Investigating Student Interaction with Competency-Based CS Education

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Abstract

Background: While Competency-Based Education (CBE) gains traction in Computer Science (CS) education, research focuses predominantly on mandatory implementations in Asian contexts, with limited evaluation of voluntary student engagement with CBE Learning Analytics (LA) tools in European Higher Education (HE).
Objective: This study investigates associations between voluntary student interaction with Atlas, a CBE LA system, and learning outcomes across performance, engagement, and perceptions in a CS course (N=1,278) using mixed-methods analysis.
Methods: The study categorized students into high-interaction (H-group, n=281), low-interaction (L-group, n=329), and no-interaction (N-group, n=668) groups based on competency feature usage patterns. Pre-intervention (n=96) and post-intervention (n=61) surveys measured confidence, usability perceptions, and CBE attitudes. The observational design with voluntary adoption introduces potential selection effects that limit causal inference.
Results: Students who interacted with Atlas were associated with significantly higher mastery in a stepwise pattern (H-group: 41.3%, L-group: 36.1% vs. N-group: 18.9%, p<.001, g=0.32-1.07) and higher passing rates (55.5% H-group, 52.8% L-group vs. 45.7% N-group). Exam performance showed a pattern consistent with a threshold-like association: any level of Atlas engagement associated with improved scores (H-group and L-group: 41.3% vs. N-group: 33.9%, p<.001, g=0.26), but usage intensity beyond initial adoption provided no additional benefit. Survey data revealed positive usability perceptions and increased confidence among users, with frustration relating to course difficulty rather than tool design.
Conclusion: These observational findings suggest that lowering barriers to initial adoption may be as important as maximizing usage intensity for exam outcomes, though mastery progress is associated with sustained engagement. This informs deployment strategies for voluntary CBE implementations in CS courses where different outcomes may follow different adoption dynamics.

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CCS Concepts

• **Applied computing** → **Education**; • **Social and professional topics** → **Computing education**; • **Information systems** → *Data analytics*; • **Human-centered computing** → *HCI design and evaluation methods.*

Keywords

Learning Analytics, Competency-Based Education, Mixed Methods, Voluntary Adoption, Student Interaction, Self-Regulated Learning

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1 Introduction

Large-scale CS courses face challenges in providing meaningful feedback and supporting individual learning progress. In these environments, students struggle with self-regulation and identifying knowledge gaps, while instructors cannot provide personalized guidance at scale [4]. CBE offers a solution by shifting focus from time-based learning to mastery of competencies, enabling students to progress based on demonstrated understanding rather than seat time [7, 40].

Three problems hinder effective learning in such courses. First, students receive aggregate grades that obscure which competencies they have mastered. A student might score 70% on an assignment without knowing if they struggle with recursion, data structures, or algorithm design [4]. This leads students to misallocate study time and struggle to monitor progress toward goals. Second, instructors cannot provide individualized feedback at scale, as educators lack resources to generate feedback for all students in large courses. Motivated students who would benefit from targeted guidance cannot access it, leading to surface rather than deep learning. Third, Learning Management Systems (LMSs) show completion status rather than competency mastery, creating a false sense of progress. Students believe they have "finished" topics when they have completed activities without achieving understanding.

To address these challenges, this work developed and deployed Atlas, a LA system for competency-based education integrated in

Artemis for a foundational CS course at Technical University of Munich (TUM). Atlas tackles each problem through automated analytics: it provides granular, real-time feedback on competencies rather than aggregate scores, enabling students to identify which skills need improvement. The system automates competency tracking and progress visualization, reducing instructor workload while providing personalized learning recommendations at scale. Atlas distinguishes between activity completion and competency mastery, showing students their actual understanding. Atlas was implemented as optional functionality, allowing students to choose their level of engagement.

This study evaluates Atlas through a mixed-methods investigation examining student interactions and outcomes. The evaluation addresses three research questions:

RQ1 **Performance** - How does the level of interaction with Atlas relate to student performance on assessments?
RQ2 **Motivation** - How does the level of interaction with Atlas relate to student engagement and motivation?
RQ3 **Perception** - How do students perceive Atlas in terms of usability and learning support?

The study employed a mixed-methods observational design combining behavioral log data from 1,278 students with pre- and post-intervention survey responses. This work contributes empirical evidence about voluntary adoption dynamics of CBE LA tools by: (1) documenting behavioral patterns and outcome differences across adoption levels in an authentic CS course context, (2) identifying threshold effects where initial engagement relates to exam performance while sustained interaction differentiates competency mastery, and (3) examining how students perceive transparency and usability when given autonomy over CBE tool adoption in European HE.

2 Related Work

This section examines theoretical foundations and empirical evidence surrounding CBE implementation in educational technology, focusing on deployment challenges and student perspectives.

2.1 CBE Implementation Landscape

CBE operationalizes mastery learning principles [23] by requiring demonstrated competency achievement before progression, shifting from time-based to proficiency-based advancement. It integrates Self-Regulated Learning (SRL) frameworks [26] by enabling students to monitor their competency status and make autonomous learning path decisions [31]. LA provides the technical infrastructure for competency tracking at scale, progress visualization, and personalized feedback supporting self-directed learning [6, 21, 25]. However, voluntary adoption may reflect pre-existing motivational differences rather than system effectiveness [30], and implementation requires careful consideration of stakeholder needs to avoid information overload [3].

