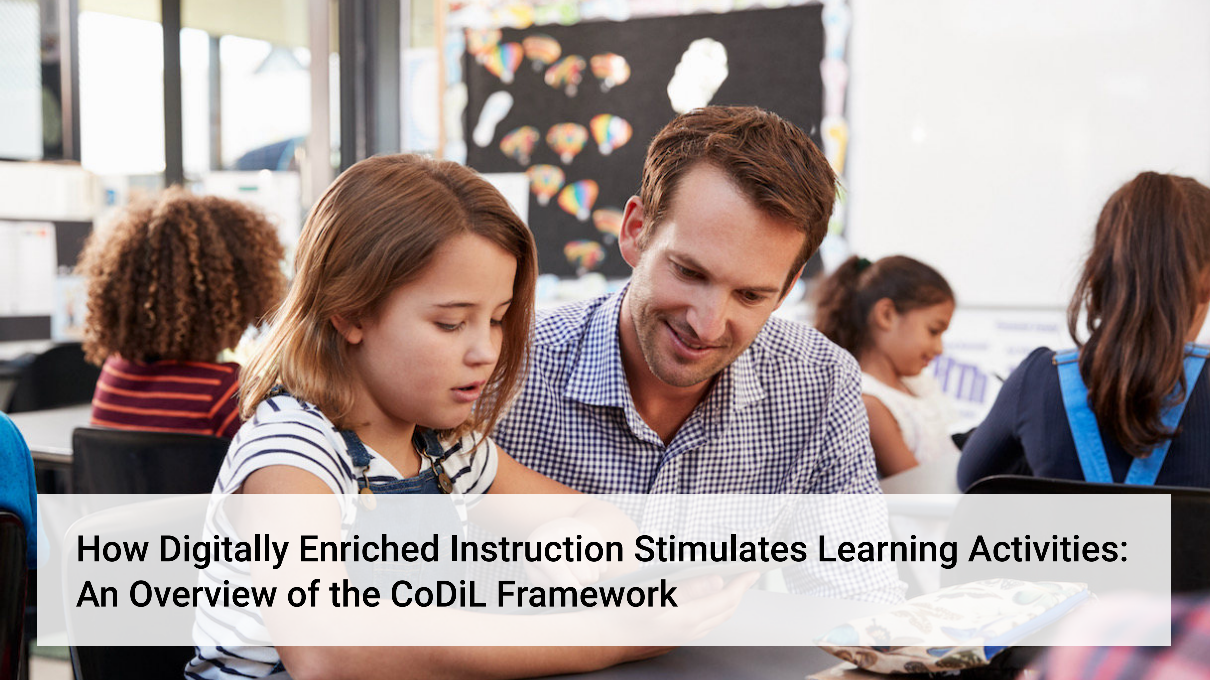
Understanding How Digital Tools Foster Mathematical Learning: Framework-Guided Investigations in Primary and Secondary Classrooms

Frank Reinhold

Institute for Mathematics Education · University of Education Freiburg
Center for Interdisciplinary Research on Digital Education · CIRDE · Freiburg

Munich, July 3rd, 2025



How Digitally Enriched Instruction Stimulates Learning Activities: An Overview of the CoDiL Framework

Introduction

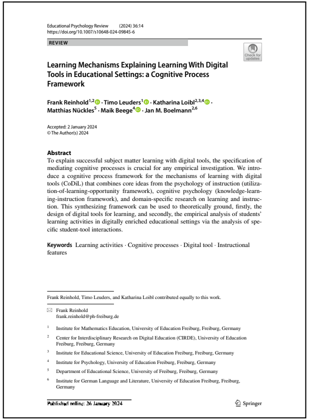
Di.ge.LL

Research Training Group: Digitally-supported teaching-and-learning environments for cognitive activation.

- **Objectives:** Development and empirical validation of research-based teaching-learning methods with digital tools for use in the classroom.
- **Research questions:** Stimulating cognitive activation in phases of learning new content.

Funded by: Baden-Württemberg

Cooperation with: Freiburg Advanced Center of Education – School of Education · DI.GE.LL



Educational Psychology Review (2024) 36:14
https://doi.org/10.1007/s10648-024-09845-6

REVIEW

Learning Mechanisms Explaining Learning With Digital Tools in Educational Settings: a Cognitive Process Framework

Frank Reinhold[1,2] · Timo Leuders[1] · Katharina Loibl[2,3,4] · Matthias Nückles[5] · Maik Beege[4] · Jan M. Boelmann[2,6]

Accepted: 2 January 2024

Abstract
To explain successful subject matter learning with digital tools, the specification of mediating cognitive processes is crucial for any empirical investigation. We introduce a cognitive process framework for the mechanisms of learning with digital tools (CoDiL) that combines core ideas from the psychology of instruction (utilization-of-learning-opportunity framework), cognitive psychology (knowledge-learning-instruction framework), and domain-specific research on learning and instruction. This synthesizing framework can be used to theoretically ground, firstly, the design of digital tools for learning, and secondly, the empirical analysis of students' learning activities in digitally enriched educational settings via the analysis of specific student-tool interactions.

Keywords Learning activities · Cognitive processes · Digital tool · Instructional features

Frank Reinhold, Timo Leuders, and Katharina Loibl contributed equally to this work.

Frank Reinhold
frank.reinhold@ph-freiburg.de

1 Institute for Mathematics Education, University of Education Freiburg, Freiburg, Germany
2 Center for Interdisciplinary Research on Digital Education (CIRDE), University of Education Freiburg, Freiburg, Germany
3 Institute for Educational Science, University of Education Freiburg, Freiburg, Germany
4 Institute for Psychology, University of Education Freiburg, Freiburg, Germany
5 Department of Educational Science, University of Freiburg, Freiburg, Germany
6 Institute for German Language and Literature, University of Education Freiburg, Freiburg, Germany

Published online: 26 January 2024
Springer

Reinhold, Leuders, Loibl, Nückles, Beege, & Boelmann. (2024). *Educ. Psychol. Rev.*

A Central Part of my Habilitation Thesis

The CoDiL Framework

Digitally-enriched settings provide instructional features that may be...

- Utilized by students during interaction with the tool which than...

