

PAPER

An Interactive Mobile Technology-Based Flipped Classroom Model for Japanese Language Instruction in Higher Education

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ABSTRACT

With the continuous advancement of information technology, the application of mobile technologies in education has expanded considerably, particularly in the domain of foreign language learning. As a key foreign language, Japanese instruction has been influenced by various factors, including learning time, instructional methods, and educational tools. Traditional classroom-based models have increasingly failed to meet the individualized and diversified learning needs of contemporary students. Consequently, the flipped classroom model, supported by interactive mobile technologies, has emerged as a focal point of foreign language pedagogy research. While existing studies have predominantly concentrated on the design and implementation of flipped classrooms, limited attention has been given to the influence of learners' circadian rhythms on learning effectiveness. In addition, Japanese learning module delivery systems have generally lacked personalization and interactivity. To address these gaps, this study aims to investigate optimal learning time period alignment for Japanese language acquisition using the dynamic time warping (DTW) algorithm and deliver personalized Japanese learning modules through interactive mobile technologies, thereby enhancing learning outcomes and fostering greater learner engagement.

KEYWORDS

interactive mobile technology, Japanese flipped classroom, dynamic time warping (DTW) algorithm, optimal learning time period, learning module delivery

1 INTRODUCTION

With the rapid advancement of information technology, the application of mobile technologies in education has deepened progressively, particularly demonstrating distinct advantages in the field of language learning [1, 2]. Traditional instructional models have become increasingly inadequate in meeting the individualized and interactive learning demands of modern students [3–6], especially within the context

Li, M. (2025). An Interactive Mobile Technology-Based Flipped Classroom Model for Japanese Language Instruction in Higher Education. *International Journal of Interactive Mobile Technologies (IJIM)*, 19(11), pp. 174–187. <https://doi.org/10.3991/ijim.v19i11.56055>

Article submitted 2025-01-23. Revision uploaded 2025-03-28. Final acceptance 2025-04-08.

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of foreign language acquisition, where substantial variation exists in learners' study schedules, learning paces, and environmental conditions. As a result, the effective integration of emerging mobile technologies into language instruction has been identified as a critical challenge in contemporary educational research [7–10]. In recent years, the flipped classroom model supported by interactive mobile technology has emerged as a prominent research focus. By leveraging technological means to coordinate classroom instruction with out-of-class learning, this model provides learners with expanded opportunities for autonomous learning and partially mitigates the constraints of time and space.

Although several studies have explored the implementation of flipped classroom models based on mobile technologies in the context of foreign language education, notable limitations remain [11–16]. For instance, Castillo-López and Figaredo [17] concentrated on the pedagogical design and instructional strategies of flipped classrooms but overlooked the impact of individual learner differences and circadian rhythms on learning outcomes. The scientific alignment of optimal learning periods was insufficiently addressed. Furthermore, while the learning module delivery system proposed by Duan et al. [18] has been widely applied, its focus has primarily remained on the dissemination of basic content, lacking support for more interactive and customized learning experiences. Therefore, the optimal learning time period alignment based on the DTW algorithm and the learning module delivery system enabled by interactive mobile technology have not been fully studied and applied.

The present study comprises two primary components. The first involves the alignment of optimal learning periods for Japanese language acquisition based on the DTW algorithm. Through algorithmic analysis of learner behavior patterns and circadian rhythm data, the most effective timeframes for individual study engagement were identified to enhance learning outcomes. The second component entails the development of a learning module delivery system within a flipped classroom framework, enabled by interactive mobile technology. This system is designed to intelligently deliver customized learning content based on learners' progress, interests, and specific needs, thereby enhancing both autonomous learning capacity and classroom interactivity. This study is expected to provide more personalized solutions for Japanese language learners while also offering new technological support for the implementation of flipped classroom models in higher education. The findings hold significant academic value and practical relevance for the ongoing advancement of technology-enhanced language instruction.

2 OPTIMAL LEARNING TIME PERIOD ALIGNMENT FOR JAPANESE LANGUAGE ACQUISITION BASED ON AN IMPROVED DTW ALGORITHM

Cognitive performance has been shown to vary significantly across different times of day, with fluctuations observed in attention, memory, and response speed during morning, afternoon, and evening periods. These physiological variations suggest that learning efficiency and effectiveness may be substantially enhanced when learning activities are aligned with an individual's optimal cognitive period. Given that Japanese, as a foreign language, demands not only extensive memorization and comprehension but also proficiency across listening, speaking, reading, and writing, ensuring that learners engage with the material during their peak cognitive states is

of critical importance. To address this, the optimal learning time period alignment was investigated based on the DTW algorithm in this study, aimed at scientifically matching learners' learning periods to maximize their advantages across different times of day to improve learning efficiency.

