Contemporary Educational Technology, 2026, **18**(4), ep705
ISSN: 1309-517X (Online)

OPEN ACCESS

Research Article

Enhancing Thai undergraduate digital competence and learning retention through project-based microlearning data analytics education

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Citation: Nantha, C., Pimdee, P., Piyachon, P., Siripongdee, S., & Janthadech, N. (2026). Enhancing Thai undergraduate digital competence and learning retention through project-based microlearning data analytics education. *Contemporary Educational Technology, 18*(4), Article ep705. https://doi.org/10.30935/cedtech/19953

ARTICLE INFO

Received: 28 Jun 2026
Accepted: 11 Oct 2026

ABSTRACT

Conventional software education in the higher education sector has remained largely demonstration-based, constraining both skill development and knowledge retention. Although both project-based learning and microlearning have proven effective individually, there is a lack of research on their simultaneous application in undergraduate data analytics education. The current study aims to address this gap by investigating the effectiveness of a project-based microlearning (PBM) educational model in enhancing the academic performance, digital skills, and learning retention of Thai undergraduate students. Using a pre-experimental repeat measures design with two cohorts of undergraduate students: business administration (n = 29; weekend-working students) and digital technology for education (n = 33; fourth-year full-time students), who participated in an 8-week intervention. Results demonstrated significant academic gains across both cohorts with a very large effect size (η^2p = .90, p < .001). Both groups developed comparable digital competencies, $t(60)$ = 0.13, p = .90, indicating successful development of applied analytics skills. However, differential retention emerged, $F(1, 59)$ = 11.04, p = .002, η^2p = .16, with business students maintaining superior knowledge (adjusted mean [M] = 16.58) compared to education students (adjusted M = 14.32) at two-week follow-up. Both cohorts reported high satisfaction (M = 4.25 and 4.23/5). It can thus be concluded that the use of PBM appears to be a promising instructional model for teaching data analytics because it involves cognitive scaffolding through microlearning and the building up of genuine competence. Nonetheless, subject relevance might play a role in retention.

Keywords: data analytics education, digital competence, microlearning, higher education, project-based learning, technology-enhanced learning, Thailand

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INTRODUCTION

Digital literacy has become a basic skill in modern higher education, especially as data-driven decision-making plays a greater role in academia, professions, and industries (European Commission, 2018; Punie & Brečko, 2013; Spante et al., 2018). Whereas undergraduates have been expected not only to consume digital information but also to process and interpret it with professional programs like spreadsheets and business intelligence (BI) software (Bond et al., 2020), digital literacy with software like Microsoft Excel and Microsoft Power BI has evolved into a critical component of modern graduate training (Victor & Ujir, 2025).

This notwithstanding, instructional strategies used in numerous software classes at institutions of higher learning remain largely teacher-centered, with a focus on demonstration and imitation exercises. Although such methods can assist in performing certain tasks effectively, they usually do not help learners acquire lasting conceptual knowledge, true problem-solving ability, or self-transfer of learned digital skills into practical situations (Victor & Ujir, 2025). Learners end up mastering simple command procedures but not the sophisticated analytical skills needed to interpret data and make decisions using dashboards (Collier & Powell, 2024; Kazika & Malambo, 2025; Singun, 2025).

This issue becomes more pronounced in digital analytics training, where learners need to simultaneously combine conceptual knowledge with its implementation and application (Mhlongo et al., 2023). Lecture-oriented software training environments that require learners to process new information alongside the interface, procedures, and tasks may impose an additional cognitive load. According to cognitive load theory, instructional approaches that minimize unnecessary processing and allow learners to structure their knowledge sequentially may significantly enhance learning efficiency (Paas & Van Merriënboer, 2020; Surbakti et al., 2024).

THEORETICAL FRAMEWORK

Theoretical Basis For Project-Based Microlearning

First, the segmentation of procedural information in microlearning helps reduce extraneous cognitive load when acquiring new skills by dividing complex material to avoid overload of working memory, according to cognitive load theory (Paas & Van Merriënboer, 2020; Surbakti et al., 2024). This theory posits that learning is most effective when the cognitive load imposed on working memory is optimized. Our use of microlearning is intended to reduce extraneous cognitive load. Secondly, multimedia learning theory (Mayer, 2024) promotes microlearning, as brief video lessons enable efficient processing of verbal-visual information through the principles of dual coding and review. Thirdly, constructivist project-based learning (PjBL) theory (Jarodzka et al., 2021; Kokotsaki et al., 2016).

Evidence exists for the efficiency of every technique used alone. In particular, microlearning works efficiently in the development of skills and minimization of cognitive load within the context of technical subjects (Jarodzka et al., 2021; Mohammed et al., 2018), while PBL is extremely efficient concerning the achievement of students' success in learning science, technology, engineering, and mathematics (Chen & Yang, 2019; Kokotsaki et al., 2016). The combination occurs when learners gain basic knowledge through microlearning without experiencing overload and then use it in PBL.

Conceptual Framework and Study Rationale

The project-based microlearning (PBM) theory posits that effectively organizing microlearning material reduces extraneous cognitive load by breaking down software processes into learning units (Wira et al., 2026). Short instructional videos are useful for efficient verbal and visual processing, whereas PjBL provides real-world settings for applying analytical skills. Competency models are used to evaluate learning outcomes, as competency encompasses not only process knowledge but also analytical thinking, problem-solving, and implementation (Surducan & Valadas, 2025; Tzafilkou et al., 2022).

This comprehensive approach is anticipated to promote self-regulation in learning, prevent learning overload, and build authentic competency (Ikhsam et al., 2026; Zakir et al., 2025). The learning process goes

through the stages of cognitive preparation, guided practice, and project-oriented application, which affect four aspects of learning:

(1) academic performance (pre and post-test),

(2) digital skills (performance indicators) (Castañeda & Villar Onrubia, 2022),

(3) memory consolidation (delayed testing), and

(4) perceptions of learners.

Since students from various fields may have varied experiences with learning data analytics (Tzafilkou et al., 2022; Victor & Ujir, 2025), discipline will serve as the basis for grouping students.

Problem Statement

In higher education, teaching complex digital analytics tools often relies on lecture-dominated, demonstration-oriented methods that prioritize procedural familiarity over applied competence. While both microlearning and PjBL have been validated separately as effective pedagogical strategies, research on their integrated implementation—specifically to support knowledge retention—remains scarce (Schneider et al., 2025). This gap is particularly critical as data analytics skills become essential across disciplines, yet evidence-based, scalable instructional models for diverse student populations are lacking. Consequently, there is a need for instructional frameworks that not only develop immediate digital competencies (DCs) but also sustain long-term learning.