Current CBE implementations span diverse platforms and approaches. Moodle provides competency frameworks with progress dashboards and automated assessment for simple tasks, though complex evaluation requires manual review. The Competency-Based Learning and Assessment System (CBLAS) integrates learning and assessment data for medical education with milestone guidance and progress visualization, achieving 82% user satisfaction [16]. The Competency-Based Guided-Learning Algorithm (CBGLA) delivers personalized learning paths with real-time feedback, demonstrating superior effectiveness compared to traditional instruction [17]. Competency-based LMSs enable self-guided learning with asynchronous materials and continuous feedback loops [32].

These implementations reveal common deployment challenges, particularly the tension between manual assessment depth and automated scalability [13]. Key barriers include inadequate digital infrastructure, faculty readiness, and institutional policy gaps [24, 43], while most systems lack sophisticated support for voluntary adoption scenarios where engagement patterns may confound effectiveness measures.

2.2 Implementation Barriers

Implementing CBE at scale presents challenges including funding constraints, faculty digital literacy gaps, and organizational silos [14], with faculty training and institutional support systems critical for transitioning from traditional models [11]. Maintaining academic rigor while enabling flexible progression [42] and integrating systems with existing infrastructure requires significant adaptations [41].

Student perspective research on CBE systems is predominantly Asia-based [1, 27, 37, 44], with limited European evaluation since 2018 [4]. Studies focus on CS [1, 4, 44] and Medicine [27, 37], examining both subject-specific and generic competencies. Sample sizes range from 50 [4] to 4,000 students [44], with methodological approaches spanning cross-sectional surveys, longitudinal designs, and mixed methods combining questionnaires, interviews, and behavioral data [1, 4, 44]. This geographic concentration limits generalizability where cultural factors significantly influence technology acceptance [18]. Single-method approaches provide incomplete understanding of complex relationships between system design, engagement, and outcomes, while mandatory implementation focus leaves voluntary adoption patterns underexplored [12].

2.3 Study Rationale

This review reveals three critical gaps in current CBE research. First, student perspective research concentrates predominantly in Asia, with no European CS HE evaluation since 2018. Second, existing CBE implementations mandate student participation, leaving voluntary engagement patterns underexplored. Third, no dedicated CBE system has been evaluated at scale in European CS HE, specifically examining the integration of behavioral analytics with student perception data in large enrollment courses. Educational technology evaluation requires combining behavioral data with subjective experiences [5, 15, 45]. This study addresses these gaps in a European university context.

3 Case Study Context

This instrumental case study was conducted at TUM, a large technical university in Germany, focusing on the implementation of CBE in a fundamental CS course. The case was selected to understand student experiences with CBE tools in university education, providing insights that extend beyond the institutional setting.

3.1 Course Context

The study took place in Functional Programming and Verification (FPV), a required second-semester course for CS bachelor students. The course focuses on formal verification of programs and functional programming principles, serving as a crucial foundation for advanced CS concepts. With an enrollment of over 1,000 students at the beginning of each semester and approximately 900 students registering for the final exam, this course represents one of the largest mandatory courses in the CS curriculum.

The course follows a traditional structure with lectures offered twice weekly and tutorial sessions conducted in smaller groups once per week. Weekly homework assignments are provided on a voluntary basis to help students prepare for the final exam at the end of the semester. Students could submit exercises in practice mode after deadlines, allowing continued engagement with course materials for learning purposes without grade penalties. The teaching team consists of 3 teaching assistants and 12 tutors who facilitate the tutorial sessions and support student learning throughout the semester.

3.2 Existing System Limitations

Prior to Atlas implementation, students received scores and feedback on exercises through Artemis, which had been used since their first semester. However, students lacked visibility into which specific skills or concepts were associated with each exercise, requiring them to independently deduce the underlying learning objectives. This opacity made it challenging for students to understand their learning progress and identify areas requiring additional focus. The existing system provided performance feedback but failed to offer the transparency and structure necessary for students to engage in effective SRL. Students could track their exercise scores but had limited insight into how these related to broader course competencies or learning progression.

3.3 Implementation Rationale

The CBE implementation emerged from a collaborative effort between this research project and the pedagogical interests of the FPV teaching team. From a research perspective, the goal was to understand the effects of Atlas as a reference implementation for CBE in authentic teaching environments. The teaching team was motivated by the potential to provide a pedagogically enriched course experience with enhanced transparency and structure.

Atlas integrates as an additional layer within the existing Artemis infrastructure, introducing a competency network that mapped course concepts and their relationships. The system was accessible to all enrolled students from the beginning of the semester but remained optional rather than mandatory. This voluntary adoption approach allowed for the investigation of student engagement patterns and self-directed use of CBE features, providing authentic insights into student preferences and behaviors when given autonomy over their learning tools.

4 Research Design and Methods

This observational study employs an ex post facto design with non-randomized, naturally occurring groups and mixed-methods data collection to examine associations between varying levels of interaction with Atlas and student outcomes. The study used objective log data to group students into high- and low-interaction categories, capturing differences in behavioral engagement and performance on assessments. Pre- and post-intervention surveys complemented these data by providing insights into students' confidence, motivation, and perceptions of usability and transparency. By combining objective behavioral traces with subjective perceptions, the study aims to provide a comprehensive understanding of patterns associated with Atlas usage across performance, engagement, and student perceptions. As an observational study with voluntary adoption, potential confounding variables including selection bias are discussed in Section 8.