A crucial step in aligning optimal learning time periods involves the extraction of features from multivariate time series data. These time series corresponding to out-of-class study sessions incorporate multiple variable dimensions, such as learning progress, study duration, and learning efficiency at various time points. Each variable contributes to a comprehensive understanding of learner behavior during self-directed study. Initially, a multidimensional piecewise fitting approach was applied to the time series data at each time point. Curve fitting was conducted across different learning dimensions, and the standard error of each fitted segment was calculated. Least squares or alternative fitting algorithms were employed to generate fitted curves for each learning dimension, producing vertical distances denoted as f_1, f_2, \dots, f_k . These measurements capture temporal trends within each variable dimension, providing accurate feature representations for subsequent DTW analysis. Formally, let $as(k)$ represent the multivariate time series associated with out-of-class learning periods, where s (with $s = 1, 2, \dots, v$) denotes the time point, and k (with $k = 1, 2, \dots, l$) denotes the variable index. The observation of the k -th variable at the s -th time point is given by $as(k)$. The standard error of the fitted segment corresponding to f_1, f_2, \dots, f_k in the u -th variable dimension is defined as:

$$r_u = \left(\sum_{j=1}^k f_j^2 \right)^{\frac{1}{2}}, u = 1, 2, \dots, l \quad (1)$$

The standard errors across all variable dimensions were aggregated to obtain the total error for a given fitted segment, denoted as $r_{SEG} = \sum_{j=1}^l \delta_j r_j$, where $\sum_{j=1}^l \delta_j = 1$, and δ_j represents the weight assigned to the error of the j -th variable. The magnitude of this total error reflects the degree of information loss across all variable dimensions within a specific time window and serves as an indicator of overall learning performance during that period. To enhance the validity of the data, a sliding window segmentation strategy was adopted. Within each window, further analysis is only conducted if the aggregated fitting error remains below a predefined maximum threshold, as illustrated in Equation (2). This approach enables dynamic identification of the most suitable learning periods while mitigating the bias that may result from analyzing isolated variables. Moreover, the multivariate features derived through this segmentation were subsequently used as inputs to the DTW algorithm, facilitating accurate matching analysis and the identification of study patterns associated with optimal learning periods.

$$r_{SEG} < SE, SE \geq 0 \quad (2)$$

Given that the multivariate time series reflect multiple dimensions of out-of-class activity in the Japanese flipped classroom—such as learning progress, efficiency, and time investment—it is deemed appropriate to fit the time series of each variable dimension using first-order polynomial functions. Empirical analysis has demonstrated that first-order polynomial fitting offers high accuracy while avoiding overfitting and reducing computational costs compared to higher-order alternatives. Accordingly, first-order polynomial fitting was employed for segment-wise modeling.

During each fitting process, the slope of the line segment and the ratio of the time span to the full sequence length were calculated for each variable dimension, thereby extracting features that capture key trends in the learning process. This allows for the identification of distinct learning characteristics across different time periods. Specifically, when a multivariate time series containing l variable dimensions is segmented into T segments, the resulting feature matrix is expressed as an $l \times T$ matrix:

$$\begin{bmatrix} (\beta_{11}, f_1), & (\beta_{12}, f_2), & (\beta_{13}, f_3), & \dots, & (\beta_{1T}, f_T) \\ (\beta_{21}, f_1), & (\beta_{22}, f_2), & (\beta_{32}, f_3), & \dots, & (\beta_{2T}, f_T) \\ & & \vdots & & \\ (\beta_{l1}, f_1), & (\beta_{l2}, f_2), & (\beta_{l3}, f_3), & \dots, & (\beta_{lT}, f_T) \end{bmatrix} \quad (3)$$

When the segment error, denoted as SE , equals zero, it indicates that the fitted result has accurately captured the original multivariate time series. Under this condition, further window segmentation is rendered unnecessary, and the original multivariate time series can be directly adopted as the result of segment fitting. During this process, β_{uk} becomes the actual observed value of the u -th variable at the k -th time point in the sequence. This mechanism prevents over-segmentation of the data during the fitting process and ensures that the model more faithfully reflects learners' actual performance across different learning periods. For each segment, a value of f_s denotes zero error, implying that the fitted curve fully coincides with the original data. Through this step, high-precision time series features can be extracted, which serve as high-quality input for the DTW algorithm. As a result, learners' optimal learning periods can be matched more accurately, thereby improving the efficiency and effectiveness of Japanese language acquisition.

In this study, the construction of the optimal learning time period alignment model based on the DTW algorithm involves four key steps. First, let the feature matrices of the extracted multivariate time series S_x and S_y be denoted as X and Y , respectively. The column vectors of the feature matrices X and Y are represented by x_u (where $u = 1, 2, \dots, T$) and y_k (where $k = 1, 2, \dots, T'$). The specific expressions are as follows:

$$\begin{aligned} X &= \begin{bmatrix} (\beta_{11}, f_1), & (\beta_{12}, f_2), & (\beta_{13}, f_3), & \dots, & (\beta_{1T}, f_T) \\ (\beta_{21}, f_1), & (\beta_{22}, f_2), & (\beta_{32}, f_3), & \dots, & (\beta_{2T}, f_T) \\ & & \vdots & & \\ (\beta_{l1}, f_1), & (\beta_{l2}, f_2), & (\beta_{l3}, f_3), & \dots, & (\beta_{lT}, f_T) \end{bmatrix} = [x_1, x_2, \dots, x_T] \\ Y &= \begin{bmatrix} (\beta'_{11}, f'_1), & (\beta'_{12}, f'_2), & (\beta'_{13}, f'_3), & \dots, & (\beta'_{1T}, f'_T) \\ (\beta'_{21}, f'_1), & (\beta'_{22}, f'_2), & (\beta'_{32}, f'_3), & \dots, & (\beta'_{2T}, f'_T) \\ & & \vdots & & \\ (\beta'_{l1}, f'_1), & (\beta'_{l2}, f'_2), & (\beta'_{l3}, f'_3), & \dots, & (\beta'_{lT}, f'_T) \end{bmatrix} = [y_1, y_2, \dots, y_T] \end{aligned} \quad (4)$$

