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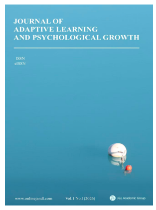

From Manual Coordination to Smart Administration: Redesigning Support Systems for Applied Courses

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ABSTRACT

This study examines how smart administrative systems can improve coordination efficiency in applied courses that require continuous management of instructors, learners, facilities, equipment, assignments, and assessment tasks. The study is designed to evaluate approximately 60 applied courses across 8 institutions before and after the adoption of a smart administration platform, collecting around 22,000 course-coordination records, 11,000 resource-booking entries, 7,500 instructor-student communication logs, 4,800 assignment-tracking records, 2,400 schedule-adjustment records, and 1,000 learner and instructor survey responses. Key variables include coordination response time, booking conflict frequency, schedule-change frequency, information delay rate, instructor workload, administrative processing time, assignment completion continuity, learner satisfaction, and perceived support quality. The study applies process mining, difference-in-differences analysis, structural equation modeling, multilevel regression, and usability evaluation to examine whether smart administration improves operational efficiency and learning support. System effectiveness is measured through conflict reduction rate, processing-time reduction, information accuracy improvement, instructor workload balance, learner support satisfaction, and course-continuity improvement. The innovation of this study lies in treating administration as a measurable educational support system rather than a background service, showing that smart coordination can directly affect learning continuity, instructional responsiveness, and resource access in applied education.

1. Introduction

Applied courses depend on the coordinated operation of multiple teaching and administrative resources, including instructors, learners, laboratories, equipment, classrooms, assignments, schedules, and assessment activities. Unlike lecture-based courses, many applied courses require these resources to be available in a specific sequence and within relatively narrow time windows. A delay or change in one activity may therefore affect several subsequent activities. Late approval of equipment, for example, can reduce practical training time, while an unexpected timetable change may simultaneously disrupt instructor availability, classroom allocation, laboratory access, assignment submission, and assessment arrangements. In many higher education institutions, these activities are still coordinated through spreadsheets, emails, messaging applications, paper forms, and separate information systems. Such fragmented arrangements increase repeated data entry,

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communication delays, booking conflicts, inconsistent records, and the risk that important information is not delivered to all relevant participants. These operational problems are closely related to the broader digital transformation of higher education, which involves not only the introduction of digital technologies but also changes in organizational processes, responsibilities, service structures, and decision-making mechanisms (F. Chen et al., 2025; Iddrisu & Fuseini, 2025). Research on collaborative teaching and teaching-resource efficiency in public art education has similarly drawn attention to the relationship between instructional organization and the effective allocation of educational resources (Lin et al., 2026). From this perspective, improving applied-course administration requires more than digitizing individual tasks; it requires a coordinated process through which teaching activities, resources, information, and responsibilities can be connected across the entire course cycle (Campbell et al., 2025; Wang et al., 2026).