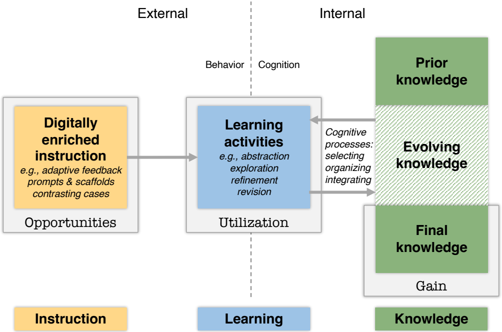
  (Utilization-of-Learning-Opportunities Framework by, e.g., Seidel, 2014)

- Stimulate behavioral (observable) and cognitive (latent) learning activities which...

  (Evidence-Centered Design Framework by, e.g., Goldhammer et al., 2021)

- Interact with prior knowledge to construct new (domain-specific) knowledge components.

  (Knowledge-Learning-Instruction Framework by Koedinger et al., 2012)



Reinhold, Leuders, Loibl, Nückles, Beege, & Boelmann. (2024). *Educ. Psychol. Rev.*

Development of Digital Learning Environments

Instruction

Aim: Evidence-based designs for digitally enriched learning environments that...

- Incorporate instructional features shaped by affordances and constraints, which...

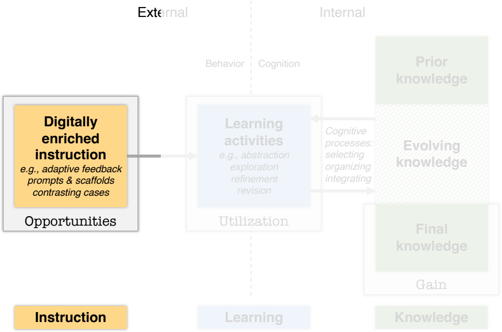
  (Greeno, 1998; Hartson, 2003; Norman, 1999; Scheiter, 2021)

- Focus established mechanisms of teaching and learning to stimulate learning processes...

  (Mayer, 2014; Schumacher & Stern, 2023; Sweller, 2020)

- With respect to the new-to-learn domain-specific knowledge components.

  (Anderson et al., 1997; Kintsch, 1991; Koedinger et al., 2012; Ritter et al., 2007)



Analyzing Learning Processes in Digital Contexts

Learning

Aim: Fine-grained insights into students' actual learning activities by...

- Considering learning an active and generative process subject to self-regulation, and...

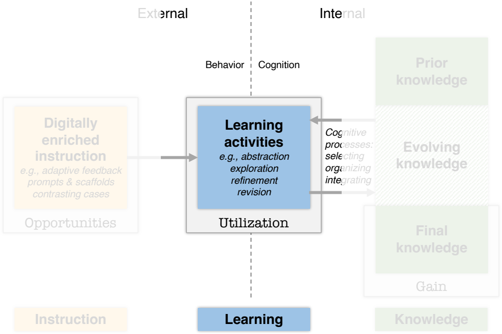
  (Fiorella & Mayer, 2015; Fredricks et al., 2004; Molenaar et al., 2023)

- Establishing theory-based links between on-task behavior and cognition while...

  (Goldhammer et al., 2017, 2021; Mislevy et al., 2012)

- Combining generic learning analytics with domain-specific process data.

  (Greiff et al., 2015; Huber & Bannert, 2023; Reinhold, Strohmaier et al., 2020)



Teaching and Learning in Competence Areas

Knowlegde

Aim: Understand learner-specific but systematic patterns of reasoning and difficulty by...

- Analyzing relevant 21st century skills in relation to subject-specific demands, ...

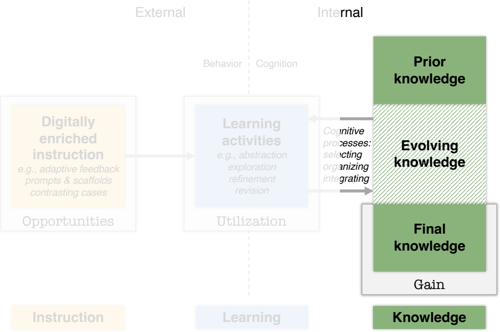
  (Bescherer et al., 2024; Martin, 2018; OECD, 2023)

- Connecting educational psychology and subject-matter didactics to...

  (Anderson et al., 1997; Kintsch, 1991; Koedinger et al., 2012; Ritter et al., 2007)

- Informing the design of digital tools through content-specific instructional insights.

  (Reinhold et al., 2024; Scheiter et al., 2022)



Teaching *frACTIONs* in Grade 6 Classrooms: Focusing Motivated Action in Learning Fractions with Digital Tools

Introduction

Pädagogische Hochschule Freiburg

The frACTIONs Project

Motivated Action in Learning Fractions with Digital Tools. Do adaptive features of digital learning environments...

- enhance engagement with learning activities...
- during training in mathematics classrooms...
- which in turn mediates learning gains?

Funded by:

Daimler und Benz Stiftung

Learning and Instruction 98 (2025) 102118

Contents lists available at ScienceDirect

Learning and Instruction

journal homepage: www.elsevier.com/locate/learninstruc

Stimulating individual learning of the concept of fraction equivalence: How students utilize adaptive features in digital learning environments mediates their effect

Maria-Martine Oppmann [a,*], Maik Beege [b], Frank Reinhold [a,c]

[a] Institute for Mathematics Education, University of Education Freiburg, Kunzenweg 21, 79117, Freiburg, Germany
[b] Institute for Psychology, University of Education Freiburg, Heinrich-von-Stephan-Straße 5a, Hölderle-Carre, Germany
[c] Center for Interdisciplinary Research on Digital Education (CIRDE), University of Education Freiburg, Freiburg, Germany

ARTICLE INFO

Keywords:
Adaption
AI in education
Log-file analysis
Equivalent fractions
Mathematics education

STRUCTURED ABSTRACT

Introduction: Students face challenges when learning fractions. To support students' understanding of equivalent fractions, adaptive support can provide a variety of benefits. The purpose of this study is to utilize real-time process data to tailor students' individual learning experience with adaptive support. We propose a mediation model to explain the positive effect of such adaptive features on learning outcomes by increased student engagement.

Method: We conducted a 90-min RCT with a total of $N = 300$ sixth-grade students. Learning about equivalent fractions, an experimental group used an adaptive digital learning environment for practice. A control group used an equivalent non-adaptive, paper-based learning environment to practice the same tasks. Our hypothesis was that the two conditions showed different engagement during practice—explaining differences in learning outcomes.

