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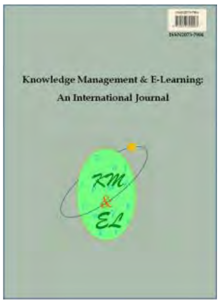

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Evaluating the impact of cloud e-learning in higher education: An empirical investigation

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Abstract: The motivation for conducting this study is to investigate the potential of Cloud e-learning to address the high-cost and high-complexity challenges of conventional learning methods for the upgraded learning processes in higher education. The overall direction of this research is driven towards how the actual usage of Cloud e-learning module affects students' perceptions and academic performance. A Cloud e-learning module is designed and developed to promote optimised resource utilisation in the e-learning processes in higher education. A pretest-posttest method was adopted to study the impact of Cloud e-learning usage among students and whether the diffusion of Cloud e-learning has caused a change in students' perceptions. The pretest-posttest results and students' academic performance were then analysed to examine the impact from the actual usage of Cloud e-learning module. The findings reveal that the change of students' perceptions is time variant, indicating students' mixed perceptions on the usage of Cloud e-learning module. Analysis evidently reveals that the use of Cloud e-learning improved students' learning performance in theoretical subjects. This research is useful to educators and ICT practitioners in making informed decisions in adopting the right ICT infrastructures to support e-learning in higher education.

Keywords: Cloud e-learning; Pretest-posttest; Academic performance; Quantitative; Survey

Biographical notes: Lillian Wang is a lecturer attached to the School of Information Technology at Monash University Malaysia. She is also a professional technologist (Ts.) and a graduate technologist, awarded by Malaysia Board of Technologists (MBOT). Her research interests are Cloud e-learning, educational technology, AR/VR & IoT in education.

1. Introduction

The outbreak of the COVID-19 pandemic in the beginning of 2020 has greatly affected people in every aspect. Education is no exception. The pandemic has exposed the inadequacies of our education system during the drastic transition from traditional physical classes to full online classes (Schleicher, 2020; Tang et al., 2021). The country's lockdown or restriction of movements in response to the pandemic has badly interrupted the conventional teaching and learning activities in universities and higher education. Amid the COVID-19 pandemic, e-learning was abruptly adopted in many countries to address the closure of higher learning institutions.

A recent study conducted by Looi (2023) examined the future learning preferences of undergraduates and identified predictors of their preferred learning mode. The survey involved 251 business undergraduates from a Malaysian private university during the closure of institutions. Findings revealed that 57% of respondents preferred blended learning in the future, aligning with similar findings in other studies (Zhou et al., 2020; Abbasi et al., 2020). The involuntary adoption of e-learning during the pandemic reduced psychological barriers to online learning, leading to a recognition of the advantages of combining modalities for future learning experiences. To accommodate these preferences, institutions should incorporate more e-learning components into conventional classroom settings.

In this inevitable situation, continuous improvements of student learning outcomes through effective action plans is imperative in order to optimise the learning outcomes of the courses offered in the higher institutions. The use of digital devices installed with various applications such as Zoom, Google Meet, WhatsApp, Facebook, YouTube, etc. have become exceptionally important in sustaining people's way of living, communication, social activities and education approaches (Ahmad et al., 2020; Tiyar & Khoshsima, 2015). Resulting from the swift transitions from conventional teaching methods to the extensive usage of digital technologies due to the pandemic, e-learning has heavily supported learning processes with information and communication technology (ICT) through the Internet, and Internet technology has been extensively used as an intermediate to design, implement and support learning processes, particularly in higher education. Many higher education institutions (HEIs) have migrated from the conventional learning methods to completely online and e-learning processes (Elgelany & Alghabban, 2017; Tang et al., 2021). The feasibility of teaching and learning has been progressively revisited with the aims to reduce the academic disruption in HEIs (Hart et al., 2019; Shah & Barkas, 2018). To support such progression, HEIs must have adequate ICT infrastructures and huge investments, and this has become a challenge to many universities in providing advanced ICT for their staffs and students (Alharthi et al., 2017; Qasem et al., 2020).

Cloud computing has appeared to be a promising solution to the issues associated with reducing ICT costs (Bosamia & Patel, 2016; Qasem et al., 2020). The usage of Cloud based web or mobile applications is growing among HEIs (Ahmad et al., 2020; Ashtari & Eydgahi, 2017). The adoption of Cloud Computing in e-learning is redefining ICT infrastructure in HEIs and infusing Cloud Computing benefits such as scalability (Divya & Prakasam, 2015; Rajput & Deora, 2017), reusability of learning content (Bosamia & Patel, 2016) and knowledge sharing in a global scale (Alajmi & Sadiq, 2016; Bosamia & Patel, 2016).

