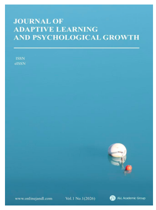
JOURNAL OF ADAPTIVE LEARNING AND PSYCHOLOGICAL GROWTH
2026 Vol. 1, No. 2, ISSN (O): 3154-7915



Can Shared Learning Facilities Reduce Educational Inefficiency Evidence from Practice-Intensive Programs

Lukas Meier[1*], Sophie Dubois[1]
[1] Department of Management, Technology and Economics, ETH Zurich, Weinbergstrasse 56/58, 8092 Zurich, Switzerland.
Corresponding Author*: Lukas Meier E-mail: lukas.meier@ethz.ch

ARTICLE INFO

Keywords

shared learning facilities
educational inefficiency
practice-intensive programs
data envelopment analysis
queueing analysis
resource use
access fairness
institutional management

Published:

05 September 2026

ABSTRACT

This study investigates whether shared learning facilities can reduce educational inefficiency in practice-intensive programs that rely on specialized rooms, equipment, instructor guidance, and repeated hands-on activities. The study is designed to collect data from approximately 45 practice-intensive programs across 12 higher education institutions over two academic semesters, including around 14,000 facility-booking records, 8,500 equipment-use logs, 5,200 supervised practice records, 3,600 learner waiting-time records, 1,200 student survey responses, and 180 administrator interviews or coordination notes. Key variables include facility utilization rate, idle-time ratio, booking success rate, peak-hour congestion, average waiting time, equipment availability, learner access frequency, course completion continuity, perceived access fairness, and satisfaction with facility support. The study applies data envelopment analysis, queueing analysis, propensity score matching, difference-in-differences analysis, and multilevel regression to compare programs before and after shared-use policy implementation and to examine whether shared facilities improve resource efficiency and learner access. Evaluation indicators include utilization improvement rate, idle-time reduction, conflict reduction, waiting-time decrease, access equity index, and learning continuity score. The innovation of this study lies in moving beyond general discussion of resource shortage and providing empirical evidence on whether shared facility governance can reduce educational inefficiency, improve access fairness, and support sustainable operation in programs with high resource dependency.

1. Introduction

Practice-intensive programs rely heavily on laboratories, simulation rooms, studios, workshops, specialist equipment, and supervised practice spaces. These facilities provide the physical conditions required for repeated training, immediate error correction, technical demonstration, and the gradual development of practical competence. Their educational value depends not only on the availability of equipment but also on whether students can obtain timely and stable access throughout a course. Previous studies have shown that learning-space design and availability affect student participation, teaching practice, collaboration, and satisfaction (Ninnemann et al., 2026; Qi & Qiao, 2026b). Research in public art education has also connected

Citation: Meier, L., & Dubois, S. (2026). Can shared learning facilities reduce educational inefficiency evidence from practice-intensive programs. *Journal of Adaptive Learning and Psychological Growth*, 1(2), 64-73.

https://doi.org/10.64744/jalpg.2026.296.

collaborative teaching arrangements with the optimization of teaching-resource efficiency, suggesting that the organization and sharing of instructional resources can influence both teaching delivery and resource use (Lin et al., 2026). Other studies have shown that the quality and organization of learning environments can shape how students engage with practical and collaborative activities (Yakin et al., 2025). Flexible layouts, suitable equipment, extended opening hours, and reliable technical support may further improve the use of active and informal learning spaces (Wang et al., 2026; Wu & Chen, 2025). These factors are particularly important in practice-intensive programs because interruptions in facility access can directly affect training schedules, assignment completion, assessment preparation, and continuity of skill development (Aybek & Kaya, 2026; Zhu et al., 2025).

