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A domain-specific perspective on adaptivity☆

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ABSTRACT

Adaptive support aims to tailor instruction to the needs of individual learners. Advances in technology have accelerated research on how such adaptivity can be achieved. While prior work demonstrates that adaptive support can enhance learning outcomes, most adaptive support relies on domain-general learner variables such as accuracy, response time, or behavioral engagement, treating learning processes largely as domain-general. But, in addition to the importance of domain-general principles of learning, decades of research in cognitive and educational psychology highlight that many learning processes are domain-specific, shaped by the conceptual, procedural, and epistemic structures of a particular domain.

In this editorial, we argue that a domain-specific perspective on adaptivity is helpful for understanding when and how adaptive support is effective. Using Plass and Pawar's (2020) framework, we discuss the role of domain specificity in three dimensions of adaptive learning environments: identifying learner variables to adapt for, measuring these variables, and adapting meaningfully in response. Domain-specific variables such as learners' misconceptions, their strategies, and their conceptual understanding require fine-grained assessment and theoretical models that link process data to learning mechanisms within a domain. Similarly, adapting instruction to these processes demands instructional models that account for domain-specific learning trajectories.

The aim of this special issue was to collect empirical studies that use process data to study domain-specific adaptive learning. It consists of nine contributions from various subject domains and one discussion paper. Collectively, these contributions demonstrate both the promise and the complexity of grounding adaptivity in domain-specific learning processes and highlight important directions for future research.

1. Introduction

One of the central promises of recent digital and artificial intelligence (AI)-supported learning technologies is their potential to be adaptive—that is, to accommodate the individual needs of learners emerging during the learning process (Plass & Pawar, 2020). Over the past decades, with an increase of research on digital technology and the advent of AI in education, research on adaptivity has made substantial technological and theoretical progress (Sailer et al., 2023; Tan et al., 2025). Yet we argue that an important gap remains: Adaptive support during learning is rarely seen from a domain-specific perspective. Addressing this gap is the focus of the present special issue with the title *Using Real-Time Process Data of Domain-Specific Learning Processes to Provide Adaptive Support for Learning and Instruction*. In this editorial, we argue why we believe a domain-specific perspective on adaptivity is needed and how the contributions in this issue advance this discussion.

1.1. What is adaptive support, and why do we need a domain-specific perspective?

Education increasingly acknowledges the heterogeneity of learners—for example, their prior knowledge, affect and motivation, or social background. Ideally, learning environments are therefore not a one-size-fits-all but accommodate these individual differences. One way to do so is by providing *adaptive* support (e.g., Aleven et al., 2016; Cronbach & Snow, 1977). Various frameworks describe and structure adaptivity in learning (e.g., Aleven et al., 2016; Bernacki et al., 2021; Van Schoors et al., 2021; Vandewaetere & Clarebout, 2013). In this

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special issue we chose to follow the conceptualization proposed by Plass and Pawar (2020) since its three dimensions of adaptive support (see Section 1.2) are also apparent in most other frameworks and offer a good structure for discussing domain-specificity. Plass and Pawar (2020) understand adaptivity as "the ability of a learning system to diagnose a range of learner variables, and to accommodate a learner's specific needs by making appropriate adjustments to the learner's experience with the goal of enhancing learning outcomes" (p. 276). Accordingly, we refer to such learning systems as *adaptive learning environments* and to the adjustments as *adaptive support*. Recent reviews and meta-analyses confirm that adaptive support can substantially foster learning (e.g., Belland et al., 2017; Chernikova et al., 2025; Major et al., 2021; Major & Francis, 2020; Van Schoors et al., 2021; Zheng et al., 2022).

Many adaptive learning environments are based on principles that apply to learning largely irrespective of the content that is learned (Nakic et al., 2015). Since many of these domain-general principles and processes of learning are transferable across domains, the same adaptations might produce comparable enhancements of the learning process, irrespective of the content. However, decades of research in cognitive and educational psychology have shown that many learning processes are also domain-specific: the representations, misconceptions, learning trajectories, and reasoning patterns that shape learning often differ substantially between mathematics, language, science, and other subjects (e.g., Schneider & Stern, 2010). Thus, treating learning processes and adaptive support purely as domain-general will possibly miss out on valuable opportunities to understand and support learning. Meaningful adaptive support should therefore align domain-general principles of learning with a comprehensive understanding of the specific domain that captures the conceptual and procedural structure of the content (Pelánek, 2025). This requires adaptive support that integrates knowledge about domain-specific learning mechanisms and interpret learner data considering them.