Research Purpose and Questions

This study examines the effectiveness of PBM for teaching Microsoft Excel and Microsoft Power BI to undergraduate students, investigating effects on academic performance, digital skills, knowledge retention, and learner satisfaction across two student cohorts (Hamad et al., 2023). Castañeda and Villar Onrubia (2022) emphasized that developing educational models that foster human emancipation in a post-digital, highly complex world is an increasingly pressing challenge.

Research questions

RQ1: Is PBM effective in improving academic performance in undergraduate data analytics education?

RQ2: Does PBM lead to gains in authentic DC performance?

RQ3: Are there differences in learning retention between groups after PBM?

RQ4: What are students' perceptions of the PBM instructional method?

Hypotheses

H1: PBM leads to gains in academic performance in undergraduate data analytics education.

H2: PBM leads to gains in performance in authentic DC.

H3: There are differences in learning retention between groups after PBM.

H4: Students report positive perceptions of the PBM instructional method.

Please note that while discipline is not a manipulated independent variable (i.e., we are not making a causal claim about the effect of major on learning), the two cohorts were examined as distinct groups. This allowed us to explore the potential moderating role of disciplinary context and prior experience on the effectiveness of the PBM framework. By comparing the outcomes of these two cohorts, we can assess whether the instructional model is robust across different student populations and identify any differential effects that may warrant further investigation.

Study Significance

The current study attempts to fill the gap in scalable, evidence-based approaches to teaching digital analytics skills to higher education students. The findings offer value to:

1. **Academics in higher education:** The PBM approach provides a solution for transforming traditional lecture-based software training to competency-based training that enhances performance and retention.
2. **Course designers:** These results guide the use of microlearning and a project-based approach in designing BI, data analytics, and digital literacy courses.
3. **Educational technology scholars:** Differences in retention provide insights into the importance of accounting for learner characteristics.
4. **Thai higher education policymakers:** This research provides local evidence of effective instructional strategies amid growing emphasis on DC development in Thailand (Imjai et al., 2025; Ueasangkomsate, 2025).

CONCEPTUAL FRAMEWORK

The conceptual framework in **Figure 1** shows the hypothesized relationships between the PBM instructional strategies (microlearning, guided practice, and PjBL), the theory-based mediators (cognitive load reduction, knowledge construction, and authentic transfer), and the four dependent variables. The discipline is incorporated into the framework as a grouping variable.

METHODOLOGY

Research Design

In this research project, a pre-experimental, repeated-measures design incorporating a comparative two-cohort study was used to determine the efficacy of the PBM instructional approach for learning data analytics at the undergraduate level. Since participants in this study were not randomly assigned to experimental and control conditions but were instead selected from intact classes in authentic instructional settings, the study has ecological validity in the instructional context. However, the lack of a non-instructional control condition implies that this study provides only preliminary evidence for PBM's potential, not a causal relationship. This study compares two groups of participants from different disciplinary backgrounds, namely Bachelor of Business Administration (BBA) and digital technology for education (DTE), to explore the possible relationship between disciplinary background and learning outcomes. In this study, two groups of participants from different disciplinary backgrounds received the instructional treatment. These included BBA students majoring in business and DTE students majoring in education.

Study Context

The research was conducted at two higher education institutions in Thailand during the 2025 academic year. The first group comprised 29 students in a BBA program within the management information systems (MIS) program at Stamford International University (STIU) in Hua Hin, Thailand. The course focused on applied data analytics to support business decision-making, using Excel and Power BI to create business performance dashboards. The second group consisted of 33 students in the DTE program at Rajamangala University of Technology Thanyaburi (RMUTT) in Pathum Thani, Thailand, studying digital technology applications.

The course aimed to build students' educational technology competencies by requiring them to develop dashboards to visualize educational data (e.g., student performance and attendance). Both courses had similar features in terms of duration (8 weeks of weekly 3-hour lectures), key content (Excel functions, data cleaning, pivoting, Power BI visualization, dashboard creation), and evaluation methods (knowledge tests and project evaluations). Nevertheless, the contexts in which the projects were conducted varied by group: the first was business-related, while the second concerned education.

Participants

The participants used in the study comprised 62 students taking data analytics-related courses in two universities in Thailand (STIU and RMUTT). The first group consisted of 29 students pursuing their BBA and taking an MIS course focused on applying data analytics skills to business decisions. The second group