Despite their educational importance, specialized facilities require substantial investment in space, equipment, maintenance, staffing, and technical support. Their utilization is also highly uneven. Some laboratories and training rooms remain underused during ordinary teaching weeks, while the same facilities may become heavily congested before examinations, project deadlines, competitions, and practical assessments. Access difficulties can be greater for students studying away from the main campus or relying on a limited number of local facilities (Asamoah & Ansong, 2025; Zhang, 2026). This imbalance creates two related problems: unused capacity during low-demand periods and insufficient access during periods of concentrated demand. Facility-management studies have explored smart-campus systems, maintenance platforms, sensor data, and building-management information as tools for improving the operation of rooms and equipment (Huang, Xu, et al., 2026; Qi & Qiao, 2026a). Research on shared scientific instruments has likewise reported progress in open access while identifying problems related to coordination, uneven utilization, and unclear management responsibilities (Al-Ibraheem et al., 2025; Zheng & Makar, 2022). These studies support the potential value of shared-use arrangements, particularly when expensive facilities can serve several programs rather than remain restricted to a single department. However, most existing studies examine facility conditions through surveys, interviews, administrative descriptions, or records from a single institution. They provide limited evidence on how students' perceived access corresponds with actual booking success, waiting time, equipment availability, idle capacity, and continuity of practical learning. A related body of research has examined efficiency in higher education through data envelopment analysis. This method has been used to compare universities, departments, and academic programs using combinations of staff, expenditure, enrollment, publications, graduates, and other inputs and outputs (Cantner et al., 2026; Zhang et al., 2025). Such studies are useful for evaluating overall institutional performance, but annual or aggregate indicators provide little information about the operational causes of poor facility efficiency (Fabre et al., 2026; Lin et al., 2020). A laboratory may appear inefficient because of restricted opening hours, equipment faults, failed reservations, low occupancy during ordinary weeks, excessive demand during peak periods, or a mismatch between scheduled capacity and actual student needs. These mechanisms cannot be identified from annual input-output data alone. Queueing analysis provides a useful complementary approach because it directly links arrival demand, service capacity, waiting time, cancellations, and congestion (Shao, 2026; Xiong & Zeng, 2026). It can therefore distinguish between insufficient total capacity and poor allocation of existing capacity. Yet queueing methods remain more common in health care, transportation, and service operations than in educational facility management. Their application to laboratories, studios, simulation rooms, and supervised-practice facilities remains limited, particularly when resource efficiency and student learning access are evaluated together (Hong et al., 2026b; VandeLoo et al., 2026). Evaluating shared-use policies also requires attention to selection bias. Institutions and programs do not necessarily adopt facility-sharing arrangements under comparable conditions. Programs facing severe shortages, high student demand, limited equipment, or persistent scheduling conflicts may have stronger incentives to enter a shared-use system. A simple comparison between participating and non-participating programs may therefore attribute pre-existing differences to the sharing policy itself. Before-and-after comparisons can face a similar problem when changes in enrollment, course structure, staffing, assessment schedules, or institutional policy occur at the same time. Propensity score matching and difference-in-differences analysis provide a stronger basis for policy evaluation when observable baseline differences are balanced and pre-intervention trends are examined carefully (Hong et al., 2026a; Sebastian et al., 2026). Combining these methods with operational records can move facility research beyond descriptive evaluations and provide stronger evidence about whether observed changes are associated with shared-use arrangements rather than with differences that already existed between programs.

Against this background, the present study aims to evaluate whether shared facilities can improve both resource efficiency and practical-learning access in higher education. The analysis covers approximately 45 practice-intensive programs across 12 higher education institutions over two academic semesters and integrates booking records, equipment-use logs, supervised-practice records, waiting-time data, student surveys, and administrator notes. Data envelopment analysis is used to assess the relative efficiency with which programs convert facility, equipment, staffing, and time resources into practical-learning outputs. Queueing analysis is applied to examine how demand intensity, available capacity, waiting time, booking failure, and congestion change across teaching periods. Propensity score matching and difference-in-differences analysis are used to compare shared-use and non-shared programs while reducing bias arising from differences in their initial conditions. Multilevel regression further accounts for the nested structure of students within programs and programs within institutions. Through this combined design, the study examines whether facility sharing increases effective utilization, reduces idle capacity and booking conflicts, shortens waiting time, improves fairness of access, and supports more continuous participation in practical training. The study also seeks to identify whether improvements in overall efficiency are accompanied by better student access rather than being achieved simply through higher occupancy or greater scheduling intensity. Its significance lies in connecting educational outcomes with the operational performance of specialized facilities and in providing institution-level evidence for decisions on resource sharing, facility investment, opening schedules, equipment allocation, and cross-program coordination. By linking efficiency measurement, congestion analysis, student experience, and policy evaluation within the same framework, the study provides a more direct basis for determining when shared-use systems can reduce duplicated investment while maintaining reliable and equitable access to practice-intensive learning resources.