Results and discussion: Results were in line with our mediation hypothesis: Using cluster analysis, we identified six user-profiles of students with differing behavioral and cognitive engagement during practice—utilizing process data (i.e., number of tasks and accuracy of solved tasks per difficulty level). These profiles were associated with different levels of perceived autonomy and competence support and perceived overload—and consequently learning outcomes. We also found a significant indirect mediation effect, emphasizing our hypothesis that adaptive support positively influences learning outcomes through its positive influence on students' actual engagement during classroom practice.

1. **Introduction**

Understanding fractions is a fundamental yet challenging aspect of mathematical learning. A critical hurdle in fraction comprehension is grasping the concept of equivalence—recognizing that different symbolic representations (e.g., 2/4 and 1/2) can denote the same numerical value (Behr et al., 1983; Kieren, 1983; Pedersen & Bjerre, 2021). Research suggests that students often struggle with this concept due to a reliance on natural number reasoning (DeWolf et al., 2015). Developing a solid understanding of equivalent fractions is crucial, as it serves as a foundation for more advanced mathematical topics, including proportional reasoning and algebra (Booth & Newton, 2012).

To support student learning, educational technologies incorporating adaptive features, such as individualized task difficulty (i.e., adaptivity) and individualized feedback, have proven effective (Hillmayr et al., 2020; see Demedts et al., 2024 for another recent study regarding fractions). From a cognitive perspective, these features can enhance germane processing by ensuring that high-achieving students engage with appropriately challenging tasks—and struggling students are not overwhelmed by inappropriately difficult tasks and receive tailored feedback addressing their specific errors—aiming at lowering their intrinsic load (Kalyuga, 2009). Beyond cognition, adaptivity and feedback can also foster motivational-emotional engagement by enhancing students' perceived competence and task suitability (Barana et al., 2021; Koenka & Anderman, 2019).

The goal of this study is to examine whether such adaptive features

This article is part of a special issue entitled: Adaptive support published in Learning and Instruction.
* Corresponding author. University of Education Freiburg, Kunzenweg 21, 79117, Freiburg, Germany.
E-mail addresses: maria.oppmann@ph-freiburg.de (M.-M. Oppmann), maik.beege@ph-freiburg.de (M. Beege), frank.reinhold@ph-freiburg.de (F. Reinhold).

https://doi.org/10.1016/j.learninstruc.2025.102118
Received 1 February 2024; Received in revised form 5 March 2025; Accepted 15 March 2025
Available online 28 March 2025

Oppmann, Beege, & **Reinhold**, (2025). *Learn. Instr.*

Introduction

Pädagogische Hochschule Freiburg

Fractions are notoriously difficult to learn

Conceptual challenge: Understanding fraction equivalence

(Behr et al., 1983; Kieren, 1983; Pedersen & Bjerre, 2021)

Aufgabe 1 Kürze so weit wie möglich.

a) $\frac{18}{72} =$ 18 : 3 = 6
72 : 9 = 8

b) $\frac{21}{63} =$ 21 : 7 = 3
63 : 9 = 7

c) $\frac{7}{7} =$ 7 : 3 = 4
7 : 4 = 3

Student from German „Hauptschule“, grade 6, after 16 lessons of fractions instruction

Fractions are notoriously difficult to learn

Conceptual challenge: Understanding fraction equivalence

(Behr et al., 1983; Kieren, 1983; Pedersen & Bjerre, 2021)

Aufgabe 7 Ergänze die fehlenden Zahlen in den Kästen.

a) $\dfrac{3}{\boxed{4}} = \dfrac{12}{28}$ b) $\dfrac{6}{8} = \dfrac{\boxed{2}}{20}$ c) $4 = \dfrac{\boxed{1}}{3}$

Student from German „Gymnasium“, grade 6, after 16 lessons of fractions instruction

Introduction

Fractions are notoriously difficult to learn

Conceptual challenge: Understanding fraction equivalence

(Behr et al., 1983; Kieren, 1983; Pedersen & Bjerre, 2021)

- Involves typical hurdles and misconceptions
  - Overgeneralization of natural number concepts, e.g., „unique representations“
  - Misinterpretation of everyday terms, e.g., „reducing should make smaller“
  - Problems with the algorithmic procedure, e.g., $\frac{5}{3} = \frac{5+3}{3+3} = \frac{8}{6}$, or $\frac{14}{45} = \frac{1}{5}$

  (Eichelmann et al., 2012; Obersteiner et al., 2015; Prediger, 2008; Reinhold, Hoch et al., 2020)

- Importance of fostering conceptual ideas before procedural training

  (Prediger, 2008; Rau et al., 2017; Van Hoof et al., 2018)

- Expanding & reducing fractions by refining & coarsening part-whole representations

  (Lamon, 2020; Reinhold, Hoch et al., 2020)

Introduction

Features of educational technology can support cognitive learning processes

Instructional challenge: Learning opportunities need to be taken to be effective

(Chi & Wylie, 2014; Reinhold et al., 2024; Seidel, 2014)

- Adaptive task difficulty can prevent cognitive overload

  (Kalyuga & Sweller, 2005; Moreno & Mayer, 2007; Sweller, 2020)

- Corrective and explanatory feedback can reduce extraneous load

  (Hattie & Timperley, 2007; Reinhold et al., 2024; Wisniewski et al., 2020)

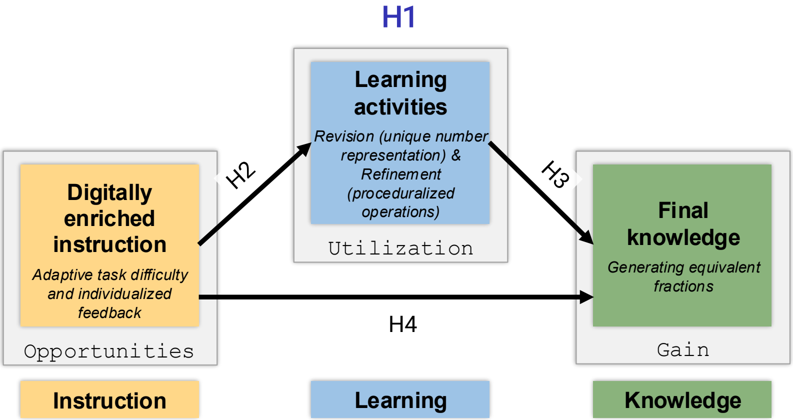
- But the effectiveness of these features in technology-based learning may depend on ...
  - Prior knowledge

