et al., 2025). Therefore, it also seems

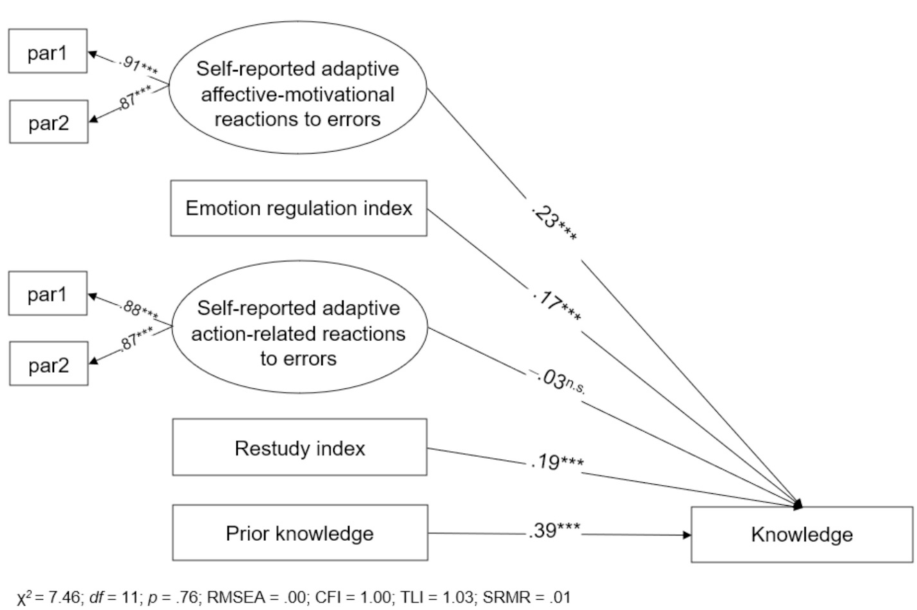

Fig. 4. Multimodal Model (*** $p < .001$, n.s. = not significant).

necessary to take a closer look at the role of (error) feedback students might receive in a learning situation to inform them about their individual errors. The fact that the emotion regulation index we derived from children's facial expressions was meaningfully related to learning gains also suggests that teachers should be encouraged to use this source of information. For example, children's facial expressions may give teachers some additional information on both successful and unsuccessful attempts at emotion regulation. Likewise, directly informing children about the value of repeating learning content when they make errors, prompting them to do so during task processing, and praising such behaviors, may further promote learning gains. In contrast, our findings suggest that teachers should not (only) rely on children's self-reports about their learning behavior but rather focus on concrete demonstrations of it in this age range.

4.2. Benefits of multimodal assessment combining self-reports and behavioral data

This study also sheds light on the usefulness of multimodal data assessment. As is often discussed in different contexts (e.g., Winne, 2010), multimodal data, or especially the inclusion of data that does not rely solely on self-reports, can be considered valuable and meaningful in measuring different constructs. Given the importance of research using multimodal data, this study can be regarded as valuable, as it is, to the best of our knowledge, the first study using behavioral indicators for measuring affective-motivational reactions to errors in primary school students using information-rich video data, and the first study using a behavioral restudy index with children, with both utilizing innovative technology-supported approaches. Overall, applying and validating such behavioral measures can be regarded as especially valuable for extending the age at which we can investigate adaptive reactions to errors and self-regulated learning, by including even younger children. Upon examining the results of our study, this value becomes even clearer: including multiple data sources in the Multimodal Model explained more variance in knowledge acquisition than the models only including either self-reported or behavioral indicators. The multimodal assessment of adaptive affective-motivational and action-related reactions to errors also enabled data analysis and interpretation on a deeper and more multifaceted level, especially regarding how participants' age possibly explains differences in their ability to self-report reactions to errors. When comparing the results of this study to previous findings focused on older students' reactions to errors, these considerations are underlined by the fact that correlations between self-reported and behavioral action-related reactions to errors were considerably larger in the study by Spear et al. (2024) with university students.

