

Original Article

FeeTap: A Smart Payment Kiosk with Facial Recognition for Automated Student Department Fee Collection

Joshua Miguel C. Calulut , Rufaida A. Lim , John Dexter V. Revelo , Caroline Therese G. Sanchez ,
Gajil J. Santos , Lemuel S. Bigay 

Author Information:

Computer Engineering Department, College of Engineering, Western Mindanao State University, Zamboanga City, Philippines

Correspondence:

eh202201752@wmsu.edu.ph

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Abstract. Traditional manual fee collection at academic institutions often leads to administrative bottlenecks and prolonged wait times. To address these inefficiencies, this study developed and evaluated FeeTap, an automated self-service payment kiosk prototype integrated with biometric facial verification. Implemented using a Raspberry Pi 4B architecture and Python's *face_recognition* library, FeeTap features a multi-denominational currency acceptor, automated change dispensing, and a dedicated mobile application for real-time transaction monitoring. Utilizing a quasi-experimental design, the researchers conducted preliminary performance testing with a purposive sample of computer engineering students to assess biometric accuracy and operational throughput. Results indicated that the facial recognition module achieved a 72.92% cumulative success rate within a three-attempt authentication protocol. The remaining 27.08% composite failure rate consisted of both recognition timeouts and misidentifications, suggesting sensitivity to environmental micro-variations. Furthermore, a paired-samples t-test of successfully authenticated participants ($n = 35$) revealed a statistically significant difference between the FeeTap and manual methods in transaction times ($t(34) = 12.59, p < .001$). For this subgroup, the FeeTap system demonstrated a 44.77% reduction in mean transaction time, from 121.06 seconds to 66.86 seconds, including recognition latency. While a strong positive correlation ($r = .77$) was observed, the high failure rate and preliminary accuracy suggest that the system currently functions as a proof-of-concept. These findings indicate that while FeeTap offers a promising alternative to manual transactions, further optimization of the biometric layer and failure-handling protocols is required for campus-wide deployment.

Keywords: API; Database; Kiosk; Facial recognition; Raspberry Pi 4B.

Self-service technological advancements have led to the introduction of kiosks in a variety of industries to increase overall efficiency, decrease transaction times, and improve customer service. The use of these kiosks has become widespread across numerous industries because they enable fast transaction processing and reduce manual intervention in operations. Self-serving kiosks reduce staff workload, maximize operational efficiency, and deliver a satisfactory user experience. According to Choi et al. (2021), quick service restaurants

have adopted the self-serving kiosk in an effort to reduce labor costs, and based on the authors' findings, almost 80% of consumers have improved convenience in restaurants with self-serving kiosks, and 70% of them attribute those restaurants to faster and more accurate service.

Numerous studies have examined the effectiveness of self-service kiosks in the Philippine setting, particularly in the fast-food chain sector. The fast-food chain can act as a prelude or a test subject for the use of technology in services that interact with the public. Tamondong et al. (2022) evaluated self-service kiosks across several fast-food chains in Manila. The results showed increased customer satisfaction and operational efficiency. However, the research also found issues with consumer acceptability, implementation costs, and the possible effects of fewer in-person encounters on employee-customer relationships. The usability of kiosk interfaces in the fast-food sector in Nueva Ecija was also examined by De Jesus et al. (2024). The authors highlighted how important sensible interface design is to improving user experience, especially for new users. Further research on consumer satisfaction in Valenzuela City by Zamora et al. (2024) showed that the use of kiosks was generally well-received.

While the implementation of self-service kiosks in the restaurant industry has persisted, the educational sector continues to rely on manual payment systems, resulting in lengthy wait times, payment generation errors, and reduced operational efficiency. Students must physically visit cashier counters to complete documents during enrollment and payment deadlines because the traditional method requires them to wait through extended processing times. In addition to the aforementioned inconveniences, these processes also require time-consuming, repetitive work from school staff.