Cloud computing is no doubt an innovative solution to address the high-cost and high-complexity challenges of the conventional e-learning (Ahmad et al., 2020; Qasem et al., 2020). However, there is no guarantee for the adoption of such a technically advanced technology due to its complex migration process. The willingness to adopt a new technology is often influenced by various factors such as individual attributes, system characteristics, organisation and social interactions (Javidnia et al., 2012; Lau & Woods, 2008a; Röcker, 2010). Thus, it is crucial to understand the factors of one's willingness to adopt Cloud e-learning in HEIs. This has inspired more research on Cloud e-learning's impact to be carried out to study how Cloud e-learning can be integrated and utilised in the context of higher education, how students respond to Cloud e-learning and whether they are using Cloud e-learning in the expected ways.

The motivation for conducting this study is to investigate the potential of Cloud e-learning to address the high-cost and high-complexity challenges of conventional learning methods for the upgraded learning processes in higher education. To the best of my knowledge, limited empirical research has been carried out to investigate the impact of Cloud e-learning module usage among students in higher education. Hence, findings obtained from this study can lead to new insights on the impacts of Cloud e-learning in higher education.

Learners in twenty-first century are visually sophisticated and accustomed to digital media. The increasing tendency towards interactive video content creation and collaborative technologies seems to validate the beliefs that enhanced educational technologies and learning systems help engaging learners in learning and improving learning productivity (Chunwijitra et al., 2013). Thus, conventional e-learning methods are no longer adequate to meet the upgraded requirements of e-learning particularly in the higher education (Ahmad et al., 2020; Bosamia & Patel, 2016; Johnson et al., 2016; Karim & Goodwin, 2013; Riahi, 2015). The great demand for e-learning content especially the multimedia element requires rapid storage growth and dynamic concurrency demands, which is not sufficient to be handled by the conventional e-learning methods. The production of multimedia e-learning content is time-consuming and costly, therefore taking advantage of the reusability and shareability of Cloud e-learning content is necessary for optimised resource utilisation. The rationale for conducting this study is the potential of Cloud e-learning to address the high-cost and high-complexity challenges of conventional learning methods for the upgraded learning processes in higher education.

2. Literature review

IT plays a very crucial role in the education field. Over the past few decades, e-learning has become a widely recognised and employed educational technology. However, in the digital era where new technologies are emerging in a rapid and drastic manner, conventional e-learning methods are becoming insufficient to deliver the requirements of upgraded e-learning methods particularly in the higher education (Ahmad et al., 2020; Bosamia & Patel, 2016; Johnson et al., 2016; Karim & Goodwin, 2013; Riahi, 2015). Higher education is highlighting more on higher order learning skills and outcomes which involves a major transformation in knowledge and communication-based society (Thomas, 2011). Fortunately, Cloud computing has emerged to be the finest solution (Bosamia & Patel, 2016). Innovative e-learning pedagogies embracing Cloud Computing can be facilitated to enable more effective knowledge transmission and engage in lifelong learning.

2.1. Emergence of cloud computing in e-learning

Cloud e-learning is the employment of Cloud Computing into e-learning as its future infrastructure to build a flourishing and sustainable e-learning (Ahmad et al., 2020; Qasem et al., 2020; Riahi, 2015). In order to appreciate how Cloud Computing is unique and better from other forms of computing, the potential values and key benefits of employing Cloud Computing in e-learning are addressed.

Karim and Goodwin (2013) discussed the emergence of Cloud Computing in e-learning and advantages of embracing Cloud Computing in e-learning. A sustainable e-learning for upgraded learning process requires a proper and comprehensive infrastructure, which also means high cost is needed for its implementation. Many educational institutions lack the proper infrastructure for adopting e-learning due to the high cost of infrastructure and implementation. Therefore, an innovative solution is needed to cater for the upgraded learning requirements (Bosamia & Patel, 2016; Karim & Goodwin, 2013; Mohammadi & Emdadi, 2014; Saidhbi, 2012). Delivering learning content effectively at anytime and anywhere with a reduced amount of investment is desired by most educational institutions (Divya & Prakasam, 2015). Employing Cloud computing in e-learning reduces cost and time needed to build and maintain the infrastructure by providing software and infrastructure as a service (Johnson et al., 2016; Karim & Goodwin, 2013; Mohammadi & Emdadi, 2014).