Existing research on higher education digital transformation has identified several organizational conditions that shape the effectiveness of digital initiatives. Clear leadership, common data standards, staff digital competence, system interoperability, and continuous user support have been repeatedly associated with successful institutional transformation (Qi & Qiao, 2026; Tsekouropoulos et al., 2025). However, digital development within universities is often uneven. Different departments may adopt scheduling tools, learning platforms, laboratory-management systems, student-information systems, and communication applications independently, producing a collection of technically functional systems that do not necessarily support a common operational process (Shao, 2026; Xiong & Zeng, 2026). This fragmentation is particularly important for applied courses because course delivery frequently crosses departmental and administrative boundaries (Huang, Xu, et al., 2026; Tiso et al., 2026). A laboratory booking may depend on approval from one unit, equipment preparation may be managed by another, teaching schedules may be controlled centrally, and assignment or assessment information may be maintained within a separate learning platform. Smart-campus research has examined digital platforms, connected facilities, data services, service accessibility, and user experience, showing that system quality, interface design, and access to digital services can influence user satisfaction and learning engagement (Elbertsen et al., 2025; Zheng & Makar, 2022). These studies provide important evidence on the value of digital infrastructure, but their unit of analysis is commonly the institution, platform, or user perception rather than the operational process through which a course is actually delivered. The distinction between digital access and operational coordination is important. A university may provide online booking, electronic approval, digital notifications, and centralized data storage while still requiring instructors or administrators to enter the same information into several systems, repeat approvals, manually reconcile timetable changes, or contact users through separate communication channels. Under these conditions, digitization may change the medium of administrative work without substantially reducing coordination costs. In some cases, additional systems may even create new forms of administrative burden through duplicate reporting, excessive notifications, parallel records, and unclear responsibility for updating information. Studies of university digitalization in China reflect a similar pattern. Institutions have expanded online service platforms, integrated information portals, scheduling systems, data centers, and digitally supported teaching environments, yet internal systems may continue to operate under different data definitions, approval rules, and management procedures (Lin et al., 2020; Yao et al., 2026). The resulting challenge is therefore not simply the availability of technology but the extent to which digital systems reorganize work across departments and convert fragmented administrative activities into a coherent service process (Grimshaw & Miozzo, 2026; Hong et al., 2026b). This issue also exposes a methodological limitation in the existing literature. Much of the evidence on digital transformation, smart-campus services, and educational technology is derived from cross-sectional surveys, interviews, adoption models, satisfaction scales, or broad institutional indicators. These approaches are useful for examining perceptions and organizational readiness, but they provide limited information about what happens inside daily operational workflows. Measures such as perceived ease of use or overall system satisfaction do not directly reveal how long an equipment request remained pending, how many times an approval was returned, how often rooms were double-booked, how frequently schedules were revised, or how many messages were required to resolve a single course change. Aggregate indicators can therefore conceal substantial process variation. Two courses may report similar levels of user satisfaction while differing considerably in approval time, communication workload, resource conflicts, and the stability of course delivery. A stronger evaluation of smart administration requires evidence that captures both users' perceptions and the actual sequence, timing, repetition, and outcomes of administrative events (Hong et al., 2026a). Process mining offers a suitable methodological basis for examining these operational characteristics because it reconstructs actual workflows from time-stamped event records. Rather than relying only on stated procedures or retrospective perceptions, process mining can identify the order in which activities occurred, the time spent between activities, repeated or reversed steps, process variants, and deviations from expected workflows. Earlier applications of process mining in education have concentrated mainly on online learning behavior, learning pathways, interaction sequences, and differences in academic performance (Li et al., 2026; Zavaleta-Sanchez et al., 2025). More recent reviews indicate that educational process-mining research remains dominated by learner clicks, course trajectories, dropout prediction, and academic progression, whereas administrative and course-support processes have received considerably less attention (Southier et al., 2026; Wu et al., 2026). This imbalance is important because the quality of educational delivery depends not only on what learners do within a course but also on the institutional processes that make teaching possible (Harbor & Ololube, 2025; Huang, Yin, et al., 2026). Laboratory availability, equipment access, schedule stability, timely communication, assessment coordination, and administrative responsiveness can directly shape the conditions under which instructors teach and learners participate. The current literature therefore leaves an important gap between research on institutional digital transformation and research on the day-to-day operation of applied courses. Cross-sectional studies provide limited evidence about changes occurring after a new administrative system is introduced, particularly when pre-existing differences among courses and institutions are substantial. Evidence from a single university or a single digital platform also provides a narrow basis for understanding applied courses whose resource requirements may differ markedly across disciplines. Administrative process data are rarely examined together with instructor workload, learner satisfaction, service support, and the continuity of course delivery. This separation makes it difficult to determine whether faster digital transactions actually reduce administrative effort or merely redistribute work among instructors, administrators, and learners. It also limits understanding of unintended effects. A platform may shorten the formal approval time for a resource request while increasing the number of required entries, notifications, or confirmation steps. Evaluating digital administration therefore requires attention to both process efficiency and the human workload created by the redesigned process.