We argue that such a domain-specific perspective on adaptivity is important—a perspective that considers what learner variables are worth adapting for, how these variables can be meaningfully assessed, and how the learning environment can adapt in ways that are sensitive to domain-specific learning processes. In the following, we further illustrate this argument using Plass and Pawar's (2020) framework.

1.2. *What makes adaptive support domain-specific?*

Plass and Pawar (2020) conceptualize adaptive support through three dimensions:

(1) Which learner variables should the learning environment adapt for?
(2) How can these variables be reliably measured? and
(3) What kind of adaptations can be made during the learning process?

Each of these questions can be considered from a domain-general and a domain-specific perspective. A domain-specific perspective on adaptivity implies that the learner variables, the methods of diagnosing them, and the instructional responses are aligned with the specific characteristics of the domain. The following sections elaborate on each of these three dimensions, and the promises and challenges of a domain-specific perspective in each of them.

1.2.1. *Domain-specific variables to adapt for*

The first of Plass and Pawar's (2020) dimensions—what learner variables should a learning environment adapt for?—describes the need for and challenge of specifying which characteristics of the learner or the learning process are relevant to provide optimal adaptive support.

Many domain-general adaptive learning environments use variables such as learners' accuracy, response time, engagement, or effort to steer adaptive support (Nakic et al., 2015). This approach follows general principles of learning, for example, the idea that instruction should be attuned to the learner's current performance level (e.g., Hardy et al., 2019; Vygotsky, 1978).

However, domain-specific learning includes specific concepts, strategies, or misconceptions that are unique to a domain and that support a comprehensive understanding of the learners' current capabilities. Considering and adapting to performance as a one-dimensional construct will possibly not address the core of these learning processes.

For example, in mathematics, learners may erroneously apply whole-number reasoning to fractions, and they may do so in different ways. When asked which of two fractions is larger, some children apply a larger-numerator-larger-fraction strategy, while others apply a larger-denominator-larger-fraction strategy (D'Erchie et al., 2025; González-Forte et al., 2023). Importantly, across a set of fraction comparison items, both types of reasoning can result in similar overall accuracy but are based on fundamentally different misconceptions. Thus, using accuracy as a measure would assign both groups of learners to the same performance group, while their way of reasoning and, therefore, their needs, are very different.

Thus, considering domain-specific variables to adapt for, possibly in concert with domain-general variables, promises better knowledge about the needs and the potential for adaptivity of individual learners than domain-general variables alone.

1.2.2. *How can domain-specific variables be assessed?*

The second dimension discussed by Plass and Pawar (2020) is how the learner variables for which the learning environment should adapt can be assessed. Ideally, this happens in real time during the learning process, so that the learning environment can adapt immediately. Generic variables such as behavioral engagement, time on task, or accuracy can often be measured relatively unobtrusively through logfile data or short self-reports. In contrast, assessing domain-specific variables—such as conceptual understanding, reasoning strategies, or misconceptions—often requires fine-grained information about the content of learning and its underlying cognitive mechanisms and their interpretation about the domain-specific theories of learning. This makes assessing domain-specific variables in real time particularly challenging.

Plass and Pawar (2020) note that while collecting more extensive and detailed real-time data is desirable for adaptivity, collecting valid data without disrupting the learning process is difficult. Particularly for domain-specific variables, this challenge is not only technical but theoretical: Assessing conceptual understanding meaningfully, for example through solving a diagnostic problem, will almost inevitably lead to training effects and learning. However, while this might pose problems for controlled research designs, it is less of an issue in real-world educational settings, where the goal is to support learning anyway. In these contexts, assessing domain-specific variables could go together with learning itself without disruption.