Riahi (2015) reviewed e-learning systems based on Cloud computing followed by discussion on advantages of Cloud e-learning (Patel & Chaube, 2014; Viswanath et al., 2012). Cloud e-learning requires only Internet enabled devices with minimal configuration. Since data is stored in the Cloud, storage space is no longer a concern as it can be bought as a service and paid as per use. Concerns on Cloud e-learning performance can be dropped since most of the e-learning applications run in the Cloud. Performance of Cloud e-learning is guaranteed as long as Internet connection is stable. Instant e-learning software updates are always available and automatically updated. In addition to that, compatibility of document format is no longer an issue since Cloud e-learning applications open files directly from the Cloud.

Bosamia and Patel (2016) presented key benefits of Cloud computing for e-learning. When Cloud computing is employed in e-learning, learning applications can be conveniently run from Cloud through Internet enabled devices, and learning processes can be facilitated through a variety of activities. Cloud e-learning provides a flexible learning environment where learners can learn any time, everywhere, and at their own pace (Qasem et al., 2019). Cloud e-learning content is easily accessible; thus, learning is on a global scale. Besides that, Cloud e-learning accommodates different learning styles and levels, which allows wide learning participation and increases learning engagement. Learners have the flexibility to select learning content that meet their level of knowledge and interest, thus learning motivation is increased and stress level is reduced. Evidence-based strategies in Cloud e-learning enable immediate feedback, progress tracking, and real time communication between instructors and learners, or among learners. Interactivity often engages learners. The reusability of Cloud e-learning content enables easy edit and update; and the shareability of Cloud e-learning content enables high portability, and easily shared among learners at any time. In sum, Cloud Computing gives a positive impact on educational system as a whole.

Ahmad et al. (2020) proposed a Cloud-based mobile learning adoption model to promote sustainable education. This research is timely as sustainability is the most essential key in view of the pandemic situation. They have identified critical success factors (CSFs) to study the adoption impact of the Cloud-based mobile learning. The results and discussions of the study validated the adoption of Cloud-based mobile learning as one of the best platforms to achieve cooperative and collaborative learning.

Qasem et al. (2020) presented a conceptual model on the continuance use of Cloud Computing in HEIs. They extended the IS continuance model by adopting constructs from IS success model and IS discontinuance model. Additional constructs such as collaboration and regulatory policy were added to predict continuance use of Cloud computing in education context. The study provided a comprehensive assessment for the adoption and intent of decision makers to utilise Cloud computing in HEIs.

Bazelais et al. (2022) investigated the impact of blended learning strategies, particularly two-stage quizzes and peer formative feedback in the context of understudied pre-university science students within CEGEP education. Their findings indicated that the implementation of robust quizzes and peer formative feedback, positively influences learning outcomes and performance in a cumulative standardized final exam. The treatment group, exposed to the quiz and feedback approaches, significantly outperformed the control group in the final exam, indicating that these approaches enhances long-term retention and fosters lasting learning outcomes compared to traditional approaches. Frequent low-stakes testing, such as quizzes, and peer formative feedback play a crucial role in the effectiveness of blended learning. These practices motivate students, shape their study approaches, and provide valuable information for improvements. These findings align with prior studies that highlight the positive impact of quizzes and peer feedback in the science field.

2.2. Implication of the cloud e-learning in this research

Cloud e-learning involves accessing educational materials and resources from a remote server via the Internet. In contrast, traditional e-learning refers to the use of locally installed software or learning management systems (LMS) to deliver educational content. The main difference between Cloud e-learning and traditional e-learning is the way that the educational content is delivered and accessed. With Cloud e-learning, learners can access the content from anywhere with an internet connection and a compatible device, such as a laptop or smartphone. This allows for more flexibility in terms of time and location, making it easier for learners to fit learning into their busy schedules. Traditional e-learning, on the other hand, requires learners to access the educational content from a specific location, such as a school or workplace, and often requires specialized software or hardware to access the content. This can limit the flexibility of learning, making it more difficult for learners to fit learning into their schedules. With this notation, it is revealed that Cloud e-learning offers greater flexibility and accessibility compared to traditional e-learning, making it a better choice for learners who want to learn on-the-go and on their own schedules.

Embracing Cloud Computing into an e-learning enhances the interoperability of learning objects by allowing the integration of different e-learning standards. The concept of Cloud e-learning delivers a cost-effective solution to educational institutions, particular in the current challenging pandemic situation. With all the key benefits, Cloud computing is a significant breakthrough for e-learning sustainability. Based on the previous definitions and the notations of all the key benefits discussed, a definition for Cloud e-learning is derived and customised for this study. Thus, in this study, Cloud e-learning is defined as "the employment of Cloud computing into e-learning as a modern scalable infrastructure to promote optimised resource utilisation and to deliver flexible learning."

