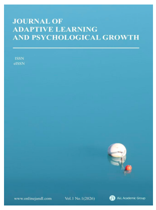
JOURNAL OF ADAPTIVE LEARNING AND PSYCHOLOGICAL GROWTH
2026 Vol. 1, No. 2, ISSN (O): 3154-7915



# Platform-Based Coordination of Instructors, Learners, and Shared Facilities

**Frank Cornelissen[1], Mark de Reuver[1*]**

[1]Educational Sciences, Research Institute of Child Development and Education, Faculty of Social and Behavioural Sciences, University of Amsterdam, Nieuwe Achtergracht 129, 1018 WS Amsterdam, The Netherlands

Corresponding Author*: Mark de Reuver E-mail: G.A.deReuver@tudelft.nl

**ARTICLE INFO**

*Keywords*
platform-based coordination
shared facilities
instructor management
process mining
social network analysis
educational administration
learner support
resource efficiency

*Published*
01 September 2026

**ABSTRACT**

This study investigates how platform-based coordination can improve the management efficiency of instructors, learners, and shared facilities in practice-intensive education programs. The study is designed to evaluate a digital coordination platform across approximately 30 practice-intensive programs in 6 institutions over two semesters, collecting around 15,000 facility-booking records, 9,000 instructor-learner appointment records, 6,800 feedback-exchange records, 4,500 task-progress updates, 2,200 administrative adjustment logs, and 900 user survey responses. Key variables include booking success rate, facility utilization rate, appointment waiting time, instructor response time, feedback turnaround time, administrative workload, task completion continuity, platform-use frequency, communication efficiency, and learner satisfaction. The study applies difference-in-differences analysis, social network analysis, process mining, multilevel regression, and usability evaluation to compare program operation before and after platform implementation. Platform effectiveness is measured by reduction in scheduling conflicts, decrease in administrative processing time, improvement in instructor-student matching efficiency, increase in resource-use transparency, and improvement in learner continuity. The innovation of this study lies in viewing educational coordination as a measurable platform-mediated process rather than a purely administrative task, showing how digital systems can integrate booking, feedback, progress tracking, and resource monitoring into a unified management mechanism for programs with complex resource dependencies.

## 1. Introduction

Practice-intensive education requires close coordination among instructors, learners, facilities, equipment, appointments, feedback, and task schedules. Unlike lecture-based courses, where teaching activities can often proceed according to relatively stable timetables, practice-intensive programs depend on multiple resources being available at the same time and in the correct sequence. A delayed appointment, unavailable room, equipment conflict, or late round of feedback can interrupt practice, postpone subsequent tasks, and weaken continuity in the learning process. These problems become more pronounced in programs that rely heavily on studios, laboratories,

**Citation: Cornelissen, F., & de Reuver, M. (2026). Platform-based coordination of instructors, learners, and shared facilities. *Journal of Adaptive Learning and Psychological Growth,* 1(2), 23-32.**


**https://doi.org/10.64744/jalpg.2026.279.**

workshops, specialist facilities, or repeated instructor–learner consultation. Universities have therefore introduced learning management systems, booking tools, communication platforms, scheduling applications, and digital dashboards to support daily teaching and administrative activities. However, the functions of these systems have often developed separately. Research on emergency online teaching showed that digital tools were frequently adopted as isolated solutions, with limited integration among teaching, administration, communication, and resource management (Avdiel & Blau, 2025; Zhang et al., 2026). This fragmented approach can improve individual activities without necessarily improving the coordination of the overall educational process. Recent research has also shown that digital monitoring can extend beyond activity tracking to support the evaluation of teaching quality and the validation of educational equity, indicating that systematically organized educational data can contribute to broader institutional assessment and decision making (Lin et al., 2026). This perspective is particularly relevant to practice-intensive education because unequal access to instructors, facilities, equipment, or timely feedback may influence learning opportunities even when course content and formal requirements remain the same (Mientus et al., 2026; Qi & Qiao, 2026).

