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Analysing student behaviour in the implementation of LAT using cloud technology in higher education institutions

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Abstract: This study examines the impact of cloud-based learning analytics tools (LAT) on student adoption intention and perceived engagement in higher education. Data were collected from 155 students familiar with cloud computing through a structured questionnaire, and SmartPLS was applied to test the relationships between technology competency, cloud computing ability, perceived usefulness (PU), perceived ease of use (PEU), and intention to adopt LAT. The results confirm that the measurement and structural models are valid and reliable. Findings show that cloud computing ability enhances technology competency, which positively influences PU and PEU, leading to higher adoption intention, with PEU exerting the strongest effect. The results underscore the importance of usability-oriented system design and cloud-related competencies in encouraging technology adoption, consistent with the technology acceptance model (TAM).

Keywords: cloud computing; learning analytics tools; LAT; technology acceptance model; TAM; technology competency; cloud computing ability; CCA; perceived usefulness; PU; perceived ease of use; PEU; higher education.

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1 Introduction

Cloud computing has evolved at such a fast pace that how learning data are managed and used in educational institutions has changed. In conclusion, the higher education landscape in Southeast Asia provides a sociotechnical context to examine factors influencing the adoption of cloud-based learning analytics tools (LAT). This region is, today, defined by two characteristics – rapid digital transformation and stark cloud literacy divergence. Focusing on this region, this study explores how ‘cloud computing ability (CCA)’ is an emerging requirement for adoption in a growing digital economy, thus offering insights as to how cultural and infrastructural differences modulate perceptions around the relative benefits and ease-of-use of educational technologies. The ability of cloud computing to provide scalable and flexible solutions makes it an effective tool for storing, processing, and analysing data in order to improve education systems. Cloud computing has also been shown in the academic literature to assist with data administration and data excellence which, when combined according to some projects within the instructional area for student path analysis, enables an improvement of this phase in adapting increasingly individual content (Musa, 2024).

Prior studies indicate that cloud infrastructure enables scalable data storage and analytics capabilities that support learning monitoring and instructional decision-making (Liu and Xu, 2022; Musa, 2024). In cloud-supported learning environments, analytics-driven insights allow educators to identify learning behaviours and preferences more efficiently, thereby supporting student engagement and academic performance (Rahhali et al., 2021; Efrianova et al., 2024).

In higher education research has come up again. Research in higher education has revealed that students' perceptions documented through self-reported instruments may be impacted by the social setting and the institutional context in which data are collected. Furthermore, even if the survey topic itself is not sensitive, responses can still mirror socially desirable patterns that are the product of academic environments and anticipated modes of behaviour. Lavidas et al. (2022) demonstrate that these contextual influences can influence the accuracy of students' self-reports about their attitudes and perceived competencies, highlighting why it is particularly important to validate psychometric instruments used to study learning-oriented non-cognitive variables in higher education.

From architecture perspective, pay-as-you-go (PAYG) and infrastructure independent feature of cloud computing that minimises the cost incurred due to processing large volume of educational data greatly facilitating LAT adoption in higher education (Kavis, 2014). This study was conducted at BINUS University as a representative example of higher education institutions in Southeast Asia that were digital transformation systems for innovation. These LAT and cloud computing capabilities influence students' learning behaviours that guide the study with the following research questions:

- 1 Is the measurement instrument used to assess technology competency (TC), CCA, perceived usefulness (PU), perceived ease of use (PEU), and intention to adopt LAT valid and reliable?
- 2 How does the integration of cloud computing technology support the implementation and effectiveness of LAT in higher education?
- 3 How do PU and PEU influence students' intention to adopt LAT (LAT) in cloud-based environments?
- 4 To what extent do students' cloud computing abilities affect their PU and ease of using LAT?

With a focus on usability and cloud competency, this study seeks to close the gap between theoretical frameworks and real-world applications of cloud-based learning analytics. This advances data-driven teaching strategies in higher education.

2 Literature review

2.1 Technology acceptance model

According to the technology acceptance model (TAM), the main factors influencing a person's intention to adopt a technology are PU and PEU (Mukred et al., 2024). In the context of cloud-based learning analytics, TAM offers a theoretical framework for investigating how students perceive analytical systems that aim to assist in academic decision making. It is well known that LAT are grounded in the systematic analysis of

students' activities, as such usability and PU become some of the most significant elements when deciding whether to use a tool or not.

In fact, TAM is commonly used in the studies of information systems and e-learning platforms; however, there has not been much applied research on TAM to cloud-based learning analytics especially among higher education institutions within Southeast Asia. This study highlights the importance of exploring whether TAM would still be relevant in this specific technology-enhanced learning environment.

2.2 *Technology competency*

TC refers to an individual's capability to effectively use and adapt computer-based technologies across different contexts. Individuals with higher levels of technological competency tend to experiment with and integrate new technologies more confidently, which plays a crucial role in the adoption of cloud computing solutions (Changchit et al., 2022). In the educational context both students and instructors increasingly rely on cloud-based applications for data analysis as well as learning management, making TC an essential prerequisite for effective system use.

Prior studies indicate that improvements in cloud-related technical skills enable users to utilise cloud resources more efficiently for academic research and analytical tasks, thereby enhancing the PU of such technologies (Changchit et al., 2022). While TC is generally associated with greater confidence in using digital systems, recent studies suggest that excessive and unregulated engagement with digital technologies may also introduce behavioural challenges.

2.3 *Cloud computing ability*

CCA refers to users' capacity to effectively utilise cloud-based systems for accessing, processing, and managing data in distributed learning environments. In higher education, such abilities are essential for supporting data-intensive academic activities and informed decision-making processes. Prior studies indicate that cloud computing skills play a significant role in enabling real-time data analysis and improving the quality of institutional and learning-related decisions (Hassan et al., 2022).