To address these inefficiencies, this study developed and evaluated FeeTap, an automated self-service payment kiosk prototype integrated with biometric facial verification. FeeTap is designed to provide an automated alternative for student fee collection, aiming to reduce human error and streamline processing times. Powered by a Raspberry Pi 4B for embedded processing, the prototype features a touchscreen interface, bill and coin acceptors for multi-denominational currency handling, and a change-dispensing module. This technology verifies user identity through biometric scans while facilitating autonomous cash payments, with a proxy payment system serving as a flexible option for students.

The development of this technology aligns with worldwide developments in digital governance and smart campus construction. Wisastra et al. (2024) suggest that high-quality self-service kiosks, in terms of system, information, and service quality, directly correlate with positive customer experiences in retail stores. While biometric systems are increasingly common in high-security infrastructure and the public sector (Čižiūnienė et al., 2024), their application in this study is presented as a localized proof-of-concept functional verification rather than as a highly robust operational system.

Incorporating biometric verification into these kiosks, such as facial recognition, provides a strong degree of identity protection. As noted by Sundar et al. (2024), biometrics uses physiological, multimodal, or behavioral characteristics of a person for verification, such as iris, face, and fingerprint. In an educational setting, facial recognition ensures that sensitive financial data and tuition payments are accessed exclusively by authorized personnel. Rija et al. (2022) assert that facial recognition technology has improved and is considered one of the best applications for payment systems to ensure account security and to improve payment efficiency. The existence of biometric payments, especially in facial recognition, has been proven by real-world applications in the retail and banking industries. For instance, Gao et al. (2025) demonstrated how providing facial recognition payment is an emerging technology that greatly increases consumer satisfaction and transaction speed in cashless payment systems. In academic settings, where manual processing and congestion are prevalent during peak periods, the implementation of similar biometric protocols is anticipated to yield comparable advantages.

The implementation of the FeeTap system offers multifaceted benefits for students, educational institutions, and even the broader community. For students, it provides a convenient way to pay fees without requiring officiating personnel or adhering to limited office transaction hours. The integration of facial verification enhances security and reduces the risk of unauthorized transactions. For universities, FeeTap minimizes administrative workload, streamlines payment processing, and reduces the errors brought by human intervention. Beyond the academic setting, FeeTap also supports financial inclusivity by encouraging digital literacy and familiarizing students with self-service transactions, which are becoming essential in today's society. The system also has the potential to contribute to economic efficiency by reducing operational costs related to manpower, utilities, and manual record-

keeping. Consequently, to validate these projected benefits, the research assessed the technical viability of the system's hardware and software components and then evaluated the facial recognition module's performance in terms of accuracy and verification in a controlled pilot environment. Finally, the research analyzed the significant difference between the manual fee collection and the FeeTap prototype in terms of transaction time.

Methodology

Research Design

This study utilized a quasi-experimental research design using a comparative approach to evaluate the effectiveness of the FeeTap prototype. The researchers selected this design because randomized assignment of participants was not feasible given the practical constraints and the specific sample pool of the study's data collection phase (Capili et al., 2024). Furthermore, it enables empirical testing of the system's proof-of-concept viability in a controlled institutional environment. By subjecting the same group of participants to both modalities, the researchers were able to isolate the impact of the kiosk's automation on transaction throughput while minimizing extraneous variables.

Participants and Sampling Technique

The target population of the study was the 114 Bachelor of Science in Computer Engineering (BSCpE) students of Western Mindanao State University (WMSU). From this population, the researchers used purposive sampling to select participants who represent the primary end users of the FeeTap system. While 85 students initially provided informed consent by signing the conforme sheet, the final experimental group was determined based on active participation and face verification. From the consenting pool, 48 students participated in the live testing phase. Following the face verification process, a final sample of $n = 35$ students, representing 30.70% of the target population, completed the full experimental procedure. Only data from these officially authenticated respondents were included in the comparative performance evaluation and statistical analysis.

