PALM: PAnoramic Learning Map Integrating Learning Analytics and Curriculum Map for Scalable Insights Across Courses

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Abstract:

This study proposes and evaluates the *PAnoramic Learning Map (PALM)*, a learning analytics (LA) dashboard designed to address the scalability challenges of LA by inte- grating curriculum-level information. Traditional LA research has predominantly focused on individual courses or learners and often lacks a framework that considers the relationships between courses and the long-term trajectory of learning. To bridge this gap, PALM was developed to integrate mul- tilayered educational data into a curriculum map, enabling learners to intuitively understand their learning records and academic progression. We conducted a system evaluation to assess PALM's effectiveness in two key areas: (1) its impact on students' awareness of their learning behaviors, and (2) its comparative performance against existing systems. The results indicate that PALM enhances learners' awareness of study planning and reflection, particularly by improving *perceived behavioral control* through the visual presentation of individual learning histories and statistical trends, which clarify the links between learning actions and outcomes. Although PALM requires ongoing refinement as a system, it received significantly higher evaluations than existing systems in terms of visual appeal and usability. By serving as an information resource with previously inaccessible insights, PALM enhances self- regulated learning and engagement, representing a significant step beyond conventional LA toward a comprehensive and scalable approach.

INTRODUCTION:

Learning analytics (LA) is an academic field that aims to optimize educational activities through the collection and analysis of educational data, and the provision of feedback. In recent years, LA has been increasingly recognized as a means of supporting self-regulated learning (SRL). SRL is a prominent learning theory that emphasizes learners' ability to actively plan, monitor, and regulate their learning processes [1], enabling them to adjust their learning strategies based on real-time data and insights [2]. To this end, LA research integrates knowledge from diverse disciplines such as computer science, education, data mining, statistics, and behavioral sciences, and has developed various tools to enhance learner autonomy.Furthermore, in recent LA research, the perspective of scalability has gained increasing attention There is a growing 1 Graduate School of Information Science and Electrical Engineering, Kyushu University, Japan. ozaki.mahiro.493@s.kyushu-u.ac.jp, 2 Division of Math, Sciences, and Information Technology in Education, Osaka Kyoiku University, Japan. chen-l68@cc.osaka-kyoiku.ac.jp, 3 Promoting Organiza- tion for Future Creators, Kyushu University, Japan. naganuma.shotaro.062@ m.kyushu-u.ac.jp, 4 Faculty of Informatics, Masaryk University, Czech Re- public. valdemar@mail.muni.cz, 5 Faculty of Information Science and Elec- trical Engineering, Kyushu University, Japan. fokubo@ait.kyushu-u.ac.jp,