After X and Y were extracted, the trend distance SF between them was computed. Trend distance serves as a critical metric for evaluating the overall similarity or dissimilarity between two multivariate time series along the temporal dimension. In this study, the trend distance accounts not only for the absolute values within

the time series but also for the temporal span and the relative variations across different dimensions. By analyzing variations in learning behavior across different time intervals, SF provides a quantitative reference for the subsequent alignment of learning periods, thereby revealing latent patterns associated with optimal learning periods. Let the subsequence formed by the u -th to the final column vector of matrix A be denoted as $A[u:-]$, and let the distance between x_u and y_k be expressed as $SF_{BA}(x_u, y_k)$. The computation is defined by the following formula:

$$SF_{DTW}(S_x, S_y) = SF_{BA}(x_1, y_1) + \text{MIN} \begin{cases} SF_{DTW}(X, Y[2:-]) \\ SF_{DTW}(X[2:-], Y) \\ SF_{DTW}(X[2:-], Y[2:-]) \end{cases} \quad (5)$$

To further refine the alignment of learning periods, a trend distance-based computational method was introduced in this study. The trend distance between two feature vectors, x_u and y_k , was measured using the function $SF_{BA}(x_u, y_k)$, which evaluates their similarity or divergence. In this context, β_{uk} denotes the observed value, while the absolute difference in time spans, $|f_u - f'_k|$, captures the temporal discrepancy between two points. When SE equals zero—indicating that all fitting errors are eliminated and data points are perfectly aligned—the trend distance calculation degenerates into the classical DTW method. Under this condition, the DTW algorithm is capable of efficiently comparing learning progress and efficiency between learners across different periods by minimizing the path distance, thereby accurately identifying the optimal learning state. This degenerated DTW process ensures that, in cases of perfect data fitting, the model can still effectively detect the most appropriate learning periods with high computational efficiency. Let e denote a global constraint condition. Let μ_s represent the weight assigned to the s -th variable during trend distance computation, with the constraint $\sum_{s=1}^l \mu_s = 1$. The differences in learning effectiveness and time span between the u -th fitted segment of S_x and the k -th fitted segment of S_y in the s -th variable dimension are represented by $|\beta_{su} - \beta'_{sk}|$ and $|f_u - f'_k|$, respectively. The weights for the learning effectiveness difference and time span difference in the s -th variable are denoted as γ_s and η_s , respectively, subject to the constraint $\gamma_s + \eta_s = 1$, where $s = 1, 2, \dots, l$. The trend distance between x_u and y_k is thus calculated as follows:

$$SF_{BA}(x_u, y_k) = \begin{cases} \sum_{s=1}^l \mu_s [\gamma_s |\beta_{su} - \beta'_{sk}| + \eta_s |f_u - f'_k|], IF |u - k| \leq e \\ \infty, IF |u - k| > e \end{cases} \quad (6)$$

The final step in constructing the optimal learning time period alignment model for Japanese language acquisition involves computing trend distances across multiple learners or time periods to identify those most conducive to effective learning. By integrating the feature matrices and corresponding trend distances from all learners, the system is capable of efficiently detecting optimal learning periods from large-scale data. These alignment results not only support the recommendation of personalized learning paths but also provide a foundation for instructors to tailor instruction according to students' learning habits and performance patterns.

3 LEARNING MODULE DELIVERY IN THE JAPANESE FLIPPED CLASSROOM BASED ON INTERACTIVE MOBILE TECHNOLOGY

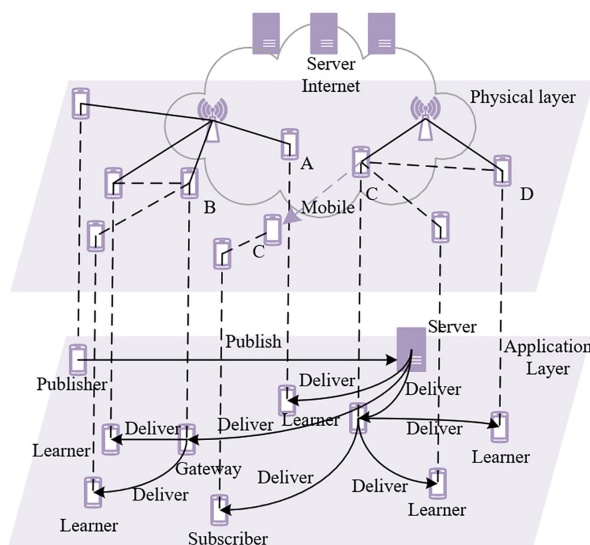


Fig. 1. System architecture of the learning module delivery framework in the Japanese flipped classroom

With the rapid advancement of information technologies—particularly the widespread adoption of mobile technologies—traditional instructional models have increasingly shifted toward more flexible, personalized, and interactive approaches. As a pedagogical model that emphasizes the integration of autonomous learning and in-class interaction, the Japanese flipped classroom depends heavily on effective support for learners during out-of-class learning periods. Through the application of interactive mobile technology, personalized learning resources and task modules can be intelligently delivered based on learners' progress, needs, and behavioral patterns. This approach enables students to make more efficient use of their out-of-class time, thereby enhancing learning effectiveness. In this study, the learning module delivery based on mobile technology was further explored, with the goal of dynamically adjusting the difficulty and depth of instructional content. This ensures that students are exposed to appropriate material at optimal times, ultimately supporting the construction of an optimized learning path and improved learning outcomes. Figure 1 illustrates the system architecture for learning module delivery in the Japanese flipped classroom environment.