Beyond that, it can be expected that multimodal assessment reduces the danger of drawing the “wrong” conclusions from the data. This issue becomes especially clear when interpreting the results regarding adaptive action-related reactions, as the behavioral restudy index and the self-reported indicator revealed quite different results. While solely interpreting the self-report indicator would have led to the conclusion that adaptive action-related reactions to errors are not important for learning in primary school students, the behavioral indicator revealed the importance of the actual realization of an adaptive adjustment of the learning behavior. Thereby, the relevance of adaptive action-related reactions to errors for learning was demonstrated.

When these results are then compared to the relations of self-reported and behaviorally assessed adaptive affective-motivational reactions to errors, the possibly beneficial effect of the students' overestimation of their emotional and motivational regulation becomes apparent, which again would not have been detected by only investigating either self-reported or behaviorally assessed reactions to errors. While behaviorally measuring action-related reactions to errors via voluntary repetitions of previous learning material has been successfully applied in other research, capturing emotion regulation through video data as an indicator of affective-motivational reactions to errors represents a new approach. Due to its novelty, no standardized procedure has yet been established. Consequently, the values defining emotion regulation were determined by visually inspecting a subset of videos, and such new approaches require replication in future research. It should also be noted that with increasing age of the participants, the suitability of this indicator may need to be reconsidered, as adults tend to display less overt emotional expressions (see e.g., Reisenzein et al., 2014). Reduced variability in such data could thus obscure potential effects. Therefore, the exploration of other physiological measures of emotional reactions (e.g., skin conductance) may be beneficial in this context.

When interpreting statistical effects of these behavioral measures of adaptive affective-motivational and action-related reactions to errors, it is important to note that neither measure fully captures the entire construct of the respective type of reaction to errors. Instead, each serves as an approximation focusing on one central aspect of the construct. Specifically, the emotion regulation index reflects a change of experienced affect (either intentionally or not) but does not capture any motivational regulation, nor does it identify children who maintained a positive affect even in response to an error (see also Reindl et al., 2020; Stockinger et al., 2025). Similarly, repeating previous learning material represents a constructive learning behavior following an error, but does not directly encompass metacognitive or planning processes. In contrast, the self-reports of adaptive reactions to errors cover the broader construct of each reaction type, which may explain the weak association between corresponding behavioral and self-report indicators. Therefore, the behavioral measures are not expected to replace the self-reports; rather, both measures should be incorporated complementarily to capture adaptive reactions to errors more thoroughly.

4.3. Limitations and future directions

Although multimodal data assessment offers numerous advantages, it also has its limitations. Most of all, as discussed above, the behavioral indicators used in this study represent only approximations of the respective types of error reactions. The specific behavioral manifestations captured by these measures do not encompass all aspects of the broader constructs. Therefore, behavioral findings should be interpreted with respect to the specific behaviors assessed, rather than as reflections of the entire construct. Future research should aim to develop additional behavioral measures that capture adaptive reactions to errors in greater detail and address the full range of underlying dimensions. In addition, differences in the results between behavioral and self-reported indicators might not only stem from limited self-assessment abilities of primary school students, but also from the often-observed tendency to respond in a socially desirable way. Even though we consider this a possibility, different studies with older students (Grassinger et al., 2018; Soncini et al., 2022; Spear et al., 2024) also used self-reported indicators for measuring adaptive reactions to errors, which have been supported by substantial validity evidence. As socially desirable response tendencies are a rather general issue of self-reports and not specifically of younger students, we deem their influence on the results of the present study not more significant than on the results of prior studies; however, potential misinterpretations cannot be ruled out entirely. At this point, it is also still unclear whether stated relations are in fact causal and whether the findings also hold for other contexts beyond mathematics education and digital learning environments in primary school.

To automatically infer facial affect, we employed EmoNet, a deep neural network trained on the large-scale AffectNet dataset. While AffectNet includes facial images of children, they are not represented as a distinct or extensively sampled subgroup. In the present study, EmoNet was used to capture relative, continuous changes in affective valence over time, rather than to infer absolute or categorical emotional states, which mitigates potential robustness issues related to age-specific differences in facial expressivity. It remains an important future endeavor to fine-tune automatic facial expression coding algorithms specifically for children's faces. In addition, due to a relatively large amount of missing video data, it cannot be completely ruled out that biases may have affected our results, even if the issue was handled with appropriate care in the statistical analysis, and differences between the students with and without video data available were ruled out on important variables.