The broader literature on digital transformation increasingly treats technology adoption as an institutional and organizational process rather than simply the introduction of new teaching tools. Digital transformation in higher education involves changes in staff responsibilities, technical support, communication procedures, administrative routines, and management structures (Nweke, 2025; Yao et al., 2026). From this perspective, the effectiveness of a digital platform depends not only on whether users adopt it, but also on whether it improves the coordination of activities across different parts of an institution. Studies of smart classrooms and smart campuses have reported improvements in accessibility, flexibility, information availability, and student engagement (Wu et al., 2026b; Zhang et al., 2021). Nevertheless, much of this evidence is based on user surveys, perception measures, or single-institution case studies. Such approaches are useful for understanding acceptance and experience, but they provide limited evidence about whether digital systems actually reduce operational delays, prevent scheduling conflicts, improve access to shared resources, or reduce the administrative effort required to keep teaching activities running (Huang et al., 2026a; Koukaras et al., 2025). A platform may receive favorable user evaluations while still producing frequent booking failures, duplicated communication, delayed responses, or repeated manual adjustments. For practice-intensive programs, these operational outcomes are particularly important because teaching progress depends on the timely connection of people, spaces, equipment, feedback, and task sequences. Learning analytics has created new opportunities to use educational records for monitoring participation, identifying patterns, and supporting teaching decisions (Mpofu & Chasokela, 2025; Shao, 2026). Predictive dashboards, for example, can help instructors identify students who may require additional support, although their effectiveness depends on factors such as timing, workload, trust, interpretability, and perceived usefulness (Zhang et al., 2026). Student-facing dashboards have also developed from simple visualizations of activity data toward systems designed to support feedback, reflection, and self-regulated learning (Huang, 2026; Michael et al., 2026). These developments demonstrate the potential value of digital records, but the dominant indicators in learning analytics remain closely related to learner behavior, including clicks, logins, submissions, participation frequency, and time spent on learning platforms (Huang et al., 2026b; Wu et al., 2026a). Such indicators provide only a partial view of practice-intensive education. A student may participate actively online but still experience repeated difficulty obtaining a studio slot, arranging instructor consultation, accessing required equipment, or receiving feedback before the next stage of a task. Similarly, an instructor may respond frequently but still face excessive scheduling adjustments or fragmented communication across different systems. Operational variables such as instructor availability, appointment success, facility access, response delay, task interruption, and administrative adjustment therefore need to be considered together with conventional learning indicators. Research on shared educational facilities provides some evidence that digital data can support more efficient resource management. Wi-Fi traces, sensor records, and occupancy data have been used to estimate classroom use and improve space planning (Alsafery et al., 2025; Zhang et al., 2025). These methods can identify when and where rooms are occupied and can reveal broad patterns of underuse or congestion. However, physical occupancy is not equivalent to effective educational coordination. Occupancy data do not explain whether a learner failed to secure a booking, whether a session was cancelled because equipment was unavailable, whether instructors had conflicting appointments, or whether repeated administrative intervention was required to resolve a scheduling problem. They also provide little information about the relationship between resource access and subsequent teaching activities. In practice-intensive programs, the educational effect of a facility depends not only on whether it is occupied but also on whether it is available to the appropriate learner at the required time, connected to the correct task, and supported by necessary instructor guidance. This distinction suggests that resource management should be studied as part of an integrated educational workflow rather than as an isolated problem of space utilization. Social network analysis and process mining offer complementary approaches for examining these coordination processes. Social network analysis can describe the frequency, intensity, and structure of instructor–learner interaction and can identify highly connected, weakly connected, or unevenly distributed communication relationships. Previous studies have used network methods to investigate online discussion, social presence, collaboration, and teaching innovation (Al-Jarf, 2026). Process mining, by contrast, reconstructs actual workflows from time-stamped event records and can identify common pathways, delays, repeated activities, bottlenecks, and deviations from expected procedures. It has been applied to learning trajectories, course behavior, and curriculum-related processes (Du et al., 2026; Xu et al., 2026). Text-based methods such as sentiment analysis have also been used to classify learner feedback and identify patterns in user responses (Pande et al., 2025). These approaches are valuable because they reveal different dimensions of educational activity, but they are commonly used in isolation. Network analysis shows who interacts with whom but does not necessarily show how an operational task progresses. Process mining shows how events unfold but may provide limited information about the quality or distribution of interpersonal relationships. Surveys and feedback analysis explain how users perceive a system but cannot by themselves establish whether observed operational performance has improved. Combining these data sources can therefore provide a more complete account of how digital coordination systems influence educational practice. Several methodological limitations also remain in the existing literature. Many studies examine one course, one department, one platform, or one institution over a relatively short period. As a result, observed differences may reflect local teaching practices, program characteristics, institutional resources, or user composition rather than the effects of the digital system itself. Operational records are also commonly fragmented across learning management systems, booking applications, institutional email, appointment tools, spreadsheets, and administrative databases. This fragmentation makes it difficult to reconstruct the complete sequence through which a learner requests a resource, receives confirmation, attends a session, obtains feedback, completes a task, and proceeds to the next stage. Another limitation concerns outcome measurement. Platform effectiveness is frequently evaluated through satisfaction, intention to use, perceived usefulness, or general participation. These measures remain important, but they provide limited evidence of operational improvement. Direct indicators such as booking success rate, waiting time, response delay, processing duration, cancellation frequency, repeated adjustment, facility utilization, administrative workload, and task interruption are more closely connected to the coordination problems that digital management systems are intended to address. Evaluating these indicators across multiple programs and institutions is therefore necessary to determine whether a platform produces measurable changes in educational operations rather than merely changes in user perceptions.