A mixed-methods approach combines objective behavioral log data with subjective survey responses. Behavioral log data captures engagement patterns and performance differences but cannot explain underlying motivations or subjective experiences [45]. Educational technology research recognizes that digital traces serve as imperfect proxies for learning processes, with validity heavily dependent on instructional context [38, 39]. Surveys complement these data by capturing student perceptions and attitudinal factors [9]. This methodological triangulation enhances construct validity by cross-validating findings through multiple data sources [28]. The convergent parallel design enables simultaneous collection during the intervention period [8].

4.1 Research Design

Data collection occurred simultaneously across the full 13-week intervention period. Figure 1 provides an overview of the complete research process, from data collection through analysis.

The intervention phase spanned the complete 13-week summer term 2025, with Atlas made available to all enrolled students from the beginning of this period. The study integrated three data collection phases: pre-intervention surveys (week 1, beginning of semester), continuous behavioral observation (weeks 1–13), and post-intervention surveys (week 13, end of semester), followed by examination data and comprehensive analysis.

4.2 Study Population

A total of 1,278 students were enrolled in FPV during the intervention period. Of these, 864 students registered for and took the final examination. All data collection was voluntary with no financial incentives or grade bonuses to maintain authentic participation patterns and ensure ethical compliance.

Based on their interaction patterns with Atlas competency features, students were categorized into three groups using total interaction counts. Interaction frequency was operationalized as the count of individual competency detail views, where students actively selected and viewed a specific competency. This metric excludes passive viewing of multiple competencies simultaneously on overview pages, focusing instead on deliberate engagement actions unlikely to be unintentional. Among the 610 students who engaged with Atlas competency features, interaction counts ranged from 1 to 79 (M=4.3, SD=6.8). A median split at 2 interactions divided these engaged students into the High-interaction group (H-group, 3–79

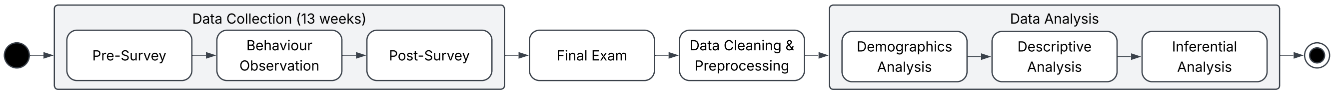

Figure 1: Overview of the research process showing data collection phases, examination timing, and analysis workflow.

interactions, n=281 enrolled, n=247 exam participants) and the Low-interaction group (L-group, 1–2 interactions, n=329 enrolled, n=267 exam participants). The No-interaction group (N-group, n=668 enrolled, n=350 exam participants) comprised students who never deliberately accessed competency details. Students in the N-group may have been passively exposed to competency information displayed on exercise pages or used the learning path for scheduling purposes, but they never actively clicked to view competency mastery progress or detailed information—the actions representing conscious engagement with CBE features for learning support.

Exam participation rates differed substantially across groups: 87.9% of H-group students (247/281), 81.2% of L-group students (267/329), and 52.4% of N-group students (350/668) registered for and took the final examination. This differential selection into exam participation represents an additional layer of self-selection beyond tool adoption, as exam performance comparisons are conditional on students' decisions to participate in assessment. Competency mastery analyses include all enrolled students regardless of exam participation, providing a complementary outcome measure less susceptible to this selection mechanism.

This categorical approach was chosen because interaction data in voluntary adoption contexts exhibits highly skewed distributions with zero-inflation, violating linear modeling assumptions [2]. Educational technology adoption research demonstrates that users naturally cluster into distinct behavioral patterns rather than showing linear engagement relationships [29]. Categorical groupings facilitate robust between-group comparisons using standardized effect sizes while remaining less sensitive to extreme outliers [34], and align with LA practices where user typologies provide interpretable insights [39]. The median split at 2 interactions represents a heuristic cutpoint for exploratory analysis; sensitivity analyses with alternative thresholds are reported to assess robustness of the findings.

4.3 Sample Characteristics

Survey participation revealed demographic insights into the student population. The pre-intervention survey (week 1, n=96) and post-intervention survey (week 13, n=61) showed consistent demographic patterns, with significant overlap between participants across both survey phases.

The sample was predominantly composed of bachelor's degree students (97.7% pre-survey, 100% post-survey) studying CS (83.9% pre-survey, 82.8% post-survey), with smaller representations from Information Systems (6.9% pre-survey, 6.9% post-survey) and Management and Technology (4.6% pre-survey, 3.5% post-survey). Most participants were in their second semester (75.6% pre-survey, 70.2% post-survey), reflecting the course's biennial offering schedule, with additional participants in fourth semester (11.6% pre-survey, 7% post-survey) and higher semesters.

Age distribution showed most participants were 18-20 years old (76.2% pre-survey, 70.4% post-survey), followed by 21-23 years (19% pre-survey, 25.9% post-survey), with the remaining participants 24 years and above. Gender distribution was predominantly male (76.2% pre-survey, 69.6% post-survey), with female participants comprising 21.4% (pre-survey) and 26.8% (post-survey), and remaining participants identifying as other gender categories.

4.4 Data Collection Methods

Data collection followed a structured three-phase approach integrated with examination data and subsequent analysis workflows. Objective behavioral data were collected continuously during the 13-week intervention period through the Artemis system,[1] capturing exercise interactions (submission scores, participation timing including practice mode usage, and completion patterns), lecture material engagement (video viewing behavior, slide access, and time spent with materials), and competency system usage (general overview access, individual competency detail viewing, mastery progress monitoring, and competency graph navigation).