Advances in learning analytics and educational technology offer new ways to capture real-time learning processes—such as logfile traces, eye tracking, and physiological or multimodal data (Ninaus & Nebel, 2021), but these data are often difficult to interpret, particularity from a domain-specific perspective (Gašević et al., 2015). Their interpretation depends on theoretical frameworks that link observable behavior to cognitive and metacognitive mechanisms within a domain (Dawson et al., 2015). One example where such data has been linked quite successfully to domain-specific processes of learning is the use of eye tracking in mathematics education (Strohmaier et al., 2020). For many other assessment methods and domains, theoretical frameworks of their interpretation are still limited. Developing and validating such frameworks represents a key step toward domain-specific adaptivity. The more precisely data can be mapped onto meaningful learning constructs within a domain, the more effectively adaptive systems can diagnose the learner's needs and, in the next step, provide adaptive support. Thus, the more information about domain-specific learning this data contains and the better this is integrated with our knowledge of its meaning in domain-specific learning processes, the more effective the adaptive support can be for learning outcomes.

1.2.3. How should the learning environment be adapted?

Finally, the last of Plass and Pawar's (2020) dimensions refers to how the learning environment should adapt in response to the assessed learner variables. Again, a domain-specific perspective on this dimension is particularly promising but also holds its own challenges. Domain-general forms of adaptivity—such as adjusting one-dimensional task difficulty, pacing, or the amount of support—follow relatively simple rules that can be applied across domains, for example, matching student's estimated performance level with the task difficulty to a zone of proximal development (Vygotsky, 1978). In contrast, adapting to domain-specific processes often requires multi-dimensional and qualitative changes to instruction.

For example, feedback that is appropriate for one type of specific conceptual error may be ineffective or even misleading for another. In complex domains, learners can follow multiple valid but distinct learning trajectories, and the system must be able to respond to these variations. Designing adaptive mechanisms therefore requires rich domain models that describe how learning within a domain unfolds, what typical errors or reasoning patterns can be expected, and which types of instructional interventions are most productive at a given point in the process. When adaptivity operates at this level—linking real-time diagnosis with principled instructional design—adaptive systems can provide meaningful, individualized domain-specific adaptive support rather than surface-level adjustments. Without deeper modelling of domain knowledge and learner processes, adaptivity risks remaining superficial and unable to address the qualitative nature of domain-specific learning. Developing systems that can adapt to domain-specific learner characteristics requires rich models of domain knowledge and the cognitive processes that support its acquisition.

2. The contributions to this special issue

For this special issue, we invited empirical studies that addressed the guiding questions outlined above. In total, nine studies are included, complemented by a discussion paper (Acevedo, 2026). As could be expected, not all nine studies addressed all three dimensions discussed above in full depth, but taken together, they provide a comprehensive landscape of the challenges and potential of domain-specific adaptive support.

Two studies relied on a generic adaptive trigger: accuracy as rates of correct and incorrect answers. Nevertheless, both situated performance within domain-specific contexts, either by providing domain-specific adaptive feedback (Oppmann et al., 2025) or by examining domain-specific learner characteristics that moderate the effect of adaptivity (Hilz et al., 2025).

Oppmann et al. (2025) used logfile data from a digital learning environment to determine students' accuracy on different fraction-equivalence tasks. Based on this process data, the system provided task-specific adaptive feedback (e.g., highlighting how to correctly transform fraction representations) and adapted task difficulty by advancing or slowing task progression. Beyond examining the effect of adaptivity, Oppmann et al. (2025) clustered students based on their cognitive, behavioral, motivational, and emotional engagement during the task. These engagement profiles predicted who benefited most from the adaptive support, demonstrating that even when adaptivity is based on performance, domain-specific engagement characteristics shape the effectiveness of adaptive support.

Hilz et al. (2025) examined how different learners engage with an existing adaptive learning environment for arithmetic, where difficulty was automatically adjusted based on performance. The study did not develop a new adaptive mechanism but used process data to explain for whom such systems are effective. Using logfile traces of practice behavior, Hilz et al. (2025) showed that students with higher mathematics test anxiety tended to end practice sessions earlier, which mediated lower learning gains. Thus, even when adaptation itself is generic (difficulty adjustment), domain-specific learner characteristics—here, mathematics anxiety—shape whether adaptive systems can unfold their intended benefits.