Lastly, it has to be taken into account that students' knowledge was measured only directly after working with the digital learning environment; to obtain a more comprehensive picture and a statement on lasting learning effects, future studies will also need to include long-term measurements of knowledge acquisition. In addition, these future research endeavors could focus more specifically on preceding factors expected to directly influence students' adaptive and maladaptive reactions to errors (e.g., interest or self-concept).

4.4. Conclusion

In summary, this study indicates that adaptive affective-motivational and action-related reactions to errors can both be considered relevant for primary school students' knowledge acquisition and should consequently be promoted in students. In case of affective-motivational reactions, self-reported perceptions seem to be just as important as observed emotional regulation processes following errors, while for action-related reactions to errors, only actual behavior relates to knowledge acquisition. These results highlight the need for a multimodal assessment when it comes to adaptive reactions to errors, as well as, from the perspective of a teacher, recognizing the importance of both students' reporting and their actions.

CRediT authorship contribution statement

A.J. Pickal: Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **J. Spear:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **D. Bryce:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **T. Hallmen:** Writing – review & editing, Software, Resources. **C.-S. Enste:** Writing – review & editing, Conceptualization. **R. Grassinger:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **E. André:** Writing – review & editing, Software, Resources. **M. Dresel:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

We have no competing interests to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2026.102927.

References

Baur, T., Heimerl, A., Lingenfelser, F., Wagner, J., Valstar, M. F., Schuller, B., & André, E. (2020). eXplainable cooperative machine learning with NOVA. *KI - Künstliche Intelligenz/German Journal of Artificial Intelligence, 34*(2), 143–164. https://doi.org/10.1007/s13218-020-00632-3

Berhenke, A., Miller, A. L., Brown, E., Seifer, R., & Dickstein, S. (2011). Observed emotional and behavioral indicators of motivation predict school readiness in head start graduates. *Early Childhood Research Quarterly, 26*(4), 430–441. https://doi.org/10.1016/j.ecresq.2011.04.001

Bernacki, M. L., Yu, L., Kuhlmann, S. L., Plumley, R. D., Greene, J. A., Duke, R. F., … 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

Bouffard, T., Vezeau, C., Roy, M., & Lengelé, A. (2011). Stability of biases in self-evaluation and relations to well-being among elementary school children. *International Journal of Educational Research, 50*(4), 221–229. https://doi.org/10.1016/j.ijer.2011.08.003

Breternitz, A., & Tulis, M. (2024). The acquisition of error competence and the value of (learning from) errors in teacher education from the perspectives of teachers in Finland and Germany. *Studia Paedagogica, 29*(2), 9–32. https://doi.org/10.5817/SP2024-2-1

Bridges, D., Pitiot, A., MacAskill, M. R., & Peirce, J. W. (2020). The timing mega-study: Comparing a range of experiment generators, both lab-based and online. *PeerJ, 8*, Article e9414. https://doi.org/10.7717/peerj.9414

de Bruijn-Smolders, M., Timmers, C. F., Gawke, J. C., Schoonman, W., & Born, M. P. (2016). Effective self-regulatory processes in higher education: Research findings and future directions. A systematic review. *Studies in Higher Education, 41*(1), 139–158. https://doi.org/10.1080/03075079.2014.915302

Burmeister, C., Beck, K., & Grassinger, R. (2024). Error climate and gender as factors influencing error reactions in primary school children. *Studia Paedagogica, 29*(2), 90–107. https://doi.org/10.5817/SP2024-2-4

Chouvalova, A., Navlekar, A. S., Mills, D. J., Adams, M., Daye, S., Anda, F.de, & Limeri, L. B. (2024). Undergraduates' reactions to errors mediates the association between growth mindset and study strategies. *International Journal of STEM Education, 11*(1). https://doi.org/10.1186/s40594-024-00485-4

Cleary, T. J., & Russo, M. R. (2024). A multilevel framework for assessing self-regulated learning in school contexts: Innovations, challenges, and future directions. *Psychology in the Schools, 61*(1), 80–102. https://doi.org/10.1002/pits.23035

Conijn, J. M., Smits, N., & Hartman, E. E. (2020). Determining at what age children provide sound self-reports: An illustration of the validity-index approach. *Assessment, 27*(7), 1604–1618. https://doi.org/10.1177/1073191119832655