3.1 Delivery system model

The learning module delivery model for the Japanese flipped classroom, developed based on interactive mobile technology, was designed to enable efficient and personalized dissemination of instructional resources via a mobile interactive platform, thereby enhancing the effectiveness of Japanese language learning. The model operates under a hybrid mobile interaction network architecture, where learning module delivery is accomplished collaboratively by nodes distributed throughout the network. A schematic representation of the model is provided in Figure 2. In traditional delivery-based systems, learning resources are typically transmitted directly from a central server to all learners. This centralized approach often leads to excessive server load and network congestion, particularly under conditions involving large data volumes and widely distributed users. By contrast, the hybrid

mobile interaction network architecture adopted in this study not only utilizes a central server but also capitalizes on the distributed characteristics of learner nodes. Specifically, certain learner nodes are assigned the role of gateway nodes. These gateway nodes are responsible not only for receiving the learning modules delivered by the server but also for further disseminating these resources to other nodes with which they come into contact—either currently or in future sessions.

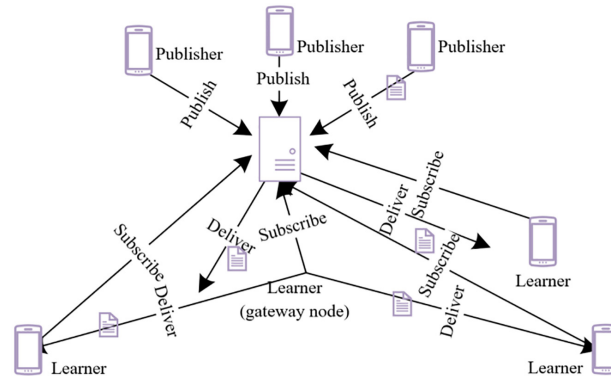


Fig. 2. Delivery system model based on the hybrid mobile interaction network architecture

In practical implementation, the learning module delivery model based on interactive mobile technology is supported by a mobile interactive platform that dynamically generates personalized learning modules through the collection and analysis of learners' behavioral data. By continuously monitoring students' learning activities in real time, the mobile platform adjusts both the content and delivery strategies of the modules to ensure that each learner receives the most appropriate instructional resources during their optimal learning periods. Within this framework, gateway nodes serve as critical intermediaries that bridge the centralized and distributed components of the mobile interaction network architecture. By interacting with nearby nodes, these gateway nodes facilitate the efficient dissemination of learning modules across a broader user base. This architecture enables the reliable delivery of learning content through the relay and transmission mechanisms provided by gateway nodes even under unfavorable network conditions or when users are widely dispersed.

3.2 Architecture of the delivery system

The learning module delivery system for the Japanese flipped classroom was designed as a two-tier architecture in this study that integrates both centralized and distributed mobile social networks (MSNs). Specifically, the system architecture combines the client/server (C/S) model with peer-to-peer connectivity among distributed nodes, allowing for dynamic adaptation across diverse communication scenarios. This hybrid structure enables not only efficient delivery of learning modules but also enhanced adaptability to varying network environments encountered by users.

The physical connection layer of the system reflects the actual communication mechanisms among nodes. All mobile nodes are capable of connecting to the server via cellular base stations or Wi-Fi access points, thereby supporting centralized communication. Under this mode, mobile nodes interact with the server to receive learning modules, which are delivered through server-initiated delivery mechanisms. This form of communication is represented by solid lines in the system model to indicate centralized routing. However, communication among mobile nodes is not solely dependent on

the centralized server. Distributed communication is also supported through opportunistic networking, particularly when two nodes come into proximity. In such instances, information can be delivered through direct communication between nodes.

In the delivery system, logical connection reflects the direction and method of information transmission. The core logic involves publishers—such as instructors or academic management platforms—delivering learning module data to the server, which subsequently transmits the content to learners. Not all learner nodes are required to receive content directly from the server, nor are all nodes responsible for forwarding information as gateway nodes. Instead, learner roles are classified into three categories based on their participation and functional contribution within the information dissemination process: gateway nodes, ordinary nodes, and isolated nodes.

3.3 Operating principle of the delivery system

To ensure the quality and efficiency of data dissemination, the learning module delivery model for the Japanese flipped classroom—enabled by interactive mobile technology—must integrate the advantages of both centralized and distributed delivery modes, especially in the hybrid MSN architecture. At the core of the delivery system lies data dissemination. To guarantee both precision and efficiency, key elements such as subscription condition matching, gateway node selection, and the identification of isolated nodes must be addressed. The publish–subscribe mechanism serves as a foundational function of the system: learners or users express their learning module preferences through subscriptions, while publishing information is the source of the system’s content delivery. Only when subscription conditions are matched can the system determine the appropriate target recipients. This process directly impacts the accuracy and effectiveness of information delivery. Given the need to support both online and offline users, the system relies not only on server-based centralized delivery but also on peer-to-peer transmission among distributed nodes to reach users who may be disconnected from the server. To ensure both accuracy and timeliness in delivery, the system must classify nodes prior to delivering content. This involves distinguishing between various learner types and determining which nodes serve as gateway nodes, which function as ordinary nodes, and which are considered isolated. This classification provides critical guidance for subsequent dissemination tasks. The operational workflow of the learning module delivery system is illustrated in Figure 3.