2. Materials and Methods

2.1 Sample and Study Setting

The study included 45 practice-intensive programs from 12 higher education institutions over two academic semesters. The programs covered engineering laboratories, clinical simulation, media production, design studios, technical workshops, and other courses that required specialist rooms or equipment. Programs were included when students needed supervised facility access for at least four practical tasks per semester. Each facility also had to use a formal booking system. Programs were excluded when they had major curriculum changes, long facility closures, or incomplete booking records. The dataset included about 14,000 facility bookings, 8,500 equipment-use records, 5,200 supervised-practice records, 3,600 waiting-time records, 1,200 student surveys, and 180 administrator interviews or coordination notes. Program size, course level, facility type, weekly practice hours, equipment value, and baseline demand were recorded as control variables.

2.2 Study Design and Comparison Groups

A matched quasi-experimental design was used to assess the effect of facility sharing. Programs that introduced cross-department or cross-institution facility sharing formed the intervention group. Programs that continued to use facilities within their own departments formed the comparison group. Programs were matched by enrollment, facility type, baseline use rate, weekly booking demand, equipment value, and supervised-practice hours. Data were collected for one semester before and one semester after the policy began. In the intervention group, eligible programs booked selected rooms and equipment through a shared platform. Access remained subject to safety rules, staff support, and equipment availability. The comparison group kept its existing booking and access rules. This design allowed changes in facility use, idle time, waiting time, booking success, and learning continuity to be compared between the two groups.

2.3 Measurement and Quality Control

Facility utilization was calculated as the share of available operating time used for approved teaching or practice sessions. Idle time was defined as available time without confirmed use. Maintenance and safety closure periods were excluded. Booking success rate was calculated as the share of valid requests that received an approved time slot. Waiting time was measured from the first booking request to confirmed access. Peak-hour congestion was measured as the ratio of booking demand to available slots during the busiest 20% of operating periods. Equipment availability was based on the number of working units after faults, repair periods, and calibration periods were removed. Learning continuity was measured using missed practice sessions, delayed tasks, and breaks between required practical stages. Access fairness and satisfaction were measured with five-point survey scales. All institutions used the same coding guide and data form. System timestamps were checked each month, duplicate bookings were removed, and 10% of the records were compared with local facility logs. Two researchers coded the interview notes independently and reviewed all disagreements.

2.4 Data Processing and Model Formulation

Booking, equipment, practice, survey, and program records were linked through anonymous institution, program, facility, and student codes. Records with missing request time, approval status, or use duration were removed from the main analysis. Use durations above the 99th percentile were checked for overnight access, equipment faults, and recording errors before exclusion. Resource efficiency was estimated with an input-oriented data envelopment analysis model:

$$\theta_j = \min_{\theta,\lambda}$$

subject to

$$\sum_{k=1}^{n} \lambda_k x_{ik} \leq \theta x_{ij}, \qquad \sum_{k=1}^{n} \lambda_k y_{rk} \geq y_{rj}, \qquad \lambda_k \geq 0$$

where x_{ij} is the facility input for program x j, y_{rj} is the access or learning output, and θ_j is the efficiency score. The effect of the sharing policy was estimated with a difference-in-differences model:

$$Y_{ipt}=\beta_0+\beta_1 S_p+\beta_2 Post_t+\beta_3(S_p\times Post_t)+u_i+v_p+\varepsilon_{ipt}$$

where Y_{ipt} is the outcome for record or student i, program p, and period t. S_p marks shared-use programs, $Post_t$ marks the post-policy period, and β_3 gives the adjusted policy effect.