In the context of LAT, CCA facilitates continuous access to student data and supports the analytical processes required to interpret learning behaviours. Users with stronger cloud-related competencies are more likely to recognise the functional value of LAT (Mukred et al., 2024). Khasawneh (2024) states that cloud-based learning tools support higher-order cognitive skills, including reasoning, interpretation, and analytical thinking, particularly among novice learners, thereby reinforcing their relevance in educational analytics contexts.

Big data driven learning analytics environments critically rely on cloud computing for scalable storage, processing and access. Cloud infrastructure combined with big data technologies enables systematic analysis of students' behaviour which is a key component for implementation of LAT in higher education institutions (Naamane, 2023). Accordingly, it follows that understanding CCA is still necessary to understand how the students perceive, adopt and interact with learning analytics systems that are enabled by a cloud.

While persistent access to both learning data and analytical resources enabled by CCA is often construed as beneficial, previous studies have indicated that sustained

exposure to digital platforms can also exacerbate tendencies toward distraction and cognitive overload across student bodies. Research on digital addiction highlights how the incentives offered by digital contexts can both facilitate academic behaviours as well as undermine students' self-regulation, indicating that cloud computing-enabled learning analytics should be designed in such a way to support more purposeful and structured engagement (Tülüba, 2023).

2.4 Perceived ease of use

When it comes to adopting requirements for new technology, users are strongly affected by their perception about ease of use of the new systems. If a system is easy to operate, a useful view is formed which explains the level of user acceptance and technology interaction. PEU directly affects PU, as indicated by previous studies, and subsequently informs users' intentions to adopt cloud-based LAT. PEU has been found to enhance intention to adopt such tools as well as the actual adoption of information systems in higher education institutions (Mukred et al., 2024). Previous studies indicate that easy engagement with the digital systems could facilitate their long-term use. The literature on digital addiction indicates that for highly accessible and engaging forms of social media, excessive use may occur where user self-control measures are not appropriately applied. This presents a tension between the UX that is useful for users versus design that is responsible, in analytics platforms (Tülüba, 2023).

2.5 Perceived usefulness

This means that the extent to which an individual perceives a specific innovation as being useful directly translates into positive results. Cloud-based solutions are presented in the context of PU, which predicts potential technology adoption. Literature more than once revealed significant correlation between perceived utility and acceptance of LAT. If students perceive cloud-based learning tools to assist them during their learning analysis then it motivates them to use LAT in order to surpass academia (Wang et al., 2022).

While the TAM is focused on general concepts like PU and ease of use, tangible examples in higher education illustrate connections between cloud services, LAT and student behaviour. Cloud-based learning management systems (LMS), such as Google Classroom and Moodle Cloud, let students access course materials, submit assignments, and manage learning activities with little technical effort. These features improve PEU, which in turn increases PU by allowing efficient tracking of learning progress through analytic tools. While PU encourages adoption intentions, research on digital addiction shows that relying too much on digital platforms can hurt academic performance. This suggests that we should look at perceived benefits alongside actual usage patterns and their effects on behaviour (Tülüba, 2023).

2.6 Intention to adopt LAT

The institution's intention to employ online tools to monitor student performance is closely linked to students' willingness to adopt learning technologies. Individuals' intention to use LAT depends mostly on their PEU and PU. Systems with intuitive and easily accessible system interfaces enable users in recognising the value of LAT. Users'

beliefs regarding the ability of LAT can improve the evaluation of student behaviour further influence adoption decisions (Mukred et al., 2024).

The evaluation of cloud-based learning analytics for usability is affected by users' positive attitude towards technology and the favourable context in use. Technological optimism enhances the PU and PEU of emerging educational technologies, ultimately leading to their adoption in educational activities. Successful adoption is when students receive adequate institutional support, including appropriate training and technical assistance. As adoption rates increase, the overall effectiveness and sustainability of learning analytics initiatives also tend to improve (Castillo-Vergara et al., 2022). Institutions must raise their optimism levels regarding technology while establishing supportive infrastructures to enable the effective integration of LAT for student behaviour analysis.

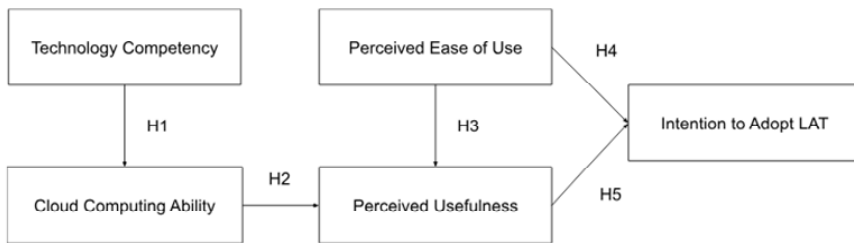
Several factors influence decisions to adopt LAT, including system usability, the practical advantages enabled by cloud computing capabilities, and users' attitudes toward technology. In order to successfully implement cloud-based LAT in education, strategies to enhance user competencies, as well as perceived efficacy and ease of use, are vital (Rodríguez Lera et al., 2021; Castillo-Vergara et al., 2022; Mukred et al., 2024; Latorre-Coscolluela et al., 2025).

However, implementing learning analytics successfully requires appropriate evaluation practices: construct conceptualisation, reliable and valid measurement instruments development, and potential sources of error identification. Measuring latent variables is particularly challenging at a methodological level that, as the *Handbook of Learning Analytics* notes, can have significant implications for individuals and institutions alike (Lang et al., 2017). Such clarity is paramount especially in the fields of learning analytics and educational data mining, where decisions to adopt tools often rest on perceptions regarding the validity and reliability of tools employed to evaluate student behaviour.