Data Gathering Procedure

Before conducting the experimental procedure, the researchers submitted a formal letter of intent addressed to the Department Head of BSCpE. The letter explained the study's objectives, the specific procedures involving students, and the request to use the necessary facility. Upon receiving the official approval, the signed letter was archived as documentation confirming that the researchers were authorized to commence data collection.

Before user testing, internal hardware and software tests were conducted on the developed kiosk to ensure preliminary technical validation of the system. To develop and train the facial recognition module, the 85 consented research respondents underwent a standardized biometric registration process. High-resolution photographs were captured from multiple perspectives, specifically frontal, left-profile, and right-profile views, to ensure the system could recognize users at varying angles. During this phase, 373 images were acquired. To maintain high feature consistency, students wearing eyeglasses were requested to be photographed both with and without them. These images were securely stored in a cloud-based database with a synchronized local backup, ensuring data redundancy and the strict preservation of participant privacy in accordance with institutional ethical standards.

The facial recognition performance testing was then conducted with 48 active participants. This subset was determined based on student availability and the logistical constraints of the on-site testing period. Testing was performed under constant, optimal lighting conditions to determine the reliability of the ResNet-based module in a controlled environment. During this phase, the researchers used a multi-trial authentication protocol, in which each participant was allowed up to 3 attempts to log in to the system. A success was recorded if the user was recognized within the three-trial window. Failures were categorized as a composite non-recognition rate, consisting of system timeouts due to non-matches or misidentifications. The system logged the cumulative recognition latency for successful attempts, which is measured from the start of the first scan to the point of successful verification, along with the final success or failure outcome.

Following the face recognition performance testing, the researchers conducted a comparative analysis of transaction efficiency between FeeTap and manual collection. This controlled comparative test was conducted among the 35 respondents who were successfully authenticated. To ensure procedural uniformity, all successfully authenticated participants performed the manual transaction cycle first, followed by the FeeTap kiosk transaction, based on a standardized payment scenario based on the official WMSU - BSCpE department fees for the first

semester of the 2025-2026 school year. Each respondent was provided with an identical set of currencies and a list of required payments to ensure consistency. The manual transaction time was recorded from the moment the respondent requested payment until the personnel issued a signed receipt. Conversely, the FeeTap transaction time was recorded from the moment the user tapped the system interface for facial login until the prototype generated a printed receipt. To minimize extraneous variables, the same personnel and identical payment lists were utilized throughout the entire procedure.

Data Analysis Procedure

The quantified data gathered from the 35 successfully verified respondents were processed and analyzed using the Statistical Package for the Social Sciences (SPSS) v20.0 to ensure mathematical precision and objective results. The analysis began with calculating the mean and standard deviation for both manual fee collection and the FeeTap prototype to describe average transaction times and the level of consistency for each method. To determine the significant difference between the manual transaction time and the FeeTap kiosk, a paired-samples t-test was performed at the $\alpha = 0.05$ level. This statistical test was specifically chosen because the study involved a single group of respondents measured under two distinct conditions: the control condition (manual transaction) and the experimental condition (FeeTap payment kiosk). This approach allowed the researchers to isolate the impact of the FeeTap technology on transaction efficiency.

Furthermore, the reliability of FeeTap's facial recognition was evaluated based on the 48 active participants from the recognition phase. The performance was determined by calculating the cumulative accuracy rate, representing the ratio of successful student verifications to the total number of participants within the three-attempt window. The formula for the accuracy rate, as shown in equation (1), was adapted from the study of Varadharajan et al. (2021):

$$Accuracy = \frac{\text{Number of correct output}}{\text{Total number of samples}} \times 100 \quad (1)$$

Ethical Considerations

Adhering to the principles established by Bellalem et al. (2023), the researchers ensured that all participants received comprehensive, accessible information about the study's objectives, with a primary focus on maintaining anonymity and data privacy. The FeeTap system's database was strictly limited to essential student records, including names, institutional emails, student identification numbers, and academic affiliations. The research methodology and data handling protocols were peer-reviewed and granted formal ethical clearance by the Universidad de Zamboanga - Research Ethics Committee (UZ-REC), confirming strict adherence to both institutional and national ethical standards. Informed consent was secured in accordance with the Data Privacy Act of 2012 (RA 10173). Technical safeguards included cryptographic password hashing via the Python *bcrypt* library and scheduled synchronization with a secure online database to maintain system integrity and prevent data loss.