2.5 Statistical Analysis

Propensity scores were estimated with logistic regression. Baseline variables included program size, facility type, utilization, booking demand, equipment value, and practice hours. One-to-one nearest-neighbor matching was used with a caliper of 0.20 standard deviations of the logit score. Group balance was accepted when standardized mean differences were below 0.10. Data envelopment analysis was used to compare program efficiency before and after facility sharing. Queueing measures were used to estimate arrival rate, service rate, traffic intensity, and waiting time during normal and peak periods. Difference-in-differences analysis tested changes in utilization, idle time, booking success, waiting time, access fairness, and learning continuity. Multilevel regression was used because students were grouped within programs and institutions. Results were reported with adjusted estimates, 95% confidence intervals, effect sizes, and ppp-values. Statistical significance was set at $p<0.05$. Sensitivity tests excluded facilities with long repair periods, programs with incomplete follow-up data, and institutions that changed booking software during the study.

3. Results and Discussion

3.1 Changes in Resource Efficiency

After propensity score matching, 20 shared-use programs were paired with 20 comparison programs. Five programs were excluded because no suitable matches were found. Baseline differences were small, and all standardized mean differences were below 0.10. Before the policy, the mean DEA efficiency score was 0.69 in the shared-use group and 0.70 in the comparison group. After the policy, the score increased to 0.84 in the shared-use group and 0.73 in the comparison group. The adjusted policy effect was 0.12 (95% CI: 0.08–0.16, $p<0.001$). The number of shared-use programs on the efficiency frontier increased from 4 to 11, while the number in the comparison group increased from 5 to 6. As shown in Fig. 1, the largest gains occurred in programs that used expensive equipment and supervised laboratories. These programs had high fixed costs but low use rates before sharing began. General studios showed smaller gains because they already had longer opening hours and fewer booking limits. The findings indicate that facility sharing is most useful for costly resources that are not fully used (Li et al., 2026; Scott et al., 2025). Li and Hong (2026) also found that DEA models with shared inputs can identify differences that are hidden in institution-level data. Scott et al. (2025) reported that larger budgets and staff numbers did not always lead to higher efficiency.

