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A Study on the Allocation of Teaching Support Personnel and Learning Completion Rate in Online Education Platforms

James R. Thompson[1], Emily K. Wilson[2], Michael A. Fraser[3]*

School of Education, University of Auckland, Auckland 1010, New Zealand

***Corresponding author:** m.fraser@university.edu.nz

Abstract

The learning completion rate of online education platforms is influenced by the service capabilities and response efficiency of teaching support personnel. This study analyzes the relationship between the allocation structure of teaching support personnel and the learning completion rate. Based on 18 consecutive months of operational data from an online education platform, the sample includes 124 courses, 312 teaching support personnel, and the learning records of over 98,000 learners. Support personnel allocation is characterized by the teacher-student ratio, average response time, and support frequency, while learning outcomes are measured by course completion rate and test pass rate. A generalized linear model is used to analyze the impact of allocation variables on learning outcomes. The results show that a 10% reduction in average response time increases the course completion rate by approximately 3.8 percentage points. These findings provide empirical evidence for optimizing the teaching support system of online education platforms.

Keywords

Online education; Teaching support; Learning completion rate; Generalized linear model; Platform operation

1.Introduction

Online education has become a mainstream pathway for continuing education, professional training, and degree attainment. Despite its rapid expansion, persistently low completion rates remain a structural challenge for many platforms. Prior research shows that dropout behavior cannot be explained solely by individual learner characteristics; instead, completion outcomes are shaped by the interaction among course workload, learner motivation, instructional design, and the provision of timely academic support [1,2]. Evidence from large-scale organizational studies further indicates that human resource configuration and service leadership significantly influence performance outcomes in complex service systems, highlighting the importance of structured support mechanisms and data-driven resource allocation [3]. In the context of online education, these insights suggest that instructional support should be treated as a strategic operational component rather than a peripheral service. However, many empirical studies in this domain rely on limited datasets or short observation windows, which constrains their applicability to long-term platform management decisions [4]. A growing body of literature examining MOOCs and other large-scale online

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courses consistently reports that insufficient feedback, delayed responses to learner inquiries, and weak interaction mechanisms are associated with elevated dropout rates [5]. Empirical analyses demonstrate that active involvement of instructors or teaching assistants in discussion forums and support channels is positively associated with course completion probabilities [6]. These findings imply that human support functions as an integral element of the learning process. Nevertheless, most prior studies focus primarily on the presence or absence of interaction rather than on measurable service characteristics such as response time, staffing intensity, or interaction frequency, thereby limiting their operational interpretability [7,8]. Research grounded in the Community of Inquiry framework emphasizes the role of teaching presence in shaping learner experience and persistence [9,10]. Quantitative studies show that teaching presence enhances satisfaction and engagement, both of which are closely linked to completion outcomes [11]. Similar conclusions have been reported across blended and fully online environments, where clarity of instructional guidance and communication effectiveness contribute to retention [12]. While these studies provide valuable theoretical perspectives, teaching presence is often operationalized through perception-based survey instruments. Such subjective measures restrict the translation of pedagogical constructs into controllable operational indicators for platform-level optimization. From an operational management perspective, a critical gap remains between pedagogical theory and actionable service parameters. Teaching support is frequently conceptualized as a latent construct without explicit linkage to adjustable variables such as staff–learner ratios, average response time, or the frequency of support interactions. Studies examining feedback responsiveness often rely on small samples or short-term experimental interventions, making it difficult to estimate how incremental improvements in support efficiency influence learning outcomes at scale [13,14]. In contrast, design-oriented approaches such as gamification or interactive content primarily target engagement mechanisms and provide limited guidance on how support resources should be allocated across heterogeneous learner populations. Learning analytics has introduced scalable models for identifying dropout risk and triggering targeted interventions [15]. Although predictive accuracy has improved substantially, these approaches are typically optimized for classification performance rather than for estimating interpretable effects of operational variables. Many datasets are restricted to single courses or institutions, and analyses rarely account for the continuous operation of multi-course, multi-staff support systems characteristic of large online platforms [16]. Consequently, empirical evidence directly linking staffing configuration and service responsiveness to measurable learning outcomes remains

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limited. Recent scholarship on student support services emphasizes that learning performance depends not only on the availability of support mechanisms but also on how these services are structured and delivered [17]. Differences in staffing models, response protocols, and service intensity complicate cross-study comparisons and hinder the development of generalizable operational benchmarks. Longitudinal empirical analyses based on continuous operational records are still scarce, particularly those integrating staffing configuration variables with standardized learning outcome indicators across diverse courses and learner cohorts. Against this backdrop, the present study investigates the association between teaching support personnel configuration and learning completion within a large-scale online education platform using 18 months of continuous operational data. Support configuration is quantified through directly controllable service indicators, including staff–learner ratio, average response time, and support interaction frequency. Learning outcomes are measured using course completion rates and assessment pass rates. A generalized linear modeling framework is employed to estimate the relationship between service configuration variables and learning outcomes in a manner that enables clear operational interpretation. By leveraging multi-course, multi-cohort platform data and focusing on adjustable service parameters, this study advances existing literature in three respects. It translates pedagogical constructs into measurable operational variables, provides longitudinal evidence on the effectiveness of staffing and responsiveness adjustments, and offers data-driven guidance for optimizing support resource allocation in large-scale online education systems.