    (Demedts et al., 2024)
  - Behavioral and cognitive engagement

    (Fredricks et al., 2004; Goldhammer et al., 2021; Reinhold, Strohmaier et al., 2020)

Research Questions and Hypotheses

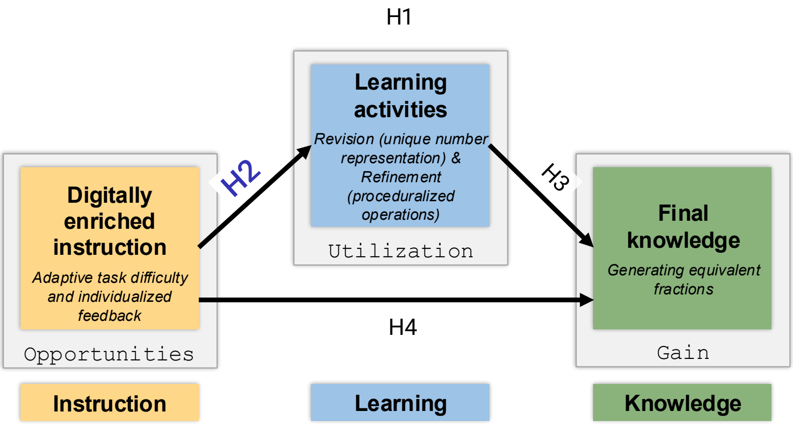
Study 1: The frACTIONs Project



Hypothesis 1:
Students differ in how they engage in the provided training material during ma-thematics lessons.

Research Questions and Hypotheses

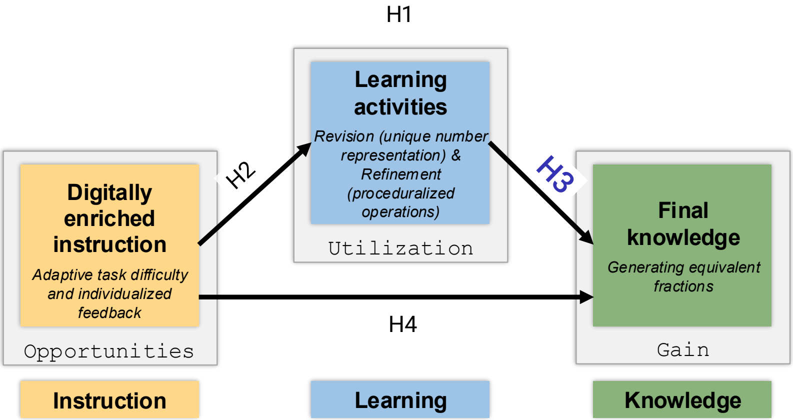
Study 1: The frACTIONs Project



Hypothesis 2:
Adaptivity and feed-back influence how students enga-ge in the provided training material.

Research Questions and Hypotheses

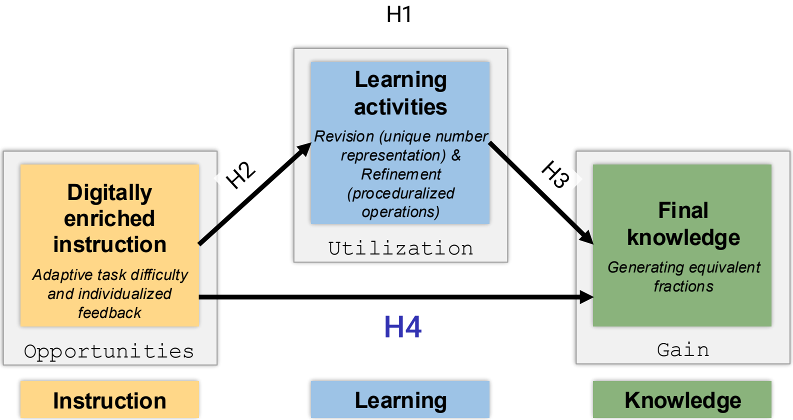
Study 1: The frACTIONs Project



Hypothesis 3:
Different engagement with the provided training material leads to differences in content-specific knowledge after training.

Research Questions and Hypotheses

Study 1: The frACTIONs Project

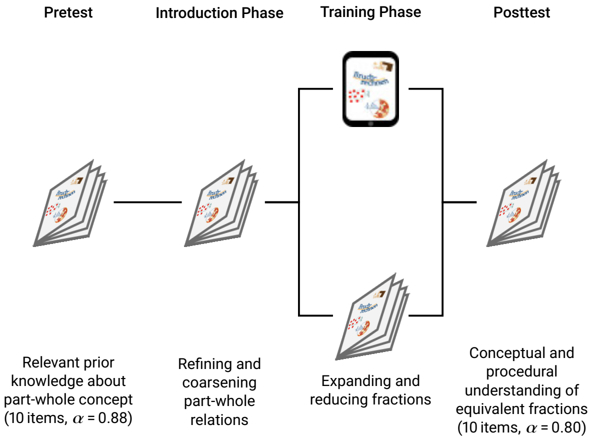


Hypothesis 4:
Adaptivity and feed-back have a posi-tive effect on stu-dents' content- spe-cific knowledge af-ter training— media-ted by engagement.

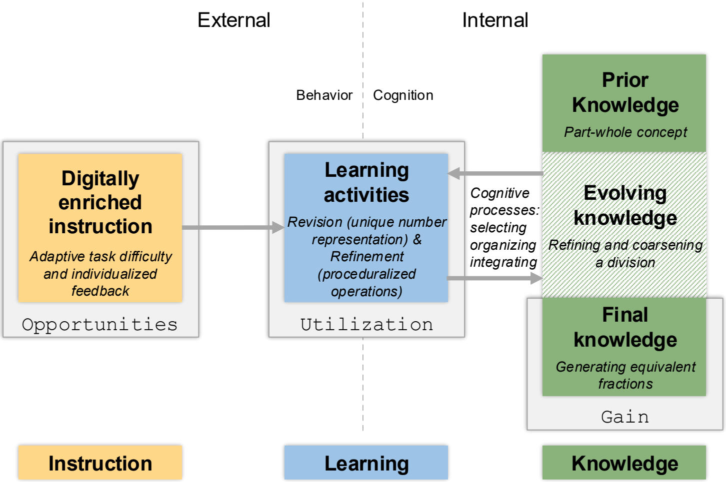
Method

Study Design

- **Sample:** Randomized controlled trial with *N* = 300 6th-grade students
- **Experimental Group (EG)**: Adaptivity & feedback (Digitally-enriched ITS)
- **Control Group (CG)**: Linear increasing difficulty & no feedback (Paper-based)
- 90 minutes intervention during regular mathematics instruction at school