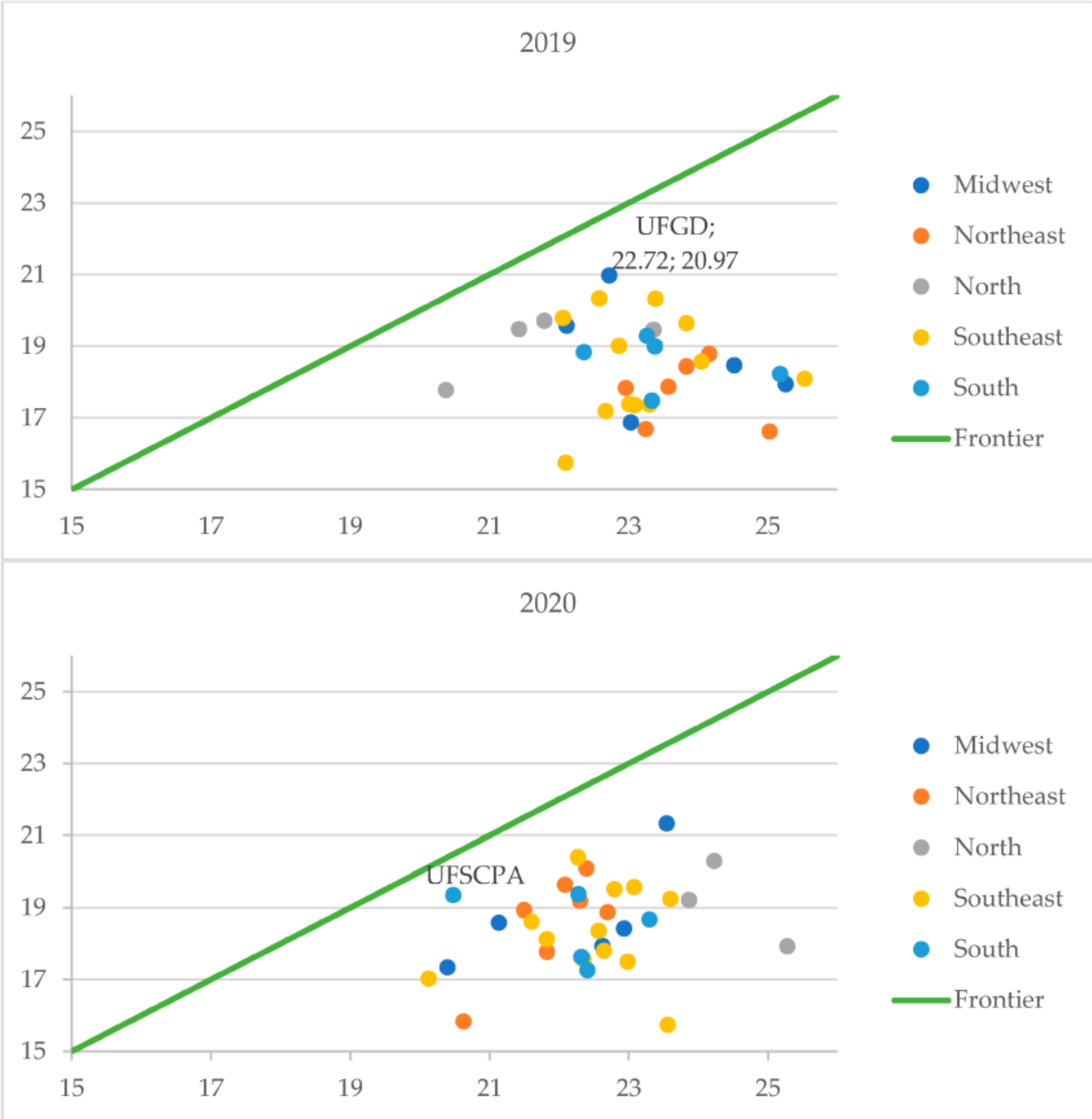


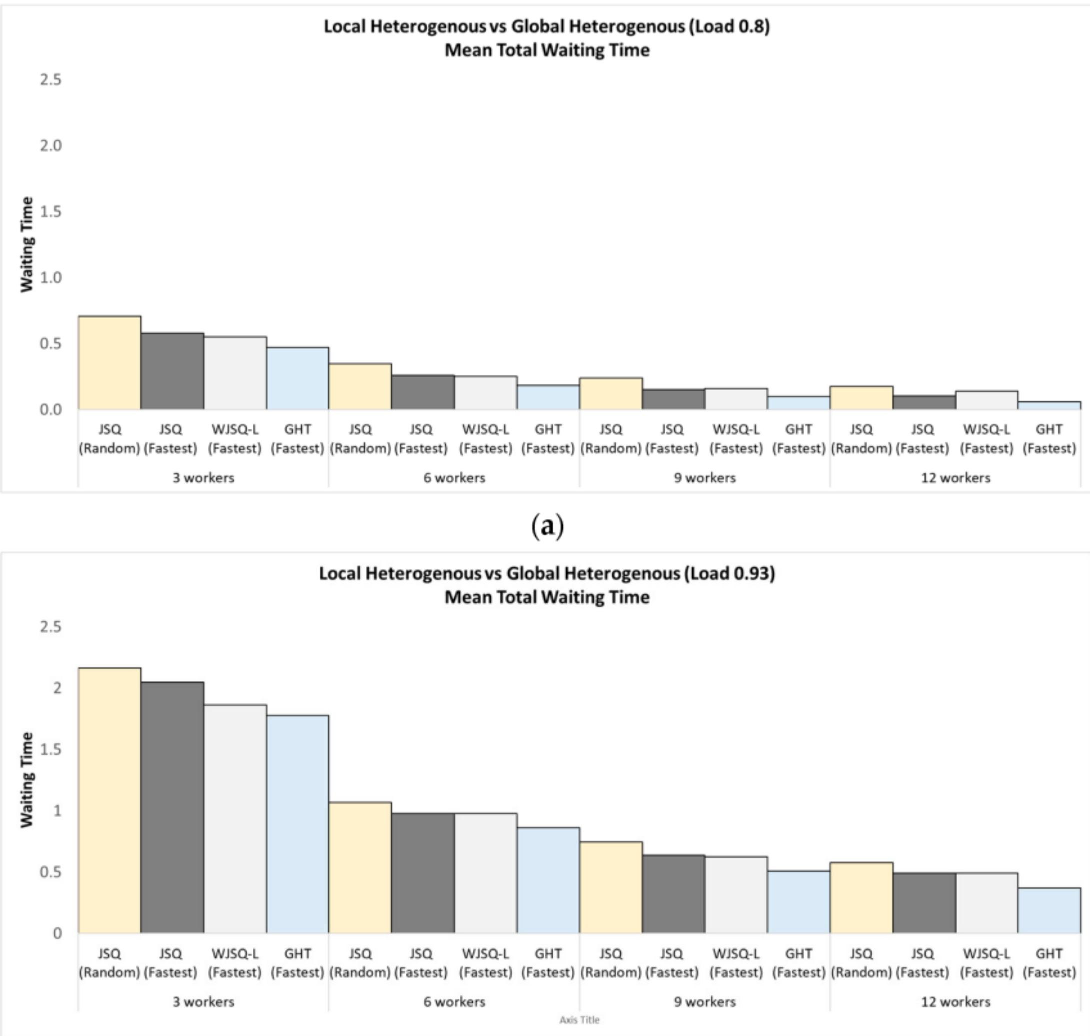
Fig. 1. Facility efficiency before and after the shared-use policy.