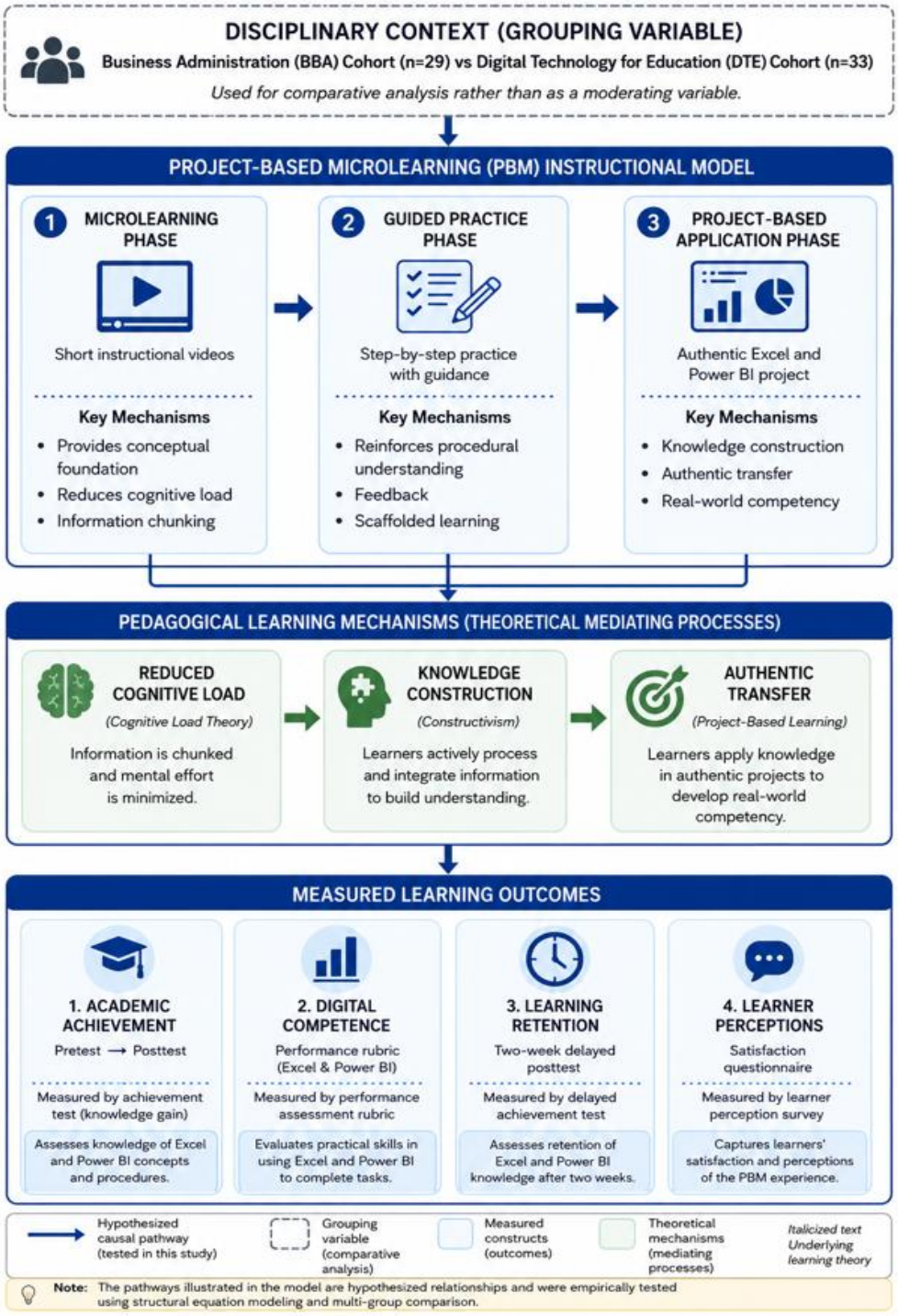


Figure 1. Conceptual framework of the study (the authors' own elaboration)

consisted of 33 DTE students enrolled in a digital technology applications course focused on educational technology competencies. Intact Cohort Sampling was adopted because implementing courses in their authentic form posed challenges. Despite coming from different disciplines, the groups had equal instructional experiences with Microsoft Excel and Power BI materials. Prior software experience was assessed using a 5-point self-rating scale (1 = no experience, 5 = expert).

Sample Size Justification

A priori power analysis was conducted using G*Power software, with a medium effect size (f = 0.25), alpha = .05, and power = .80, to determine the minimum required sample size for group comparisons using a

Table 1. Authentic assignments between groups

Aspect	BBA assignment	DTE assignment
Context	Retail business	Educational administration
Dataset type	Sales transactions, customer data, product categories	Attendance, assignment marks, and course completion
Task a	Clean data using Excel formulas	Clean data using Excel formulas
Task b	Create pivot tables for sales trends	Analyze student performance trends
Task c	Build an interactive Power BI dashboard (filters/drill-down)	Build an educational dashboard (at-risk student indicators)
Task d	Present recommendations to management	Present recommendations for interventions
Software	Excel + Power BI	Excel + Power BI
Task structure	4-step process (clean → analyze → visualize → recommend)	4-step process (clean → analyze → visualize → recommend)
Aspect	BBA Assignment	DTE Assignment

repeated-measures design. The required minimum sample size was approximately 54 participants. Therefore, with a total of 62 participants, the study had sufficient power for its intended analysis. Nonetheless, the sample size is relatively small, which reduces the power to detect small effects and to perform multivariate analysis.

Project-Based Microlearning Instructional Intervention

The testing and analysis were conducted over eight weeks using a PBM instructional strategy. This instruction intervention involved the following three instructional stages.

The microlearning preparation phase (week 1-2)

The students participated in short instructional video sessions (5-10 minutes each) covering procedures in Excel and Power BI. These videos covered data cleansing, formula use, pivot tables, visualization design, and dashboard creation. These videos could be accessed online on the learning management system. This is supported by Mailizar et al. (2022), who suggested that digital literacy and social presence significantly influenced teachers' acceptance of online professional development, thereby validating the extended technology acceptance model in this context.

The guided practice phase (week 3-5)

The students worked on scaffolded in-class activities based on microlearning content to reinforce their procedural knowledge through practical application. These activities involved increasingly difficult tasks, such as creating charts, pivot tables, and multi-page dashboards.

The project-based application phase (week 6-8)

The students created project work related to authentic dashboard-based analytics.

Examples of Authentic Assignments

Even though both cohorts performed identical tasks involving similar software use and cognitive skills (data cleaning, analysis, visualization, and recommendations), the tasks differed in context, corresponding to their respective disciplines (**Table 1**). For instance, the BBA cohort had a dataset on retail sales, which relates to business analytics, while the DTE cohort used a dataset on academic performance.

Instruments

Four research instruments were devised and validated.

Project-based microlearning instruction

The PBM instruction was designed and implemented after a detailed synthesis of the literature on blended learning, PjBL, and microlearning principles. To validate the model's structural integrity, a questionnaire assessing its quality and appropriateness was prepared and distributed to five experts in instructional design, measurement and evaluation, and information technology. The model met all the necessary evaluation criteria before its implementation.

Academic achievement test

Achievement in conceptual and procedural knowledge was assessed using a knowledge test developed by the researcher. This test was based on conceptual and procedural knowledge of Excel and Power BI. This test covered several topics, including spreadsheet functions, data management, visualization concepts, dashboards, and analytical processes. This test was administered as a pre-test, a post-test, and a 2-week retention test. It had 20 multiple-choice questions, with 5, 8, and 7 items for conceptual knowledge, procedural knowledge, and analytical reasoning, respectively.

Authentic digital competency assessment

An authentic DC assessment was conducted using an applied analytics competency rubric as a performance-based approach. Student dashboards were assessed against six major competencies that include: data preparation (15 points), analytical reasoning (20 points), dashboard design (15 points), visualization (15 points), functional realization (20 points), and problem solving (15 points), for a maximum of 100 points. The assessment was carried out based on standard rubrics.

Learner perceptions scale

Learner perceptions of the PBM instructional framework were assessed using a structured questionnaire focusing on instructional clarity, usability, engagement, usefulness, and learning. Items were scored based on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Validity and Reliability

A panel of subject-matter experts in educational technology, digital analytics instruction, and higher-education teaching verified the validity of all instruments. Item relevance was determined using item-objective congruence (IOC).

Reliability was determined for each of the instruments as follows: KR-20/Cronbach's alpha for the achievement test; Cronbach's alpha for the questionnaire; and inter-rater reliability for the rubric.

Procedure For Data Collection

The systematic data collection was carried out over a period of ten weeks following the chronological order provided in **Figure 2**. Quantitative and qualitative data were collected across four main evaluation phases to measure growth in academic performance, application of digital skills, and pedagogical reception.