Results and Discussion

Initial Functional Verification

Hardware Testing

To ensure the operational stability of the FeeTap kiosk during extensive periods of usage, the researchers conducted a functionality verification on each hardware component. The hardware components subjected to testing included the Raspberry Pi 4B, web camera, touch screen monitor, bill acceptor, coin acceptor, receipt printer, and coin hopper. Each component was evaluated against multiple operational metrics specific to its function, such as change dispensing for the coin hopper, bill validation for the acceptors, and thermal printing for the receipt module. The researchers performed three trials for each metric per component to verify consistent performance and reliability. A successful trial was defined as the component responding correctly to the input without error or latency. The accuracy rate for each hardware device was then calculated using equation (1), based on the ratio of successful trials to the total number of trials performed.

Table 1 summarizes hardware testing for all components integrated into the FeeTap system. The results demonstrate that all hardware devices operated with 100.00% accuracy, responding correctly to all inputs without failure. These findings indicate that the system hardware is sufficiently stable to process transactions reliably, ensuring that no technical interruptions will compromise subsequent data collection from respondents.

Table 1. Summary of Hardware Testing

Hardware Component	Accuracy (%)
Raspberry Pi 4B	100.00%
Web Camera	100.00%
Touch Screen Monitor	100.00%
Bill Acceptor	100.00%
Coin Acceptor	100.00%
Receipt Printer	100.00%
Coin Hopper	100.00%

Software Testing

The FeeTap ecosystem comprises several specialized modules, with primary functional testing focused on the kiosk interface, the admin management portal, and the mobile application. Each platform underwent its specific unit and system testing to ensure data integrity and cross-platform synchronization.

Kiosk Interface

The kiosk interface serves as the primary software layer of the FeeTap system, facilitating real-time transactions by mediating communication between the device manager and the centralized database. To ensure high system availability, the interface supports both direct student transactions and authorized proxy access. This secondary feature was implemented as a contingency measure for emergency scenarios, allowing students to fulfill payment obligations through a consented representative when direct kiosk interaction is not possible.

Table 2. Summary of Kiosk Interface Functional Test Cases

Type	Module	No. of Trials	Total Passed	Accuracy (%)
Student	Verification	10	10/10	100.00%
	Payment	10	10/10	100.00%
	Receipt Printing	10	10/10	100.00%
	Change Dispensing	10	10/10	100.00%
Proxy	Verification	10	10/10	100.00%
	Payment	10	10/10	100.00%
	Receipt Printing	10	10/10	100.00%
	Change Dispensing	10	10/10	100.00%

Table 2 presents the summary of the test cases conducted for FeeTap's kiosk interface, covering both student and proxy transactions. The system underwent ten trials for each operational module to assess both reliability and functional performance. All tested modules, including verification and automated change dispensing, achieved a 100.00% success rate. These results demonstrate that the software logic can perform all required processes without error, providing a stable foundation for subsequent biometric and efficiency evaluations.

Admin Management Portal

The admin management portal serves as the centralized control interface of the FeeTap system, designed to oversee the data flow across the entire ecosystem. This platform provides the system administrator with the necessary tools to manage student records, financial transactions, and penalty assessments. Additionally, the portal includes a maintenance mode toggle, a critical safety feature that allows for technical adjustments and system updates without compromising active data or user security during downtime.