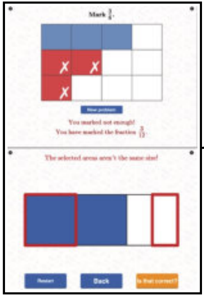


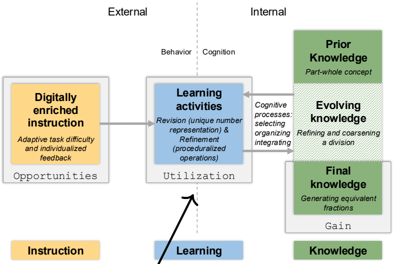
Method

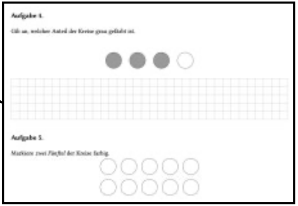


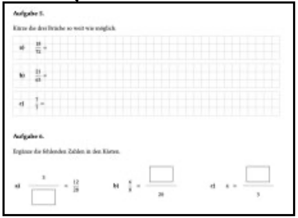
External
Internal
Behavior
Cognition
Prior Knowledge
Part-whole concept
Digitally enriched instruction
Adaptive task difficulty and individualized feedback
Opportunities
Learning activities
Revision (unique number representation) & Refinement (proceduralized operations)
Utilization
Cognitive processes: selecting organizing integrating
Evolving knowledge
Refining and coarsening a division
Final knowledge
Generating equivalent fractions
Gain
Instruction
Learning
Knowledge

Method









Linking on-task behavior to learning activities.

Derived process measures during training phase:

- Number of worked-on tasks in each difficulty cluster
- Solution rate in each difficulty cluster

Results

Hypothesis 1: Different engagement with training material

Gaming the System

only engaging with low levels of difficulty · low success rates · rushing through large amount of tasks

The Average

moderate success rates · low number of worked-on tasks · mostly tasks of medium difficulty

Accelerated Experts

skipping low levels of difficulty · high success rates · most worked-on tasks on highest difficulty

Accelerated Workers

high success rate in easiest tasks · moderate success in medium tasks · not reaching highest difficulty

Slowed-down Experts

trapped in low levels of difficulty · high success rates · only few to no tasks of highest difficulty

Industrious Experts

high success rates · medium number of worked-on tasks · barely reaching highest difficulty levels

k-Means Cluster Analysis of 14 metric process indicators per student—derived from 11,071 observations

Results

Hypothesis 2: Features influence engagement

Gaming the System

The Average

Accelerated Experts

Accelerated Workers

Slowed-down Experts

Industrious Experts

Multinomial logistic regression: $X^2(5) = 96.68$, $p < 0.001$

Results

Hypothesis 3: Different engagement leads to different posttest outcomes

Gaming the System

The Average

Accelerated Experts

Accelerated Workers

Slowed-down Experts

Industrious Experts

One-way ANOVA: $F(5, 257) = 14.45$, $p < 0.001$, $\eta_p{}^2 = 0.22$

Results

Hypothesis 4: Engagement mediates success of adaptive features

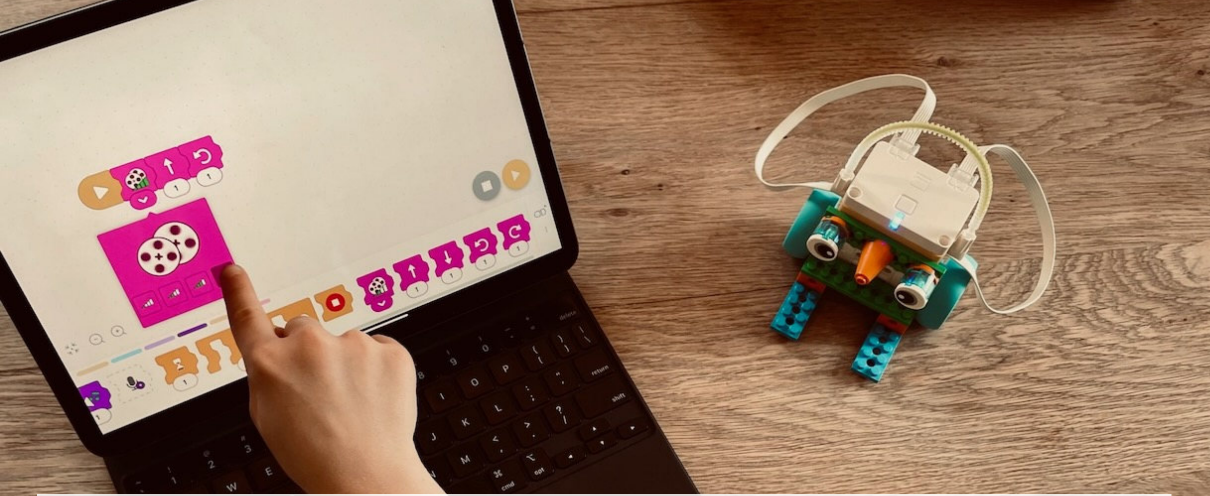
- **Welsh *t*-Test.**

	Control		Experimental					
Scale	*M*	*SD*	*M*	*SD*	*t*	*df*	*p*	*d*
Posttest Outcome	7.172	4.884	7.295	5.009	−0.216	297.555	0.830	0.025

But: Both low-engaged worst performing subgroup (Gaming the system), and high-engaged best performing subgroup (Accelerated Experts) overrepresented in EG

- **Structural equation model.** Significant indirect path in line with hypothesis:

$$\beta = -0.173^{*} \qquad \mathrm{CFI} = 0.992, \mathrm{TLI} = 0.991, \mathrm{RMSEA} = 0.023$$



Teaching *Computational Thinking* in Grade 2 and 3 Classrooms: LEGO®-Enriched Programming in Mathematics

Introduction

The COMPI.LE Project

Understanding learning processes in early CT education.