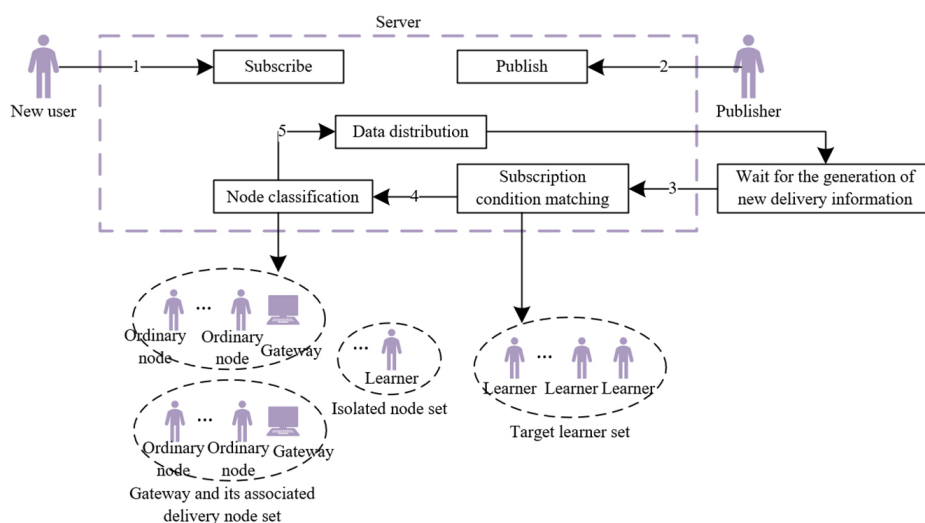


Fig. 3. Operational workflow of the learning module delivery system in the Japanese flipped classroom

4 EXPERIMENTAL RESULTS AND ANALYSIS

According to the experimental data illustrated in Figure 4, the proposed method demonstrated substantially superior performance in comparison to traditional approaches on both the short-term and long-term datasets. In the short-term dataset, when the accuracy of learning period matching ranged from 0.8 to 1.0, the proposed method achieved a matched result count of 195, significantly outperforming the Minkowski distance (16), DTW distance (64), and singular value decomposition (SVD) (80). Similarly, on the long-term dataset, the proposed method continued to exhibit a strong advantage. Within the accuracy range of 0.6 to 1.0, the method yielded 134 accurate matches, compared to 32, 54, and 58 for the Minkowski distance, DTW distance, and SVD methods, respectively. Although some variation in accuracy was observed across intervals for the baseline methods, their performance consistently fell short of the proposed model.

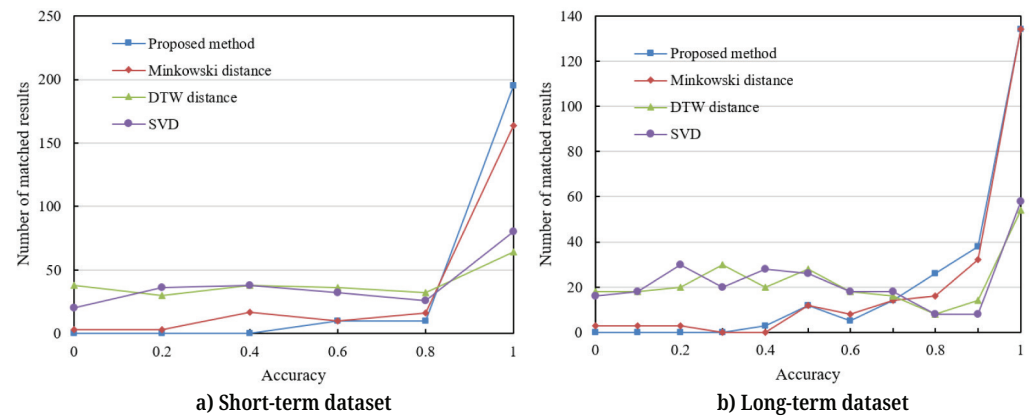


Fig. 4. Experimental results of different methods for matching optimal Japanese learning periods

Table 1. Expected accuracy values of different methods for matching optimal Japanese learning periods across four data types

Data Type	Proposed Method			Minkowski Distance			DTW Distance			SVD		
	Short	Mid	Long	Short	Mid	Long	Short	Mid	Long	Short	Mid	Long
Learning platform records	0.99	0.95	0.95	0.91	0.94	0.91	0.88	0.56	0.55	0.74	0.63	0.56
Mobile device monitoring data	1	1	1	0.97	0.76	0.57	0.55	0.65	0.51	0.91	0.83	0.71
Language test evaluation data	0.87	0.74	0.74	0.62	0.88	0.74	0.62	0.82	0.75	0.46	0.46	0.45
Survey feedback data	0.95	0.91	0.91	0.87	0.95	0.91	0.85	0.51	0.46	0.48	0.43	0.37

Table 2. Comparison of computational complexity between the proposed method and the traditional DTW algorithm

Data Type	Mean Length	Length Range	Segmentation Error	Proposed Method			DTW Distance			Processing Time Ratio
				Short	Mid	Long	Short	Mid	Long	
Learning platform records	58	(46,94)	0.02	0.97	0.95	0.91	0.94	0.91	0.88	0.42
Mobile device monitoring data	246	(245,248)	315	1	1	0.97	0.78	0.57	0.55	0.11
Language test evaluation data	14	(14,14)	0	0.88	0.74	0.62	0.88	0.74	0.62	1
Survey feedback data	15	(7,25)	0	0.95	0.91	0.85	0.95	0.91	0.85	1