3 Methods

3.1 Research model

A quantitative research design was employed in this study to confirm the antecedent variables of intention to use LAT. The research model was related to five constructs: TC, CCA, PEU, PU and intention to adopt LAT (IAL) The study considered the principal concepts in TAM in that are technology proficiency, CCA, ease of use, usefulness and utilisation of LAT however other ideas such as satisfaction with a user is regarded. It looks at specific cases in order to understand the drives behind the measuring. For example, LMS platforms (Google Classroom, Moodle Cloud), collaboration tools (e.g., Google Docs, Microsoft365), and cloud-based storage services (e.g., AWS Educate and Google Cloud Platform) were referred to. In these contexts that reinforce the notions of PEU and PU, adoption constructs are directly related to the integration and efficacy of cloud-based LAT in higher education.

Figure 1 Research model

3.2 Sampling technique and sample size determination

In this study, we conducted a close-ended survey based on questionnaires using non-probability sampling focused on university students who are continuously involved in academic activities using cloud-based services. Specifically, a convenience-based purposive sampling approach was applied, whereby participants were selected based on their accessibility and prior experience with cloud-based educational tools. A non-probability purposive sampling technique was employed to ensure that respondents had sufficient experience with cloud-based services to provide informed responses. Sample size construction was determined by the statistical power analysis. Following Cohen's (1988) guidelines, a medium effect size ($f^2 = 0.15$), a conventional significance level of 0.05, and a desired statistical power of 0.80 were adopted. An a priori power analysis indicated that the final sample of 155 respondents was adequate for partial least squares structural equation modelling (PLS-SEM) estimation. While the sample size is sufficient for model estimation using PLS-SEM, the findings are not intended for statistical generalisation across all higher education institutions in Southeast Asia and should be interpreted within the context of the sampled population.

A total of 282 responses were obtained initially. However, before the analyses, data screening and data cleaning were performed to ensure reliability and quality of the information. Respondents with incomplete answers, interrupted response pattern or straight-lining behaviour were excluded. After the data cleaning procedure, 155 complete responses were kept for further analysis, which exceeded the minimum size of sample suggested by Hair et al. (2019), guaranteeing an appropriate statistical power to perform PLS-SEM analysis. The inclusion criteria required respondents to be active university students who regularly use cloud-based services for academic purposes. The exclusion criteria included incomplete questionnaires, inconsistent response patterns and straight-lining behaviour. The questionnaire was distributed online using Google Forms, and participation was voluntary. Only responses that met the inclusion criteria were retained for analysis.

3.3 Participant recruitment

We recruited undergraduate student participants from the university who regularly use cloud-based educational tools using a non-probability sampling method. Initially, 282 responses were collected and based on analytical criteria, there remained 155 complete questionnaires. The final sample was sufficient to satisfy the statistical power analysis requirement for PLS-SEM (Cohen, 1988).

3.4 Questionnaire

A four-point Likert scale in this study was utilised from 1 (strongly disagree) to 4 (strongly agree). We intentionally avoided a neutral option in order to minimise central tendency bias and to urge respondents to take a clear stance on each statement. This approach is considered appropriate when respondents are expected to have sufficient familiarity with the research object, thereby improving the discriminative power of the measurement scale. Previous studies have also applied forced-choice Likert scales to obtain more decisive attitudinal responses.

Table 1 Likert scale

<i>Score</i>	<i>Criteria</i>
1	Strongly disagree
2	Do not agree
3	Agree
4	Strongly agree

3.5 Ethical consideration

This study involved human participants through an anonymous, non-invasive questionnaire. According to the institutional research policy of the authors' university, formal ethical clearance is not required for survey-based studies that do not involve clinical intervention, vulnerable populations, or the collection of personally identifiable or sensitive data.

Participation in the study was entirely voluntary. Prior to data collection, all respondents were informed about the purpose of the research, the use of the collected data for academic purposes only, and their right to withdraw at any time. Informed consent was obtained electronically before participants completed the questionnaire. All responses were kept confidential and analysed in aggregate form only.

3.6 Data analysis

Descriptive and inferential statistics were used to derive information from quantitative data analysis which was carried out using the SmartPLS software. As a first step, descriptive statistics was used for data collection through the demographic data of the participants. Ultimately, we tested the hypotheses and identified a possible link between the relevant variables using the partial least squares structural equation modelling or PLS-SEM for short. Through the use of Likert-scale responses, we determined the statistical significance and trends concerning students' experiences with cloud-based learning analytics.

4 Research hypothesis

H1 TC has a positive impact on CCA.

H2 CCA has a positive impact on PU.

- H3 PEU has a positive impact on PU.
 H4 PEU has a positive impact on IAL.
 H5 PU has a positive impact on IAL.

Table 2 Variables

<i>Technology competency</i>	
TC1	Understanding the basic concepts of information technology
TC2	Skill in completing tasks using software or applications
TC3	Experience in learning new technologies
TC4	Confidence in facing technological changes
<i>Cloud computing ability</i>	
CCA1	Understanding the basic concepts of cloud computing
CCA2	Ability to use cloud services (e.g., AWS, Google Cloud, Azure)
CCA3	Security and data management in cloud environments
CCA4	Ability to integrate cloud with other applications
CCA5	Efficiency in using the cloud for data storage and analysis
<i>Perceived ease of use</i>	
PEU1	Accessibility of cloud technology without complex technical support
PEU2	The innovation and regularity of cloud technology interfaces
PEU3	Ease of use of cloud technology
PEU4	Convenience in interacting with cloud technology features
<i>Perceived usefulness</i>	
PU1	Effectiveness in analysing student behaviour
PU2	Improving the quality of data-based learning strategies
PU3	Data-based monitoring of student academic performance
PU4	Support for achieving institutional academic goals based on data
<i>Intention to adopt LAT</i>	
IAL1	Interest in using LAT in academic processes
IAL2	Willingness to learn and adopt LAT in daily activities
IAL3	The belief that LAT can improve the quality of learning
IAL4	Most likely to use LAT in the near future

5 Results

5.1 Demographic characteristics of respondents

The respondents consisted of a balanced gender distribution (50.2% male and 49.8% female). Most respondents were aged 20 years or above (63.5%) and were predominantly from information systems (74.6%) and computer science (24.4) majors. The majority of participants were familiar with cloud computing (96.8%). Commonly used cloud services included Google Drive, Zoom, Amazon Web Services, Dropbox, Adobe Creative Cloud,

and Google Cloud, indicating high exposure to cloud-based applications among the respondents.