Phase 1: Baseline evaluation (week 1)

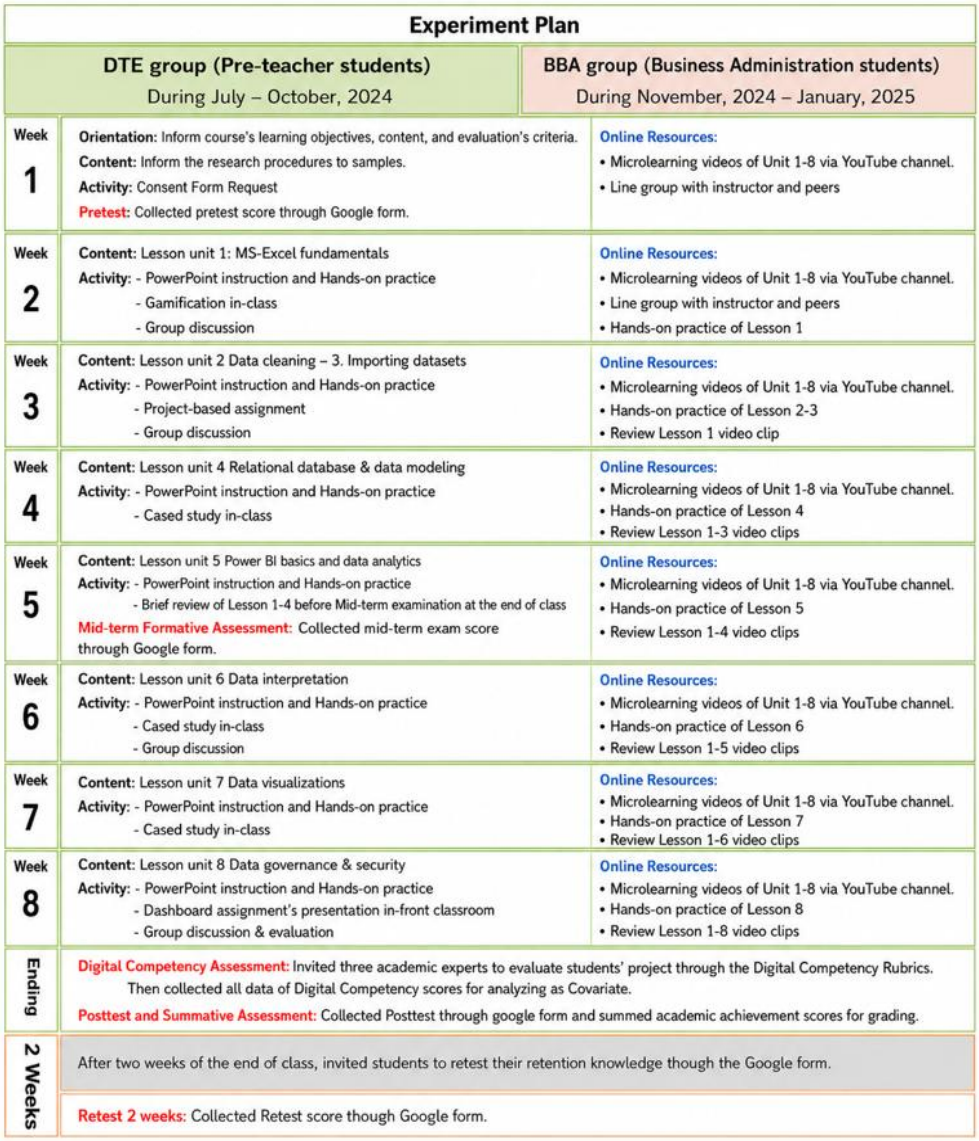
Before the learning program was introduced, a baseline assessment was conducted in the first week of the academic semester. The pre-test of academic achievement (AA) was conducted on all the undergraduate students (N = 62) in the BBA and DTE classes. The purpose of this phase was to establish a baseline of students' knowledge prior to the new learning program.

Phase 2: Intervention and continued scaffolding (week 2-week 7)

During the ongoing interventional period, PBM instructions were implemented. The students learned through digestible microlearning packages, which enabled them to progress through the steps. Empirical data on learning processes and milestone activities were collected during this phase as students performed their core project tasks.

Phase 3: Immediate post-intervention evaluation (week 8)

As soon as the PBM interventional program concluded in Week 8, a multi-dimensional rubric score evaluation was conducted. Firstly, the students undertook the AA post-test to evaluate their knowledge gain. Secondly, the students' final group projects were evaluated using the validated DC rubric to assess their professional competency. Finally, a 5-point Likert-scale satisfaction survey was conducted to evaluate student feedback on the five specified instructional dimensions of PBM.



Experiment Plan		
	DTE group (Pre-teacher students) During July – October, 2024	**BBA group (Business Administration students)** During November, 2024 – January, 2025
Week 1	**Orientation:** Inform course's learning objectives, content, and evaluation's criteria. **Content:** Inform the research procedures to samples. **Activity:** Consent Form Request **Pretest:** Collected pretest score through Google form.	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Line group with instructor and peers
Week 2	**Content:** Lesson unit 1: MS-Excel fundamentals **Activity:** - PowerPoint instruction and Hands-on practice - Gamification in-class - Group discussion	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Line group with instructor and peers • Hands-on practice of Lesson 1
Week 3	**Content:** Lesson unit 2 Data cleaning – 3. Importing datasets **Activity:** - PowerPoint instruction and Hands-on practice - Project-based assignment - Group discussion	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Hands-on practice of Lesson 2-3 • Review Lesson 1 video clip
Week 4	**Content:** Lesson unit 4 Relational database & data modeling **Activity:** - PowerPoint instruction and Hands-on practice - Cased study in-class	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Hands-on practice of Lesson 4 • Review Lesson 1-3 video clips
Week 5	**Content:** Lesson unit 5 Power BI basics and data analytics **Activity:** - PowerPoint instruction and Hands-on practice - Brief review of Lesson 1-4 before Mid-term examination at the end of class **Mid-term Formative Assessment:** Collected mid-term exam score through Google form.	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Hands-on practice of Lesson 5 • Review Lesson 1-4 video clips
Week 6	**Content:** Lesson unit 6 Data interpretation **Activity:** - PowerPoint instruction and Hands-on practice - Cased study in-class - Group discussion	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Hands-on practice of Lesson 6 • Review Lesson 1-5 video clips
Week 7	**Content:** Lesson unit 7 Data visualizations **Activity:** - PowerPoint instruction and Hands-on practice - Cased study in-class	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Hands-on practice of Lesson 7 • Review Lesson 1-6 video clips
Week 8	**Content:** Lesson unit 8 Data governance & security **Activity:** - PowerPoint instruction and Hands-on practice - Dashboard assignment's presentation in-front classroom - Group discussion & evaluation	**Online Resources:** • Microlearning videos of Unit 1-8 via YouTube channel. • Hands-on practice of Lesson 8 • Review Lesson 1-8 video clips
Ending	**Digital Competency Assessment:** Invited three academic experts to evaluate students' project through the Digital Competency Rubrics. Then collected all data of Digital Competency scores for analyzing as Covariate. **Posttest and Summative Assessment:** Collected Posttest through google form and summed academic achievement scores for grading.	
2 Weeks	After two weeks of the end of class, invited students to retest their retention knowledge though the Google form. **Retest 2 weeks:** Collected Retest score though Google form.	

Figure 2. The intervention plan (the authors' own elaboration)

Phase 4: Assessment of temporal persistence and retention of knowledge (week 10)

To assess temporal persistence and knowledge retention, a delayed tracking phase was undertaken in Week 10. After two weeks without any intervention or learning sessions, the same academic test was re-administered for the students.