Against this background, this study evaluates the implementation of a smart administration platform across approximately 60 applied courses in eight higher education institutions using data collected before and after platform adoption. The study integrates course-coordination records, resource-booking data, communication logs, assignment records, schedule-change records, and user surveys to examine course administration as a connected operational process rather than as a set of isolated administrative functions. Process mining is used to reconstruct actual course-support workflows and identify delays, repeated activities, bottlenecks, and unusual process paths. Difference-in-differences analysis is employed to estimate changes associated with platform adoption while accounting for temporal differences between implementation and comparison conditions. Multilevel regression is used to examine variation across courses and institutions, recognizing that resource intensity, staffing arrangements, and institutional practices may influence the effects of digital coordination. Structural equation modeling further examines the relationships among system quality, support quality, administrative workload, user satisfaction, and course continuity. By combining objective event records with perceptual and organizational measures, the study seeks to determine not merely whether users accept a smart administration platform, but whether the platform changes how applied courses are actually coordinated. Specifically, the research examines its capacity to reduce processing time and resource conflicts, improve information accuracy and access to teaching resources, limit unnecessary administrative workload, and maintain stable course delivery when schedules or resource conditions change. The significance of the study lies in shifting the evaluation of higher education digitalization from platform availability and general user satisfaction toward measurable changes in operational processes. It also extends educational process mining beyond learner behavior to the administrative infrastructure supporting teaching and provides multi-institutional evidence on how digital coordination can contribute to more efficient, reliable, and sustainable delivery of applied courses.

2. Materials and Methods

2.1 Sample and Study Setting

The study covered 60 applied courses from eight higher education institutions during two consecutive 16-week semesters. The courses included engineering practice, digital media, laboratory science, business simulation, vocational training, and design instruction. A course was included when it required at least three types of support work, such as room booking, equipment use, assignment tracking, schedule adjustment, or teacher–student communication. Courses with fewer than 20 students, fully online courses, and courses with incomplete records were excluded. The final sample included about 2,400 students, 180 instructors, and 95 administrative staff members. The dataset contained about 22,000 coordination records, 11,000 resource-booking entries, 7,500 communication logs, 4,800 assignment records, and 2,400 schedule-change records. A total of 1,000 valid survey responses were also collected. Course size, subject area, institution type, equipment demand, assessment method, and staff–student ratio were recorded as control variables.

2.2 Experimental Design and Control Conditions

A matched before-and-after design was used. Thirty courses started using the smart administration platform in the second semester and formed the intervention group. The other 30 courses continued to use email, spreadsheets, paper forms, and separate booking systems. These courses formed the control group. Each intervention course was matched with a control course based on subject area, class size, equipment demand, assessment method, and initial coordination workload. Data were collected for one semester before platform use and one semester after platform use. The platform combined timetable updates, resource booking, assignment reminders, approval tracking, and message delivery. The control group received no new administration system during the study. Random assignment was not possible because platform use depended on institutional conditions. Matching and baseline controls were therefore used to reduce group differences.

2.3 Measurement Procedures and Quality Control

Administrative performance was measured from system logs and checked against institutional records. Coordination response time was defined as the time between request submission and the first valid response. Booking conflict frequency was calculated as the number of overlapping or rejected bookings per 100 requests. Information delay rate was the percentage of notices delivered after the required time. Administrative processing time covered the period from request submission to final approval. Assignment continuity was measured by on-time submission rate, missed-task frequency, and interruptions caused by schedule or resource changes. Instructor workload was measured by weekly coordination hours, repeated data-entry actions, and manual follow-up actions. Learner satisfaction and support quality were measured with five-point Likert scales. Three experts in educational management reviewed the survey items. A pilot test was conducted with 80 participants. A Cronbach's alpha value of 0.70 or above was accepted. Records with missing timestamps, repeated identifiers, or incorrect event orders were checked against the original files. Two researchers separately reviewed 10% of the event logs. Differences were resolved through joint review. Courses with more than 20% missing data were removed from the main analysis.