Table 3. Summary of Admin Management Portal Functional Test Cases

Module	No. of Trial	Total Passed	Accuracy (%)
Login Module	10	10/10	100.00%
Account Management	10	10/10	100.00%
Penalties Management	10	10/10	100.00%
Payment Management	10	10/10	100.00%
Transaction History	10	10/10	100.00%
Logs Module	10	10/10	100.00%
Settings Module	10	10/10	100.00%

Table 3 presents the summary of the functional test results for the admin management portal. Each administrative module underwent 10 trials to evaluate its data-processing accuracy and system reliability. All tested modules, ranging from secure credential authentication to real-time transaction logging, achieved a 100.00% success rate.

These results indicate that the administrative software performs all required management functions correctly and consistently, ensuring that the backend data remains synchronized with the physical kiosk operations.

Mobile Application

The FeeTap mobile application was implemented to provide end-users with a seamless platform for monitoring their financial status within the system. This application allows students to track payment schedules, view penalty lists, and access their complete transaction histories in real-time. A critical component of the mobile suite is the proxy access management module, which enables students to authorize representatives and receive instant push notifications about proxy-led transactions, ensuring security and transparency even when the student is not physically present at the kiosk.

Table 4. Test Phase Summary of Mobile App Software Test Cases

Module	No. of Trial	Total Passed	Accuracy (%)
Login Module	10	10/10	100.00%
View Payments	10	10/10	100.00%
View Penalties	10	10/10	100.00%
Transaction History	10	10/10	100.00%
Proxy Access	10	10/10	100.00%
Proxy Access Notification	10	10/10	100.00%

Table 4 presents the summary of the functional test results for the mobile application. Each module underwent ten trials to assess system reliability and operational performance across various user-end scenarios. The testing results demonstrated that all modules, including secure mobile app authentication and real-time push notifications, achieved a 100.00% success rate. These findings confirm that the mobile application fulfills all functional specifications and maintains synchronized data integrity with the centralized FeeTap database.

Face Recognition Performance

The testing procedure examined the performance of the ResNet-based facial recognition module implemented using Python's *face_recognition* library. As the primary authentication gateway for FeeTap, this module is responsible for student verification and transaction authorization. The evaluation assessed the system's ability to accurately and immediately identify registered participants across various operational scenarios, ensuring secure and seamless access.

Accuracy

To assess the system's functional sufficiency, the researchers used cumulative accuracy as the primary evaluation metric. During the testing phase, the 48 active participants were allowed up to 3 authentication attempts per session. A correct recognition was recorded if the system successfully identified the student within this three-trial window. Conversely, incorrect recognition occurred when the system timed out without a match or misidentified the user as another student.

Table 5. Test Phase Summary for the Accuracy Testing of Face Recognition

Total Students Tested	Correct Recognitions	Incorrect Recognitions	Facial Recognition Accuracy (%)
48	35	13	72.92%

Table 5 presents the results of the functional testing conducted on the facial recognition system. Using the accuracy formula in equation (1), the ResNet-based module successfully identified 35 out of 48 active participants, yielding a cumulative accuracy rate of 72.92%. While the kiosk was placed in a controlled environment with optimized lighting to minimize interference, the 27.08% failure rate across 13 instances highlights the module's sensitivity to micro-variations.

For a financial kiosk, these errors present different challenges. While misidentifications pose a direct threat to transaction security, timeouts and non-recognitions create significant barriers to the user experience. Even under controlled conditions, factors such as the facial angle relative to the sensor or subtle shadows cast by the kiosk housing likely obscured the fine-grained geometric features required by the ResNet model. This is consistent with Mutalova et al. (2025), who noted that inconsistent luminance and shadowing can significantly degrade classification precision in institutional settings.

A 27.08% failure rate represents a substantial hurdle for daily operations. In a real-world implementation, this would lead to frequent queue disruptions and necessitate a more robust recognition algorithm. Consequently, while the hardware and software integration is reliable as a working prototype, the biometric layer requires optimization, such as improved hardware positioning and algorithmic refinement, to move beyond a proof-of-concept toward a robust campus solution.

To maintain the integrity of the transaction data, only the 35 successfully authenticated students proceeded to the timing tests, isolating the efficiency of successful transaction cycles while acknowledging that failure-handling protocols would introduce additional latency in a live deployment.