Table 3 Demographic

<i>Variable</i>	<i>Category</i>	<i>Percentage</i>
Gender	Male	50.2%
	Female	49.8%
Age	< 20	36.6%
	≥ 20	63.5%
Major	Information systems	74.6%
	Computer science	24.4%
	Management	0.2%
	Law	0.4%
	Social science	0.4%
	-	0.4%
Familiar with cloud	Yes	96.8%
	No	3.2%
Cloud services used	Amazon Web Services (AWS)	60.9%
	Google Cloud	53.4%
	Dropbox	60.6%
	Google Drive	63.8%
	Adobe Creative Cloud	56.6%
	Zoom	62%
	Never used cloud services	4.7%

5.2 *Evaluation of outer model*

The initial stage of structural model analysis is assessing the outer model. This helps assess the reliability and validity of the indicators used to measure latent variables. An outer model is another term for a measurement model that includes indicators associated with the constructs it represents. Therefore, it is crucial to ensure that the chosen indicators accurately represent the concepts being studied.

5.3 *Convergent validity*

The determination of whether indicators of a construct are strongly correlated and meaningful indicators of similar constructs is made through the use of convergent validity. Researchers generally accept a threshold of 0.7 for the loading factor to be a fairly strong and reliable indicator. Hair et al. (2019) state that a value of 0.7 for the outer loading is accepted. The indicators of the study have a loading factor of 0.7, satisfying the validity criterion.

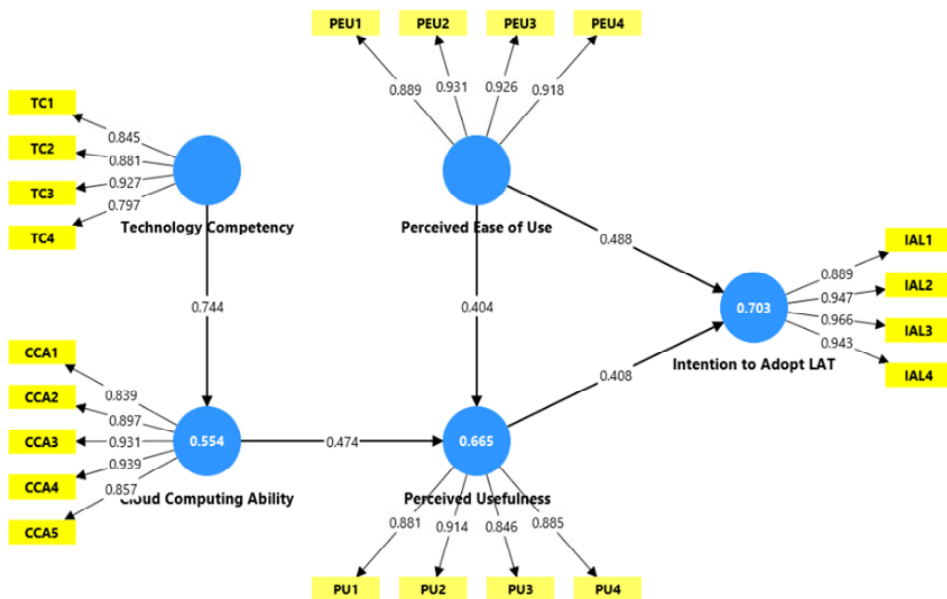
In addition, convergent validity was assessed using the AVE. Hair et al. (2019) recommend an AVE value of at least 0.50, indicating that a construct explains more than

half of the variance of its indicators. The results show that all constructs achieved AVE values above 0.50, confirming adequate convergent validity.

Table 4 Average variance extracted (AVE)

	Average variance extracted (AVE)
Cloud computing ability	0.799
Intention to adopt LAT	0.877
Perceived ease of use	0.826
Perceived usefulness	0.778
Technology competency	0.746

Figure 2 Outer loading (see online version for colours)



5.4 Discriminant validity

The heterotrait-monotrait (HTMT) ratio method is used in the present research to test discriminant validity. Validity of discriminating the construction of a research model from other constructions is called discriminating validity. This feature ensures that the variable capturing different construction is not high correlated and thus the construction represents some distinct aspect of the study.

Discriminant validity was achieved as evidenced in Table 6, as all HTMT values were below 0.85. Hair et al. (2019) also declare that a HTMT value below 0.85 shows that each construction is discriminated from the other models in the overall model.

Table 5 Outer loading

<i>Variables</i>	<i>Indicators</i>	<i>Outer loading</i>	<i>Validity</i>
Technology competency	Understanding the basic concepts of information technology	0.845	Valid
	Skill in completing tasks using software or applications	0.881	Valid
	Experience in learning new technologies	0.927	Valid
	Confidence in facing technological changes	0.797	Valid
Cloud computing ability	Understanding the basic concepts of cloud computing	0.839	Valid
	Ability to use cloud services (e.g., AWS, Google Cloud, Azure)	0.897	Valid
	Security and data management in cloud environments	0.921	Valid
	Ability to integrate cloud with other applications	0.939	Valid
	Efficiency in using the cloud for data storage and analysis	0.857	Valid
	Perceived ease of use	Accessibility of cloud technology without complex technical support	0.889
The innovation and regularity of cloud technology interfaces		0.931	Valid
Ease of use of cloud technology		0.926	Valid
Convenience in interacting with cloud technology features		0.918	Valid
Perceived usefulness	Effectiveness in analysing student behaviour	0.881	Valid
	Improving the quality of data-based learning strategies	0.914	Valid
	Data-based monitoring of student academic performance	0.846	Valid
	Support for achieving institutional academic goals based on data	0.885	Valid
Intention to adopt LAT	Interest in using LAT in academic processes	0.889	Valid
	Willingness to learn and adopt LAT in daily activities	0.947	Valid
	The belief that LAT can improve the quality of learning	0.966	Valid
	Most likely to use LAT in the near future	0.943	Valid