Based on the results presented in Table 1, the proposed method consistently outperformed traditional approaches in terms of accuracy across all datasets. For the learning platform records, the proposed method achieved accuracy values of 0.99, 0.95, and 0.95 for short-term, mid-term, and long-term datasets, respectively—exceeding those of Minkowski distance (0.91, 0.94, 0.91), DTW distance (0.88, 0.56, 0.55), and SVD (0.74, 0.63, 0.56). In the mobile device monitoring data, the proposed method reached a perfect accuracy score of 1.00 across all datasets. In contrast, other methods exhibited significantly reduced performance, particularly on the long-term dataset. For the language test evaluation data, the proposed method also demonstrated superior performance, with accuracy values of 0.87, 0.74, and 0.74. These values remained consistently higher than those obtained using Minkowski distance (0.62, 0.88, 0.74) and SVD (0.46, 0.46, 0.45). In the survey feedback data, the proposed method achieved accuracy values of 0.95, 0.91, and 0.91 across the three datasets. These results outperformed all other methods, particularly in the long-term dataset, where the accuracy values for Minkowski distance and DTW distance fell below 0.6.

As shown in Table 2, substantial differences in computational complexity were observed between the proposed method and the traditional DTW algorithm across various datasets. For the learning platform records, the processing time ratio for the proposed method was 0.42, indicating significantly lower computational cost across short-term, mid-term, and long-term datasets. In contrast, DTW exhibited consistently higher processing times under the same conditions. In the mobile device monitoring data, the proposed method achieved a processing time ratio of 1.00, suggesting that its computational speed was nearly identical to that of DTW. However, in the long-term dataset, DTW demonstrated markedly higher computational complexity. For both the language test evaluation data and survey feedback data, the computational complexity of the proposed method was found to be on par with that of DTW, as indicated by a processing time ratio of 1. These datasets presented minimal variation in algorithmic efficiency. Nevertheless, for large-scale datasets such as those derived from mobile device monitoring, DTW demonstrated higher computational complexity and achieved a processing time ratio of 0.11, indicating its high computational burden when dealing with large amounts of data, which leads to slower processing speeds.

Table 3. Statistical results of learning module delivery in the Japanese flipped classroom

Week	Number of Gateways		Number of Isolated Nodes	Number of Failure Nodes	Load Rate (%)	Average Latency (s)
	G-Type Gateways	F-Type Gateways				
2	1	1	4	11.256	82.352	132548.215
4	1	0	3	12.265	86.512	125635.789
8	1	2	3	11.245	86.235	124523.235
11	1	1	4	4.256	82.362	132562.265
15	1	0	5	4.289	78.215	156985.265

As shown in Table 3, the test results of the learning module delivery system for the Japanese flipped classroom reflect variation in gateway node distribution, isolated node counts, failure node occurrences, network load rate, and average latency across different weeks of operation. For example, in Week 2, the number of gateways was 2, the number of isolated nodes was 4, and the number of failed nodes was 11. The network load rate was recorded at 82.352%, and the average latency reached

132548.215 seconds. Over time, fluctuations in network load and node failure counts were observed. For instance, the number of failed nodes increased from 12 in Week 4 to 14 in Week 11. Load rate also varied considerably, with Week 4 reaching a peak of 86.512%, compared to 78.215% in Week 15, indicating differences in system pressure across weekly intervals. Average latency followed a similarly non-linear trend. While latency in Week 2 was 132548.215 seconds, it decreased significantly to 124523.235 seconds in Week 8, suggesting improvements in system responsiveness under certain network conditions. Overall, the proposed learning module delivery system based on interactive mobile technology demonstrated a degree of load adaptability. Although higher network loads and node failures were recorded during certain weeks-particularly Week 8-the system maintained relatively stable performance across time. These results support the system’s potential for robust operation in real-world, dynamic learning environments.