Two studies used more fine-grained performance data, allowing for a detailed basis for adaptivity even with fewer tasks (Huang et al., 2025; Obergassel et al., 2025).

Huang et al. (2025) used a virtual classroom environment to foster pre-service teachers' visual attention and noticing. Performance was operationalized as noticing behavior captured via eye tracking (which events were visually attended) and self-reports (which events were noticed). Based on this diagnosis, learners received adaptive feedback including a personalized description of their noticing pattern and recommendations for improvement. Here, adaptive feedback was more effective than generic feedback. While the intervention targeted a professional skill rather than a content domain, it still relied on domain-specific performance indicators derived from classroom practice and frameworks of noticing.

Obergassel et al. (2025) compared two approaches to adaptivity in an open-ended social psychology quiz: adaptation based on generic self-reported cognitive load versus adaptation based on domain-specific self-assessed performance (criterion-based confidence ratings after each item). In both conditions, adaptation meant adjusting the difficulty of subsequent tasks. This is the only study in the issue that directly contrasted adaptivity based on a generic versus a domain-specific learner variable. Only the cognitive-load–based adaptation led to higher learning gains compared to a non-adaptive control condition, suggesting that domain-general indicators may be more informative than domain-specific self-evaluations in guiding adaptivity in this context.

In addition to performance, two studies used domain-specific aspects of participants' task solutions as a basis for adaptive support (Demedts et al., 2024; Nickl et al., 2024).

Demedts et al. (2024) used logfile data to assess not only accuracy but also conceptual error patterns in number line fraction tasks—for example, treating the numerator and denominator as independent whole numbers or difficulties in grasping the meaning of a unit. Each incorrect placement was automatically matched to a known misconception category, and the system generated explanatory adaptive feedback tailored to that specific misconception (e.g., prompting learners to reason about proportionality instead of whole-number logic). Whereas this domain-specific adaptation did not lead to differences in cognitive outcomes, the study revealed that domain-specific feedback can be beneficial in terms of reducing mathematics anxiety and supporting students' mathematics motivation, showing that domain-specific feedback can improve learning without negative motivational effects.

Nickl et al. (2024) investigated how pre-service teachers diagnosed students' mathematical proof solutions in a video-based simulation while taking notes. These notes were automatically analyzed and coded for three domain-specific indicators of proof skills. Based on which indicators were present or missing, the system offered adaptive scaffolding in real time, directing attention to overlooked proof elements and prompting higher-quality reasoning. Adaptive scaffolding led to more elaborate diagnostic reasoning than non-adaptive support, demonstrating how domain-specific process data can drive meaningful adaptivity.

Finally, three studies did not implement adaptive learning environments but investigated which variables and mechanisms are promising for future domain-specific adaptive support (Brand et al., 2025; Horvers et al., 2025; Schons et al., 2024).

Brand et al. (2025) examined learning processes in productive failure and vicarious failure in statistics to identify which learner characteristics and process patterns could serve as meaningful input for future domain-specific adaptivity. Using logfile traces, think-aloud data, and self-reports, the study captured how learners with different individual prerequisites engaged with tasks and how these process profiles related to domain-specific perceived competence and prior knowledge. The findings provide a foundation for future adaptivity by outlining who benefits and how individual learning processes differ within a domain-specific context.

Horvers et al. (2025) explored how emotional responses unfold within an adaptive practice environment. While the system adapted task difficulty based on performance, the study additionally captured real-time emotion data, including facial-expression coding and electrodermal activity, to assess how students reacted to feedback. Although emotions were not yet used to trigger adaptivity, the study demonstrated the feasibility and added value of incorporating domain-specific emotional process data and highlighted how affective signals could enrich adaptive decisions beyond performance alone.

Schons et al. (2024) examined the diagnostic activities of pre-service teachers. By analyzing logfile data, they identified different modes of cognitive engagement during diagnostic reasoning. These modes predicted assessment accuracy and therefore represent a promising proxy of learning processes that future adaptive systems could build on. Through this detailed analysis, Schons et al. (2024) lay the groundwork for using domain-specific logfile data for meaningful adaptive support.