3.2 Facility Use, Idle Time, and Booking Conflicts

The mean facility utilization rate increased from 61.8% to 77.4% in the shared-use group. The comparison group showed a smaller increase from 63.1% to 65.0%. The difference-in-differences estimate was 13.7 percentage points (95% CI: 10.2–17.1, $p<0.001$). The idle-time ratio in the shared-use group decreased from 29.6% to 16.8%, while the comparison group changed only from 28.9% to 27.6%. Booking success increased from 72.4% to 86.7% under the shared-use policy. The increase in the comparison group was only 2.4 percentage points. Booking conflicts in the shared-use group also fell from 9.8 to 5.6 per 100 requests. Administrator records showed that the shared platform helped staff find unused periods and move practice sessions to facilities with available capacity. The greatest gains occurred when departments had different teaching schedules. Sharing was more difficult when facilities followed different safety rules or required specialist staff. Wu et al. (2026) found that real-time campus data and shared dashboards can support resource planning. Fernández et al. (2025) also reported that smart facility systems can lower operating costs. The present results show that digital tools are more useful when institutions also apply common booking rules and clear access procedures (Fernández Cerero et al., 2025; Wu et al., 2026).

3.3 Waiting Time and Access Fairness

Mean waiting time in the shared-use group decreased from 4.3 to 2.6 days. The comparison group showed only a small change from 4.1 to 3.9 days. The adjusted policy effect was −1.54 days (95% CI: −1.92 to −1.16, $p<0.001$). Peak-hour congestion in the shared-use group fell from 1.21 requests per available slot to 0.94, while it remained above 1.10 in the comparison group. Learner access frequency increased from 2.8 to 3.5 sessions per semester. The access equity index also rose from 0.74 to 0.84. Programs with low baseline access gained more than programs that already had enough equipment. This change reduced the access gap between large and small programs. As shown in Fig. 2, the largest decrease in waiting time occurred during peak demand. The difference was smaller during normal periods because both systems had unused capacity. Huang et al. (2026) found that a common queue can reduce waiting when service units have similar capacities. They also noted that different resource types need separate assignment rules. The same pattern was observed here. Shared booking reduced waiting time, but direct assignment remained necessary for equipment with different operating speeds, safety rules, or staff needs (Huang, Yin, et al., 2026; Nanteza, 2025). Nanteza (2025) also found that shared laboratories can improve access, although equal access still depends on suitable technical and teaching support.



(a)

(b)

Fig. 2. Average waiting time under shared and department-based booking during normal and peak periods.