2.Materials and Methods

2.1 Sample and Study Context

This study used operational records from an online education platform collected over an 18-month period. The dataset included 124 online courses offered in continuing and professional education programs. After removing incomplete and invalid records, data from 98,214 learners were retained for analysis. Teaching support services were provided by 312 staff members responsible for answering learner questions, managing course discussions, and offering academic guidance. Course durations ranged from 4 to 16 weeks. All courses followed a unified platform structure that included recorded lectures, assignments, and scheduled assessments. Learners accessed course materials asynchronously and were able to request support throughout the learning period.

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2.2 Study Design and Control Strategy

The analysis followed a comparative observational design to examine how differences in teaching support were associated with learning outcomes. Courses were classified based on variations in support conditions, including staff–learner ratio and response speed. To limit the influence of course difficulty and content differences, comparisons were conducted within the same course across different time periods when possible. Courses that underwent major content or syllabus changes during the study period were excluded. This approach allowed learning outcomes to be compared under different support conditions while keeping course content unchanged.

2.3 Measurement Procedures and Quality Control

Teaching support was described using three indicators: staff–learner ratio, average response time, and frequency of support interactions. Response time was defined as the time interval between a learner's first request and the corresponding reply from support staff, as recorded by the platform. Learning outcomes were measured using course completion status and assessment pass rates. Data cleaning procedures removed duplicate entries, missing records, and abnormal timestamps caused by system interruptions. Random checks were performed to confirm the accuracy of recorded interaction times.

2.4 Data Processing and Model Specification

Before analysis, continuous variables were standardized to reduce differences in scale. Course completion was treated as a binary variable, while assessment performance was analyzed as a proportional outcome. A generalized linear model was used to estimate the association between teaching support indicators and learning outcomes. For course completion, the following logistic regression model was applied:

$$\text{logit}(p_i)=\beta_0+\beta_1 R_i+\beta_2 T_i+\beta_3 F_i+\varepsilon_i,$$

where p_i represents the probability that learner iii completed the course, R_i denotes the staff–learner ratio, T_i indicates average response time, and F_i refers to support interaction frequency. Assessment pass rates were analyzed using a linear regression model to estimate the effects of support-related variables.

2.5 Statistical Analysis and Sensitivity Checks

Statistical analyses were conducted using standard statistical software. Model parameters were estimated using maximum likelihood methods, and 95% confidence intervals were reported. Multicollinearity among explanatory variables was evaluated using variance

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inflation factors. Sensitivity checks were performed by re-running the models using course-level averages and by excluding courses with extremely large or small enrollments. Similar coefficient patterns across these analyses were used to confirm result stability.

3.Results and Discussion

3.1 Response time as a practical determinant of course completion

Over the 18-month observation period, response time showed a clear and stable relationship with course completion after accounting for differences across courses and learner cohorts. A 10% reduction in average response time was associated with an increase of approximately 3.8 percentage points in completion rate. This result suggests that completion outcomes are sensitive to how quickly learner questions are addressed, rather than to the mere availability of support channels [18, 19]. Previous studies have noted that support is most effective when delivered at specific points in the learning process, such as early participation stages and assessment periods, where uncertainty and workload tend to be higher.