Latency

In addition to functional accuracy, the operational performance of the face recognition module was evaluated based on processing latency, as this metric is critical for assessing the system's viability in a high-traffic campus environment, where delayed authentication could result in significant user congestion. Following the methodology of Pecolt et al. (2025), the average processing time, calculated across diverse lighting conditions, serves as a primary indicator of computational efficiency and overall system performance. This evaluation is necessary because, as posited by Oroceo et al. (2022), biometric systems must satisfy rigorous latency and energy-efficiency requirements, as excessive processing times often lead to a surge in hardware resource consumption and a degraded user experience.

Table 6. Summary of Facial Recognition Processing Time

Metric	Value
Minimum Recognition Time	2.87 seconds
Maximum Recognition Time	5.93 seconds
Average Recognition Time	4.11 seconds

Table 6 shows the summary results of performance testing of the face recognition system, conducted with 48 active student participants, focusing on the time taken for each recognition process. The system evaluation measured its recognition speed by recording the minimum and maximum recognition times and the average recognition duration. The system achieves a minimum face recognition time of 2.87 seconds and a maximum of 5.93 seconds while maintaining an average recognition time of 4.11 seconds. It is important to note that this average represents the cumulative time to success. For the authenticated users requiring multiple attempts within the three-trial protocol, this figure includes the duration of all attempts until a match was found. To ensure the mathematical reliability of these results, the average recognition time was calculated using equation (2), representing the average temporal cost per successful authentication:

$$Average = \frac{Sum\ of\ values}{Number\ of\ values} \quad (2)$$

This measured average latency aligns with the requirement of a prototype-level proof of concept. While recent studies into algorithmic enhancements, such as the use of the Chinese remainder theorem to optimize local binary patterns, have successfully reduced batch processing times (Adigun et al., 2024), the FeeTap system utilizes a ResNet-based architecture specifically tuned for sequential, real-time user authentication. The 4.11-second response time aligns with the operational requirements of a self-service kiosk, offering a significant speed advantage over other embedded deep learning implementations, which have reported execution times as high as 11 seconds on similar Raspberry Pi hardware (Orostegui et al., 2021). These results serve as a preliminary baseline, suggesting that while the entry point is rapid for recognized users, future iterations must involve stress testing across diverse demographics to ensure robustness during peak high-traffic periods.

Comparative Analysis of FeeTap Transaction Efficiency

To determine the significant difference between the transaction times of FeeTap and manual transactions, the researchers conducted a comparative performance analysis, focusing on the subset of $n = 35$ successfully authenticated and consented participants who completed the entire transaction cycle. By isolating this cohort, each student was subjected to both a manual transaction and a kiosk transaction thereafter, under identical payment scenarios. It is important to note that this comparison evaluates the kiosk's internal processing speed rather than its total operational throughput, as the 13 participants who encountered recognition failures were excluded to isolate the performance of the transaction modules themselves.

Table 7. Paired Samples Statistics of Manual and FeeTap Transactions ($n = 35$)

Method of Transaction	Mean (seconds)	Std. Deviation (seconds)	Std. Error Mean (seconds)
Manual	121.06	34.98	5.91
FeeTap	66.86	14.73	2.49

Table 7 presents the descriptive statistics for both transaction modalities. The results show that for the successfully authenticated group, the average FeeTap transaction time of 66.86 seconds is substantially faster compared to its manual counterpart of 121.06 seconds, representing a 44.77% reduction. This equates to a mean time savings of 54.20 seconds per user. However, this efficiency gain is conditional upon successful verification. In a real-world deployment, the previously observed 27.08% non-recognition rate would necessitate manual intervention, introducing operational latency not captured by this specific timing comparison.