Statistical Analysis

SPSS version 26.0 was used for all analyses. Statistical significance was set at $p < .05$. We report effect sizes (partial η^2 and Cohen's [1992] d) alongside 95% confidence intervals (CIs) to indicate practical significance, in accordance with best practices that emphasize estimation over hypothesis testing (Metsämuuronen, 2026). To evaluate the effectiveness of the PBM intervention, four analytical approaches were employed:

Academic achievement over time

A mixed-design analysis of variance (ANOVA) was conducted with time (pre-test vs. immediate post-test) as the within-subjects factor and cohort (BBA vs. DTE) as the between-subjects factor. This analysis determined whether academic performance improved significantly following the intervention and whether improvement patterns differed between cohorts. Partial η^2 was reported as the effect size measure.

Table 2. Participant demographic characteristics by cohort

Characteristic	BBA cohort (n = 29)	DTE cohort (n = 33)	Test statistics	p-value
Institution type	Private (weekend)	Public (full-time)		
Student status	Working students	Fourth-year students		
Age, M (SD)	22.34 (2.11)	20.82 (0.58)	$t(60) = 3.992$	< .001
Gender, n (%)			$\chi^2(1) = 1.644$	.200
Male	7 (24.1%)	13 (39.4%)		
Female	22 (75.9%)	20 (60.6%)		
Prior experience[1], M (SD)				
Excel	1.76 (0.83)	3.42 (0.50)	$t(60) = -9.689$	< .001
Power BI	0.17 (0.38)	0.15 (0.36)	$t(60) = 0.220$	.827
Work experience (years), M (SD)	2.35 (1.42)	0.08 (0.25)	$t(60) = 9.020$	< .001
Prior analytics course (≥ 1), n (%)[2]	9 (31.0%)	33 (100%)	$\chi^2(1) = 31.174$	< .001
Daily computer use (hrs), M (SD)	2.33 (1.70)	1.12 (0.49)	$t(60) = 4.073$	< .001

Note. [1] Self-rated on 5-point scale (1 = no experience, 5 = expert); [2] Binary conversion from number of courses completed (0 = no prior course, 1 = at least one prior course); BBA students were working professionals attending weekend classes; DTE students were full-time fourth-year students; Prior analytics coursework was collected as the number of courses completed and converted to binary (0 = no prior course, 1 = at least one prior course) for Chi-square analysis

Learning retention

An analysis of covariance (ANCOVA) was performed to compare retention between cohorts, with immediate post-test scores included as a covariate to control baseline differences in post-intervention performance. This approach isolated the effect of cohort membership on knowledge sustainability beyond immediate learning gains.

Digital competence

An independent-samples *t*-test compared authentic DC scores across cohorts to assess whether the PBM framework led to equitable development of DC among learner populations.

Learner perceptions

Descriptive statistics (means [Ms] and standard deviations [SDs]) summarized student satisfaction ratings, providing insights into the acceptability and perceived value of the PBM instructional approach.

RESULTS

Participants

In total, 62 undergraduate students from two Thai universities participated in this study. There were 29 students enrolled in the BBA program (75.9% female) at STIU (a private university) who attended weekend lessons while working simultaneously (M = 2.35 years of work experience, SD = 1.42). There were 33 fourth-year students in the DTE program (60.6% female) enrolled at RMUTT (a public technical university), with little work experience (M = 0.08 years, SD = 0.25). Both cohorts received instruction in Thai with English-language software interfaces.

Prior Experience

Prior software experience was assessed using a 5-point self-rating scale (1 = no experience, 5 = expert). Both cohorts reported minimal Power BI experience (BBA M = 0.17, SD = 0.38; DTE M = 0.15, SD = 0.36), with no significant difference, $t(60) = 0.220$, $p = .827$. However, significant baseline differences emerged in Excel experience, $t(60) = -9.689$, $p < .001$, with DTE students reporting substantially higher familiarity (M = 3.42, SD = 0.50) than BBA students (M = 1.76, SD = 0.83).

For prior analytics coursework experience, data were collected on the number of courses completed and then converted to a binary format (0 = no prior course, 1 = at least one prior course) for chi-square analysis. All DTE students (100%) had completed at least one previous analytics course, compared to only 31.0% (n = 9) of BBA students, $\chi^2(1) = 31.174$, $p < .001$. Full demographic characteristics are presented in **Table 2**.

Table 3. The results of the instruments' quality

Instrument/metric component	Validation method/statistical index	Value/range	Result
PBM instruction	Expert evaluation (N=5)		
Feasibility standard	5 Likert's scale (M/SD)	4.93/0.26	Excellent
Accuracy standard	5 Likert's scale (M/SD)	4.85/0.37	Excellent
Propriety standard	5 Likert's scale (M/SD)	4.80/0.41	Excellent
Utility standard	5 Likert's scale (M/SD)	4.65/0.49	Excellent
Overall quality & appropriateness	5 Likert's scale (M/SD)	4.80/0.40	Excellent
AA test	Tryout (n=30, 40 items)		
Content validity	IOC index	0.80-1.00	Valid
	Item difficulty index (p)	0.20-0.80	Acceptable
Norm-referenced metrics	Item discrimination index (r)	0.04-0.91	Acceptable
	KR-20	0.9078	High reliability
Criterion-referenced metrics	Brennan's B-index	> 0.20	High
	Lovett's RL coefficient	0.8989	High reliability
DC rubric scoring consistency	Expert IRR (N = 2, n = 20)		
	Average IRR reliability	0.981	Agreement
	95% CI	0.953-0.993	Highly stable
Satisfaction questionnaire	Expert evaluation (N = 5)		
Content validity	IOC index	0.94-1.00	Valid
Internal consistency	Cronbach's alpha	0.89	Good

Table 4. The results of learning outcomes' descriptive stats (n = 62)

DV outcomes/ measurement phase		Cohort	*N*	*M*	*SD*	Skewness	Kurtosis
AA	Pre-test baseline	BBA	29	11.24	2.45	-0.20	-0.35
		DTE	33	9.70	2.49	0.28	-0.67
	Post-test (immediate outcome)	BBA	29	16.62	1.95	-0.66	-0.12
		DTE	33	15.18	3.01	-0.43	-0.84
	Retest (2-week retention)	BBA	29	16.55	1.96	-0.53	-0.33
		DTE	33	14.36	3.23	-0.46	-0.68
DC	Post-intervention composite score	BBA	29	82.01	14.32	-0.63	-0.54
		DTE	33	81.58	11.95	-0.41	-0.60

Note. AA was evaluated via a 20-point examination. DC was measured via a rubric scale with a maximum baseline score of 100

Instrument Quality

The psychometric analyses and quality indices for all four research tools used in the current interventional study are summarized in **Table 3**, in which the AA test, revised by five experts, shows satisfactory content validity (IOC = 0.80-1.00). Pilot testing showed that item difficulty and discrimination were acceptable, with high internal consistency reliability (KR-20 = 0.91). The valid DC rubric had extremely high inter-rater reliability with ICC = 0.95-0.99.