Against this background, the present study evaluates a digital coordination platform designed to connect instructor–learner appointments, facility booking, feedback exchange, task updating, and administrative adjustment within a unified management environment. The study covers approximately 30 practice-intensive programs across six institutions over two academic semesters and integrates multiple forms of operational and user-level data. The dataset contains approximately 15,000 facility-booking records, 9,000 instructor–learner appointment records, 6,800 feedback exchanges, 4,500 task updates, 2,200 administrative adjustment logs, and 900 survey responses. Rather than evaluating the platform primarily through adoption or satisfaction, the study examines whether its implementation changes the actual coordination processes through which educational activities are organized and completed. Difference-in-differences analysis is used to estimate changes before and after platform implementation while accounting for differences between implementation and comparison settings. Social network analysis is employed to examine changes in the structure and intensity of instructor–learner interaction, while process mining reconstructs operational workflows and identifies delays, repeated adjustments, bottlenecks, and interruptions. Multilevel regression is further used to examine whether observed effects vary across individual users, programs, and institutions. The empirical analysis focuses on both efficiency and continuity. Key outcomes include scheduling conflicts, booking success, waiting time, feedback delay, administrative processing time, repeated adjustment, instructor–learner matching efficiency, facility utilization, resource transparency, administrative workload, and task continuity. Examining these outcomes together makes it possible to determine whether improvements in one part of the system are accompanied by improvements elsewhere, or whether coordination problems are simply transferred from one stage to another. The study therefore treats educational coordination as an interconnected process rather than a collection of independent digital functions. This approach also allows platform performance to be evaluated at multiple levels: individual interactions between instructors and learners, operational workflows within programs, and institutional differences in resource organization and implementation conditions. The significance of the study lies in establishing a more process-oriented framework for evaluating digital management in practice-intensive education. Conceptually, it extends research on educational digitalization beyond content delivery, platform adoption, and learner activity by treating coordination among people, facilities, feedback, and task progress as a measurable component of educational quality. Methodologically, it integrates quasi-experimental analysis, social network analysis, process mining, multilevel modelling, operational records, and survey evidence within the same evaluation framework. This combination provides a stronger basis for distinguishing perceived platform value from measurable changes in organizational performance. Practically, the results can help institutions identify where coordination failures occur, which resources generate repeated bottlenecks, how instructor availability affects learner progress, and whether digital integration reduces the need for manual administrative intervention. The study may also provide evidence for improving resource allocation and access transparency across programs, thereby supporting more consistent learning opportunities in environments where access to facilities, instructors, and timely feedback directly affects educational progress. By linking digital management to observable changes in scheduling, interaction, resource use, feedback, and task continuity, the study provides a framework for assessing whether educational platforms improve not only how information is recorded, but also how practice-intensive education is actually organized and delivered.

## 2. Materials and Methods

### 2.1 Study Setting and Sample

This study included 30 practice-based education programs from six institutions. Data were collected over two semesters. The programs covered design studios, engineering laboratories, media production courses, clinical skills training, and vocational workshops. Programs were included when they used shared facilities, arranged regular instructor–learner meetings, and enrolled at least 80 learners. The dataset contained about 15,000 facility-booking records, 9,000 appointment records, 6,800 feedback records, 4,500 task-progress updates, and 2,200 administrative adjustment logs. The survey included 900 valid responses from 620 learners, 180 instructors, and 100 administrative staff members. Learners were aged 18–32 years. The instructor group included full-time teachers, laboratory supervisors, and part-time tutors. Programs with major curriculum changes, facility renovation, or incomplete records were excluded.