D'Mello, S. K., Craig, S. D., & Graesser, A. C. (2009). Multimethod assessment of affective experience and expression during deep learning. *International Journal of Learning Technology, 4*(3/4), 165–187. https://doi.org/10.1504/IJLT.2009.028805

Donaldson, M., Sun, X., Chimgee, A. E., & Hwang, M. (2025). How do young children respond to mistakes? *Journal of Research in Childhood Education*. https://doi.org/10.1080/02568543.2025.2465582

Dresel, M., Daumiller, M., Spear, J., Janke, S., Dickhäuser, O., & Steuer, G. (2025). Learning from errors in mathematics classrooms: Development over 2 years in dependence of perceived error climate. *The British Journal of Educational Psychology, 95*(1), 180–196. https://doi.org/10.1111/bjep.12697

Dresel, M., Schober, B., Ziegler, A., Grassinger, R., & Steuer, G. (2013). Affektiv-motivational adaptive und handlungsadaptive Reaktionen auf Fehler im Lernprozess [Affective-motivational adaptive and action adaptive reactions on errors in learning processes]. *Zeitschrift für Pädagogische Psychologie/German Journal of Educational Psychology, 27*(4), 255–271. https://doi.org/10.1024/1010-0652/a000111

Ekman, P., & Friesen, W. (1978). *Facial Action Coding System: A technique for the measurement of facial movement*. Consulting Psychologists Press.

Grassinger, R., & Dresel, M. (2017). Who learns from errors on a class test? Antecedents and profiles of adaptive reactions to errors in a failure situation. *Learning and Individual Differences, 53*, 61–68. https://doi.org/10.1016/j.lindif.2016.11.009

Grassinger, R., Scheunpflug, A., Zeinz, H., & Dresel, M. (2018). Smart is who makes lots of errors? The relevance of adaptive reactions to errors and a positive error climate for academic achievement. *High Ability Studies, 29*(1), 37–49. https://doi.org/10.1080/13598139.2018.1459294

Hallmen, T., Schiller, D., Vehlen, A., Eberhardt, S., Baur, T., Withanage Don, D., & André, E. (2025). DISCOVER: A data-driven interactive system for comprehensive observation, visualization, and exploration of human behavior. *Frontiers in Digital Health, 7*, Article 1638539. https://doi.org/10.3389/fdgth.2025.1638539

Jacobs, J. E., Lanza, S., Osgood, D. W., Eccles, J. S., & Wigfield, A. (2002). Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. *Child Development, 73*(2), 509–527. https://doi.org/10.1111/1467-8624.00421

Jansen, R. S., van Leeuwen, A., Janssen, J., Jak, S., & Kester, L. (2019). Self-regulated learning partially mediates the effect of self-regulated learning interventions on achievement in higher education: A meta-analysis. *Educational Research Review, 28*, Article 100292. https://doi.org/10.1016/j.edurev.2019.100292

Käfer, J., Kuger, S., Klieme, E., & Kunter, M. (2019). The significance of dealing with mistakes for student achievement and motivation: Results of doubly latent multilevel analyses. *European Journal of Psychology of Education, 34*(4), 731–753. https://doi.org/10.1007/s10212-018-0408-7

Kapur, M. (2010). Productive failure in mathematical problem solving. *Instructional Science, 38*(6), 523–550. https://doi.org/10.1007/s11251-009-9093-x

Krajewski, K., Dix, S., & Schneider, W. (2020). *DEMAT 2+: Deutscher Mathematiktest für zweite Klassen [DEMAT 2+: German mathematics test for second graders]*. Hogrefe.

Lewinski, P., den Uyl, T. M., & Butler, C. (2014). Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. *Journal of Neuroscience, Psychology, and Economics, 7*(4), 227–236. https://doi.org/10.1037/npe0000028

Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Structural Equation Modeling: A Multidisciplinary Journal, 9*(2), 151–173. https://doi.org/10.1207/S15328007SEM0902_1

Makowski, D., Ben-Shachar, M. S., Wiernik, B. M., Patil, I., Thériault, R., & Lüdecke, D. (2025). modelbased: An R package to make the most out of your statistical models through marginal means, marginal effects, and model predictions. *The Journal of Open Source Software, 10*(109), 7969. https://doi.org/10.21105/joss.07969