Descriptive Statistics

Tracking measures for description were employed to establish a thorough profile summary of student performance results based on the instructional design PBM. Comparative analysis examined the performance of the BBA business group (n = 29) and the DTE educational group (n = 33). Tests for distributional normality revealed that the skewness statistics ranged from -0.66 to 0.28, whereas the kurtosis statistics varied from -0.84 to -0.12, meeting the structural parametric criterion of ±1.5. Further assumption checks for the statistical tests (e.g., homogeneity of variances and sphericity) were conducted, and all were satisfied.

As shown in **Table 4**, the descriptive growth pattern of AA was fairly consistent across both groups. The BBA group showed growth from a pre-test mean of M = 11.24 (SD = 2.45) to a peak post-test mean of M = 16.62 (SD = 1.95), with decent retention, as evidenced by the 2-week retest mean of M = 16.55 (SD = 1.96). Similarly, the DTE group achieved similar growth results as well, having risen from the initial pre-test mean of M = 9.70 (SD = 2.49) to a post-test mean of M = 15.18 (SD = 3.01), followed by a minimal variability in retention on retest (M = 14.36, SD = 3.23). Regarding the post-test DC, the empirical indicators showed a balanced trend in competence acquisition between the two groups. The business group achieved a high descriptive standard (M = 82.01, SD = 14.32), which was equally matched by the education group's results (M = 81.58, SD = 11.95).

Table 5. The results of a mixed-design ANOVA

Source/effect	SS	df	MS	*F*	*p*	η_p^2
Time (pre- vs. post-test)	884.29	1	884.29	560.51	< .001	.90
Time × cohort	0.04	1	0.04	0.02	.88	< .001
Error (time)	94.65	60	1.58			
Intercept	20,418.87	1	20,418.87	2,747.35	< .001	.98
Cohort (BBA vs. DTE)	38.71	1	38.71	5.21	.03	.08
Error	445.93	60	7.43			

Table 6. The results of an ANCOVA effects

Source of variation	SS	df	MS	*F*	*p*	η_p^2
Covariate: Post-test	73.91	1	73.91	10.96	.002	0.16
Cohort (BBA vs. DTE)	74.44	1	74.44	11.04	.002	0.16
Error	397.77	59	6.74			
Total	15,286.13	62				
Corrected total	647.53	61				

Academic Achievement Change

From **Table 5**, it is clear that the results of the mixed ANOVA did not yield a significant interaction effect between time and academic groups, $F(1, 60) = 0.02$, p = .88, partial $\eta^2 < .001$. Conversely, a highly robust and statistically significant main effect of time was observed, $F(1, 60) = 560.51$, p < .001, partial $\eta^2 = .90$, indicating a massive and meaningful shift in conceptual understanding from pre-test to post-test conditions across the entire sample.

The impact of student discipline (cohort) was also significant, $F(1, 60) = 5.21$, p = .03, partial $\eta^2 = .08$, indicating that, when combining the time variables, the business cohort (BBA) achieved a significantly higher mean achievement outcome than the education cohort (DTE).

Learning Retention

Table 6 shows that the ANCOVA analysis indicated that the covariate had a significant and reliable effect on the next retention scores, $F(1, 59) = 10.96$, p = .002, partial $\eta^2 = .16$. In this regard, the finding strengthens the essential empirical requirement for the application of statistical adjustment on baseline immediate scores. The homogeneity of regression slopes assumption was tested and found to be satisfied (cohort × post-test interaction: $F(1, 58) = 0.02$, $p = .89$), justifying the use of ANCOVA.

Importantly, the effect of cohort, while controlling for the effect of the immediate post-test performance, is still statistically significant at $F(1, 59) = 11.04$, $p = .002$, partial $\eta^2 = .16$. Using the Bonferroni correction for the pairwise comparison showed that the BBA business cohort had a significantly greater adjusted mean retention score (adjusted $M = 16.58$, SE = 0.48) than the DTE education cohort (adjusted $M = 14.32$, SE = 0.45), and thus a mean difference of 2.260 points (95% CI [0.90, 3.62], $p = .002$).

It is clear from the above results that, although the PBM model led to quick success for both groups of students, the business group achieved much better long-term knowledge sustainability. There were differences in retention performance of the two groups when assessed after two weeks. Students in the BBA business group performed almost all at their post-test level ($M = 16.55$ vs. $M = 16.62$), while the DTE education students performed worse ($M = 14.36$ vs. $M = 15.18$).

Digital Competence

An independent t-test was used to examine whether a statistically significant difference existed in post-intervention DC outcomes between the two undergraduate disciplines (BBA, $n = 29$ vs. DTE, $n = 33$). For the primary DC construct, Levene's test for equality of variances was non-significant ($F = 0.59$, $p = .446$), indicating that the assumption of homogeneity of variances was satisfied.

As shown in **Table 7**, the independent t-test indicated no statistically significant difference between the two cohorts, $t(60) = 0.13$, $p = .90$, 95% CI for the difference [-6.23, 7.09]. The post-test DC mean score for the business track (BBA) ($M = 82.01$, $SD = 14.32$) was statistically equivalent to that of the education track (DTE) ($M = 81.58$, $SD = 11.95$). Comparative analysis revealed no statistically significant difference in overall DC

Table 7. The results of an independent t-test comparison

Variable/cohort	*N*	*M*	*SD*	Levene's *F*	Levene's *p*	*t*	df	*p*	Mean difference	95% CI of difference
DC				0.59	*.45*	0.13	60	.90	0.43	[-6.23, 7.09]
BBA	29	82.01	14.32							
DTE	33	81.58	11.95							

Table 8. A table on top

Cohort/satisfaction dimension		*M*	*SD*	Skewness	Kurtosis	Interpretation
BBA cohort (n = 29)	Instructional content	4.30	0.67	-0.67	-0.37	Highest
	Micro-learning	4.26	0.63	-0.43	-0.56	Highest
	PjBL	4.22	0.71	-0.63	-0.51	Highest
	Learning activities	4.19	0.58	-0.56	-0.20	High
	Assessment and feedback	4.28	0.68	-0.73	-0.28	Highest
	Overall total (BBA)	4.25	0.59	-0.64	0.18	Highest
DTE cohort (n = 32)	Instructional content	4.24	0.54	-0.35	-0.70	Highest
	Micro-learning	4.20	0.59	-0.32	-0.58	High
	PjBL	4.16	0.66	-0.44	-0.60	High
	Learning activities	4.28	0.43	0.08	-0.46	Highest
	Assessment and feedback	4.27	0.831	-0.77	-0.55	Highest
	Overall total (DTE)	4.23	0.34	-0.13	-0.49	Highest

performance between the two cohorts. Both groups demonstrated strong applied competency outcomes in dashboard construction, data preparation, visualization, and analytical interpretation. These findings suggest that the PBM instructional model supported equitable competency development across disciplinary contexts.