3.4 Learning Continuity and Management Implications

The share of learners who experienced breaks between required practical tasks decreased from 24.6% to 13.2% in the shared-use group. The comparison group showed a smaller reduction from 23.8% to 21.9%. The mean learning continuity score increased from 3.31 to 4.02 on the five-point scale. Satisfaction with facility support increased from 3.38 to 4.11. Multilevel regression showed that booking success was positively related to learning continuity ($\beta=0.28, p<0.001$). Waiting time was negatively related to continuity ($\beta=-0.21, p<0.001$), while equipment availability had a positive effect ($\beta=0.19, p=0.003$). Administrator records showed that sharing worked best when institutions used common facility names, current availability data, standard safety approval, and clear cost rules. About 18% of delayed shared bookings were linked to missing safety training or unclear technical support. Sharing across departments within the same institution was therefore easier than sharing across institutions. Huang et al. (2026) also found that shared university programs often face problems caused by separate management systems and short-term planning. Formal rules and stable administrative support are therefore needed. The study covered only two semesters and did not use random policy assignment. Some outcomes were also based on student surveys and administrator records. Future research should examine maintenance costs, equipment wear, and changes in practical skill performance over longer periods.

4. Conclusion

This study found that shared learning facilities can reduce waste and improve access in practice-intensive programs. After the shared-use policy was introduced, facility use increased, idle time fell, and more booking requests were approved. Average waiting time decreased from 4.3 to 2.6 days, while the access equity index rose from 0.74 to 0.84. Facility sharing also reduced breaks between required practical tasks and improved student satisfaction with facility support. This study combines efficiency analysis, queueing measures, matching methods, and multilevel models to assess resource use and learner access in the same framework. The results show that shared use is most effective for costly equipment and supervised spaces with low initial use rates. The findings can guide cross-department booking, equipment allocation, opening-hour planning, and future investment in practical training facilities. However, the study covered only two semesters and did not use random assignment. Some measures were also based on surveys and administrative records. Future studies should use longer observation periods and examine maintenance costs, equipment wear, and changes in practical skill performance.

References

1. Al-Ibraheem, A., Brink, A., Lee, S. T., De Los Reyes, A., Paez, D., Craviolatti, P. S., ... & Sathekge, M. M. (2025, November). Implementation of radiotheranostics: challenges, barriers, and IAEA-driven strategies for sustainable access. In Seminars in Nuclear Medicine (Vol. 55, No. 6, pp. 1032-1044). WB Saunders.
2. Asamoah, M. K., & Ansong, J. D. (2025). Building resilience in higher education by addressing infrastructure and financial resource challenges in Ghana. SN Social Sciences, 5(7), 78.
3. Aybek, S., & Kaya, E. (2026). Pre-service teachers' perspectives on online learning and its challenges in higher education. Humanities and Social Sciences Communications, 13(1), 695.
4. Cantner, U., Grashof, N., Grebel, T., & Zhang, X. (2026). Rethinking excellence: the