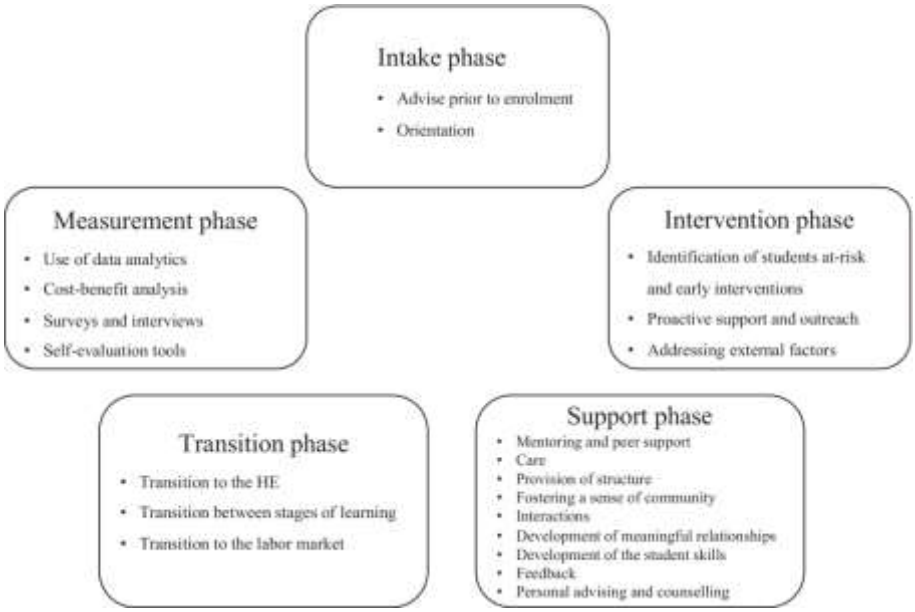

Figure 1 Conceptual illustration of how teaching support interventions are distributed across key stages of the online learning cycle, highlighting points where timely support is most relevant to learner retention.

3.2 Staff–learner ratio and support frequency under operational constraints

The staff–learner ratio was related to completion outcomes, but its effect size decreased once response time was included in the model. This indicates that staffing levels influence learning outcomes mainly through their effect on service delays and workload pressure. Similar observations have been reported in online support research, where service performance is better reflected by delivery speed than by nominal capacity. Support frequency per learner did not show a linear relationship with completion. Moderate levels of interaction were associated with higher completion, whereas very frequent contacts likely reflected repeated clarification

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needs or unresolved difficulties. This finding supports the view that interaction counts capture both service activity and underlying learning friction, and should therefore be interpreted together with timing and course context [20, 21].

3.3 Assessment pass rates and indirect effects of timely support

Assessment pass rates followed a related but distinct pattern compared with completion. Faster responses were more strongly associated with pass rates in courses that required iterative problem solving or applied assignments. In such courses, delayed responses can interrupt task progress and increase the risk of missed or incomplete submissions. Existing research suggests that teaching support often affects performance indirectly, by helping learners maintain study pace and reduce uncertainty, rather than by directly improving test scores. Shorter response times likely support this process by closing feedback loops and enabling learners to resolve obstacles before disengagement occurs [22].

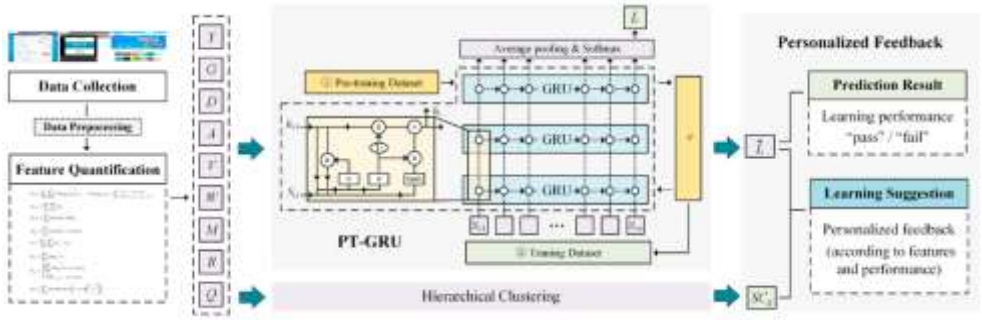

Figure 2 Process flow of a personalized feedback system that uses learner performance data to guide support actions in online learning.

3.4 Comparison with previous studies and operational relevance

Compared with prior studies that rely on survey data, short interventions, or single-course analyses, these results provide platform-level evidence linking service delivery characteristics to learning outcomes over an extended period. The findings reinforce earlier conceptual work emphasizing that support effectiveness depends on when and how it is delivered during the learning process. Importantly, the results indicate that reducing response delays is a more reliable approach than increasing interaction volume alone. From an operational perspective, this points to practical measures such as request triage, workload balancing during assessment weeks, and clearly defined response-time targets. At the same time, the observational design means that unobserved factors, such as instructor communication style, may still influence results [23]. Controlled adjustments to response-time policies in future studies would help strengthen causal interpretation.

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4.Conclusion

This study analyzed how teaching support settings relate to learning outcomes on an online education platform using long-term operational records. The results indicate that response time is closely associated with course completion and assessment success, while staffing size and interaction volume show weaker effects once response speed is taken into account. By expressing teaching support through concrete service indicators, this study extends existing work that relies mainly on perception-based measures. The findings support the view that teaching support can be examined as a service process with measurable performance attributes. From a practical perspective, improving response workflows and handling peak demand appear more effective than increasing staff numbers alone. Several limitations should be noted. The observational design does not allow full causal interpretation, and unmeasured instructional factors may still affect outcomes. Future research could apply controlled service adjustments and multi-platform data to test the stability and general applicability of these findings.

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