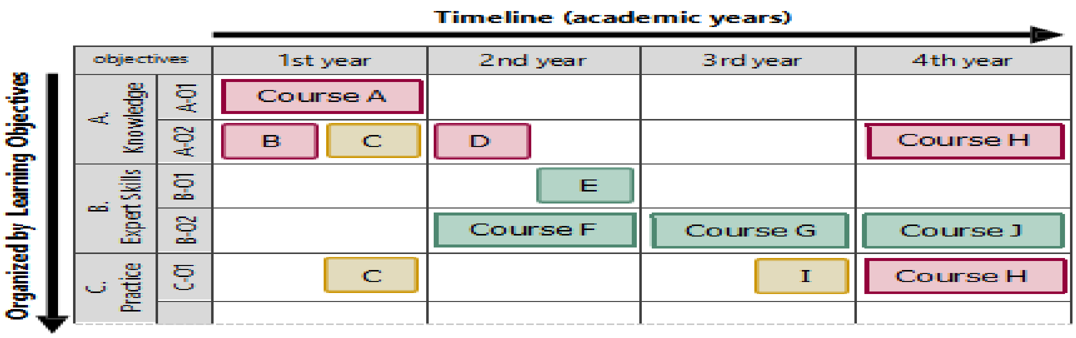

Fig. 1. Illustration of the curriculum map overview

demand for LA systems that can handle large-scale data and support diverse learners and environments. For instance, Lonn et al. [3] developed an infrastructure with a univer- sity IT department to enable real-time support across an entire institution. Additionally, Ruipe´rez-Valiente et al. [4] proposed a system for visualizing and analyzing learning data in massive open online courses, where each course may have over 100,000 learners. These efforts highlight signifi- cant progress toward scalable implementations of LA across varied educational settings. In parallel, LA dashboards have been developed to support SRL, course recommendation, and competency tracking, showing positive impacts on student performance [5], [6], [7], [8].However, most of these studies primarily focus on individ- ual courses or learners, often relying on short-term learning data. As a result, their applicability to long-term support and curriculum-level integration remains limited. University education is inherently designed as an integrated curriculum rather than as an isolated individual course [9]. For example, foundational knowledge in mathematics influences students' understanding of physics and statistics, demonstrating that different courses are interconnected and shape learning out- comes. Without feedback that accounts for such cross-course interdependencies, support for learners is likely to remain fragmented, making it difficult for LA to achieve its essential goal of providing comprehensive learning support.

- Curriculum maps do not explicitly show detailed learn- ing content, course interrelations, or dependencies in learning progression.
- Students unfamiliar with the curriculum's structure or intent may struggle to interpret and use the map effec- tively.
- Curriculum maps lack linkage to individual learning outcomes, limiting integration with LA dashboards and syllabus systems.

Furthermore, many studies in this field have concluded with technical validation or the design of LA dashboards and have not progressed to system implementation or providing feedback to students. Although research on user interface de- sign, system architecture, and data processing has highlighted the potential of LA in educational support, studies presenting systems that are directly usable by learners remain limited [16], [17], [18]. As a result, while the theoretical usefulness of LA at the curriculum level has been discussed, efforts to translate these findings into practical applications remain another underexplored challenge.

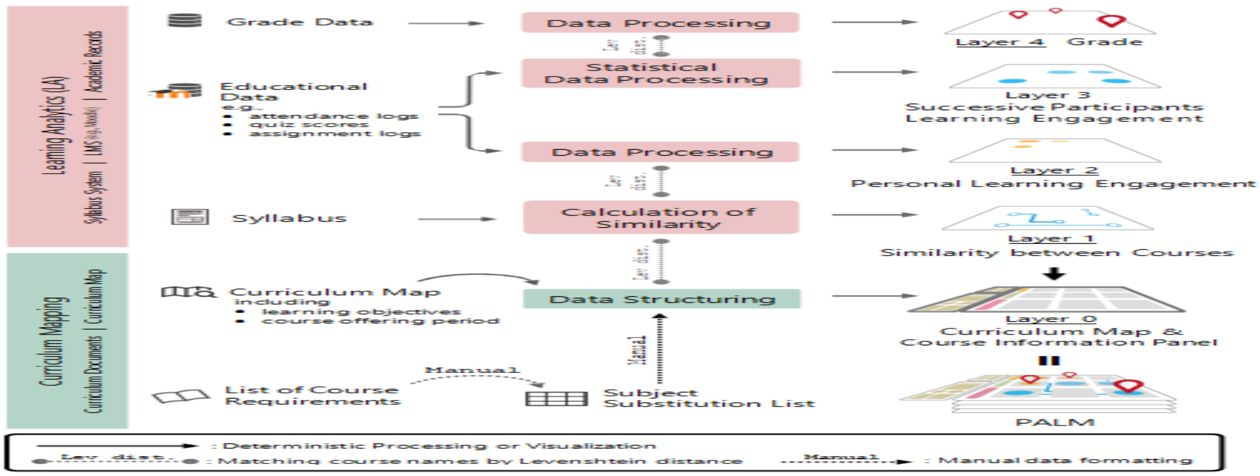

Fig. 2. Design concept of PALM

effective use of cross-curricular learning data by extend- ing the traditional scope of LA, which primarily focuses on individual courses and learners. Through this approach, PALM makes a comprehensive and scalable contribution to enhancing learners' SRL (planning and reflection) and engagement. To the best of our knowledge, no previous research has implemented such a system as a concrete application or evaluated it with users. Based on the above, the following points were set as the research questions:

RQ1 How does PALM influence students' attitudes and intentions regarding their self-regulated learning be- haviors, such as study planning and reflection?

RQ2 How do students evaluate PALM as a LA dashboard, particularly its curriculum map interface incorporating multilayered LA information, in comparison with exist- ing systems (e.g., LMS, syllabi, traditional curriculum maps)?

By addressing these research questions, this study exam- ines the role of PALM as a LA dashboard and provides insight into changes in learners' behavioral intentions and system evaluations. Ultimately, this study aims to contribute to providing long-term learning support across the entire curriculum.