3. Method

A pretest-posttest research was adopted to study the impact of Cloud e-learning usage among students and whether the diffusion of Cloud e-learning has caused a change in students' perceptions. Students' perceptions may change over time (Bhattacherjee & Premkumar, 2004). Gaining a first-hand experience on the Cloud e-learning could have led students to a different perception from the initial perception. Pretest-posttest research is "a common experimental method where participants are studied before and after the experimental manipulation to measure the degree of change occurring as a result of intervention" (Dimitrov & Rumrill, 2003). In pretest-posttest design, a contrast between means in which the pretest and posttest means measured with the same precision is computed (Kirk, 2013). In other words, each student was observed twice on a relevant variable to observe the inferred changes due to the diffusion of Cloud e-learning.

3.1. Sampling

In this study, non-probability convenience sampling approach was selected. Since probability sampling is time and cost consuming due to large sample requirement (Hair et al., 2010), and it is difficult to choose a sample randomly (Alreck & Settle, 2003), therefore this study sough experienced online learning users from IT faculty at a private university in the southern region of Malaysia. Undergraduate students who enrolled in two IT subjects, namely Knowledge Management (KM) and Data Communications & Networking (DCN), irrespective of age, gender, year of study and IT major partaken in the survey voluntarily. These students were conveniently accessible to the researcher. More importantly, they possessed basic knowledge and ability in handling educational technology, thus suited to represent a body of computer literate students who would be interested to adopt Cloud e-learning in their studies. It is believed that with the acceptance of Cloud e-learning as a learning approach, it can be generalised and expanded to cater other courses in the university and possibly to other HEIs. Data collection was completed when an adequate response obligatory for statistical analysis is achieved.

3.2. Research design and procedure

A Cloud e-learning module was developed for the pretest-posttest experiment. Prior to the experiment, students who enrolled in Knowledge Management (KM) and Data Communications & Networking (DCN) subjects were given an introduction on the Cloud e-learning module and its relevance to their curriculum. They were going to learn via the Cloud e-learning module throughout the trimester. They were being informed that they would be completing a survey by the end of the trimester to input their states of mind after using the Cloud e-learning module. Following the introduction and explanation session, students were given a pre-test survey to gauge their initial perceptions on Cloud e-learning.

Students were given approximately three months (twelve academic weeks) to have a hands-on experience with Cloud e-learning module. In the learning process, students can flexibly browse the learning content available in different formats, do assignment collaboratively, complete real-time quizzes, etc. Proper guidance was provided along the way to guarantee an optimised experience on the Cloud e-learning module. The experiment was concluded after three months, and a posttest assessment was conducted to gauge students' perceptions once again. After a three-month hands-on experience, students' perceptions pertaining the factors on behavioral intention and actual usage of Cloud e-learning could be more accurately evaluated.

Since this is a non-probability convenience sampling, researcher is able to conveniently approach every student in KM and DCN class to ensure the students have participated the survey properly and voluntarily. All the 285 students gave full cooperation and answered the questionnaire to input their perceptions after using the Cloud e-learning module, thus the response rate of the survey was 100%. Data were then fed into SmartPLS 3 for statistical analysis.

Last but not least, students' academic performance for two batches of students from KM and DCN subjects were compared to investigate the impacts of the use of Cloud e-learning module. A quasi-experimental research design with intact groups was adopted. A quasi-experimental design by definition lacks random assignment and it is an experiment that is carried out after the groups have been formed or the groups are pre-existing (White & Sabarwal, 2014). It also promotes natural settings of an experiment because a random reassignment of students might create artificiality in the research setting with the students' knowledge of participation in the experiment (Tan, 2012).

In order to maintain the natural settings of the students, the groups were formed during the students' enrolment into KM and DCN subjects. Due to the administrative constraints such as teaching workload consideration, timetable and venue arrangements, thus the number of students for the groups was beyond the researcher's control. The study used a quasi-experimental design with pre-existing groups to investigate the effects of a Cloud e-learning module on students' academic performance in KM and DCN subjects. The group that experienced the module was designated as the experimental group, while the group that did not was designated as the control group. The experimental group accessed the Cloud e-learning module platform to watch videos and attempt activities and quizzes at their own pace, with their performance evaluated through a final exam. In contrast, the control group learned the subjects through the campus learning management system (MMLS), where PowerPoint slides or reading notes were uploaded, and they attended classes and performed activities and quizzes in class. Their performance was also evaluated through a final exam at the end of the trimester. The instrument used to compare the academic performance is the final exam questions for the respective trimesters. Independent samples *t*-test for two batches of students were analysed to measure students' performance. The final exam questions across the two trimesters were made sure to be similar in syllabus, format and learning outcomes for both subjects.