### 2.2 Experimental Design and Control Setting

A phased rollout design was used to assess the effect of the platform. Eighteen programs began using the platform at the start of the second semester and formed the intervention group. The other 12 programs continued to use email, spreadsheets, and existing booking tools and formed the control group. The first semester served as the baseline period, while the second semester served as the follow-up period. The two groups were matched by enrollment size, instructor–learner ratio, number of shared facilities, weekly practice hours, booking success rate, and prior use of digital tools. The platform included four modules: facility booking, instructor appointments, feedback exchange, and task tracking. The control programs kept their normal procedures during the study and received platform access after data collection.

### 2.3 Measurements and Quality Control

Platform performance was measured using system logs, administrative records, and survey data. Booking success rate was calculated as the number of approved bookings divided by the total number of valid requests. Facility utilization was calculated as actual use time divided by total available time. Appointment waiting time was measured from the submission of a learner request to the confirmed meeting time. Instructor response time and feedback turnaround time were obtained from system timestamps. Administrative workload was measured by the monthly number of manual schedule changes, conflict-handling actions, and booking corrections. Task continuity was defined as the share of tasks completed without an interruption longer than seven days. User satisfaction, communication efficiency, ease of use, and resource transparency were measured with five-point Likert scales. All timestamps were converted to the same time zone. Test records and duplicate entries were removed. Two researchers independently coded 10% of the administrative records. Cohen's kappa was above 0.82 for all coded variables. Survey items with factor loadings below 0.50 were removed, and Cronbach's alpha was above 0.78 for all final scales.

### 2.4 Data Processing and Model Formulation

Records were linked using anonymous user, program, facility, and event IDs. Personal information was removed before analysis. Waiting time and response time showed right-skewed distributions and were transformed using the natural logarithm. Values above the 99th percentile were winsorized to reduce the effect of unusual system records. The effect of platform use was estimated with the following difference-in-differences model:

$$Y_{ipt}=\beta_0+\beta_1 Treat_p+\beta_2 Post_t+\beta_3(Treat_p\times Post_t)+\gamma X_{ipt}+\mu_p+\tau_t+\varepsilon_{ipt}$$

where $Y_{ipt}$ is the outcome for user or event $i$ in program $p$ during period $t$. $Treat_p$ identifies intervention programs, while $Post_t$ identifies the second semester. The coefficient $\beta_3$ represents the estimated effect of platform use. $X_{ipt}$ includes enrollment size, instructor workload, facility type, weekly practice hours, and prior digital experience. Program and time effects are represented by $\mu_p$ and $\tau_t$.

Facility utilization was calculated as:

$$U_{fp}=\frac{\sum_{j=1}^{n}T_{jfp}^{used}}{T_{fp}^{available}}\times100\%$$

where $T_{jfp}^{used}$ is the verified use time for booking $j$, and $T_{fp}^{available}$ is the total available time for facility $f$ in program $p$.

### 2.5 Network, Process, and Statistical Analysis

Appointment and feedback records were used to build instructor–learner networks. Users were treated as nodes, while appointments and feedback exchanges were treated as weighted links. Network density, degree centrality, instructor workload, and response concentration were calculated for each program and semester. Process mining was used to trace events from booking requests to facility use and from task submission to instructor feedback. The analysis identified delayed responses, repeated approvals, skipped steps, and manual corrections. Multilevel models were used because users were grouped within programs and institutions. Mixed-effects logistic regression was used for binary outcomes, while linear mixed models were used for continuous outcomes. Standard errors were clustered at the program level. Monthly baseline data were used to test the parallel-trend assumption. Robustness tests excluded the first four weeks after platform rollout, removed programs with low platform use, and repeated the analysis with propensity-score weighting. Statistical significance was set at $p<0.05$, and effect sizes with 95% confidence intervals were reported.