2.4 Data Processing and Model Formulation

Course, user, and task records were linked through coded identifiers. All time fields were changed to the same format, and repeated events were removed. Values below the first percentile or above the ninety-ninth percentile were capped at these limits. Process mining was used to rebuild the main work paths and identify repeated steps, long waiting times, and unusual process orders. The effect of the platform was estimated with the following difference-in-differences model:

$$Y_{ict}=\beta_0+\beta_1 \mathrm{Treatment}_c+\beta_2 \mathrm{Post}_t+\beta_3(\mathrm{Treatment}_c \times \mathrm{Post}_t)+\gamma X_{ict}+u_i+v_c+\varepsilon_{ict}$$

where Y_{ict} is the outcome for observation i, course c, and period t. $\mathrm{Treatment}_c$ identifies courses using the platform, while Post_t identifies the period after platform use. The coefficient β_3 shows the net effect of the platform. X_{ict} includes course size, subject area, equipment demand, and baseline workload. u_i and v_c represent institution-level and course-level effects. A coordination efficiency index was also calculated as follows:

$$\mathrm{CEI}=\sum_{j=1}^{m} w_j z_j$$

Where z_j is the standardized value of indicator j, and w_j is the weight estimated by confirmatory factor analysis. Response time, conflict rate, information delay, and processing time were reverse-coded. Higher index values therefore showed better coordination efficiency.

2.5 Statistical Analysis and Model Validation

Multilevel regression was used because the records were grouped within courses and institutions. Structural equation modeling was used to test the links among system usability, administrative workload, support quality, learner satisfaction, and course continuity. Model fit was checked with the comparative fit index, Tucker–Lewis index, root mean square error of approximation, and standardized root mean square residual. Monthly data collected before platform use were used to test the parallel-trend assumption. Additional tests used different matching rules and removed courses with major staff changes. Separate analyses were also conducted by course type and equipment demand. Missing survey values were estimated through multiple imputation when the missing rate was below 10%. Standard errors were grouped at the course level. Statistical significance was set at $p<0.05$. All personal information was removed before analysis. Only the research team could access the administrative records. Participants were informed about the study, and survey participation was voluntary.

3. Results and Discussion

3.1 Changes in Coordination Processes and Processing Time

Process mining showed clear changes after the platform was introduced. Before implementation, most requests followed six steps: submission, manual review, staff transfer, resource checking, approval, and user notice. Some requests returned to earlier steps because information was missing or resources were unavailable. After implementation, the median number of steps decreased from six to four, while the number of common process paths fell from 42 to 27. Repeated transfers and manual status checks were the main steps removed. As shown in Fig. 1, the longest delays before implementation occurred between request submission and staff review. Automatic task routing and reminder functions reduced these waiting times. Mean response time decreased from 18.6 to 10.9 h in the intervention group. The control group showed only a small decrease from 17.9 to 17.1 h. The difference-in-differences estimate was −6.8 h (95% CI: −8.1 to −5.5, $p<0.001$). Total processing time decreased by 34.7%, while repeated approval actions decreased by 31.2%. These results show that event logs can identify delays and repeated administrative steps. Previous process-mining studies mainly examined student activity and learning paths (H. Chen et al., 2025; Real & Pimentel, 2025). The present study extends this method to course administration, where instructors, staff, facilities, and course tasks are part of the same process.