Table 6 Discriminant validity

	<i>CCA</i>	<i>IAL</i>	<i>PEU</i>	<i>PU</i>	<i>TC</i>
CCA					
IAL	0.811				
PEU	0.766	0.834			
PU	0.831	0.830	0.810		
TC	0.810	0.761	0.779	0.814	

5.5 Cronbach alpha

Reliability of the constructs was assessed in this study using Cronbach's alpha test. According to Hair et al. (2019), Cronbach's alpha value > 0.7 is considered satisfactory to good.

Table 7 shows that all Cronbach's alpha values are above 0.7, in other words, they are satisfactory to good. Related to this threshold, Hair et al. (2019) states that the indicators appropriately measure the same construct.

Table 7 Cronbach alpha

	<i>Cronbach's alpha</i>	<i>Reliability</i>
CCA	0.937	Reliable
IAL	0.953	Reliable
PEU	0.936	Reliable
PU	0.904	Reliable
TC	0.886	Reliable

5.6 Composite reliability

The internal consistency of the variables is shown in Table 8 where the composite reliability was more than 0.7. Unrepeated values submitted to the analyses meet the reliability standards, indicating that the constructions are being considered consistently and reliably.

Table 8 Composite reliability

<i>Variables</i>	<i>Composite reliability</i>	<i>Reliability</i>
CCA	0.943	Reliable
IAL	0.959	Reliable
PEU	0.939	Reliable
PU	0.905	Reliable
TC	0.893	Reliable

5.7 Common method bias assessment

Common method bias (CMB) may occur in studies using self-reported questionnaires from a single data source. Therefore, Harman's single-factor test was conducted following Hair et al. (2019). The results show that the first unrotated factor explains 63% of the total variance, indicating a potential common method effect. However, Hair et al. (2019) emphasise that this test is a preliminary diagnostic and may overestimate CMB. In this study, 282 responses were initially collected, and after data screening and cleaning procedures, 155 valid responses were retained, which may influence the variance structure but was necessary to improve data quality. Additionally, procedural remedies such as respondent anonymity, clear item wording, and the use of established measurement scales were applied. Thus, CMB is unlikely to substantially affect the interpretation of the study results.

Table 9 Harman single-factor test

Factor	<i>Total variance explained</i>					
	<i>Initial eigenvalues</i>			<i>Extraction sums of squared loadings</i>		
	<i>Total</i>	<i>% of variance</i>	<i>Cumulative %</i>	<i>Total</i>	<i>% of variance</i>	<i>Cumulative %</i>
1	13.394	63.780	63.780	13.026	62.030	62.030
2	1.205	5.738	69.518			
3	0.980	4.668	74.186			
4	0.827	3.937	78.123			
5	0.778	3.704	81.827			
6	0.584	2.783	84.610			
7	0.514	2.448	87.058			
8	0.412	1.963	89.021			
9	0.368	1.751	90.772			
10	0.315	1.500	92.272			
11	0.261	1.243	93.515			
12	0.244	1.161	94.675			
13	0.210	1.000	95.675			
14	0.191	0.912	96.587			
15	0.162	0.770	97.357			
16	0.157	0.749	98.106			
17	0.104	0.493	98.599			
18	0.098	0.466	99.065			
19	0.091	0.434	99.499			
20	0.069	0.327	99.826			
21	0.036	0.174	100.000			

5.8 Inner model

The significance of the structural model relationships was assessed using a non-parametric bootstrapping procedure with 5,000 resamples, as recommended by Hair et al. (2019).

Table 10 Path coefficient

	<i>Original sample</i>	<i>T statistics</i>	<i>P values</i>
CCA -> PU	0.474	6.303	0.000
PEU -> IAL	0.488	7.257	0.000
PEU -> PU	0.404	5.156	0.000
PU -> IAL	0.408	5.929	0.000
TC -> CCA	0.744	16.424	0.000

From the results shown in Table 10, we can see that the path coefficients confirm the hypothesis; all coefficients are statistically significant as all T-stats > 1.96 and P-values < 0.05 .

Indeed, it is evident from Table 11 that the R-square values are more than 0.5 which shows that the model has a moderate to strong explanatory power. Hair et al. (2019) considers that the score of R^2 above 0.75 is strong, 0.50 is moderate and 0.25 is weak.

Table 11 R-square

<i>Variables</i>	<i>R-square</i>
Cloud computing ability	0.554
Intention to adopt LAT	0.703
Perceived usefulness	0.665

Table 12 shows that relationships such as CCA \rightarrow PU, PEU \rightarrow PU, PU \rightarrow IAL and TC \rightarrow CCA exert even moderate effects, while the only strong effect is PEU \rightarrow IAL (0.355), based on Hair et al. (2019). criteria. This suggests that these variables contribute significantly to the model.

Table 12 F-square

	<i>f-square</i>	<i>Criteria</i>
CCA \rightarrow PU	0.323	Moderate
PEU \rightarrow IAL	0.355	Strong
PEU \rightarrow PU	0.235	Moderate
PU \rightarrow IAL	0.248	Moderate
TC \rightarrow CCA	1.242	Moderate

All Q^2 predict values shown on Table 13 are more than 0, i.e., indicate predictive relevance. According to Hair et al. (2019), the model is likely to have strong predictive power for dependent variables when the Q^2 predict is above 0.