Two surveys captured student data across the intervention period. The pre-intervention survey (week 1, n=96) established baseline demographics including program of study, semester standing, age, and gender. The post-intervention survey (week 13, n=61) measured student perceptions and attitudes regarding confidence, system usability, and competency-based learning approaches, while also collecting demographic information from new participants who had not completed the pre-intervention survey. Response rates reflected the voluntary participation model, with 7.5% of enrolled students (96/1278) participating in the pre-survey and 4.8% (61/1278) in the post-survey. Significant overlap existed between pre- and post-survey participants, allowing for longitudinal analysis of perception changes.

Survey instruments employed single-item measures for **usability**, **transparency**, **confidence**, and **frustration**, assessed on 5-point Likert scales (ranging from "strongly disagree" to "strongly agree"). All items were custom-developed to align with the specific CBE context and Atlas system features, enabling focused assessment of concrete perceptions while minimizing respondent burden in the voluntary survey context. While single-item measures preclude calculation of internal consistency reliability metrics, they are appropriate for measuring specific, unambiguous constructs. These measures were specifically designed to support RQ2 (examining the relationship between system usage and learning experiences) and RQ3 (understanding student perceptions of Atlas).[2]

[1]Data processing and anonymization procedures are documented in the Jupyter notebooks included in the replication package.
[2]Complete survey instruments and demographic questionnaires are available in the replication package.

4.5 Mixed-Methods Integration

The mixed-methods design directly supports the study's research questions through the integrated analysis workflow shown in Figure 1. Objective log data enable grouping students into interaction categories for examining performance outcomes (RQ1) and engagement patterns (RQ2), while surveys provide complementary insights into confidence, motivation, and perceptions (RQ3). This integration enables comprehensive triangulation, combining objective behavioral traces with subjective perceptions to cross-validate findings.[3]

5 System Integration

Atlas was available to all enrolled students throughout the 13-week summer term 2025. Students discovered competency-based features organically through their course interactions within the familiar Artemis environment.

The primary discovery mechanism occurred when students accessed exercises or lecture materials, where they could see linked competencies displayed alongside the content. This integration ensured that competency information was contextually available during students' natural learning activities rather than requiring separate navigation to dedicated CBE interfaces. Competency links were visible for all course activities except exam tasks, preserving assessment integrity while maintaining educational transparency. Additionally, the pre-intervention survey informed students about Atlas availability without pressuring adoption, maintaining the voluntary nature essential for authentic engagement patterns.

5.1 User Interface Design

Students interacted with a competency model comprising 18 competencies that comprehensively covered the FPV curriculum. Each competency presented students with three key information components: a descriptive title capturing the main concept, a detailed description outlining expected learning outcomes and techniques, and clear progress visualization showing their advancement toward mastery. Figure 2 illustrates what students saw when viewing an individual competency, including progress indicators and linked learning resources.

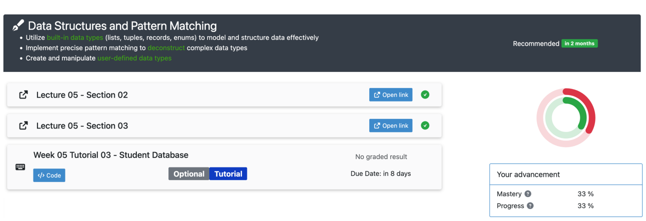

Figure 2: Student view of a competency in the User Interface.

When students accessed competencies, they could see all linked lecture units and exercises displayed as cards with clear status indicators, enabling them to identify which materials supported specific learning goals. As shown in Figure 2, students could view lecture materials with direct access links, tutorial and homework exercises with their current completion status, and due dates for upcoming activities. The right-side progress panel provided visual feedback through circular progress indicators showing both overall competency mastery and individual progress percentages, allowing students to make informed decisions about their study focus.

5.2 Competency Progress Tracking

Students' competency mastery progress was calculated based on their successful completion of linked learning activities. The system advanced progress when students passed automated assessment tests for coding exercises or achieved passing scores on multiple-choice submissions, directly integrating competency advancement into the existing evaluation processes students were already familiar with from previous semesters. Progress visualization provided students with immediate feedback on their mastery progress through visual indicators that updated in real-time as they completed course activities. Students could view their overall progress across all competencies as well as detailed progress for individual competencies, enabling both broad course overview and focused skill development tracking.

For research purposes, Atlas tracked various student interactions with the system, including viewing individual competency details, checking competency progress indicators, accessing the competency overview page, navigating the competency graph visualization, and engaging with competency-linked learning path recommendations. Student categorization into interaction groups was based specifically on the frequency of deliberate competency detail views—instances where students actively clicked to view detailed information about a specific competency. This metric was selected as it represents conscious engagement with CBE features for learning support, distinct from passive exposure to competency information displayed elsewhere in the interface. This design maintained the educational value of competency transparency while preserving fair evaluation conditions during high-stakes assessments.

5.3 Enhanced Learning Features

Beyond basic competency tracking, students could access a competency graph visualization showing relationships between different course concepts. The adaptive learning path functionality integrated this feature and provided personalized recommendations for lecture units and exercises based on individual progress patterns. The learning path presented students with a structured sequence of suggested activities tailored to their current competency levels, recommending specific lectures to review or exercises to complete. Students could choose to follow these AI-generated recommendations or explore the course materials independently. The graph visualization helped students orient themselves within the broader competency network and understand conceptual connections between course topics.