Learner Perceptions

Descriptive statistics and diagnostic tests were performed to conduct an in-depth evaluation of undergraduate students' satisfaction with instruction across five dimensions, in accordance with the PBM approach. The survey considered the views of the BBA group (n = 29) and the DTE group (n = 32; one student in this cohort did not complete the satisfaction questionnaire). To verify distributional validity prior to parametric tests, univariate normality was assessed.

Skewness coefficients ranged from -0.77 to 0.08, and kurtosis estimates ranged from -0.70 to -0.20, both comfortably within the usual ±1.5 range, implying a normal distribution of satisfaction levels.

Table 8 shows that, according to the empirical baseline, both target audiences reported an extremely high level of overall satisfaction with the PBM instruction. In particular, the BBA business group achieved an overall satisfaction mean score of M = 4.25 (SD = 0.59; interpreted as "highest level"), which is close to the mean of the DTE education group, i.e., M = 4.23 (SD = 0.34; interpreted as "highest level"). Regarding sub-dimensions, distinct differences in students' attitudes were identified. Thus, within the BBA business group, the highest mean score (M = 4.30, SD = 0.67) was obtained for instructional content, while learning activities had the lowest local mean score within the cluster (M = 4.19, SD = 0.58).

On the other hand, the DTE group reported their maximum satisfaction with learning activities (M = 4.28, SD = 0.43), while the lowest local mean score was for PjBL (M = 4.16, SD = 0.66). Therefore, these results show that while the former group valued localized content and the usefulness of software delivery, the latter paid more attention to learning sequences and interactive tasks within the PBM framework. Students in both groups demonstrated highly positive acceptance of the instructional approach.

DISCUSSION

Summary of Findings

The current study was conducted to determine the efficacy of the PBM pedagogical approach in enhancing students' digital analytics capabilities. There were significant gains in terms of academic performance among both groups, with an effect size being very large (η^2p = .90). There were high levels of authentic digital capability among students (M = 82.01 and 81.58 on a scale of 100) as well as high levels of satisfaction among

students (*M* = 4.25 and 4.23 on a scale of 5). However, retention results varied significantly between the groups.

The Synergistic Effect of Microlearning and Project-Based Instruction

The improvements in academic performance observed in both groups may be attributed to the use of microlearning and PjBL (Franklin, 2026; Luo & Li, 2025). As for cognition, microlearning can reduce cognitive load by decomposing complex procedural information. The suggestion is consistent with the theory of cognitive load, which posits that reducing extraneous cognitive load leads to greater learning effectiveness, particularly in technical subjects (Gkintoni et al., 2025). The large effect size (η^2p = .90) in the experiment supports the claim that microlearning is efficient at managing cognitive load (Monib et al., 2025). In addition, brief instructional videos allowed repeating the information at one's own pace.

In addition, the project-oriented aspect facilitated further knowledge construction by enabling students to apply analytical knowledge to the practical activity of designing dashboards (Kokotsaki et al., 2016). Indeed, according to constructivist theory, application helps students integrate theoretical knowledge into practice (Jarutkamolpong & Kwangmuang, 2025). The similar assessment results for both groups (*M* = 82.01 and *M* = 81.58 out of 100) indicate students' success in applying their knowledge in real-world situations. It is an extension of previous research by Collier and Powell (2024) and Surducan and Valadas (2025), which stressed the importance of authentic performance ability as a key aspect of DC.

Context Within the Discipline and Differences in Retention

While there were clear gains in immediate learning across both cohorts, differences in retention emerged over the two weeks. The BBA learners maintained their performance level (*M* post-test = 16.62 vs. *M* retention = 16.55), whereas the DTE learners showed signs of deterioration (*M* post-test = 15.18 vs. *M* retention = 14.36). Controlling for immediate post-test performance, the adjusted mean difference between the two cohorts was 2.26 points.

The most straightforward alternative explanation of this difference could be the considerable gap in pre-existing analytics coursework experience. All DTE learners (100%) completed at least one previous analytics course, while only 31% of BBA learners have. Pre-existing knowledge made DTE learners illusorily competent and potentially decreased their interest in engaging with the PBM microlearning content. In turn, BBA learners who lacked prior exposure to formal analytics education might experience a novelty effect, which could make them more interested in foundational content.

There is evidence that the perceived relevance of digital skills to future career activities affects engagement and knowledge retention (Collier & Powell, 2024; Tzafilkou et al., 2022; Victor & Ujir, 2025). Still, the current study does not operationalize the construct of relevance or other potential mediators, such as motivation and self-regulation, which can also influence learning outcomes in a specific educational context.

Equitable Development of Authentic Digital Competence

One major achievement of this study is demonstrating that the PBM teaching method led to the development of authentic DC across different academic cohorts. Unlike traditional methods of evaluating learners by testing their knowledge, this study assessed learners' competencies through a practical project in which they had to prepare data, visualize, reason analytically, and implement dashboards. This is significant given that DCs are more about performance than just knowing how to use software (Anistyasari et al., 2024; Collier & Powell, 2024; Surducan & Valadas, 2025).

The similarities in competency outcomes identified across different cohorts suggest that the PBM model shows potential as an adaptive teaching approach to support the development of transferable digital analytics competencies in diverse higher education environments. This research outcome builds on previous studies by scholars such as Tuamsuk and Subramaniam (2017), whose results showed that DCs varied across cohorts and depended on institutional context. This research takes it one step further by suggesting that initial skill acquisition may be similar across cohorts, but knowledge retention depends on the field of study.

Practical Implications For Educational Practice

The results of the study are actionable recommendations for higher education course instructors and curriculum developers.

For course design

The PBM approach gives a replicable formula for instructing complicated software packages. Course instructors need to design their courses in such a way that they include

(a) video modules (5-10 min long) on basic concepts,

(b) gradually more complicated hands-on practice activities, and

(c) project-based tasks where students will need to integrate several skills.

Such a structure accounts for the cognitive challenges of learning technical skills and supports authentic skill acquisition (Kokotsaki et al., 2016; Mohammed et al., 2018).

For retention improvement

Given the varying retention levels, course instructors might explore ways to improve knowledge sustainability in the long run, especially for students studying outside business disciplines. These could be spaced-repetition activities, extended project assignments, or direct links to students' fields of study (Ikhsam et al., 2026). Using micro-review sessions after an initial learning experience might prove useful.

For disciplinary adaptation

According to this research, relevance is an important factor determining retention success. Project contexts should be tailored to students' professional identities (such as analysis of educational datasets by education students and not business data, and of clinical datasets by healthcare students). Such adaptation could improve students' perception of relevance and help increase retention rates (de los Ángeles Domínguez-González et al., 2025; Tzafilkou et al., 2022).