## 3. Results and Discussion

### 3.1 Changes in Scheduling and Facility Use

Platform use improved scheduling and facility management. In the intervention group, the booking success rate increased from 78.6% in the first semester to 91.4% in the second semester. The control group showed a smaller increase, from 79.2% to 81.1%. The difference-in-differences estimate was 10.9 percentage points and was significant ($p<0.001$). Facility utilization increased from 61.7% to 74.2% in the intervention group, compared with an increase from 62.3% to 64.1% in the control group. The adjusted effect was 10.7 percentage points. Mean appointment waiting time fell from 30.8 to 18.1 h, while the monthly number of manual schedule changes decreased by 27.6%. Figure 1 shows that most gains appeared after the fourth week of platform use. This pattern may reflect the time needed for users to become familiar with the booking process. Facility opening hours remained unchanged during the study. The increase in use was therefore mainly related to fewer empty periods between sessions and faster reuse of cancelled time slots. Earlier smart-campus studies found that linked operational data can support resource monitoring and space management (Krishna, 2025; Xiong & Zeng, 2026). The present study adds booking success, waiting time, and schedule changes to the analysis. These measures provide more detail than room occupancy alone.


*Fig. 1. Booking success, facility use, waiting time, and administrative changes before and after platform use.*

### 3.2 Instructor–Learner Interaction and Feedback Efficiency

The platform changed both the amount and distribution of instructor–learner interaction. Network density increased from 0.084 to 0.107 in the intervention programs. This increase means that learners contacted a wider range of instructors. Network centralization decreased from 0.39 to 0.28, while the share of appointments handled by the busiest 10% of instructors fell from 44.8% to 36.5%. Thus, appointments were distributed more evenly across instructors. Median instructor response time decreased from 25.6 to 14.8 h. The share of feedback returned within 48 h increased from 62.7% to 79.4%. Communication efficiency rose from 3.38 to 4.06, and learner satisfaction increased from 3.51 to 4.12 on the five-point scale. These effects remained significant after controlling for instructor workload, program size, and earlier experience with digital tools. Previous studies reported that dashboards can support teaching decisions, but their value depends on clear information, timely use, and instructor trust (Bergamaschi et al., 2025; Hong et al., 2026). A similar pattern was found here. Programs with weekly platform-use rates below 60% showed smaller gains in response time. Platform performance therefore depended not only on system functions but also on regular instructor use.

### 3.3 Workflow Paths and Coordination Bottlenecks

Process mining showed clear changes in booking, appointment, and feedback workflows. Before platform use, 54.2% of facility requests followed the standard path from submission to approval, confirmation, and verified use. After implementation, this share increased to 73.6%. Repeated approval steps decreased from 17.9% to 8.1%, while cases requiring manual correction fell from 13.8% to 6.0%. Mean booking processing time decreased from 18.6 to 10.2 h. Similar changes were found in the feedback process. The share of tasks moving directly from submission to instructor review and completed feedback increased from 58.9% to 76.7%. Figure 2 shows that the main delay before implementation occurred between instructor assignment and appointment confirmation. This delay became shorter after the platform displayed instructor availability and issued conflict warnings. The final process model reached a fitness value of 0.88 and a precision value of 0.81. These values indicate that the model covered most observed paths while limiting unsupported paths. Alshammari and Zhang (2025) used process mining to detect repeated steps, skipped activities, and unusual learning paths. The present study applies this method to educational management and links workflow paths with time, workload, and facility use. It also extends earlier studies that focused mainly on learner behavior within one course or one digital system (Alshammari & Alkhwaldi, 2025; Li et al., 2026).