- Investigates how **engagement with CT activities** can be enhanced through age-appropriate instructional design.
- Focuses on **primary school mathematics classrooms** using block-based programming and tangible tools.
- Addresses the open question of **how underlying learning processes unfold** during early CT instruction.

Computers and Education Open 8 (2025) 100260

Contents lists available at ScienceDirect

Computers and Education Open

journal homepage: www.sciencedirect.com/journal/computers-and-education-open

Introducing computational thinking to second and third graders. Programming whole paths outperforms step-by-step navigation in maze tasks

Frank Reinhold [a,b,*], Priska Sprenger [a], Gunnar Staniczek [c]

[a] Institute for Mathematics Education, University of Education Freiburg, Freiburg, Germany
[b] Center for Interdisciplinary Research on Digital Education (CIRDE), University of Education Freiburg, Freiburg, Germany
[c] State Media Center Baden-Württemberg (Landesmedienzentrum BW, LMZ), Karlsruhe, Germany

ARTICLE INFO

Keywords:
Computational thinking
Maze task
Algorithmicizing
Programming
Sequencing
Primary education

ABSTRACT

Computational Thinking (CT) has been considered one of the 21st century skills that already primary school students should develop. In this study we compared different methods for guiding a real object through a training maze task to teach $N = 70$ second and third graders basic computational thinking concepts, i.e., basic directions and sequences. Students in the experimental condition used the LEGO® Education SPIKE™ Essential-Set and Scratch-based icon blocks software to navigate a maze, while the control group used regular LEGO®-Sets and verbal commands. Results supported our hypotheses: Students in the experimental condition outperformed those in the control condition, produced longer sequences and more sequence commands to direct their object through the maze, and a positive relationship was observed between sequence length and posttest performance. Furthermore, mediation analysis revealed that the effect of the intervention on posttest achievement was influenced by the use of longer sequences. Our study underpins that Scratch-based block programming combined with robot-like real-world devices is a promising way to utilize CT in (early) primary education—and deepens our knowledge about how students engage in relevant learning activities.

1. Introduction

For several years, Computational Thinking (CT) has been considered one of the 21st century skills that all students should develop [13,15,25,28]. Meanwhile, a discussion about CT has developed internationally, resulting in CT being increasingly integrated into schools and curricula worldwide [4]—not as a single trend, but rather "constitute[ing] a change that is likely to continue in the long term" (p. 353). Despite this increasing importance of CT, there is still no specific, universally accepted definition of computational thinking [23,27]. Shute et al. [20] define CT as "the conceptual foundation required to solve problems effectively and efficiently (i.e., algorithmically, with or without the assistance of computers) with solutions that are reusable in different contexts" (p. 142). Thus, CT is not limited to learning programming syntax but develops the universal ability to think conceptually and solve problems at multiple levels of abstraction [5,11,25,27]. Such problem-solving skills are essential—especially for learning mathematics. In order to solve mathematical problems effectively and efficiently with reusable solutions, basic activities that promote skills in the context of CT are, for example, decomposition, abstraction, or algorithm design [5,15,20]. In this article, we focus on the specific computational thinking concept 'basic directions and sequences' [23]—which can be considered one of the most basic concepts of CT that students can (and should) learn from an early age [25,28].

1.1. Computational thinking in young age groups

Introducing CT at an early age represents an important novel and innovative approach [13,24], especially given that this developmental stage traditionally focuses on more foundational skills such as literacy and numeracy [3]. Recent studies suggest that CT is a unique set of cognitive skills that develops differently across age groups and is influenced by various cognitive abilities, including numerical and mathematical skills, verbal reasoning, and visuospatial skills [23]. Since CT concepts such as logical sequencing, pattern recognition, and problem-solving are often perceived as abstract and challenging for

* Corresponding authors.
E-mail address: frank.reinhold@ph-freiburg.de (F. Reinhold).

https://doi.org/10.1016/j.caeo.2025.100260
Received 14 September 2024; Received in revised form 10 April 2025; Accepted 1 May 2025
Available online 2 May 2025

Reinhold, Sprenger, & Staniczek, (2025). *Comp. Educ. Open*

Introduction

What is Computational Thinking

- Computational Thinking (CT) is considered one of the **21st-century skills** that all students should develop

  (Manches & Plowman, 2017; OECD, 2023; Wing, 2006; Yildirim & Uluyol, 2023)

- CT is increasingly being **integrated into schools and curricula internationally**

  (Broley et al., 2024)

- No universally accepted definition; however: *„the conceptual foundation required to solve problems effectively and efficiently (i.e., algorithmically, with or without the assistance of computers) with solutions that are reusable in different contexts"*

  (Shute et al., 2017; see also Tsarava et al., 2022; Yeni et al., 2023)

- CT supports the ability to think **abstractly** and to **solve problems**

  (Büscher, 2024; Lee & Lee, 2024; Wing, 2006; Yeni et al., 2023)

Pädagogische Hochschule Freiburg

Activities and Processes in the Context of CT

- A qualitative study with 11- to 13-year-olds using ‘Turtlecoder’ revealed differences in activities such as:
  - Reusing and modifying code
  - Decomposing problems
  - Testing and evaluating solutions
  - **Algorithmic thinking**
  - Abstraction
  - Generalization

  (Büscher, 2024; see also Brennan & Resnick, 2013; Selby & Woollard, 2013)
- Those differences in the problem-solving processes among 11- to 13-year-olds suggest that these processes might be even more heterogeneous in **younger students**.