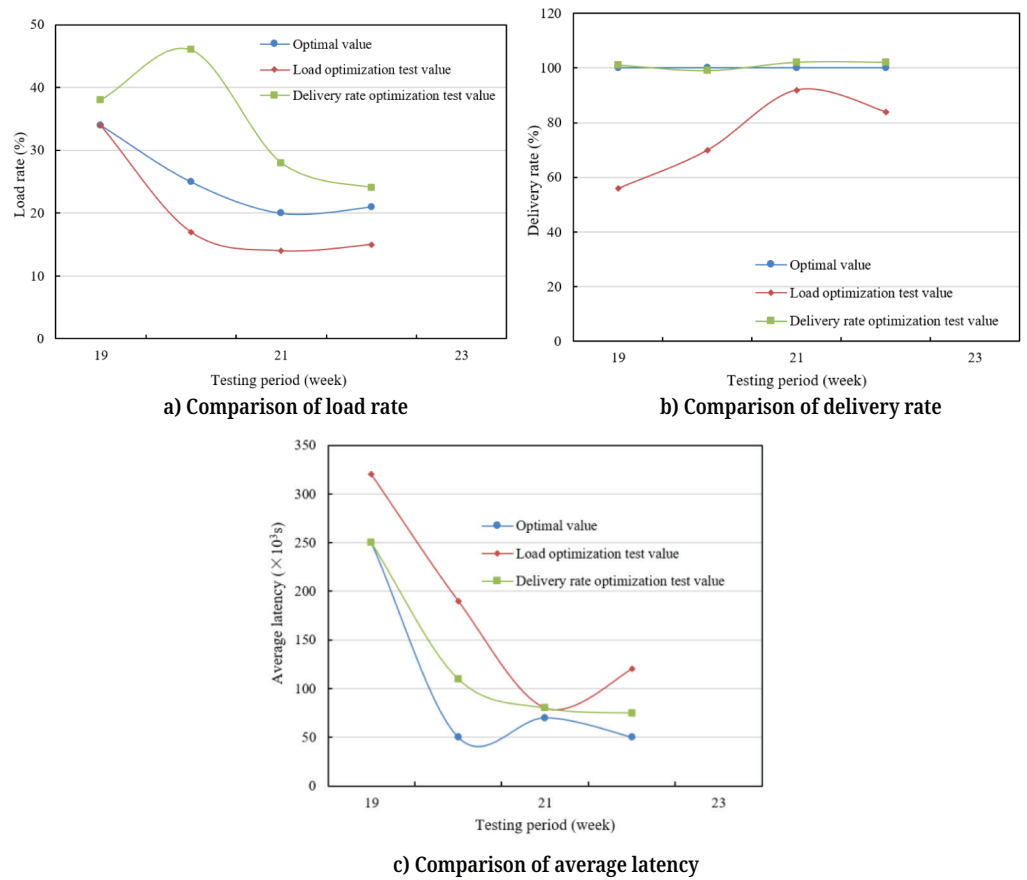


Fig. 5. Performance testing of the learning module delivery algorithm in the Japanese flipped classroom

According to the performance evaluation results shown in Figure 5, the system’s load rate, delivery rate, and average latency exhibited varying behaviors under different optimization strategies. In the load rate comparison, significant differences were observed across strategies as testing progressed. Under optimal conditions, the load rates recorded were 34%, 25%, and 20%. In contrast, under load optimization, the corresponding values dropped to 34%, 17%, and 14%, indicating that load optimization was effective in reducing system load, particularly during Week 21 and Week 23. The delivery rate comparison revealed that under optimal conditions, the delivery rate remained consistently at 100%. In contrast, under load optimization,

delivery rates were recorded at 56%, 70%, and 92%. While some reduction was noted following optimization, the delivery rate still remained at a relatively high level. More notably, after applying delivery rate optimization, the delivery rates further increased to 101%, 99%, and 102%, confirming that the applied optimization strategy significantly enhanced the delivery performance of the system. In the average latency comparison, latency values under optimal conditions were 250 seconds, 50 seconds, and 70 seconds, respectively. Following load optimization, the average latencies increased to 320 seconds, 190 seconds, and 80 seconds. Despite this increase, the concurrent improvement in delivery rate was considered sufficient to offset the impact of the added delay. With delivery rate optimization, average latencies were recorded at 250 seconds, 110 seconds, and 80 seconds, respectively, suggesting that this strategy was able to maintain relatively low latency while also achieving high delivery efficiency.

5 CONCLUSION

This study focused on the personalized optimization of Japanese language learning, especially how to provide more targeted learning experiences through efficient algorithms and interactive mobile technology within the context of a flipped classroom model. First, a method for matching optimal learning periods in Japanese language acquisition was developed based on the DTW algorithm. By analyzing learners' study behaviors and circadian rhythms, students were helped to identify the most suitable time periods for learning, thereby enhancing learning efficiency. Second, the design and implementation of a learning module delivery system enabled by interactive mobile technology was undertaken. This system was designed to intelligently deliver customized learning content based on each learner's progress, interests, and needs. The aim was to strengthen self-directed learning capabilities and promote classroom interaction, thereby providing technical support for the flipped classroom. Through these approaches, an effective technological pathway for personalized Japanese language learning was established, with broader implications for innovation in educational models and the practical deployment of adaptive learning technologies. According to the experimental results, the proposed method demonstrated clear advantages across multiple performance dimensions. In the experiments involving optimal learning period matching using the DTW-based algorithm, consistently higher accuracy was achieved in comparison with traditional methods, particularly within datasets derived from learning platform records and mobile device monitoring. These findings confirm the effectiveness of the proposed method in improving the matching effect of learning time periods. Meanwhile, the interactive mobile technology-based learning module delivery system exhibited favorable performance under real-world testing conditions. Load optimization, delivery rate optimization, and latency control were shown to be effective. Across various weekly test scenarios, the system achieved lower latency and higher delivery rates, ensuring that personalized content was delivered in a timely and efficient manner—thereby fostering greater engagement in interactive learning activities.

However, despite the promising outcomes achieved in terms of algorithmic accuracy and system optimization, several limitations remain. First, the quantity of data and the sample size used in the experiments were relatively limited, which may restrict the generalizability of the findings to large-scale deployment scenarios. Second, fluctuations in system stability and computational efficiency were observed under extreme load conditions, particularly when processing large-scale datasets

such as those derived from mobile device monitoring. Future research should therefore aim to expand the dataset size and diversify sample sources in order to verify the system's applicability across broader operational contexts. Enhancing computational efficiency, improving algorithmic robustness, and exploring more diverse personalized delivery strategies will also be critical to further advancing instructional quality and learning outcomes. In summary, this study not only provides an innovative technological solution for the Japanese flipped classroom model but also contributes valuable practical insights toward the implementation of personalized learning schemes and the promotion of flipped classroom pedagogies in higher education settings.