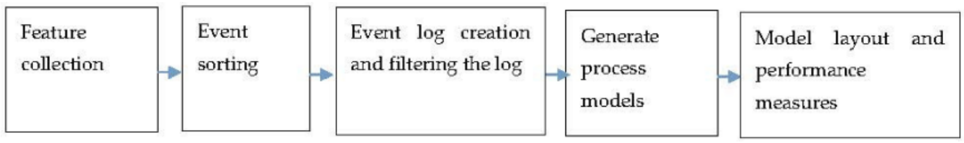



*Fig. 2. Main workflow paths and process delays before and after platform use.*

### 3.4 Overall Platform Effect and Practical Implications

The multilevel models confirmed that platform use was related to better program operation after differences among users, programs, and institutions were considered. Platform implementation increased the probability of uninterrupted task completion by 13.6 percentage points ($p<0.001$). Learners in the intervention group were 1.71 times more likely to complete practice tasks by the planned date than those in the control group. Platform use was also associated with higher satisfaction ($\beta=0.47$, 95% CI: 0.35–0.59) and lower administrative workload ($\beta=-0.31$, 95% CI: −0.42 to −0.20). The effects were strongest in design studios and engineering laboratories. These programs required both instructor support and access to specialized facilities. Smaller effects were found in programs that used standard classrooms and had fewer booking limits. The results remained stable after the first four weeks were removed and after propensity-score weighting was applied. These findings indicate that a shared platform is most useful in programs where people, facilities, and task schedules are closely linked. Earlier dashboard research also found that information is more useful when it supports clear actions rather than only presenting descriptive data. Smart-campus studies have reached similar conclusions about the value of shared records for daily management. This study was limited to two semesters, and programs were not assigned at random. System logs also missed some communication that took place outside the platform. In addition, the study measured task continuity rather than final learning outcomes. Future studies should use longer observation periods and examine changes in skill development, course completion, and learning performance.

## 4. Conclusion

This study found that a shared digital platform improved the coordination of instructors, learners, and facilities in practice-based education. After implementation, booking success and facility use increased. Appointment waiting time, feedback delay, manual schedule changes, and administrative workload decreased. Instructor–learner contact was also distributed more evenly. Process analysis found fewer repeated approvals, skipped steps, and manual corrections. Platform use was further linked to better task continuity and higher learner satisfaction. The main contribution of this study is the use of one framework to measure booking, appointments, feedback, facility use, and task progress. The combined use of difference-in-differences analysis, network analysis, process mining, and multilevel models helped identify both the size and source of the observed changes. The results may support the management of laboratories, studios, workshops, clinical training spaces, and other programs that rely on shared resources. However, the study covered only two semesters, and the programs were not randomly assigned. Some communication outside the platform was not recorded. The analysis also focused on task continuity rather than final learning outcomes. Further research should use longer study periods and examine changes in skill development, course completion, and academic performance.

**Acknowledgments**
We are grateful to all respondents who participated in this study.

**References**

1. Al-Jarf, R. (2026). Collaborative learning and teaching in digital environments: A systematic review of two decades of research. *Journal of Computer Science and Technology Studies, 8*(4), 25-40.
2. Alsafery, W., Rana, O., & Perera, C. (2025). SpaceSense: Exploring the Use of Sensors Data to Understand Occupants' Behavior in Heterogeneous Study Space Types. *ACM Journal on Computing and Sustainable Societies, 3*(3), 1-38.
3. Alshammari, S. H., & Alkhwaldi, A. F. (2025). An integrated approach using social support theory and technology acceptance model to investigate the sustainable use of digital learning technologies. *Scientific Reports, 15*(1), 342.
4. Avdiel, O., & Blau, I. (2025). Building resilience: Technological adaptation and enhancing collaboration among educators and learners in flexible emergency learning spaces. *Education Sciences, 15*(12), 1596.
5. Bergamaschi, A., Giambruno, C., Morales, P., Forkosh-Baruch, A., Hanuka, S., & Hershkovitz, A. (2025). Empowering Schools with Data: How Can We Achieve Effective Use of Educational Dashboards for Teachers and Principals?.
6. Du, Y., Chen, Z., Liu, Q., & Dong, Y. (2026). Co-identification of Vibration, Structural Looseness, and Surface Damage in Industrial Equipment Operation Videos.
7. Hong, Z., Chen, H., & Xu, T. (2026). Real-Time Capacity Risk Forecasting for Low-Latency Financial Trading Cloud Platforms. Available at SSRN 7118180.
8. Huang, J., Xu, T., Yang, J., & Yin, J. (2026a). Blockage Early Warning and Financial Impact Quantification in the Monthly Closing Process of Fintech Companies. Available at SSRN 7179198.
9. Huang, J., Xu, T., Yang, J., & Yin, J. (2026b). A Graph Neural Network Approach for Financial Data Validation and Risk Identification in Large-Scale Intercompany Transactions. Available at SSRN 7175058.
10. Huang, R. (2026). Less Is More: When Data Augmentation Hurts Small CNN Generalization. *Journal of Computer and Communications, 14*(7), 1-11.
11. Koukaras, C., Hatzikraniotis, E., Mitsiaki, M., Koukaras, P., Tjortjis, C., & Stavrinides, S. G. (2025). Revolutionising educational management with AI and wireless networks: a framework for smart resource allocation and decision-making. *Applied Sciences, 15*(10), 5293.
12. Krishna, S. M. (2025). Smart campus ecosystems: Designing digital twins for educational infrastructure and strategic management. *Eksplorium-Buletin Pusat Teknologi Bahan Galian Nuklir, 46*(1), 1279-1293.
13. Li, J., Zhang, Y., & Gu, Y. (2026). Chain-Hash Audit Framework with Trusted Anchoring for Tamper-Evident Evidence Lifecycle Management.
14. Lin, T., Spivack, Z., & Chen, A. (2026). Monitoring Teaching Quality and Validating Educational Equity in Public Art Education. Available at SSRN 6512778.
15. Michael, J., Santoso, H. B., & Junus, K. (2026, July). Design and Evaluation of the Regulate Dashboard: An Action-Oriented Student-Facing Self-regulated Learning Dashboard for Higher Education Students. In International Conference on Human-Computer Interaction (pp. 295-316). Cham: Springer Nature Switzerland.