Merrick, M., & Fyfe, E. R. (2023). Feelings on feedback: Children's emotional responses during mathematics problem solving. *Contemporary Educational Psychology, 74*. https://doi.org/10.1016/j.cedpsych.2023.102209

Metcalfe, J. (2017). Learning from errors. *Annual Review of Psychology, 68*, 465–489. https://doi.org/10.1146/annurev-psych-010416-044022

Miao, R., Yang, P., Li, S., Kong, K., & Wang, X. (2026). From facial expressions to academic performance: Affective computing reveals the serial mediating roles of emotional valence and self-regulated learning. *Computers in Human Behavior, 177*, Article 108902. https://doi.org/10.1016/j.chb.2025.108902

Mollahosseini, A., Hasani, B., & Mahoor, M. H. (2019). AffectNet: A database for facial expression, valence, and arousal computing in the wild. *IEEE Transactions on Affective Computing, 10*(1), 18–31. https://doi.org/10.1109/TAFFC.2017.2740923

Oser, F., & Spychiger, M. (2005). *Lernen ist schmerzhaft. Zur Theorie des negativen Wissens und zur Praxis der Fehlerkultur [Learning is painful. On the theory of negative knowledge and the practice of error culture]*. Beltz.

Peirce, J. W. (2019). PsychoPy2: Experiments in behavior made easy (Version 2024.2.4) [Computer software]. In *Open Science Tools*. https://www.psychopy.org/psychopy.org.

Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research. *Educational Psychologist, 37*(2), 91–105. https://doi.org/10.1207/S15326985EP3702_4

Pekrun, R., Lichtenfeld, S., Marsh, H. W., Murayama, K., & Goetz, T. (2017). Achievement emotions and academic performance: Longitudinal models of reciprocal effects. *Child Development, 88*(5), 1653–1670. https://doi.org/10.1111/cdev.12704

Peugh, J. L., & Enders, C. K. (2004). Missing data in educational research: A review of reporting practices and suggestions for improvement. *Review of Educational Research, 74*(4), 525–556. https://doi.org/10.3102/00346543074004525

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In *Handbook of self-regulation* (pp. 451–502). Elsevier. https://doi.org/10.1016/B978-012109890-2/50043-3.

R Core Team. (2024). *A language and environment for statistical computing*. R foundation for statistical computing (version 4.4.1) [computer software]. https://www.R-project.org.

Reindl, M., Tulis, M., & Dresel, M. (2020). Profiles of emotional and motivational self-regulation following errors: Associations with learning. *Learning and Individual Differences, 77*, Article 101806. https://doi.org/10.1016/j.lindif.2019.101806

Reisenzein, R., Junge, M., Studtmann, M., & Huber, O. (2014). Observational approaches to the measurement of emotions. In *International handbook of emotions in education* (pp. 580–606). Routledge.

Roebers, C. M., & Spiess, M. (2017). The development of metacognitive monitoring and control in second graders: A short-term longitudinal study. *Journal of Cognition and Development, 18*(1), 110–128. https://doi.org/10.1080/15248372.2016.1157079

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2). https://doi.org/10.18637/jss.v048.i02

Schmitz, B., & Wiese, B. S. (2006). New perspectives for the evaluation of training sessions in self-regulated learning: Time-series analyses of diary data. *Contemporary Educational Psychology, 31*(1), 64–96. https://doi.org/10.1016/j.cedpsych.2005.02.002

Schrader, C., & Grassinger, R. (2021). Tell me that I can do it better: The effect of attributional feedback from a learning technology on achievement emotions and performance and the moderating role of individual adaptive reactions to errors. *Computers & Education, 161*, Article 104028. https://doi.org/10.1016/j.compedu.2020.104028

Soncini, A., Matteucci, M. C., Tomasetto, C., & Butera, F. (2025). Supportive error feedback fosters students' adaptive reactions towards errors: Evidence from a targeted online intervention with Italian middle school students. *The British Journal of Educational Psychology, 95*(1), 92–106. https://doi.org/10.1111/bjep.12679

Soncini, A., Visintin, E. P., Matteucci, M. C., Tomasetto, C., & Butera, F. (2022). Positive error climate promotes learning outcomes through students' adaptive reactions towards errors. *Learning and Instruction, 80*, Article 101627. https://doi.org/10.1016/j.learninstruc.2022.101627

