Longitudinal Examination of Affective, Motivational, Self-Regulatory, and Engagement Processes in Statistics (LEARN-STAT)

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Why Study SRL in Statistics?

The Challenge: Statistics Is a Demanding Gateway Course

Higher education demands self-regulated learning (SRL) ⚠

- Students must independently manage workload and motivation (Faas et al., 2018; Wolters & Brady, 2021)
- Engagement often declines early and accelerates only shortly before exams (Mefferd & Bernacki, 2023; Schwerter et al., 2026a; von Keyserlingk et al., 2025b)
- Consistent, distributed engagement relates to higher exam performance (Schwerter & Brahm, 2024; von Keyserlingk et al., 2025a)

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Statistics: high cognitive and emotional demands

- Business & social-science students frequently report anxiety toward quantitative material (Brown & Kass, 2009; Lunardon et al., 2024, 2025)
- Statistics/math anxiety is consistently associated with lower achievement (Barroso & Ganley, 2021; Macher et al., 2013)
- Anxiety reflects low-control–high-value appraisals that undermine self-effica[illegible] engagement ([illegible], 2006; [illegible] et al., 2023)

What We Have Learned From Our Prior Work

Digital practice works — but engagement is the bottleneck

- Additional online practice **increases exam performance** (Schwerter & Brahm, 2024; Schwerter et al., 2022); retrieval practice improves quiz performance **causally** (Schwerter et al., 2026a)
- But: lower-achieving students need *more* attempts for the same gain — and engage **less** (Schwerter et al., 2025)
- Motivational beliefs and self-set goals relate to achievement **through sustained weekly engagement**; within students, engagement responds to the gap between intended and realized practice (Schwerter et al., in progress)

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What behavioral traces alone cannot show us ?

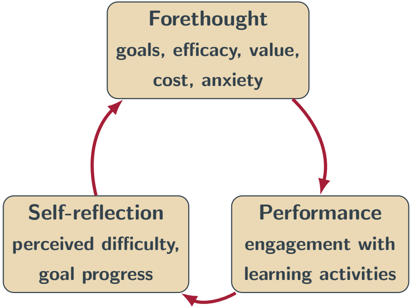
- How students **monitor** progress, **experience** difficulty or anxiety, and **revise** their standards over time
- A digital event is not automatically evidence of a regulatory process — interpretation requires theory and context (Schwerter et al., 2026b; Winne, 2020)

The Gap: SRL Is Cyclical — but Rarely Measured That Way

- Cyclical SRL models: **forethought** → **performance** → **self-reflection**, feeding back into the next cycle (Pintrich & Zusho, 2007; Zimmerman, 2002)
- Motivational states *fluctuate* within a semester and predict achievement (Benden & Lauermann, 2022; Fryer et al., 2022)

But: no study has modeled the **week-to-week co-development** of anxiety, self-efficacy, value/cost, perceived difficulty, goals, *and* learning behavior in an authentic course

→ We cannot yet see **when and how adaptive SRL cycles break down**



Cyclical SRL framework (Zimmerman, 2002)

⇒ We need repeated state measures paired with weekly trace data.

Research Questions

- **RQ1 – Fluctuation:** How do affective experiences, metacognitive judgments, and engagement behaviors **fluctuate within students** across the semester?
- **RQ2 – Forethought $\rightarrow$ Behavior:** Do metacognitive experiences (e.g., perceived difficulty) and affective states **predict subsequent engagement** in digital learning opportunities?
- **RQ3 – Feedback loops:** Do engagement behaviors **feed back** into subsequent affective and metacognitive states, forming **adaptive or maladaptive SRL cycles**?
- **RQ4 – Outcomes:** How do these dynamics relate to **exam performance**?
- **RQ5 – Intervention:** Does prior participation in the **SoL2L intervention** (1st-semester math course) affect the relations in RQ1–RQ4?

Definitions

Adaptive cycle: difficulty signal $\rightarrow$ *increased* engagement $\rightarrow$ improved performance.
Maladaptive cycle: negative affect (anxiety) $\rightarrow$ *disengagement* $\rightarrow$ decline.

The Digital Environment

Setting: A Large Authentic Statistics Course

Sample-based Data Analysis (SBDA)

- Compulsory 3rd-semester statistics course, University of Hohenheim
- BA Economics & Business and related programs
- ~**700–900 students**, winter term 2026/27
- Probability-based inference: probability, random variables, estimation, hypothesis testing

Why this course?