16. Mientus, L., Wulff, P., Nowak, A., & Borowski, A. (2026). When AI Feedback Was Still in Its Infancy: An Exploratory Comparison of Early AI Feedback Attempts on Preservice Physics Teachers' Reflective Writing. *Education Sciences, 16*(2), 301.
17. Mpofu, S., & Chasokela, D. (2025). Data-informed decision-making: using analytics to drive strategic management in higher education. In Building Organizational Capacity and Strategic Management in Academia (pp. 103-138). IGI Global Scientific Publishing.
18. Nweke, P. O. (2025). THE role of digital administrative system in transforming organizational culture in higher institution. *International Journal of Studies in Education, 21*(1), 184-197.
19. Pande, S. D., Kumar, S., Kathole, A. B., Joshi, R. R., Ahammad, S. H., Dhabliya, D., & Rahman, M. Z. U. (2025). A novel chatbot driven by sentiment analysis using a capsule network and BiLSTM for online user feedback on consumer electronics. *IEEE Transactions on Consumer Electronics, 71*(3), 7933-7946.
20. Qi, C., & Qiao, X. (2026). Using AI to Monitor AI: Automated Operations Through Log-Driven Intelligence. Available at SSRN 6795840.
21. Shao, W. (2026). Design and Implementation of an Open-Source Security Framework for Cloud Infrastructure. arXiv preprint arXiv:2604.03331.
22. Wu, J., Wu, D., Zhang, J., & Peng, Y. (2026a). Generative AI Feedback in Junior High School Artistic Creation Evaluation. Available at SSRN 7244838.
23. Wu, J., Zhang, J., Wu, D., & Peng, Y. (2026b). Visual Transformation Mechanisms for Integrating Digital Cultural Heritage Resources into Junior High School Art Curricula.
24. Xiong, W., & Zeng, Y. (2026). Multi-Layer Coupled Diagnosis of Energy Efficiency Degradation in Complex Building MEP Systems and Identification of Optimization Boundaries. Available at SSRN 7121782.
25. Xu, T., Zhang, J., & Zhu, W. (2026). Reproducible Modeling Pipelines and Cross-Window Stability in Subprime Auto Loan Credit Risk Assessment. Available at SSRN 6893861.
26. Yao, G., Zheng, J., Wang, Z., Zhang, W., Han, R., Zhao, C., ... & Liu, R. (2026, March). V-pruner: A fast and globally-informed token pruning framework for vision transformer. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 40, No. 40, pp. 34396-34404).
27. Zhang, G., Xu, Y., Zhang, M., Wang, S., & Lin, N. (2021). The brain network in support of social semantic accumulation. *Social cognitive and affective neuroscience, 16*(4), 393-405.
28. Zhang, Y., Wang, J., & Gu, W. (2026, February). Research on the Construction and Effectiveness of a Computer-Aided Systematic Training Framework for Wind Farm O&M Quality Amidst High Personnel Turnover. In Proceedings of the 2nd International Conference on Digital Management and Information Technology (pp. 647-651).
29. Zhang, Z., Tong, Y., & Gao, Y. (2026). Causal Representation Learning for Explainable Early Warning in High-Stakes Decision Systems.
30. Zhang, Z., Wang, J., Li, Z., Wang, Y., & Zheng, J. (2025). Anncoder: A mti-agent-based code generation and optimization model. *Symmetry, 17*(7), 1087.