The analysis of the data highlights a critical difference in system reliability. The manual process exhibited a high standard deviation of 34.98 seconds, indicating significant volatility attributed to human-centric factors such as record retrieval latency and interpersonal miscommunication (Hirsch, 2026). In contrast, the FeeTap system demonstrated operational consistency with a significantly lower standard deviation of 14.73 seconds. As highlighted by El Omda et al. (2024), this reduction in variance suggests that the automated system yields a more standardized and predictable transaction experience.

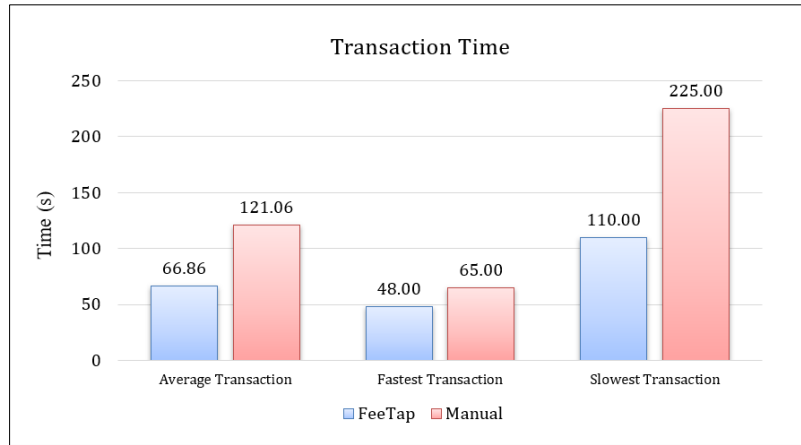
**Figure 1.** Transaction Time Comparison Between FeeTap and Manual Transactions

Figure 1 illustrates the comparative distribution of transaction durations between the FeeTap kiosk and the manual payment process. The data show that FeeTap's operational range is consistently lower than that of the manual control group. A critical observation is that the maximum recorded transaction time of 110.00 seconds remains below the calculated average manual transaction time of 121.00 seconds. While this suggests that the kiosk can outperform manual methods even in its worst-case scenarios, failed transactions due to authentication failures are not represented in this distribution. In actual campus usage, a failure to access the system represents the highest possible latency, as it requires the user to restart the process or seek administrative assistance.

Beyond algorithmic processing, the physical handling of currency introduced distinct operational differences between the two modalities. The FeeTap prototype utilized a rigid change dispensing logic, exclusively issuing change in 5-peso denominations. In contrast, the manual method allowed the personnel the freedom to provide change in any available denomination. Furthermore, the manual testing phase utilized a single designated personnel. While this ensured a consistent baseline for this study, it is expected that transaction times would vary with different staff members due to differences in manual dexterity and clerical speed. Consequently, these results are viewed as a preliminary baseline. The variance in maximum transaction times confirms a significant reduction in peak processing durations when utilizing the kiosk, as the automated workflow effectively narrows the performance window. However, further testing involving varied currency hardware configurations and multiple personnel is necessary to fully validate the system's robustness across diverse institutional settings.

Before the inferential analysis, a paired-samples correlation was conducted to evaluate the relationship between the manual and FeeTap transaction durations. This step ensures that the participants' performance was consistent across both testing environments.

Table 8. Paired Sample Correlations for FeeTap Transaction and Manual Transaction ($n = 35$)

Comparison	r	p
FeeTap Transaction & Manual Transaction	.77	< .001

Table 8 presents the correlation results for the two transaction methods. The coefficient of $r = .77$ indicates a strong positive relationship between the manual and FeeTap transaction times. This correlation serves as a supporting detail, suggesting that the results were not the product of random variance or extreme alterations in participant behavior during the two phases of the test. As noted by Putri et al. (2025), such a correlation indicates that the relative speed of participants was consistent; those who were slower in manual handling, which was likely attributed to currency handling, were also on the slower end of the kiosk distribution. This confirms that the observed efficiency gains are likely due to the system architecture rather than to accidental variations in the sample's performance.