6 Results

This section presents findings examining associations between Atlas interaction levels and outcomes, reporting quantitative results from behavioral data and performance metrics, followed by survey

[3]Complete analysis code and statistical procedures are provided in the replication package for reproducibility.

findings (week 13, n=61) on student perceptions and attitudes.[4] Students were categorized into High-interaction (H-group, 3+ competency detail views), Low-interaction (L-group, 1-2 views), and No-interaction (N-group, 0 views) based on deliberate engagement with competency features.

6.1 Student Performance on Assessments (RQ1)

Mastery progress is computed for all enrolled students (N=1,278) who engaged with the course content, as competency advancement occurs automatically through exercise completion regardless of exam registration. Mastery progress represents a completion-based proxy derived from passing linked activities and assessments, rather than a validated measure of latent competence. Figure 3 illustrates the distribution of average mastery progress per user across the three interaction groups. Students in the H-group (N = 281) achieved the highest mastery progress (M = 41.3%), followed by the L-group (M = 36.1%) and the N-group (M = 18.9%). The density distributions reveal a clear stepwise pattern (No < Low < High), with the H-group shifted toward higher mastery values. Moreover, the N-group exhibited a broader spread concentrated at lower progress levels, whereas the H-group was more tightly distributed around higher mastery. Despite being the largest group, students in the N-group consistently underperformed compared to their peers.

Given the non-normal distribution of interaction data typical in voluntary adoption contexts, the non-parametric Kruskal-Wallis test [22] was used to compare mastery progress across the three interaction groups, as it does not assume normality or homogeneity of variance. The test confirmed a significant effect of interaction group on mastery progress, H(2)=249.05, p<.001. Post hoc comparisons using Dunn's test [10] with Bonferroni correction were conducted to identify specific group differences, as this non-parametric approach is appropriate for pairwise comparisons following a significant Kruskal-Wallis test. Hedges' g effect sizes are reported as descriptive standardized measures to support interpretability and comparison across outcomes, while statistical inference is based on the nonparametric tests. The analysis revealed that the H-group significantly outperformed both the L-group (p = .001, Hedges' g = 0.32) and the N-group (p < .001, g = 1.07). The L-group scored significantly higher than the N-group (p < .001, g = 0.81).

Figure 4 presents exam performance across the three interaction groups. Both the H-group (M = 41.3%) and the L-group (M = 41.3%) achieved average exam scores above the passing threshold of 37.5%, whereas the N-group (M = 33.9%) remained below this benchmark. The distributions show that students without interaction were more concentrated at failing scores, while those engaging with Atlas were more consistently situated around or above the threshold. These comparisons are conditional on exam participation and may be subject to selection bias, as students who chose to take the exam likely differ systematically from those who did not across all interaction groups.

The Kruskal-Wallis test indicated significant differences between groups, H(2)=13.62, p<.001. Post hoc tests revealed no difference between the H- and L-groups (p=1.00, $g \approx 0.00$), but both groups significantly outperformed the N-group (H-group vs. N-group: p=.005, g=0.26; L-group vs. N-group: p=.006, g=0.26). These findings indicate that any level of interaction with Atlas correlated with higher exam performance, particularly with respect to surpassing the passing threshold. However, greater intensity of interaction (H- vs. L-group) was not associated with additional exam performance benefits. This pattern is consistent with a threshold-like effect for exam outcomes, where initial adoption relates to performance differences but additional usage intensity provides diminishing returns.

Passing rates provide further evidence for this trend (Table 1). The H-group achieved the highest passing rate (55.5%), followed by the L-group (52.8%), whereas the N-group recorded the lowest rate (45.7%). Pairwise comparisons using relative risk and odds ratios confirmed that students in the H-group were significantly more likely to pass than those in the N-group (RR = 1.21, OR = 1.48, p=.028, Holm-adjusted). P-values were computed using a two-proportion z-test (one-sided, testing whether the first group's proportion exceeds the second) and Holm-adjusted across the three pairwise comparisons. The comparison between the L- and N-group pointed in the same direction (RR = 1.16, OR = 1.33), though this difference did not reach significance after correction (p=.081). The analysis revealed no difference between the H- and L-group (RR = 1.05, OR = 1.11, p=.27).