PROPOSED SYSTEM: "PALM"

A. *Design Concept*

This section outlines the design concept of the proposed system, *PAnoramic Learning Map (PALM)*. The objective

of PALM is to implement a representation method that links educational support information from the perspective of LA to curriculum maps that serve as *hubs* for educational management. PALM is inspired by geographic information systems (GIS), which overlay various types of information as layers on a base map to visualize correlations and trends among map elements. In this analogy, as shown in Figure 2, the base map corresponds to the curriculum map, whereas the information layers represent the data derived from LA (collected through existing systems). Users can customize the types of data displayed on the curriculum map to achieve visualizations tailored to their specific purposes.

Figure 2 illustrates the various layers and the correspond- ing data sources required to construct them. As arranged along the pink and green rectangles, these data types were

Course Relevance Lines (Layer 1): The relationships between courses are visualized using blue lines, with thicker lines indicating stronger connections between course blocks. Textual data such as *course overview* and *lecture plan* from syllabi were vectorized using TF-IDF [19], and cosine similarity was computed to visualize these relationships. The resulting visualizations were found to be reasonably valid by learners (see Section III-B and IV-B).

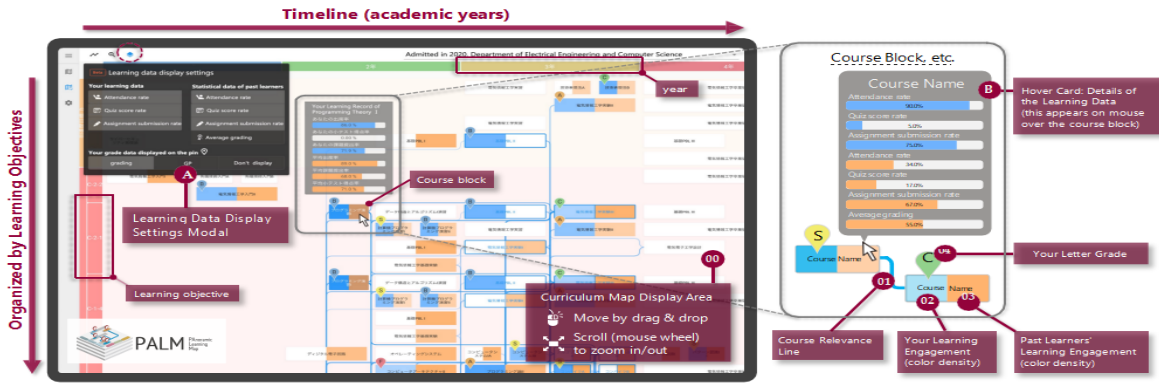

Fig. 3. User interface of PALM

EVALUATION METHOD

To evaluate PALM, a user survey was administered to 29 participants, consisting of undergraduate students from the Department of Electrical Engineering and Computer Science at Kyushu University and master's students who graduated from the same department. The survey passed an ethical review, and the participants agreed to the data use policy. As shown in Figure 4, the survey consisted of three steps:1. completing a pre-questionnaire, (2) usage of PALM, and (3) completing a post-questionnaire. All responses were collected within two weeks. The survey included questions focusing on *system evaluation* and *effectiveness evaluation*, alongside evaluation of *course relevance lines*, feedback on usability and convenience, and requests for additional features.