Table 9. Paired Sample t-test Result for FeeTap Transaction and Manual Transaction ($n = 35$)

Comparison	95% Confidence Interval of the Difference		df	t	p
	Lower	Upper			
FeeTap Transaction & Manual Transaction	45.45 seconds	62.95 seconds	34	12.59	< .001

To determine whether the observed reduction in transaction time was statistically significant, a paired-samples t-test was conducted to assess whether the mean difference between the two modalities was likely to occur by chance. Table 9 shows the paired-sample t-test results between FeeTap transactions and manual transactions at the 95% significance level. Since the p-value is significantly lower than the alpha level of 0.05, there is a statistically significant difference between the manual and FeeTap systems in terms of transaction times. The magnitude of this difference is further clarified by the 95% confidence interval, which ranges from 45.45 to 62.95 seconds. This interval suggests that if the test were repeated under similar conditions, the mean time savings provided by the kiosk would consistently fall within this range. Because the entire confidence interval is positive and does not cross zero, it provides robust justification that the FeeTap system reliably outperforms manual methods across the student population.

The high t-value of 12.59 underscores the strength of the comparison, as a larger t-score indicates how large the difference between the two sample sets is relative to the variance (Chicco et al., 2025). This efficiency is largely attributed to the decentralization of the payment process, which eliminates the administrative latency associated with human-to-human interaction (Borbon, 2024). However, the researchers emphasize that these findings represent a prototype-level proof of concept. While automated record-keeping and currency verification are highly efficient, the overall service velocity in a campus-wide deployment would depend heavily on improving the biometric success rate. Without addressing the 27.08% non-recognition rate, the theoretical efficiency gains of the kiosk would be partially offset by the administrative burden of handling failed login attempts.

Conclusion

The development and evaluation of the FeeTap payment kiosk demonstrates that integrating biometric facial recognition with automated currency-handling hardware significantly optimizes the student fee collection process. This research successfully established a functional baseline for automated academic transactions, proving that the system is significantly faster than traditional manual methods. The comparative analysis revealed that FeeTap achieved a mean transaction time of 66.86 seconds, representing a 44.77% reduction from the manual average of 121.06 seconds. Statistical validation via a paired-samples t-test ($t(34) = 12.59, p < .001$) confirms that this improvement is a direct result of the system's automated architecture rather than external factors or individual participant pace.

Regarding biometric performance, the ResNet-based module yielded a cumulative accuracy rate of 72.92% within a three-attempt authentication protocol. The observed 27.08% failure rate is acknowledged as a composite of recognition timeouts and misidentifications. While this level of accuracy ensures a layer of accountability superior to unverified manual transactions, it highlights that the biometric layer remains in a preliminary stage. The system's consistent hardware-software synchronization confirms its operational viability as a departmental

prototype, successfully fulfilling its role as a localized proof-of-concept for a controlled, single-site environment.

However, these findings are considered preliminary due to specific methodological and technical limitations. The study's sample size and the use of a non-randomized testing sequence suggest that further evaluations are required. Future research should prioritize stress-testing the hardware and software under high-traffic conditions and across a more diverse set of user demographics to ensure robustness. Furthermore, while the ResNet model can create individual face models, the biometric layer still requires significant refinement. Furthermore, while the ResNet model can create individual face models, the biometric layer requires significant refinement through dataset optimization and more granular failure logging.

These findings suggest that while the FeeTap prototype successfully establishes a functional operational baseline for automated academic payments, further technical optimization of the biometric and hardware layers is required to ensure the reliability necessary for campus-wide implementation.

Contributions of Authors

Author 1: conceptualization, prototype development, manuscript writing, data gathering, data analysis, prototype testing

Author 2: conceptualization, software development, manuscript writing, data gathering, data analysis, prototype testing

Author 3: prototype development, manuscript writing, data gathering, data analysis

Author 4: prototype development, data gathering

Author 5: conceptualization, manuscript consultation

Author 6: conceptualization, manuscript consultation

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Conflict of Interests

The authors declare no conflicts of interest regarding the publication of this paper.

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