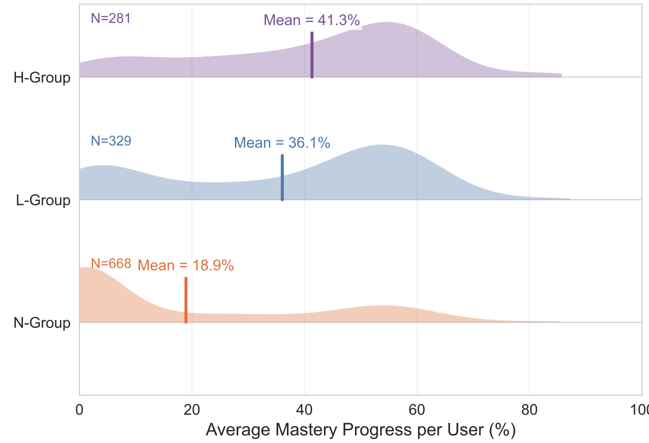

Figure 3: Average Mastery Progress per Interaction Group

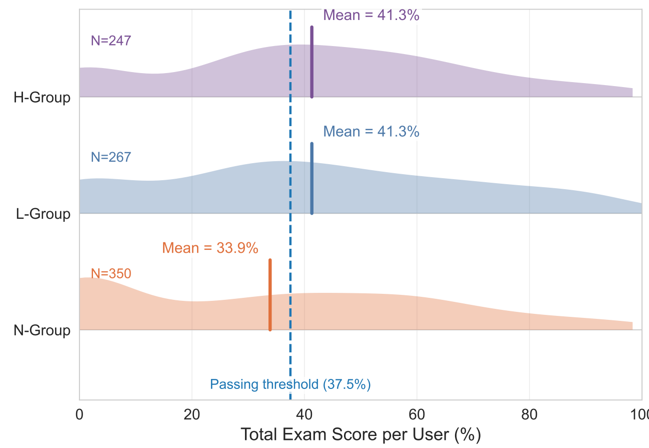

Figure 4: Exam Score per Interaction Group

[4]The survey questions are available in the replication package.

Across all three performance indicators—competency mastery, exam scores, and exam passing rates—a consistent pattern emerged: students who interacted with Atlas outperformed those who did not.

Table 1: Passing Rate per interaction group

Group	Took Exam	Passed	Passing Rate (%)
High	247	137	55.5
Low	267	141	52.8
No	350	160	45.7

6.2 Student Engagement and Motivation (RQ2)

To assess how interaction with Atlas relates to motivation and engagement, the analysis examined usage of the practice mode, the proportion of students who started the learning path, and the number of interactions with the learning path. Students in the H-group completed on average more practice exercises (M = 8.02) than those in the L-group (M = 6.60) and the N-group (M = 3.31) (see Table 2). However, the Kruskal–Wallis test revealed no significant differences in practice mode usage across interaction groups, H(2)=4.41, p=.110, suggesting that practice behavior operates independently of competency feature engagement.

Learning path interaction showed a similar pattern (Table 3). Nearly half of the H-group (49.8%) started the learning path, compared to 30.4% in the L-group and only 19.5% in the N-group. All pairwise differences were significant, with the H-group more likely to initiate the learning path than both the L- (RR = 1.64, OR = 2.27, p<.001) and N-group (RR = 2.56, OR = 4.11, p<.001), and the L-group more likely than the N-group (RR = 1.56, OR = 1.81, p<.001).

Among students who engaged with the learning path, the H-group averaged 7.56 interactions per user, compared to 4.13 in the L-group and 2.63 in the N-group. The Kruskal–Wallis test confirmed significant differences, H(2)=75.87, p<.001. Post hoc analysis showed that the H-group interacted significantly more often than both the L- (p<.001, Hedges' g=0.23) and N-group (p<.001, g=0.44), and the L-group also exceeded the N-group (p=.006, g=0.16).

Taken together, these results reveal engagement differences primarily in structured learning activities: greater interaction with Atlas correlated with higher uptake of the learning path and more sustained learning path interactions, though practice mode usage showed no significant differences across groups.

Table 2: Use of Practice Mode per Interaction Group

Group	Avg. Exercises with Practice Mode
High	8.02
Low	6.60
No	3.31

Table 3: Percentage of Students who Started the Learning Path

Group	Started Path (%)	Avg. Path Interactions
High	49.82	7.56
Low	30.40	4.13
No	19.46	2.63

6.3 Students' Perception of Usability and Learning Support (RQ3)

Survey responses provide insights into how students perceived Atlas. Figure 5 visualizes these results. Regarding usability, the majority of students agreed (50.0%) or strongly agreed (3.1%) that the system was easy to use, while only a small fraction disagreed (15.6%) or strongly disagreed (3.1%). Perceptions of transparency were similarly favorable, with 58.1% agreeing and 6.5% strongly agreeing that Atlas provided clarity and insights into the learning goals, while fewer than 13% expressed disagreement.

In terms of confidence, 35.3% of students agreed and 20.6% strongly agreed that they felt confident about passing the exam, while only about 14% disagreed. At the same time, frustration with the course was not uncommon: 38.9% of students agreed and 8.3% strongly agreed that they felt frustrated when thinking about the course.

Exploratory analysis examined the relationship between confidence and frustration among survey respondents who engaged with Atlas (n=29 after filtering for interaction and missing data). Spearman correlation revealed a statistically significant moderate negative correlation between confidence and frustration (ρ=-0.45, p=.013), suggesting higher confidence associates with lower frustration, though the constructs remain distinct. Among respondents, 13.8% reported both high confidence (rating ≥4) and high frustration simultaneously, with 25.0% of high-confidence students also reporting high frustration. Notably, we did not detect a significant correlation between frustration and system usability (ρ=0.25, p=.185) or transparency (ρ=-0.11, p=.557). While statistical power is limited by sample size (n=29), we did not detect a relationship between frustration and tool characteristics in this sample. One possible explanation is that frustration relates primarily to course difficulty rather than system design, though measurement limitations may obscure other effects and alternative explanations remain plausible. Overall, students perceived Atlas as a usable and transparent system that supported their learning. They feel confident in navigating the demands of a difficult course.

6.4 Sensitivity Analyses

To assess the robustness of findings to the choice of group cutpoint, sensitivity analyses re-examined primary outcomes using alternative thresholds and continuous associations. Results remained qualitatively consistent across specifications, supporting the stability of observed patterns.