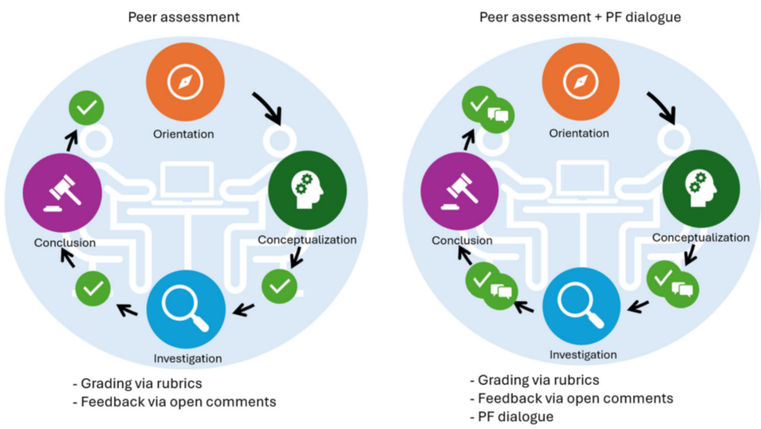

Fig. 1. Administrative workflows before and after the smart platform was introduced.

3.2 Resource Access and Course Continuity

The platform also improved room and equipment allocation. Booking conflicts in the intervention group decreased from 8.7 to 3.9 cases per 100 requests, which represents a reduction of 55.2%. The control group changed only slightly, from 8.2 to 7.7 cases per 100 requests. The adjusted platform effect was −4.3 conflicts per 100 requests ($p<0.001$). The mean time required to resolve a schedule change fell from 23.4 to 13.1 h. Late notices decreased from 14.8% to 6.5%, while the control group remained close to its baseline level. These changes were followed by better course continuity. The on-time assignment rate increased by 6.8 percentage points. The proportion of tasks affected by unavailable equipment or late schedule changes decreased by 3.1 percentage points. The effect was stronger in laboratory, engineering, and design courses than in courses with limited equipment use. These courses usually include more booking and approval steps, so they benefit more from shared scheduling and automatic conflict checks. Earlier smart campus studies described digital platforms as tools for improving access, governance, and campus services (Liang et al., 2025; Surjawan et al., 2025). However, most studies used broad indicators and did not measure the time needed to complete individual course requests. The current results show that resource coordination directly affects teaching. A booking conflict may reduce practice time, delay assignments, and force instructors to revise the course plan.

3.3 Workload, Support Quality, and User Experience

Instructor workload decreased after platform implementation, although the change varied across tasks. Average weekly coordination time fell from 5.8 to 4.3 h, while manual follow-up actions decreased by 36.5%. Repeated data entry decreased by only 18.7% because three institutions still required staff to enter some information into older systems. Weekly administrative processing time also fell from 6.4 to 4.8 h per course. Learner satisfaction with support increased from 3.54 to 4.00 on a five-point scale, while the instructor score increased from 3.38 to 3.77. The structural model in Fig. 2 showed that system usability was positively related to information accuracy ($\beta=0.43, p<0.001$). Information accuracy was positively related to support quality ($\beta=0.51, p<0.001$), while administrative workload was negatively related to support quality ($\beta=-0.27, p=0.004$). Support quality was also associated with learner satisfaction ($\beta=0.62, p<0.001$) and course continuity ($\beta=0.38, p<0.001$). The indirect effect of usability on course continuity through information accuracy and support quality was 0.14 ($p=0.002$). These results indicate that satisfaction did not depend only on interface design. It was also linked to fewer missed notices, faster responses, and more accurate information. Earlier smart campus studies mainly used cross-sectional survey data to examine system quality and user satisfaction. The present study combines survey data with actual communication and processing records, which provides stronger evidence of the link between system use and course support.

