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Impact of Predictive Learning Analytics with Formative Learning Feedback on Exam Failure Rates

Elmar Junker, Silke Deschle-Prill, André Kajtar, Nicole Kraus, Christine Lux, Birgit Naumer, Anne Sanewski, Jannis Finn Schmidt, Ulrich Wellisch

Rosenheim Technical University of Applied Sciences, Germany

elmar.junker@th-rosenheim.de, birgit.naumer@th-rosenheim.de

ABSTRACT: The **poster** presents the results of the project "Feedback based on Analytics of Teaching and Studying meets Individual Coaching"[1] for 2024 and 2025. Using predictive learning analytics, students receive personalized insights into potential exam outcomes, fostering learning progress. In a physics course for industrial engineering students, AI models are trained on six years of historical data integrating indicators from prior knowledge and Moodle activity into explainable models with logistic regression. The feedback design, co-developed with students, combines motivational emails with peer coaching, improved learning objectives and quiz question feedback. The emails deliver the AI-generated predictions, individualized learning recommendations, benchmarks with peers, and guidance on support resources. About 95% of students engage with the service, which is conducted with consent and under a robust data protection framework. 80% of students indicate that the feedback emails are being motivating and almost half changed their learning behavior. Failure rates show a downward trend. The poster presents the overall framework and the outcomes.

Keywords: Predictive Learning Analytics, explainable Artificial Intelligence (xAI), Coaching, Failure Rate, Learning Behavior, Feedback

1 MOTIVATION AND GOALS

The heterogeneity of freshmen in STEM subjects at German universities has increased since around 2000, while their prior knowledge has declined. Consequently, many technical disciplines show high failure and dropout rates, despite didactical advances. Evidence-based didactics (Schäfle and Junker, 2023) and predictive learning analytics (Schwir et al., 2023) offer promising approaches to enhance learning processes and reduce these shortcomings through adaptive, data-informed instruction.

By analyzing student data traces and comparing with previous cohorts, personalized so-called 'LAKI' emails are sent twice per semester to support learning progress. They provide graphical peer benchmarks, AI-based exam predictions, individualized learning recommendations, and guidance on support resources including customized learning materials with subject-specific feedback.

2 METHODOLOGY

Course design & data set: The approach is applied in a physics course for Industrial Engineering students, largely unchanged since 2014 in terms of instructor, learning objectives, exams, active learning (JiTT and PI) (Schäfle and Junker, 2023). Students receive a 10–15% bonus for preparatory

[1] FANTASTIC-project

online quizzes. Machine learning models are trained on data from 2014/15–2019/20, using 431 “true freshmen”; retake students are excluded. AI models predict final exam results in 2024 and 2025.

AI design: Over 100 indicators are identified, whose partial aggregation into a dataset demanded extensive preprocessing and missing-value handling. To provide qualified feedback, intrinsically explainable models, mainly binary logistic regression (Hosmer and Lemeshow, 2000), are used to assign students to risk categories (A-E from high to low pass probability) for individualized feedback. Feature selection used stepAIC. For threshold determination (fail/no fail) specificity is prioritized as performance measure to minimize false predictions of passing the exam.

The feedback design of the LAKI emails is based on the three-level model by Hattie and Timperley (2007). Students are surveyed after each email, and their responses inform the ongoing iterative development process. The three levels are: (i) Feed Up – Learning objectives: Overview of the required knowledge and skills for successful course completion; (ii) Feed Back – Learning status: automated feedback on online quiz questions, mock exam tasks, and bi-semesterly graphical summaries of prior knowledge, quiz results, activity, and AI prognosis (A-E); (iii) Feed Forward – Next steps: Concrete guidance to improve learning processes, covering content mastery, self-management, and learning techniques. Additionally, trained tutors support students as peer coaches.

3 RESULTS AND DISCUSSION

Examples of the feedback emails sent can be found here[2].

In student surveys conducted after the LAKI emails, the self-reported change in learning behavior ranged between 50% (n=62, Dec 24), [illegible] (n=63, Jan 25), and 54% (n=54, May 25). Students reported focusing more on identified weaknesses, creating study plans aligned with learning goals, spending more time on weaker topics in learning groups, and using text books more thoroughly. The AI-generated prognosis for the midterm exam was reported as motivating by 70% of students (n=74, Dec 24). Additionally, 88% (n=74) found the learning status graphics helpful, and 85% (n=74) found the feedback texts helpful. Overall, 80% (n=74) indicated that the LAKI emails had a motivating effect.

The prediction models achieved high performance, with metrics ranging from 0.7 to 0.9 (see Table 1). Table 2 reports the mean failure rates for all students and for freshmen only, comparing exams with and without LAKI emails, and with and without bonus points (i.e. the raw end-of-year exam results). Clear differences are observable: with bonus points, there is a trend toward improvement with LAKI emails ($p = 0.12$–0.14) while without bonus points the improvement is significant ($p = 0.02$–0.04).

Table 1: Performance metrics on test data of the logistic regression models
(388 data for training, 43 data for testing)

	Sensitivity (Recall)	Specificity	Accuracy	Precision	F1 (class0)	F1 (class1)
AI Model 2024	0.74	0.71	0.72	0.67	0.74	0.70
AI Model 2025	0.62	0.91	0.77	0.87	0.81	0.72

[2] https://t1p.de/PRO-Aktjv-LAKI-email-English Original in German: https://t1p.de/PRO-Aktjv-LAKI-email-Deutsch

Table 2: Average exam failure rates (FR)

(number of students: 2014-2023: all=813, freshmen=638, 2024-2025: all=115, freshmen=86)

(standard deviations 10-13%)

	øFR 2014-2023 no LAKI	øFR 2024-2025 LAKI	FR Decrease absolute	FR Decrease relative
All exams	39.1	30.6	8.5	22%
Freshmen only	31.3	24.0	7.3	23%
All exams without bonus	47.4	35.2	12.2	26%
Freshmen without bonus	41.8	27.2	14.6	35%

However, these aggregate results were inconsistent, confounded by differing exams and cohorts: A year-on-year analysis with similar exams revealed a significant failure reduction in 2024 (using the 2023 exam, $p < 0.01$, Junker et al. 2025). However, no improvement was observed in 2025 (using an exam similar to 2017). This highlights the key methodological challenge of creating comparable control conditions as in common medical research. The discrepancy may reflect differences in academic strength between cohorts, an interpretation supported by our 2025 predictive model, which indicated a significantly stronger cohort in 2024 ($p = 0.01$).

Since 2025, increased use of genAI (like ChatGPT) for preparatory online quizzes may reduce learning outcomes and complicate data analytics. In the future, students should be clearly informed about the downsides of using genAI instead of thinking things through themselves.

In addition, LAKI model predictions themselves are expected to decline in accuracy when the intervention successfully influences students' learning behavior. These considerations are critical for the design of future research.

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