Table 13 Q-square

<i>Variables</i>	<i>Q² predict</i>
Cloud computing ability	0.550
Intention to adopt LAT	0.654
Perceived usefulness	0.621

Table 14 Collinearity statistics

	<i>CCA</i>	<i>IAL</i>	<i>PEU</i>	<i>PU</i>	<i>TC</i>
CCA				2.084	
IAL					
PEU		2.259		2.084	
PU		2.259			
TC	1.000				

All values of VIF, as indicated in Table 14 are less than 3 illustrating the absence of multicollinearity issues (Hair et al., 2019). The predictor variables are independent, overall the model is stable and CCA has a VIF of 1.000 and other relationships are in the range of 2.084 to 2.259.

5.9 Model fit

Table 15 shows that the value for the SRMR was 0.096 and it lies within the acceptable range (0.08–0.10) as stipulated by Hair et al. (2019). This shows the model fits reasonably.

Table 15 Model fit

<i>Estimated model</i>	
SRMR	0.096

5.10 Hypothesis test

Table 16 shows that all path coefficients (O) are positive with T statistics > 1.96 (P = 0.000) with respect to all the relationships in the model. This means that each of the independent variables has significance to its dependent variable.

Table 16 Total effects

	<i>Original sample (O)</i>	<i>T statistics (O / STDEV)</i>	<i>P values</i>
CCA -> IAL	0.194	4.160	0.000
CCA -> PU	0.474	6.303	0.000
PEU -> IAL	0.654	12.503	0.000
PEU -> PU	0.404	5.156	0.000
PU -> IAL	0.408	5.929	0.000
TC -> CCA	0.744	16.424	0.000
TC -> IAL	0.144	3.822	0.000
TC -> PU	0.353	5.414	0.000

6 Discussion

In this study, the analysis of student behaviour refers to the researchers' examination of students' perceptions and adoption patterns toward cloud-based LAT, while the questionnaire responses solely reflect students' experiences as end-users. The study aimed to assess the integration of cloud computing for adopting and using learning analytics tool (LAT) in higher education using TAM as the framework of the study. The findings provide strong empirical support for the model. In addition, it further adds to the literature by emphasising the importance of students' knowing their cloud computing in spite of there being literature that highlight this aspect for students in social sciences and humanities disciplines.

6.1 Instrument validation of the measurement model (RQ1)

This study also aimed to validate the measurement instrument used to assess TC, CCA, PU, PEU, and intention to adopt LAT (RQ1). The results of the measurement model evaluation indicate that the instrument demonstrates satisfactory validity and reliability. All indicator loadings exceed the recommended threshold of 0.70, confirming strong indicator reliability. In addition, all constructs achieved AVE values above 0.50, indicating adequate convergent validity and confirming that the constructs explain more than half of the variance of their respective indicators.

Additional discriminant validity was demonstrated via the HTMT ratio. None of the HTMT values exceeded the conservative threshold value of 0.85, indicating that each construct is distinct from one another at the empirical level and captures a unique conceptual domain. As presented in Table 2, reliability analysis through Cronbach's alpha and composite reliability also exhibited values beyond the suggested cut-off levels for all variables, indicating strong internal consistency. These results are consistent with the measurement model evaluation guidelines (Hair et al., 2019).

In addition, Harman's single factor test was used to assess potential CMB. Though the first factor accounted for over 50% of the total variance, Hair et al. (2019) emphasise that this test is a preliminary diagnostic and it serves to overestimate common method effects. We used procedural remedies and rigorous data screening to reduce such bias. Collectively, the findings validate the measurement instrument and suggest high reliability of measures for all constructs used here, which ensures that the structural relationships investigated in this study can be interpreted with adequate degrees of confidence.

6.2 Cloud computing integration and the effectiveness of LAT (RQ2)

Results showed that accessibility of the cloud computing boosts PU and also PEU. The groundwork laid by cloud computing, which provides a technological infrastructure, is the technology open to higher education that shows how LAT's function fluence as an agent of transformation makes direct impact. These students blend multiple learning resources, administer data storage and perform analyses. This is why this feature add extends and enhances usage of LAT. Furthermore, it also ensures that LAT will help you in your academics which is a good thing.

These results confirm previous research on how cloud technologies are revolutionising education. Applications in education that process and analyse large volumes of data need to be scalable, extensible and collaborative. These key features for success are not present in traditional e-learning systems but they can be seen in LAT solutions when offered via the cloud. Cloud-based LMS can make it easier for students to access course materials, while real-time data analytics can help ensure that students are able to keep better track of their progress. In this paper, the focus becomes on cloud integration, emphasising how it benefits LAT usage and adoption in higher education institutions.

6.3 Influence of PU and ease of use on adoption intention (RQ3)

The structural model demonstrates that PU and PEU can both accurately predict the extent to which students will adopt LAT, with PEU being most relevant. The structural model analysis results indicate that PEU positively and significantly influences the IAL. Indeed, it can be seen that with PEU having the highest effect power in our model as illustrated through its f-square value of (0.355). More interesting however is the fact that PEU is the strongest predictor; this would mean if LAT are to be successfully adopted developers need to focus more on designing intuitive user-friendly interfaces as opposed to trying to cram in the most features possible. This matches the truth that students are more inclined to work with data-driven tools if there's a low technical barrier for them to be able to pay their fees.

This aligns with several major components of the TAM (Davis, 1991), which posits that PEU is consistently a dominant factor for individuals when adopting during early adoption stages. That is important in order for the design not to require too much deep thinking about – especially as relates to higher education, where students are on so many different digital platforms. Usability-based designs help to detect technical problems causing students to hesitate from using LAT, and thus they would involve them in their academic life (Davis, 1991; Mukred et al., 2024).