- Abstract, probability-heavy content → anxiety, low self-efficacy, and mid-semester disengagement especially likely
- Same cohort took the **SoL2L intervention** in their 1st-semester math course → long-term intervention effects testable (RQ5)

Delivered through the **Lernkompass / Course Hub**: a bilingual, university-hosted web application complementing the institutional LMS (ILIAS).

The Course Hub: One Environment, Everything Weekly

Learning materials

- Annotated slide decks (PDF) with saved-page & progress tracking
- Lecture videos
- Exercise sheets & Questions-for-Review (Q4R)
- R materials, datasets, JupyterHub/GitLab links
- Formative self-tests & practice quizzes with immediate feedback (repeated retrieval)

Built-in self-monitoring

- Q4R & exercises as **interactive checklists**
- Per item, students self-record: processing status, perceived difficulty, understanding, repetition priority, clarification need, private notes
- Condensed into a **personal learning-progress overview** (students) and an **aggregated dashboard** (lecturers)

The platform makes both learning behavior and self-evaluation observable.

Four Linked Data Streams

Trait survey (Week 1)
self-efficacy, value, cost, statistics anxiety, GAD-7, SRL tendencies, course goals

Weekly micro-survey
8 single items at first login of each learning week (14 weeks)

Digital trace data
passive events + explicit learning-accounting markings

Performance
quiz results, final exam scores & grades

↓

Linked via pseudonymized one-way hash IDs (GDPR-compliant, opt-in consent)

- **Passive traces:** material impressions, slide-page progress, video events, Q4R/exercise access → objective, performance-phase engagement indicators
- **Explicit learning accounting:** item-level difficulty/understanding/repeat-need markings → student-controlled indicators of metacognitive monitoring (append-only history → within-person change modelable)
- Traces show the *behavior*; the micro-surveys recover the *internal states* that generate it → reduces common-method bias

The Weekly Micro-Survey: 8 Items, Once per Week

Self-reflection on last week

1. Perceived difficulty of last week's content
2. How well content was understood

Current states

3. Statistics anxiety
4. Self-efficacy
5. Interest

Prospective (forethought)

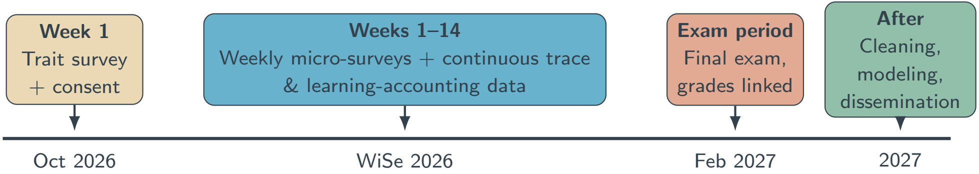
6. Weekly process goal (intended practice)
7. Updated exam-grade goal
8. Goal-progress self-evaluation

Design decisions

- Administered at **first login** of the learning week, *before* students access practice materials
- Single items → minimal burden, consistent weekly response
- Indexes forethought states + brief reflection on the prior week
- Finer-grained monitoring (item-level difficulty, understanding, repeat-need) comes from the platform's learning-accounting data instead

Design & Analysis

Study Timeline at a Glance



- **Participation:** voluntary, opt-in informed consent (GDPR Art. 6(1)(a)), opt-out at any time; ethics approval sought before data collection
- **Incentives:** vouchers to support participation across the full semester
- **Data protection:** one-way hash IDs; key encrypted, held by lecturer only; analyses on pseudonymized data on German university servers

Analytic Approach

Within-person dynamics (RQ1–RQ3)

- Multilevel vector-autoregressive (mlVAR) / dynamic structural equation models (DSEM)
- Lagged relationships between weekly affective, motivational, metacognitive, and behavioral indicators
- Weekly indicators **person-mean centered** → isolate within-person fluctuations
- Between-person predictors (trait anxiety, baseline self-efficacy, SoL2L participation) explain **heterogeneity** in dynamics (RQ5)

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Linking dynamics to achievement (RQ4)

- Final exam performance predicted from **preregistered summary indicators** of trajectories and engagement patterns
- Regularized regression models

Expected Contribution & Road Ahead

Theory

- First week-to-week model of the **co-development** of anxiety, self-efficacy, value/cost, perceived difficulty, goals, and engagement in an authentic course
- Empirically identifies when **adaptive vs. maladaptive SRL cycles** emerge (Pintrich & Zusho, 2007; Zimmerman, 2002)

Practice

- Foundation for **adaptive learning support** in large quantitative gateway courses

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Next step

- Pilot for a **DFG Sachbeihilfe**: a SMART trial (sequential multiple-assignment randomized trial) of adapted SoL2L intervention modules — *what works, for whom, and when*

Appendix

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