Finally, in his discussion, Acevedo (2026) provides a conceptual anchor for the special issue and situates the other contributions in this framework. Acevedo (2026) highlights how domains differ in epistemic structures, knowledge representations, typical misconceptions, and learning trajectories. Building on the contributions in this issue, Acevedo offers a critical analysis of conceptual, methodological, analytical, and instructional challenges in using real-time process data for adaptive support, emphasizing the need for theoretically interpretable indicators, careful decisions about granularity and timing, and adaptive interventions that align with domain-specific goals. The discussion concludes with priorities for future research, including stronger construct-to-data mappings, rigorous validation of multimodal indicators, transparent and ethical implementations, and closer collaboration between domain experts, learning scientists, and data scientists to design adaptive systems that are both technically sophisticated and instructionally meaningful.

3. Conclusions and next steps

Taken together, the contributions in this special issue demonstrate how domain specificity matters for all three dimensions of adaptivity described by Plass and Pawar (2020): what learner variables systems adapt for, how these variables are assessed, and how learning environments respond. Across domains as diverse as mathematics, social psychology, and classroom perception, the studies illustrate both the potential and the complexity of grounding adaptivity in domain-specific learning processes.

Three overarching conclusions emerge. First, while adaptivity was often implemented through domain-general indicators such as learners' accuracy or behavioral engagement, meaningful adaptive support can be provided by connecting these measures to domain-specific learning mechanisms. When robust domain-specific theories are available, generic indicators can still point towards a domain-specific variable to adapt for, but learners' misconceptions, reasoning strategies, and affective responses might take on different meanings and require different actions depending on the domain. Thus, it is possible to provide domain-specific adaptive support even if only the third dimension by Plass and Pawar (2020) is considered domain-specifically and generic variables are interpreted with a domain-specific lens.

Second, measuring domain-specific learner variables in real time remains challenging—not only in terms of the measurements' reliability but also in terms of interpretability within domain-specific theories. Although advances in learning analytics and multimodal data collection provide increasingly rich process data, their educational value depends on the availability of domain-specific theories that specify how these data reflect learning. Without this interpretive bridge, more data do not necessarily yield better adaptation.

Third, adapting instruction to domain-specific learning processes is inherently complex. Even within content areas, learners may follow multiple valid trajectories, and effective support must account for interactions among cognitive, motivational, and metacognitive processes. Achieving this requires not just sophisticated algorithms but also models of instruction that describe how learning unfolds in that domain. Such models are, however, often not yet available and need to be established through preparatory fundamental and theoretical research. Many studies in this special issue did not yet put adaptive support into reality or did it in a somewhat preliminary way.

The contributions in this issue show progress toward each of these challenges but also underline that domain-specific adaptivity is still in its early stages. While research has gathered a good understanding of the potential of adaptivity, it is now time to transfer this knowledge into domain-specific theories and learning environments. Moreover, recent advances in AI offer new opportunities: technologically advanced models can process multimodal data, identify patterns in learner behavior, and generate personalized feedback in real time and in human-like interaction (Sailer et al., 2023; Tan et al., 2025). However, these developments do not automatically resolve the challenge of domain specificity. General-purpose AI systems are not inherently aligned with the conceptual and pedagogical structures of specific domains and individual differences between learners in these domains (e.g., Strohmaier et al., 2025). Harnessing their potential for education therefore requires coupling them with domain-specific models of learning and instruction and maintaining alignment with educational goals and values.

In this sense, the studies presented here not only advance our understanding of how domain-specific adaptivity can be realized today but also provide conceptual groundwork for designing the adaptive learning systems of the future—systems that are theoretically grounded, data-informed, and meaningfully responsive to the processes that characterize learning within specific domains. But for this, we need a domain-specific perspective on adaptivity.

CRediT authorship contribution statement

Anselm Strohmaier: Conceptualization, Writing – original draft, Writing – review & editing. **Fien Depaepe:** Conceptualization, Writing – original draft, Writing – review & editing. **Michael Nickl:** Conceptualization, Writing – original draft, Writing – review & editing. **Andreas Obersteiner:** Conceptualization, Writing – original draft, Writing – review & editing.

Data availability

No data was used for the research described in the article.

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