Alternative cutpoints (High ≥5 and High ≥10 interactions) yielded similar patterns for all three outcomes. For mastery progress, all pairwise comparisons maintained significance and comparable effect sizes (original: H vs N g=1.07; cutpoint=5: g=1.05; cutpoint=10: g=1.07). Exam score comparisons remained significant for H vs N and L vs N across all cutpoints, with H vs L consistently showing no difference (p≥.214 across all specifications). Passing rate patterns persisted, with H-group advantage over N-group significant across cutpoints (original: RR=1.21, p=.028; cutpoint=10: RR=1.31, p=.036).

Continuous associations between interaction count and outcomes (Spearman correlations) corroborated the categorical findings. Interaction frequency correlated positively with mastery progress (ρ=0.44, p<.001, n=1,278) and exam score (ρ=0.12, p<.001,

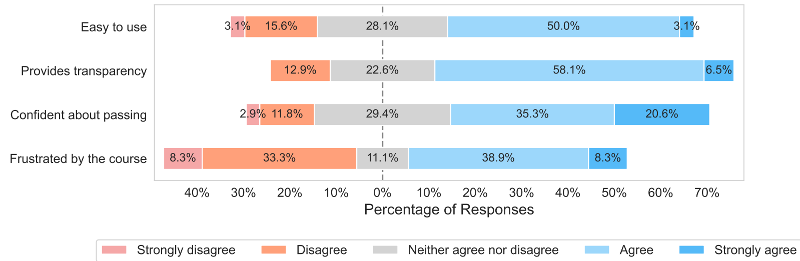

Figure 5: Students' Perception of Usability and Transparency (Percentages rounded to one decimal place)

n=865), with the stronger mastery correlation consistent with the stepwise pattern observed in categorical analyses. The moderate mastery correlation and weaker exam correlation align with the threshold interpretation: mastery benefits scale with interaction intensity, while exam performance shows diminishing returns beyond initial adoption. Detailed sensitivity analysis results are provided in the replication package.

7 Discussion

This study examined associations between student interaction with Atlas and outcomes across performance, engagement, and perception. Given the observational design, all findings represent associations rather than causal effects. The findings reveal consistent patterns linking system interaction with measurable performance differences and positive student attitudes, while also highlighting the nuanced nature of these associations. Initial adoption may matter more for summative performance, while sustained interaction primarily differentiates formative mastery progress.

Students who interacted with Atlas demonstrated higher mastery progress in competencies, with similar patterns appearing in exam performance. Both exam scores and passing rates exceeded those of students who did not engage with the system. Importantly, while the H- and L-group differed in mastery progress, their exam performance and passing rates were similar.

> **Observation 1: Finding RQ1 - Engagement Threshold Effect:** CBE tool interaction is associated with performance outcomes, with a threshold pattern where initial engagement correlates with exam results regardless of usage intensity.

Competency engagement patterns may reflect students reaching minimum performance thresholds, after which traditional study strategies or individual differences such as prior knowledge and motivation play a stronger role. However, given the observational design, alternative explanations include that students with different motivational profiles self-selected into usage patterns. This self-selection pattern aligns with educational technology research showing that motivated students typically engage more extensively with optional learning tools and achieve better academic outcomes due to their intrinsic motivation and increased practice [36]. Importantly, this pattern does not diminish the value of CBE systems for these students. Even highly motivated learners benefit significantly from the transparency and progress tracking that Atlas provides, as manual self-monitoring of competency development across complex curricula can be challenging and error-prone. The automated mastery tracking eliminates the cognitive overhead of self-assessment while providing clear, objective feedback about learning progress that motivated students can leverage to optimize their study strategies.

Atlas interaction showed associations with structured learning engagement indicators. Students in the H- and L-group were significantly more likely to start and engage with the learning path than those with no interaction, though practice mode usage showed no significant differences across groups.

> **Observation 2: Finding RQ2 - Structured Learning Engagement:** CBE interaction is associated with higher learning path adoption and more sustained structured learning engagement, with particularly strong associations for guided learning activities.

This finding is particularly relevant in the context of self-directed learning, where sustaining student motivation remains a persistent challenge [33]. The embedding of practice opportunities and clear progression paths in Atlas correlates with engagement patterns that may reinforce persistence, though the causal direction remains unclear. System interaction and learning path usage suggest potential positive feedback patterns: students who engage more with CBE tools may become more invested in following guided learning sequences, though the directional relationship between engagement and outcomes requires further investigation.

> **Observation 3: Main Finding: CBE Tool Value in Self-Paced Environments:** In auto-grading environments with self-paced learning opportunities, students perceive value in transparent competency tracking and progress visualization, with such usage associated with increased engagement in voluntary learning activities and differences in outcomes.

Survey responses complement these findings by shedding light on students' perceptions of Atlas.

> **Observation 4: Finding RQ3 - Valued Transparency:** Students perceive CBE tools as usable and confidence-building, particularly valuing transparency and progress visibility even in high-frustration learning environments.

These characteristics are critical determinants of sustained system adoption in learning contexts [19, 20]. A considerable proportion of students reported experiencing frustration with the course. The moderate negative correlation between confidence and frustration (ρ=-0.45, p=.013) indicates that while higher confidence generally associates with lower frustration, these constructs remain distinct—evidenced by 25% of high-confidence students also reporting high frustration. Critically, we did not detect a relationship between frustration and tool characteristics (usability and transparency) in this sample. One interpretation consistent with this pattern is that frustration relates primarily to course difficulty rather than system design, though alternative explanations remain plausible given the exploratory nature and limited sample size of these analyses.