6 REFERENCES

- [1] S. Alam, "Measuring the effects of mobile and social networking technology on the enhancement of English language skills: A comparative study," *International Journal of Interactive Mobile Technologies (IJIM)*, vol. 19, no. 1, pp. 79–92, 2025. <https://doi.org/10.3991/ijim.v19i01.51427>
- [2] B. Klimova and L. H. Al-Obaydi, "Use of mobile applications for Foreign language learning among university students: Needs and functions," *International Journal of Interactive Mobile Technologies (IJIM)*, vol. 17, no. 12, pp. 28–39, 2023. <https://doi.org/10.3991/ijim.v17i12.38541>
- [3] R. Schmid, C. Pauli, R. Stebler, K. Reusser, and D. Petko, "Implementation of technology-supported personalized learning—its impact on instructional quality," *The Journal of Educational Research*, vol. 115, no. 3, pp. 187–198, 2022. <https://doi.org/10.1080/00220671.2022.2089086>
- [4] S. Rojanasarot, A. Milone, R. Balestrieri, and A. L. Pittenger, "Personalized learning in an online drugs and US health care system controversies course," *American Journal of Pharmaceutical Education (AJPE)*, vol. 82, no. 8, pp. 1001–1007, 2018. <https://doi.org/10.5688/ajpe6391>
- [5] V. K. Reddy *et al.*, "Personalized learning pathways: Enabling intervention creation and tracking," *IBM Journal of Research and Development*, vol. 59, no. 6, pp. 1–14, 2015. <https://doi.org/10.1147/JRD.2015.2456711>
- [6] V. Lertnattee and B. Wangwattana, "Personalized learning in microscopic method for identification of herbal medicines," in *Personalized Learning*. London, UK: Routledge, 2023. <https://doi.org/10.4324/9781003448952-3>
- [7] M. Saqlain, "Evaluating the readability of English instructional materials in Pakistani Universities: A deep learning and statistical approach," *Education Science and Management*, vol. 1, no. 2, pp. 101–110, 2023. <https://doi.org/10.56578/esm010204>
- [8] L. Bradley, "The mobile language learner-use of technology in language learning," *Journal of Universal Computer Science*, vol. 21, no. 10, pp. 1269–1282, 2015.
- [9] C. T. B. Ho, Y. T. Chou, and P. O'Neill, "Technology adoption of mobile learning: A study of podcasting," *International Journal of Mobile Communications*, vol. 8, no. 4, pp. 468–485, 2010. <https://doi.org/10.1504/IJMC.2010.033837>
- [10] P. Arisaputra and A. Zahra, "Indonesian automatic speech recognition with XLSR-53," *Ingénierie des Systèmes d'Information*, vol. 27, no. 6, pp. 973–982, 2022. <https://doi.org/10.18280/isi.270614>
- [11] D. N. Mawardi, C. A. Budiningsih, and Sugiman, "Blended learning effect on mathematical skills: A meta-analysis study," *Ingénierie des Systèmes d'Information*, vol. 28, no. 1, pp. 197–204, 2023. <https://doi.org/10.18280/isi.280122>

- [12] A. Kukulska-Hulme and O. Viberg, "Mobile collaborative language learning: State of the art," *British Journal of Educational Technology*, vol. 49, no. 2, pp. 207–218, 2018. <https://doi.org/10.1111/bjet.12580>
- [13] O. Shkvyr, H. Dudchak, N. Kazakova, O. Polianovska, and N. Sivak, "Mathematical modeling of information technology integration in digital education: A regional perspective," *Ingénierie des Systèmes d'Information*, vol. 28, no. 3, pp. 603–610, 2023. <https://doi.org/10.18280/isi.280308>
- [14] M. Gutiérrez-Colón, A. D. Frumuselu, and H. Curell, "Mobile-assisted language learning to enhance L2 reading comprehension: A selection of implementation studies between 2012–2017," *Interactive Learning Environments*, vol. 31, no. 2, pp. 854–862, 2023. <https://doi.org/10.1080/10494820.2020.1813179>
- [15] N. A. Chua *et al.*, "The belief of Mandarin foreign language educators in differentiated instruction based on student characteristics," *International Journal of Sustainable Development and Planning*, vol. 19, no. 2, pp. 629–635, 2024. <https://doi.org/10.18280/ijmdp.190220>
- [16] R. P. Curasma *et al.*, "Arduino and mBlock projects to enhance computational thinking in first-year engineering students," *Mathematical Modelling of Engineering Problems*, vol. 12, no. 1, pp. 241–252, 2025. <https://doi.org/10.18280/mmep.120125>
- [17] J. Castillo-López and D. D. Figaredo, "Characterisation of flipped classroom teaching in multigrade rural schools," *South African Journal of Education*, vol. 42, no. 1, pp. S1–S14, 2022. <https://doi.org/10.15700/saje.v42ns1a2211>
- [18] G. Duan, R. Mahajan, R. Manepalli, and H. Azimi, "EMIB and advanced substrate packaging technologies to enable heterogeneous integration (HI) applications," *Japanese Journal of Applied Physics*, vol. 63, no. 2, p. 020803, 2024. <https://doi.org/10.35848/1347-4065/ad125a>

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