For assessment design

Because there is a strong association between post-test scores and digital skills, tests can be used to measure students' knowledge levels. In the meantime, retention data suggest that end-of-instruction scores may reflect more knowledge than students actually possess, implying the need to administer a delayed test to assess knowledge accurately. Thus, the proposal is to conduct tests two to four weeks after the instruction (Collier & Powell, 2024).

For the scalability of the application

The use of short videos and PjBL activities enables the implementation of the PBM model across different instructional approaches, such as flipped and online learning. Institutions planning to increase digital literacy in scalable ways will likely benefit from applying this model, as it has proven effective (Zakir et al., 2025).

Contributions to the Literature

This paper contributes to the existing literature in several ways. Firstly, the current paper contributes to the extant knowledge about integrated instructional design in digital analytics learning. Even though there have been separate studies on the use of the PjBL approach (Kokotsaki et al., 2016) and the microlearning approach (Mohammed et al., 2018), there is very little empirical evidence of their practical implementation. The current paper empirically confirms the theoretical hypothesis that integrating the two approaches will improve learners' grades and skills (Zakir et al., 2025).

Secondly, the current research addresses a gap in understanding the moderating role of discipline in instructional effectiveness. While previous research has focused on the initial acquisition of skills, the current study shows that disciplinary context may affect knowledge sustainability.

In addition, this study makes an important contribution to the methodology of DC assessment by using both authentic performance-based assessment and conventional tests. Together, these two types of

assessment give a more complete overview of the results achieved than either one on its own (Anistyasari et al., 2024; Surducan & Valadas, 2025). Also, the results of this study confirm the feasibility of adapting the PBM method to different institutional settings, indicating that this teaching approach can be scaled up.

Limitations

There are several limitations worth mentioning. First, there were some differences between groups before the experiment started – BBA students were experienced workers. In contrast, DTE students were fourth-year full-time students and had technical superiority from the beginning, yet BBA students still demonstrated better retention. This makes any causal comparison impossible. Second, using a pre-experimental design (intact groups and no control group) makes it impossible to draw any causal conclusions. Third, differences in the organizational setting (private international vs public technical institution) may affect the findings. Fourth, the limited sample size (n = 62) makes it hard to generalize from this study. Fifth, unmeasured mediators (motivation, self-regulation, relevance, and cognitive load) render theoretical explanations only speculative. Last, a two-week retention period may not be sufficient to measure knowledge sustainability.

Future Research

The study's findings and limitations suggest several potentially promising directions for future research:

1. **Methodological rigor:** Further research on PBM is recommended to be conducted with large sample sizes and controlled experimental designs, particularly RCTs and quasi-experimental designs with control groups. This will enhance the strength of cause-and-effect inference on the PBM model's efficacy.
2. **Mediating mechanisms:** Research incorporating measures of motivation, engagement, self-regulated learning, and cognitive load would provide greater insight into the mechanisms underlying the development of DC. Future work should directly measure perceived relevance, cognitive load, and self-regulated learning strategies to test the theoretical explanations proposed in this study.
3. **Long-term outcomes:** The use of longitudinal assessment periods, such as three- and six-month intervals, would help assess the sustainability of the instruction and determine the optimal reinforcement spacing.
4. **Discipline-specific studies:** Comparative research on PBM effectiveness across disciplines such as the arts, sciences, and health-related fields can provide useful information about the effects of discipline on the instructional process.
5. **Various DC domains:** Further research might be devoted to implementing PBM in other domains of DCs, such as artificial intelligence literacy, BI education, learning data science, and computational thinking. It will enable assessment of the generalizability of the proposed framework across various technical subjects.
6. **Characteristics of the learners:** An analysis of the effect of learners' personal characteristics (like knowledge, self-efficacy, learning styles) on PBM effectiveness is necessary to be able to make personalized recommendations to the teachers.

CONCLUSIONS

The present paper demonstrates that PBM can be regarded as a suitable model of digital analytics instruction for undergraduates, which shows very large effect sizes on the immediate performance (η^2p = .90) and very high levels of endorsement of authentic digital skills acquisition (M = 82.01 and 81.58 on a scale of 100). Furthermore, the significant difference in knowledge retention among business students (M = 16.55 vs. 14.36 on a delayed post-test) supports the hypothesis that the perceived relevance of the discipline to learning contributes to knowledge sustainability.

The results presented above provide useful insights for educators at higher education institutions seeking scalable, pedagogically grounded ways to implement technology-enhanced learning. The framework introduced above (PBM) provides a replicable framework that combines the benefits of microlearning and authentic application through project-based assignments. At the same time, the differential effects of

knowledge retention call for deliberate efforts to ensure knowledge sustainability for different types of learners—especially those from unrelated disciplines.

Future directions for research into the mechanisms of DC formation include the Impact that relevance, self-regulation of learning processes, and cognitive load can have as mediators. With universities now paying greater attention to developing digital literacy, evidence-based teaching frameworks, such as PBM, will become increasingly relevant to professional preparation.

Author contributions: Cherisa Nantha: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, validation, visualization, writing – original draft, writing – review & editing; **Paitoon Pimdee:** conceptualization, formal analysis, investigation, visualization, writing – original draft; **Patjai Piyachon:** funding acquisition, resources, software, validation; **Surapong Siripongdee:** conceptualization, data curation, investigation, methodology, supervision, writing – review & editing; **Nitidhorn Janthadech:** data curation, funding acquisition, resources, software, validation. All authors approved the final version of the article.

Funding: The authors received no financial support for the research and/or authorship of this article.

Ethics declaration: This study was approved by the Institutional Review Board at King Mongkut's Institute of Technology Ladkrabang on 8 September 2024 with approval number EC-KMITL_67_077. All research procedures strictly adhered to the ethical guidelines for research involving human participants. Prior to participation, researchers fully informed all students about the objectives, procedures, potential risks, and benefits of the study. All participants provided written informed consent and ensured the confidentiality of their personal information throughout the research process. The researchers assured participants that their involvement was voluntary and that they could withdraw from the study at any time without penalty. The research team upheld the highest standards of ethical conduct to protect the rights and well-being of all participants.

AI statement: During the preparation of this manuscript, the authors used Google Translate to assist with translating the original Thai content into English. The authors used Grammarly Premium to refine language for clarity and consistency. AI tools (specifically ChatGPT, Gemini, and GPT-5.3) were used in a limited capacity to assist with the visual refinement and redesign of figures to improve clarity and presentation, and to suggest alternative phrasing for clarity. They did not use any AI tools to generate the study's conceptual framework, data, analysis, or interpretations. All content, including figure accuracy and underlying academic meaning, was reviewed and verified by the authors, who take full responsibility for the integrity of the work.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

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