This research also highlights the relevance of human-computer interaction concepts to the design of self-proctoring technology. Students are much more likely to use a cloud-based application when it comes to storing or sharing their work in some way. There is no learning curve using the software, it is fairly intuitive. This will really affect companies that are looking to adopt LAT.

6.4 The role of students' cloud computing abilities (RQ4)

These results confirm that students with strong cloud computing skills have a greater knowledge of PU and PEU. It reaffirms the need to teach digital literacy so students can understand what these concepts mean. High skilled students managing cloud services are more likely to perceive LAT as beneficial. These skills are in virtual collaboration, data security and resource consolidation. Students possessed with these capabilities were also more likely to perceive LAT as easy to use.

This extends previous work on TAM by identifying cloud computing expertise as an important external variable that indirectly influences adoption intentions through PU and PEU. Previous studies often examined general computer self-efficacy, but this study builds on that idea by focusing on competencies that are specific to the cloud. This description highlights that students must have a strong understanding of cloud literacy for LATs to be deployed successfully. This requirement is primarily due to the use of cloud-based infrastructures.

6.5 Theoretical and practical contributions

This research contributes to the extant body of knowledge by introducing cloud computing as a domain-specific antecedent of PU and PEU in decision support systems (DSS), thereby expanding the TAM. This enhancement contributes to the growing body of literature that positions the TAM within emerging digital learning environments,

particularly in educational systems that rely on cloud computing resources (Gupta et al., 2022; Mukred et al., 2024).

From a pragmatic perspective, the findings indicate that higher education institutions should consider allocating resources to cloud literacy training to empower students to effectively engage with cloud-based systems (Al-Madhagy et al., 2021). In addition, it is important for the creators of LAT to focus on usability and develop systems that are easy to use and accessible by users in order to increase acceptance (Castillo-Vergara et al., 2022). Hence, there is encouragement for institutions to effectively use cloud infrastructure to enable data-driven decision making that supports the educational process and collaborative learning (Rahhali et al., 2021). Moreover, incorporating LAT within current academic functions like performance assessment and course management can make it more frequently used and embraced (Lang et al., 2017).

This research adds to the existing literature by identifying cloud computing in DSS as domain-specific predecessors that can be examined empirically for PU and PEU, which will add value to TAM construct. This advancement adds a growing line of research that applies TAM for emergent digital learning spaces, specifically in fields where education tools are formed on cloud computing resources.

From a practical standpoint, the findings suggest that higher education institutions should:

- 1 Make an investment in cloud literacy instruction to guarantee that students can interact with cloud-enabled systems efficiently.
- 2 Make sure that systems are easy to use, accessible, and involve little technical work by giving usability a priority in LAT design.
- 3 Make use of cloud infrastructure for data-driven educational decision-making, scalability and collaborative learning.
- 4 To further emphasise LAT's utility and acceptability, integrate it with current academic operations, such as performance monitoring and course administration.

6.6 Limitations and future research

Despite the significant findings, this study has several limitations that should be acknowledged. First, the sample size of 155 students from a single institution may limit the generalisability (external validity) of the results to the broader population of higher education students. Future studies should aim for a larger, more diverse sample across multiple geographic regions and disciplines to validate the model's robustness.

Second, this study gave more attention to 'behavioural intention' than 'actual usage'. Even if intention is a solid predictor of behaviour according to the TAM, the use gap still falls in between the student's intent to employ cloud-based LAT and engagement with that platform. To extend beyond self-reported metrics, future research should also address this discrepancy by including objective usage data, system access logs, platform analytics and activity trackers.

Third, the study is cross-sectional, which captures data at a single moment in time. As technology adoption does not happen in an isolated event but rather as a process, we recommend to adopt a longitudinal approach to observe how the increasingly experienced students' perceptions of what constitutes 'CCA' and 'PU' change over time. Lastly, this

study only examined the student perspective, therefore adding educator and/or administrator perspectives could lend to a more robust understanding of institutional challenges and/or pedagogical advantages which exist through implementation of LAT via cloud technology.

7 Conclusions

It is found that cloud computing adoption in LAT contexts-significantly influenced by being user-led readiness and positive perceptions. This is one of the prerequisites for it to be integrated. Yet, with respect to increases in performance and outcomes on the system-wide arena a common metric of effectiveness it lacks. Integration is still open and needs further empirical evidence to have an impact on the field improve the educational quality as they foster academic participation and allow data-driven decision-making. All of these four research questions are in the affirmative answered by the research. First, the direct impact of cloud enabler on LAT through PEU and usefulness regarding proficiency is greatly validated. Second, PU and PEU have significant impacts to students' intention of using LAT, still where the usability has the strongest effect. Third, students with high cloud computing proficiency perceived LAT attitudes positively, indicating technology know-how can promote adoption.

Practically, these findings suggest two key implementation strategies for higher education institutions considering the adoption of LAT:

- 1 strengthening of standards in technology and in cloud computing with measures such as training, workshops and tools in the real context
- 2 design of the system is emphasised to be used through usability guarantee ensuring intuitive interfaces, user-friendly features, support always on.

By addressing both technological preparedness and usability, institutions can encourage stronger LAT adoption and promote data-driven learning methodologies in Southeast Asia and other regions.

Ease of use heavily influences willingness to adopt LAT, underscoring the importance of clarity in design and support. Developing from TAM, this work emphasises direct access within cloud-centric LAT schemes while staying focused on central concepts. When users identify tangible benefits, institutions cannot stop at seamless functioning – they need to demonstrate specific advantages such as instant feedback or personalised learning pathways. Results suggest feasible deployment paths yet indicate TAM remains salient among universities in Southeast Asia.