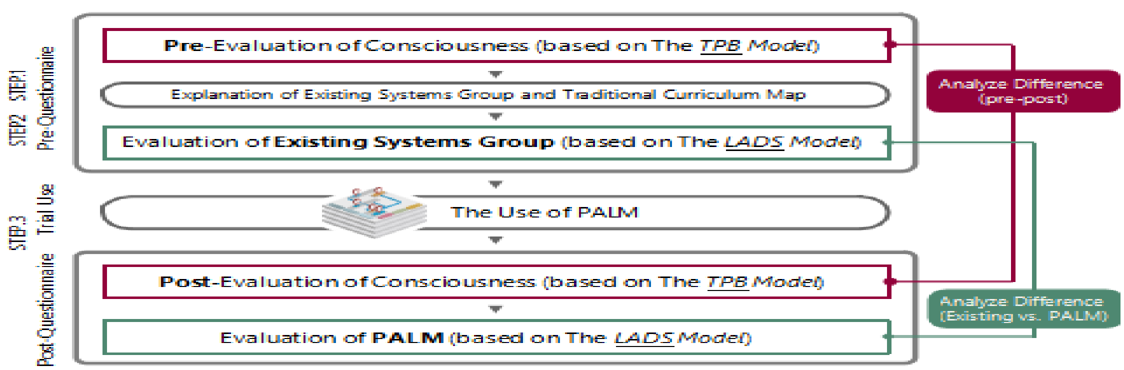

Fig. 4. Experimental procedure for system evaluation

between them in their regular use. In this evaluation, partic- ipants were asked to comprehensively consider the elements within these systems and provide an overall assessment of the existing systems group. The survey comprised 28 items derived from the ***LAD Success Questionnaire (LADS)*** [26], a validated framework designed to assess the success of learning analytics dashboards across five factors: (1) *visual attraction*, (2) *usability*, (3) *understanding level*, (4) *per- ceived usefulness*, and (5) *behavioral changes*. To support validity, we used identical questions to those which were validated in previous studies [27]. A pre-survey was con- ducted to evaluate the existing systems, with items phrased as "The existing systems are/have. . . ," while the post-survey assessed PALM, using the phrasing "PALM is/has. . . " All responses used a seven-point Likert scale. The differences in their evaluations were clarified by applying statistical tests to the evaluations of the existing system group and PALM. This followed the same procedure described in Section III-

A. For each participant, the factor scores of the LADS were averaged, normality was tested using the Shapiro-Wilk test, and a paired t-test (two-tailed) was conducted.

RESULTS:

The normality test (Shapiro-Wilk test) indicated that, out of the four factors analyzed, all except *attitude* met the assumption of normality. Subsequently, paired t-tests were performed for all of the factors, and the results are presented in Table I. For the *attitude* factor, which did not meet the normality assumption, a supplementary analysis was

Fig. 5. Screenshots of the existing systems (traditional curriculum map | attendance confirmation in LMS | web syllabus)

TABLE I
PRE- AND POST-USE COMPARISON

Factor (TPB)	mean (SD) pre	mean (SD) post	t	$\lvert d_D \rvert$
Intention	5.1 (1.07)	5.7 (0.83)	−4.1***	0.77
Attitude	5.0 (0.67)	5.6 (0.90)	−4.3***	0.80
Subjective norm	3.9 (1.32)	4.4 (1.47)	−3.1 **	0.58
Behavioral control	4.1 (1.10)	5.3 (0.87)	−6.5***	1.21

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE II
COMPARISON BETWEEN EXISTING SYSTEMS AND PALM

Factor (LADS)	mean (SD) existing	mean (SD) PALM	t	$\lvert d_D \rvert$
Visual attraction	3.4 (1.05)	6.0 (0.60)	−12.9***	2.40
Usability	3.7 (1.07)	5.9 (0.77)	− 9.9***	1.84
Understanding level	3.8 (1.07)	6.1 (0.74)	− 9.3***	1.72
Perceived usefulness	4.0 (1.15)	5.7 (0.80)	− 7.5***	1.39
Behavioral changes	3.7 (1.15)	5.3 (0.87)	− 6.9***	1.29

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

conducted using the Wilcoxon signed-rank test [28], a non- parametric alternative. However, because the results of both the t-test and Wilcoxon test were consistent, leading to the same conclusions regarding rejection, only the results of the t-test are reported in this study. The tables present the mean and standard deviation of the ratings for each factor on a seven-point scale, including the t-value, significance level, and effect size d_D, with values above 0.8 generally considered large effects [24].Statistical analysis revealed that, based on the TPB model comparison, post-use ratings were significantly higher than pre-use ratings for most factors, suggesting that the use of PALM had a positive impact on users' perceptions and behavioral intentions. Although a large statistically signifi- cant difference at the 0.1% level was not observed for the *subjective norm* factor, a significant effect was found at the 1% level. Effect size analysis indicated that *behavioral control* showed a large effect, whereas *intention*, *attitude*, and *subjective norm* showed only moderate effects.

DISCUSSION & CONCLUSION

This study addressed the limitation of current LA research, which tends to focus on individual courses or learners. We proposed the *PAnoramic Learning Map (PALM)*, an LA dash- board that incorporates a curriculum mapping perspective, and conducted an initial evaluation for its broader educational application.Limitations of this study include the lack of support for dynamic data updates, which poses a challenge for practical implementation in large-scale settings. Furthermore, the po- tential for instructor involvement and the long-term impact on a broader student population remain under-investigated. Future research will therefore focus on the continuous de- velopment of the system while conducting further studies toward its scalable and practical deployment.

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