Introduction

Foundational Concepts for Promoting CT

- A central concept for the early development of CT is the *„ability to formulate and solve problems by relying on the fundamental concepts of computing, and using logic-syntax of programming languages“*

  (Román-González et al., 2017)

- In assessment contexts, often operationalized as **basic directions and sequences**

  (Román-González et al., 2017; Shute et al., 2017; Tank et al., 2024; Tsarava et al., 2022; Zapata-Caceres et al., 2020; Zhang & Wong, 2024)

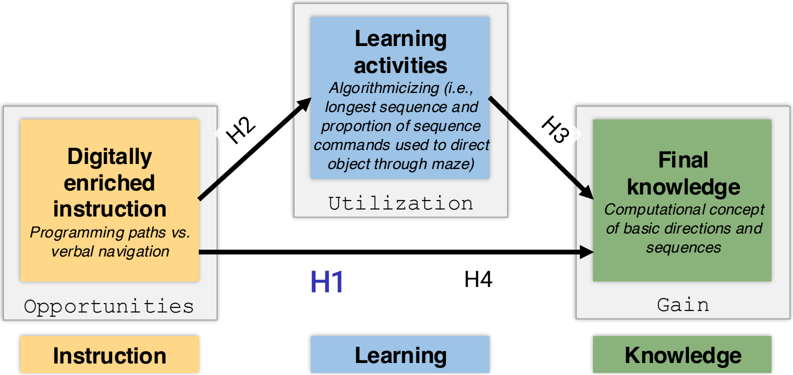
- Plausible starting point for CT interventions with young learners:
  - Focus: **Algorithmic thinking** as explicit articulation of at least two steps in a sequence

    (Büscher, 2024)
  - Implemented in block-based digital CT learning settings or in „unplugged“ CT activities

    (Ersozlu et al., 2023; Tank et al., 2024; Zhang & Wong, 2024)

Research Questions and Hypotheses

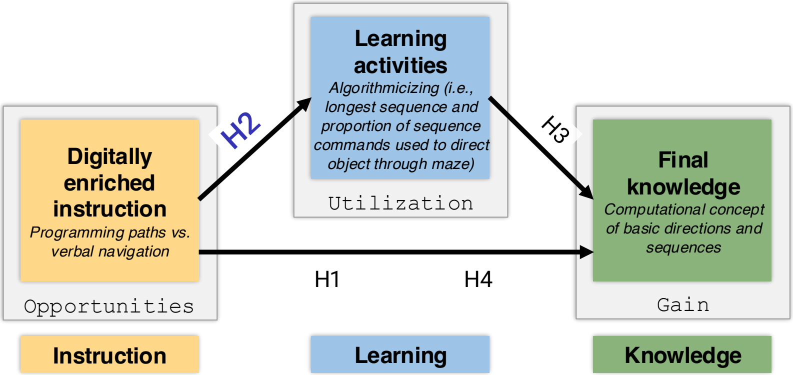
Study 2: The COMPI.LE Project



Hypothesis 1:
Programming paths in maze tasks outperforms unplugged verbal navigation when learning the computational concept of basic directions and sequences for the first time.

Research Questions and Hypotheses

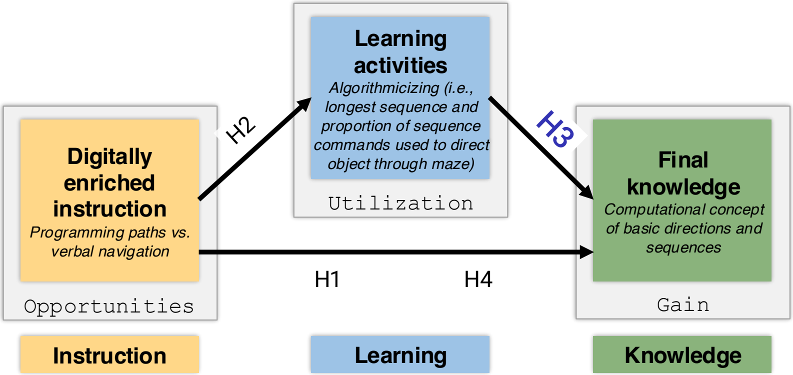
Study 2: The COMPI.LE Project



Hypothesis 2:
Programming paths (vs. unplugged verbal navigation) influences how algorithmicizing processes are stimulated during learning.

Research Questions and Hypotheses

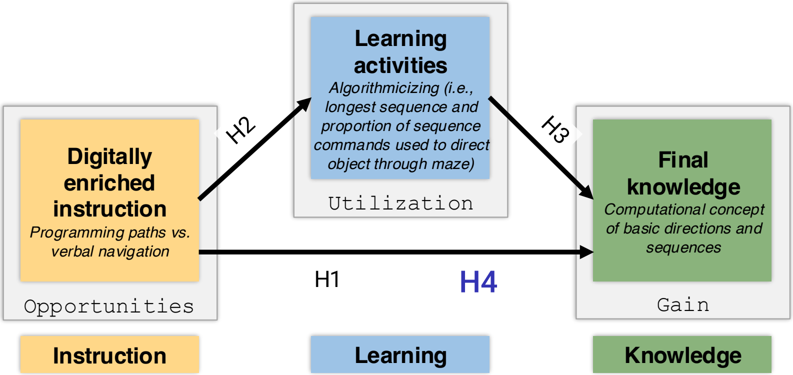
Study 2: The COMPI.LE Project



Hypothesis 3:
Different Algorithmicizing processes lead to differences in content-specific knowledge after training.

Research Questions and Hypotheses

Study 2: The COMPI.LE Project



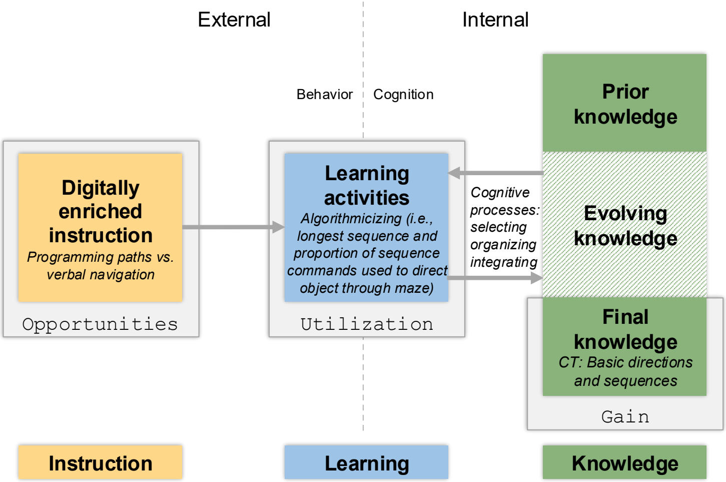
Hypothesis 4:
The effect of programming whole paths vs. verbal navigation is mediated by algorithmicizing processes during learning.