impact of the Excellence Initiative on the relative productivity of German universities. Science and Public Policy, scag048.
5. Fabre, N., Laroche, F., Eboli, L., Mazzulla, G., & Bouzouina, L. (2026). Are punctual and regular train lines efficient? Re-evaluating regional railway performance with a service quality-integrated DEA framework. Research in Transportation Business & Management, 65, 101590.
6. Fernández Cerero, J., Montenegro Rueda, M., Román Graván, P., & Fernández Batanero, J. M. (2025). ChatGPT as a digital tool in the transformation of digital teaching competence: A systematic review. Technologies, 13(5), 205.
7. Hong, Z., Chen, H., & Xu, T. (2026a). Long-Horizon Load Stability Testing and Degradation Forecasting for High-Concurrency Cloud Storage. Available at SSRN 7115859.
8. Hong, Z., Chen, H., & Xu, T. (2026b). Real-Time Capacity Risk Forecasting for Low-Latency Financial Trading Cloud Platforms. Available at SSRN 7118180.
9. Huang, J., Xu, T., Yin, J., & Yang, J. (2026). Data Quality Monitoring and Intelligent Scheduling Optimization in Financial Data Workflow Automation. Available at SSRN 7179338.
10. Huang, J., Yin, J., Yang, J., & Xu, T. (2026). Construction of Audit Evidence Chain and SOX Control Verification Mechanism for Transaction-level Financial Data in High Volume E-commerce Platform. Available at SSRN 7179259.
11. Li, J., Zhang, Y., & Gu, Y. (2026). Chain-Hash Audit Framework with Trusted Anchoring for Tamper-Evident Evidence Lifecycle Management.
12. Lin, N., Xu, Y., Yang, H., Zhang, G., Zhang, M., Wang, S., ... & Li, X. (2020). Dissociating the neural correlates of the sociality and plausibility effects in simple conceptual combination. Brain Structure and Function, 225(3), 995-1008.
13. Lin, T., Chen, A., & Spivack, Z. (2026). Research on Collaborative Piano Teaching Models and Teaching Resource Efficiency Optimization in Public Art Education Systems. Available at SSRN 6284818.
14. Nanteza, A. (2025). Reducing patient wait times: a digital booking system for consultant doctor appointment at Nakasero Hospital.
15. Ninnemann, K., Keser Aschenberger, F., Çetinkaya-Yıldız, E., Apaydın, S., Schneidt, J., Ipser, C., ... & Geister, S. (2026). Unlocking student satisfaction with campus. The role of availability and accessibility of informal learning spaces. Higher Education Research & Development, 1-21.
16. Qi, C., & Qiao, X. (2026a, May). From Traditional Machine Learning to Large Language Models: The Evolution of Infrastructure from an Engineering Perspective. In 2026 6th International Symposium on Computer Technology and Information Science (ISCTIS) (pp. 503-506). IEEE.
17. Qi, C., & Qiao, X. (2026b). Using AI to Monitor AI: Automated Operations Through Log-Driven Intelligence. Available at SSRN 6795840.
18. Scott, G. Y., Aborode, A. T., Adesola, R. O., Khan, M., Elebesunu, E. E., Oluwaseun, A. A., ... & Olapade, S. (2025). Enhancing vaccine quality and accessibility: strategies for efficient storage and distribution in resource-constrained environment. Outbreak Management and Response, 1(1), 2443439.
19. Sebastian, P., Zhang, Y., & Hull, D. M. (2026). A comparative analysis of difference-in-differences estimators in observational educational evaluation research. Studies in Educational Evaluation, 89, 101594.

20. Shao, W. (2026). Design and Implementation of an Open-Source Security Framework for Cloud Infrastructure. arXiv preprint arXiv:2604.03331.
21. VandeLoo, A. D., Malta, N., Stillwagon, K., Guyard, V., Aponte, E., Fernandez, T., ... & Forest, C. R. (2026). An Interactive Patch Clamping Simulation to Teach and Train Electrophysiology: AD VandeLoo et al. Biomedical Engineering Education, 6(1), 57-65.
22. Wang, Y., Wang, Y., Yin, X., Arias, R., & Chen, J. (2026). Research on Dynamic Assessment of Glucose-Lipid Metabolism and Personalized Drug Response Prediction Based on Wearable Multimodal Sensing.
23. Wu, C., & Chen, H. (2025). Research on system service convergence architecture for AR/VR system.
24. Wu, J., Wu, D., Zhang, J., & Peng, Y. (2026). Generative AI Feedback in Junior High School Artistic Creation Evaluation. Available at SSRN 7244838.
25. 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.
26. Yakin, A., Agus, A. H., Baharun, H., & Mundiri, A. (2025). Transforming organizational culture in Islamic educational institutions: Cultivating a quality-oriented learning environment for academic excellence. Journal of Educational Management Research, 4(4), 1711-1731.
27. Zhang, Z. (2026). A Study on Multimodal Product Understanding and Assembly Guidance Optimization in e-commerce for Complex Consumer Goods. Available at SSRN 6734559.
28. 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.
29. Zheng, J., & Makar, M. (2022). Causally motivated multi-shortcut identification and removal. Advances in Neural Information Processing Systems, 35, 12800-12812.
30. Zhu, W., Yao, Y., & Yang, J. (2025). Real-Time Risk Control Effects of Digital Compliance Dashboards: An Empirical Study Across Multiple Enterprises Using Process Mining, Anomaly Detection, and Interrupt Time Series.