In short, cloud-based LMS platforms integration, collaborative tool and scalable storage confirm that cloud technologies improve PEUs and PUs in various degrees and have real-world metrics on LAT effectiveness and student behaviour. This encompasses more structure, and autonomy, improved virtual collaboration and higher preparedness for industry-oriented competencies. Accordingly, not only does cloud computing enable the adoption of LAT, but it also improves its successful implementation and sustainability in education. Furthermore, the measurement tool used in this study was factually verified and showed satisfactory reliability and validity scores, thus represents a strong basis to investigate cloud-based learning analytics adoption in higher education.

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References

- Al-Madhagy, T-H.G. et al. (2021) ‘Software as a service (SAAS) cloud computing: an empirical investigation on university students’ perception’, *Interdisciplinary Journal of Information, Knowledge, and Management*, Vol. 16, pp.213–253 [online] <https://doi.org/10.28945/4740>.
- Castillo-Vergara, M. et al. (2022) ‘Technological acceptance of Industry 4.0 by students from rural areas’, *Electronics (Switzerland)*, Vol. 11, No. 14 [online] <https://doi.org/10.3390/electronics11142109>.
- Changchit, C., Cutshall, R. and Changchit, C. (2022) ‘An empirical study to examine drivers of personal cloud computing usage’, *Journal of Electronic Commerce in Organizations*, Vol. 20, No. 1 [online] <https://doi.org/10.4018/JECO.298642>.
- Cohen, J. (1988) *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed., Lawrence Erlbaum Associates, Hillsdale, NJ.
- Davis, F.D. (1991) ‘User acceptance of information technology: system characteristics, user perceptions and behavioral’, *International Journal of Man-Machine Studies*, Vol. 38, No. 3, pp.475–487.
- Efrianova, V. et al. (2024) ‘Formative assessment of student’s academic achievements in mobile learning environments’, *International Journal of Interactive Mobile Technologies*, Vol. 18, No. 11, pp.52–63 [online] <https://doi.org/10.3991/IJIM.V18I11.49045>.
- Gupta, C., Fernandez-Crehuet, J.M. and Gupta, V. (2022) ‘Measuring impact of cloud computing and knowledge management in software development and innovation’, *Systems*, Vol. 10, No. 5 [online] <https://doi.org/10.3390/systems10050151>.
- Hair Jr., J.F. et al. (2019) *Multivariate Data Analysis*, 8th ed., Cengage Learning, Hampshire.

- Hassan, A. et al. (2022) ‘To adopt or not to adopt? The determinants of cloud computing adoption in information technology sector’, *Decision Analytics Journal*, Vol. 5 [online] <https://doi.org/10.1016/j.dajour.2022.100138>.
- Kavis, M.J. (2014) *Architecting the Cloud: Design Decisions for Cloud Computing Service Models (SaaS, PaaS, and IaaS)*, John Wiley & Sons, Hoboken, New Jersey.
- Khasawneh, M.A.S. (2024) ‘The effectiveness of cloud computing in developing critical thinking skills among early childhood students’, *International Journal of Data and Network Science*, Vol. 8, No. 4, pp.2459–2468 [online] <https://doi.org/10.5267/j.ijdns.2024.5.012>.
- Lang, C. et al. (2017) *Handbook of Learning Analytics*, Society for Learning Analytics Research (SoLAR) [online] <https://doi.org/10.18608/hla17>.
- Latorre-Coscolluela, C., Sierra-Sánchez, V. and Vázquez-Toledo, S. (2025) ‘Gamification, collaborative learning and transversal competences: analysis of academic performance and students’ perceptions’, *Smart Learning Environments*, Vol. 12, No. 1 [online] <https://doi.org/10.1186/s40561-024-00361-2>.
- Lavidas, K., Apostolou, D. and Papadakis, S. (2022) ‘The effects of social desirability on students’ self-reports in two social contexts: lectures vs. lectures and lab classes’, *Education Sciences*, Vol. 12, No. 3, pp.1–10, <https://doi.org/10.3390/educsci12030148>.
- Liu, Z. and Xu, X. (2022) ‘Studying the impact of health education on student knowledge and behavior through big data and cloud computing’, *Scientific Programming*, Vol. 2022 [online] <https://doi.org/10.1155/2022/4160821>.
- Mukred, M. et al. (2024) ‘The adoption and use of learning analytics tools to improve decision making in higher learning institutions: an extension of technology acceptance model’, *Heliyon*, Vol. 10, No. 4 [online] <https://doi.org/10.1016/j.heliyon.2024.e26315>.
- Musa, A.M.H. (2024) ‘The effect of cloud computing on accounting information quality: empirical study in Saudia Arabia’, *International Journal of Data and Network Science*, Vol. 8, No. 3, pp.1369–1378 [online] <https://doi.org/10.5267/j.ijdns.2024.4.006>.
- Naamane, Z. (2023) ‘A systematic literature review: benefits and challenges of cloud-based big data analytics’, *Issues in Information Systems*, Vol. 24, No. 1, pp.291–304 [online] https://doi.org/10.48009/1_iis_2023_125.
- Rahhali, M., Oughdir, L. and Jedidi, Y. (2021) ‘E-learning recommendation system for big data based on cloud computing’, *International Journal of Emerging Technologies in Learning*, Vol. 16, No. 21, pp.177–192 [online] <https://doi.org/10.3991/ijet.v16i21.25191>.
- Rodríguez Lera, F.J. et al. (2021) ‘Measuring students acceptance and usability of a cloud virtual desktop solution for a programming course’, *Applied Sciences (Switzerland)*, Vol. 11, No. 15 [online] <https://doi.org/10.3390/app11157157>.
- Tülübaş, T. (2023) ‘A holistic investigation of the relationship between digital addiction and academic achievement among students’, *Participatory Educational Research*, Vol. 10, No. 4, pp.2006–2034.
- Wang, Y. et al. (2022) ‘Research on abnormal behavior prediction by integrating multiple indexes of student behavior and text information in big data environment’, *Wireless Communications and Mobile Computing*, Vol. 2022 [online] <https://doi.org/10.1155/2022/1902155>.