Method

Study Design

- Randomized controlled trial with $N = 70$ 6th- and 7th-grade students in pairs
- **Procedure:** 5 min (Pretest), 30 min (Intervention), 10 min (Posttest)
- **Intervention:** Assembly phase and Labyrinth phase; story-based navigation through a complex arctic maze (19 commands necessary)
  - **EG:** LEGO® SPIKE™ Essential with Scratch-based Icon-Block programming
    (e.g., Ersozlu et al., 2023; Zhang & Wong, 2024)
  - **CG:** Regular LEGO®-Set with „unplugged" verbal control commands
    (e.g., Hsu et al., 2018)
- **Process data analysis:** Videography of all sessions; coding of all commands, the sequence commands, and the length of the sequence commands

Method

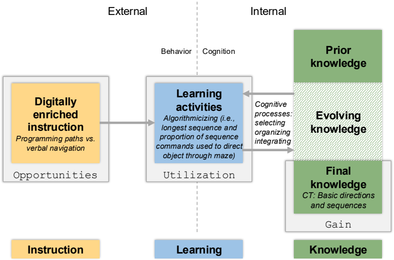

External
Internal
Behavior
Cognition
Prior knowledge
Digitally enriched instruction
Programming paths vs. verbal navigation
Opportunities
Learning activities
Algorithmicizing (i.e., longest sequence and proportion of sequence commands used to direct object through maze)
Utilization
Cognitive processes: selecting organizing integrating
Evolving knowledge
Final knowledge
CT: Basic directions and sequences
Gain
Instruction
Learning
Knowledge

Method

Fig. 2a: Experimental condition (front view)

Fig. 2b: Control condition (front view)

Fig. 2c: Experimental condition (side view)



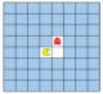


Fig. 3a: Instructional item

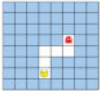


Fig. 3d: Posttest item 3

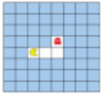


Fig. 3b: Pretest item 1 and Posttest item 1

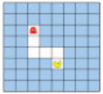


Fig. 3e: Posttest item 4

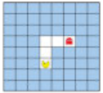


Fig. 3c: Posttest item 2

Pac-Man labyrinth tasks

(e.g., Tsarava et al., 2022; Zapata-Cáceres et al., 2020)

Results

Hypothesis 1: Different engagement with training material

	Model 0		Model 1		Model 2		Model 3	
Fixed effects	*OR (SE)*	*p*	*OR (SE)*	*p*	*OR (SE)*	*p*	*OR (SE)*	*p*
Prior knowledge	—	—	2.68 (1.25)	0.034	3.22 (1.49)	0.011	3.79 (1.71)	0.003
Grade level [2 → 3]	—	—	—	—	3.92 (1.74)	0.002	3.82 (1.63)	0.002
Condition [Ctr. → Exp.]	—	—	—	—	—	—	3.36 (1.42)	0.004
Random effects	*Var*	*PCV*	*Var*	*PCV*	*Var*	*PCV*	*Var*	*PCV*
Student (N = 70)	1.96	—	1.79	8.7%	1.39	22.3%	1.10	20.8%
Item (k = 4)	0.80	—	0.80	—	0.81	—	0.82	—
Model characteristics	*Estimate*	*p*	*Estimate*	*p*	*Estimate*	*p*	*Estimate*	*p*
R^2 (marginal)	0.000	—	0.038	—	0.114	—	0.172	—
R^2 (conditional)	0.456	—	0.462	—	0.469	—	0.478	—
AIC	340.905	—	338.356	—	330.309	—	323.538	—
X^2	—	—	4.549	0.033	10.047	0.002	8.772	0.003

Results

Hypothesis 2: Features influence engagement

	Longest sequence		Relative number of sequences	
Predictors	*IRR (SE)*	*p*	*Est. (SE)*	*p*
Prior knowledge	0.80 (0.12)	0.144	0.93 (0.45)	0.874
Grade level [2 → 3]	2.35 (0.34)	<.001	2.21 (0.98)	0.073
Condition [Ctr. → Exp.]	8.96 (2.00)	<.001	4.80 (2.12)	<.001

Results

Hypothesis 3: Different engagement leads to different posttest outcomes

Prediction of solution probabilities for items in the posttest:

Longest sequence:	$OR = 2.20^{***}$	$95\%\ CI\ [1.36, 3.55]$
Relation of sequence commands:	$OR = 1.95^{**}$	$95\%\ CI\ [1.22, 3.14]$

Results

Hypothesis 4: Engagement mediates success of digital features

Indirect Paths in Mediation Model:

Longest sequence:	$\beta = 0.614^{**}$
Relation of sequence commands:	$\beta = 0.053^{ns}$

Investigating the Role of Digital Tools in Fostering Learning: Insights from CoDiL-Studies in Mathematics Classrooms

Discussion: Study 1 (The frACTIONs Project)

Implications

- **Engagement** with learning activities is **essential** to realizing the potential of adaptive instructional features.
- Scaffolds worked for high-achieving students—but **distracted low-achieving students** and even hindered their learning.
- **Data-driven classification** of student engagement patterns offers a promising basis for **tailoring instruction**.

Limitations and Future Directions

- Control group received **non-digital instruction**—limiting conclusions about adaptivity effects per se.
- **Short duration** of the intervention may have been insufficient to produce measurable learning effects.
- Future work should explore **long-term implementations** and **disentangle affordances** of adaptivity and feedback.

Discussion: Study 2 (The COMPI.LE Project)

Implications

- Findings **extend prior research on CT instruction**, demonstrating that CT integration is feasible in primary school.
- **Block-based programming** outperformed unplugged instruction—due to more engagement in algorithmic thinking.
- The study demonstrates how **CT can be meaningfully integrated** early within regular math instruction.

Limitations and Future Directions

- **Small sample size** limits statistical power and generalizability—but keep large effects in mind.
- **Short intervention** limits insight into long-term learning and development of CT skills.
- Future work should **broaden CT content** beyond basic sequences and directions and explore age-specific support needs.

Thank you for your attention.

Pädagogische Hochschule Freiburg

Prof. Dr. Frank Reinhold

University of Education Freiburg
Institute for Mathematics Education

frank.reinhold@ph-freiburg.de
https://frankreinhold.education/
@Reinhold_Edu

cirde
Center for Interdisciplinary Research on Digital Education

https://www.ph-freiburg.de/cirde/


F. Reinhold


T. Leuders


K. Loibl


M. Nückles


J. M. Boelmann

Study 1: frACTIONs


M. Beege


M.-M. Oppmann


Study 2: COMPI.LE


P. Sprenger


G. Staniczek