This pattern aligns with SRL frameworks where competency visibility supports self-efficacy independent of task difficulty [26, 31]. One possible explanation is that Atlas supports students in feeling capable of navigating course demands by providing clear, actionable feedback about their progress, even when the subject matter itself presents significant challenges; however, testing this mechanism would require controlled experimental designs that isolate tool effects from self-selection. The coexistence of high confidence and high frustration among some students is consistent with the hypothesis that transparent progress tracking builds confidence through mastery awareness while course content difficulty generates frustration—two separate dimensions of the learning experience. This finding underscores the importance of distinguishing between frustration caused by system usability issues and frustration inherent to demanding academic subjects—a critical consideration for CBE tool design in challenging educational contexts.

The results highlight consistent associations between CBE platform usage and both performance differences and positive learning perceptions. For instructors and institutions, students who engage with CBE tools demonstrate substantial differences in mastery and exam readiness patterns, with system interaction and learning path engagement co-occurring with more structured SRL behaviors. The presence of frustration despite positive perceptions points to the need for additional support mechanisms such as adaptive scaffolds or targeted feedback.

Beyond educational effectiveness, practical deployment considerations merit discussion. Initial Atlas setup requires competency modeling and learning resource mapping, representing significant upfront instructor effort comparable to comprehensive syllabus development. However, once configured, the system operates with minimal ongoing maintenance beyond routine content updates. Institution-wide deployment would require instructional design support and faculty training infrastructure rather than per-course instructor effort. Future work will focus on developing streamlined onboarding processes and reusable competency frameworks to reduce initial setup burden.

8 Limitations

This study acknowledges several methodological constraints that warrant careful consideration when interpreting the findings. Following Runeson and Höst [35], the limitations are organized according to validity threats.

Construct validity presents challenges in defining and measuring "engagement" within competency-based learning contexts, as traditional metrics (login frequency, session duration, feature utilization) may inadequately represent meaningful learning interactions in CBE environments. The voluntary adoption model creates ambiguity between genuine engagement and self-selection bias, complicating the interpretation of usage patterns as indicators of educational effectiveness. Additionally, the mastery progress metric is operationalized as a completion-based proxy (passing linked activities and assessments) rather than a validated measure of latent competence, making it inherently coupled to general engagement and course participation. This coupling constrains causal interpretation, as students who engage more extensively with course activities naturally achieve both higher mastery progress and greater Atlas interaction, making it difficult to separate tool effects from underlying behavioral patterns.

Internal validity is fundamentally limited by the observational design, which prevents causal inference about CBE tool effectiveness. The voluntary participation model creates systematic selection bias, as students engaging with Atlas likely possess distinct motivational profiles, academic abilities, learning strategies, and prior knowledge compared to non-participants. This self-selection confounds any observed relationships between tool usage and outcomes, as the same student characteristics that predict tool adoption likely also predict superior academic performance regardless of tool availability. Additionally, differential exam participation rates across groups (H-group: 87.9%, L-group: 81.2%, N-group: 52.4%) introduce potential collider bias in exam performance comparisons, as these analyses condition on a post-adoption decision that may itself be influenced by both tool usage and student characteristics. Without randomized assignment or comprehensive baseline measures, the study cannot distinguish whether observed differences reflect tool effects or pre-existing characteristics of students who choose to engage with optional academic resources. While randomized controlled designs could establish causal relationships, such approaches would be ethically and practically challenging in authentic university courses.

External validity faces substantial constraints due to the study's narrow scope: single institution, single course, and single semester timeframe. The specialized CS content focusing on programming and formal verification may not translate to other disciplines or educational levels. The voluntary adoption may produce engagement patterns differing from mandatory implementation scenarios, as voluntary participants typically represent early adopter populations. Cultural and institutional factors specific to the German HE system may limit applicability to other contexts, while the single cohort design prevents generalization across different time periods or student populations.

Reliability is enhanced through detailed documentation, mixed-methods triangulation, and public availability of anonymized data and analysis code via Zenodo. However, interpretation of behavioral log data requires assumptions about user intentions that may vary across research teams, while survey responses remain susceptible to contextual influences that could vary across implementations. The voluntary participation model introduces selection effects that may manifest differently in alternative settings or time periods.

9 Conclusion

This study provides empirical evidence of associations between CBE tool usage and student outcomes in a CS course. Students who interacted with Atlas were associated with significantly higher competency mastery and exam performance, with any meaningful engagement correlating with positive outcomes.

Students perceived Atlas as usable and transparent, reporting increased confidence despite course challenges. The study demonstrates how combining behavioral data with student perceptions provides comprehensive insights into CBE tool adoption.

This research contributes empirical evidence of student experiences with CBE in authentic educational settings and provides descriptive insights about user experiences and associated performance patterns. For practice, findings reveal associations between initial adoption and performance differences, and highlight student preferences for competency information embedded in familiar Learning Management System rather than separate interfaces.

Future research opportunities include incorporating additional motivation measures, expanding evaluation to different disciplines and populations, and conducting longitudinal studies across degree programs. Most critically, randomized controlled designs where ethically feasible could establish causal relationships.

Acknowledgments

In accordance with ACM/IEEE guidelines, we disclose that we used AI tools to assist with grammar enhancements, reformulations, and general text editing throughout this paper. To facilitate replication and further research, we provide a package at Zenodo[5] containing details about the survey instruments, anonymized data, and analysis scripts.

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