Song, H. S., Kalet, A. L., & Plass, J. L. (2016). Interplay of prior knowledge, self-regulation and motivation in complex multimedia learning environments. *Journal of Computer Assisted Learning, 32*(1), 31–50. https://doi.org/10.1111/jcal.12117

Spear, J., Burmeister, C., Dresel, M., & Grassinger, R. (2025). Assessing adaptive reactions to errors in primary school children. *European Journal of Psychological Assessment*. https://doi.org/10.1027/1015-5759/a000922

Spear, J., Tulis, M., & Dresel, M. (2024). Knowledge effects of action-related reactions to errors. *Educational Psychology, 44*(9–10), 1092–1105. https://doi.org/10.1080/01443410.2024.2426549

Spinath, B., & Spinath, F. M. (2005). Longitudinal analysis of the link between learning motivation and competence beliefs among elementary school children. *Learning and Instruction, 15*(2), 87–102. https://doi.org/10.1016/j.learninstruc.2005.04.008

Stiensmeier-Pelster, J., & Heckhausen, H. (2018). Causal attribution of behavior and achievement. In J. Heckhausen, & H. Heckhausen (Eds.), *Motivation and action* (pp. 623–678). Springer International Publishing. https://doi.org/10.1007/978-3-319-65094-4_15.

Stockinger, K., Nett, U. E., & Dresel, M. (2025). Interwoven systems: Towards an integrative framework of students' motivational and emotional self-regulation. *Educational Psychologist*, 1–21. https://doi.org/10.1080/00461520.2025.2591934

Sturgess, J., Rodger, S., & Ozanne, A. (2002). A review of the use of self-report assessment with young children. *British Journal of Occupational Therapy, 65*(3), 108–116. https://doi.org/10.1177/030802260206500302

Terhürne, P., Schwartz, B., Baur, T., Schiller, D., Eberhardt, S. T., André, E., & Lutz, W. (2022). Validation and application of the Non-Verbal Behavior Analyzer: An automated tool to assess non-verbal emotional expressions in psychotherapy. *Frontiers in Psychiatry, 13*, Article 1026015. https://doi.org/10.3389/fpsyt.2022.1026015

Toisoul, A., Kossaifi, J., Bulat, A., Tzimiropoulos, G., & Pantic, M. (2021). Estimation of continuous valence and arousal levels from faces in naturalistic conditions. *Nature Machine Intelligence, 3*(1), 42–50. https://doi.org/10.1038/s42256-020-00280-0

Tulis, M., & Dresel, M. (2025). Effects on and consequences of responses to errors: Results from two experimental studies. *The British Journal of Educational Psychology, 95*(1), 143–161. https://doi.org/10.1111/bjep.12686

Tulis, M., Steuer, G., & Dresel, M. (2016). Learning from errors: A model of individual processes. *Frontline Learning Research, 4*(4), 12–26. https://doi.org/10.14786/flr.v4i2.168

Wang, Y., & Sperling, R. A. (2020). Characteristics of effective self-regulated learning interventions in mathematics classrooms: A systematic review. *Frontiers in Education, 5*. https://doi.org/10.3389/feduc.2020.00058. Article 58.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review, 92*(4), 548–573. https://doi.org/10.1037/0033-295X.92.4.548

Winne, P. H. (2010). Improving measurements of self-regulated learning. *Educational Psychologist, 45*(4), 267–276. https://doi.org/10.1080/00461520.2010.517150

Zachariou, A., & Whitebread, D. (2019). Developmental differences in young children's self-regulation. *Journal of Applied Developmental Psychology, 62*, 282–293. https://doi.org/10.1016/j.appdev.2019.02.002

Zhang, Q., & Fiorella, L. (2023). An integrated model of learning from errors. *Educational Psychologist, 58*(1), 18–34. https://doi.org/10.1080/00461520.2022.2149525

Zhao, B. (2011). Learning from errors: The role of context, emotion, and personality. *Journal of Organizational Behavior, 32*(3), 435–463. https://doi.org/10.1002/job.696

Zhao, B., & Olivera, F. (2006). Error reporting in organizations. *Academy of Management Review, 31*(4), 1012–1030. https://doi.org/10.5465/AMR.2006.22528167