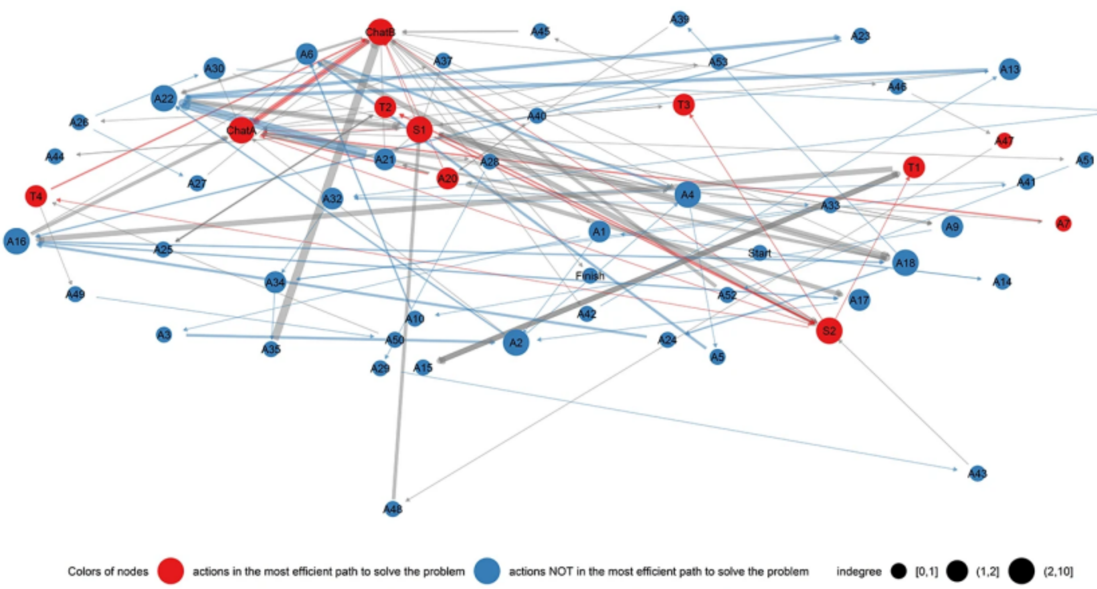

Fig. 2. Links among system usability, information accuracy, workload, support quality, satisfaction, and course continuity.

3.4 Differences Across Courses and Study Limits

The size of the platform effect differed across institutions and course types. Multilevel analysis showed that 12.4% of the variation in processing time occurred at the institutional level, while 9.1% occurred at the course level. Courses with high equipment demand showed a 42.6% reduction in processing time. The reduction was 24.8% in courses with low equipment demand. Institutions that linked the platform with existing timetable and identity systems also showed larger gains than institutions that kept separate databases. The main estimates changed by less than 8% under different matching rules. The pre-intervention trend test also found no significant difference between the two groups ($p=0.47$). However, 11.6% of instructors reported that automatic reminders were too frequent. Some staff members also continued to use private spreadsheets as backup records. These findings show that a new platform may add work when old and new systems are used at the same time. This result agrees with previous studies showing that digital tools cannot solve divided work rules, repeated reporting, or unclear staff duties on their own (Hammerschmidt et al., 2025; Wu & Chen, 2025). The study also has several limits. Course assignment was not random, the observation period covered only two semesters, and some informal communication was not recorded. Long-term maintenance costs were not examined. Even so, the use of multiple institutions, event records, and survey data provides more reliable evidence than a single-site survey. The findings suggest that smart administration works best when it removes repeated steps, links existing systems, and allows users to control notices and approvals.

4. Conclusion

This study assessed how a smart administration platform affected applied courses across eight institutions. The platform reduced response time, processing time, booking conflicts, and repeated approval steps. It also improved information accuracy, lowered instructor coordination workload, and supported more stable assignment completion and course delivery. The effects were stronger in courses with high equipment and scheduling needs. This finding shows that smart administration is especially useful in courses with complex resource demands. The study combined process records, survey data, and multilevel analysis in one research design. This method linked administrative performance with learning support and course continuity instead of relying only on user opinions. The results also show that technology alone cannot improve course management. Clear work rules, shared data, and links with existing systems are also required. The proposed method can help institutions improve booking, scheduling, approval, and communication processes in applied courses. However, the study used non-random group assignment, covered only two semesters, and did not record all informal communication. Future studies should use larger samples, longer observation periods, and cost data to assess the long-term effects of smart administration.

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