3.3. Cloud e-learning module design and development

To investigate students' actual usage and whether students' perceptions change over time, a Cloud e-learning module is developed and customised to support Knowledge Management (KM) and Data Communications & Networking (DCN) subjects for testing purpose.

Both KM and DCN are core subjects for IT faculty in the university. Due to the conceptual nature of these subjects, teaching KM and DCN in a conventional way can be very challenging. Therefore, a Cloud e-learning module is developed to facilitate learning for these two subjects. The Cloud e-learning module transforms learning into a personalised learning platform and eventually lead to the achievement of the prescribed learning outcomes of the subjects.

The availability of a wide range of Web 2.0 and Cloud tools has made it relatively easy to build the Cloud e-learning module. The general functions of Cloud e-learning module are similar to that of other learning management systems, such as file sharing (upload and download), announcement, discussion and comments, among others. On top of that, Cloud e-learning module supports additional features and functions to provide more flexibility to students in personalising their learning.

Cloud e-learning objects are available in different formats such as read/write, aural, visual and multimodal to suit different types of learners. Cloud e-learning module allows students to collaboratively work on their assignments, share their additional learning materials, submit their works, and receive feedback or comments from their lecturers and peers. Cloud e-learning module also allows students to take online assessments anytime and receive immediate assessment results. In sum, Cloud e-learning enables a more personalised and interactive learning, which is suited and preferred by the new technology savvy generations. Fig. 1 presents the list of developed Cloud e-learning modules.

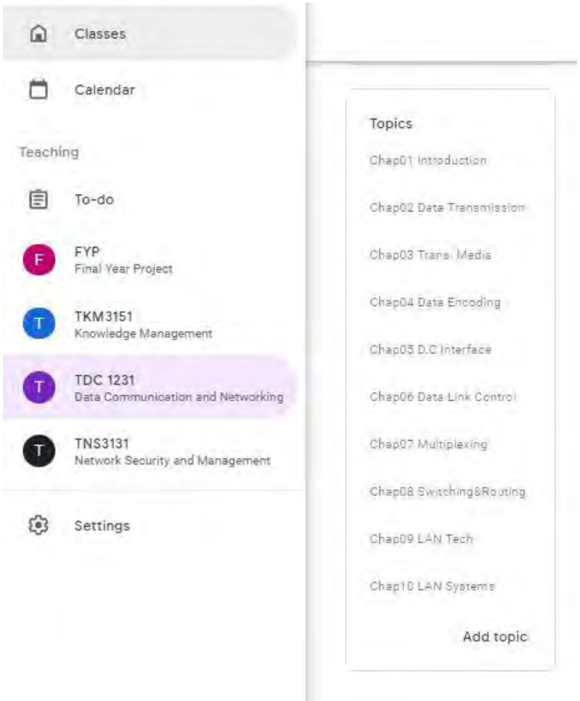

Fig. 1. List of developed cloud e-learning modules

Incorporated into Google classroom is the Blendspace, where all the Cloud e-learning objects are compiled and shared to students. Multiple modes of Cloud e-learning objects are provided in multiple formats and modalities, for example, still infographics, animated diagrams, short videos, interactive web, etc. Fig. 2 presents the compilation of learning content in different modes on Blendspace platform.

Accomplishing the core of the Cloud e-learning framework, learning strategy (i.e., learning objectives, introduction and summary) is incorporated into every module to produce a comprehensive instructional experience. Learning objectives serve as the hub of the lesson by describing the anticipated instructional outcomes after the learners have experienced the Cloud e-learning module.

Learning content, activities and assessment developed in the form of Cloud e-learning objects would assist learners to achieve the learning objectives. EdPuzzle was adopted to develop learning activities for each topic. EdPuzzle is a costless assessment-centred instrument that enables educators and learners to create interactive online videos by inserting either open-ended questions, multiple-choice questions or comments on a video. During the activity, students can watch video and answer some quizzes to enhance their understanding on a particular topic. Fig. 3 presents an example of a complete Cloud e-learning module developed in this study.

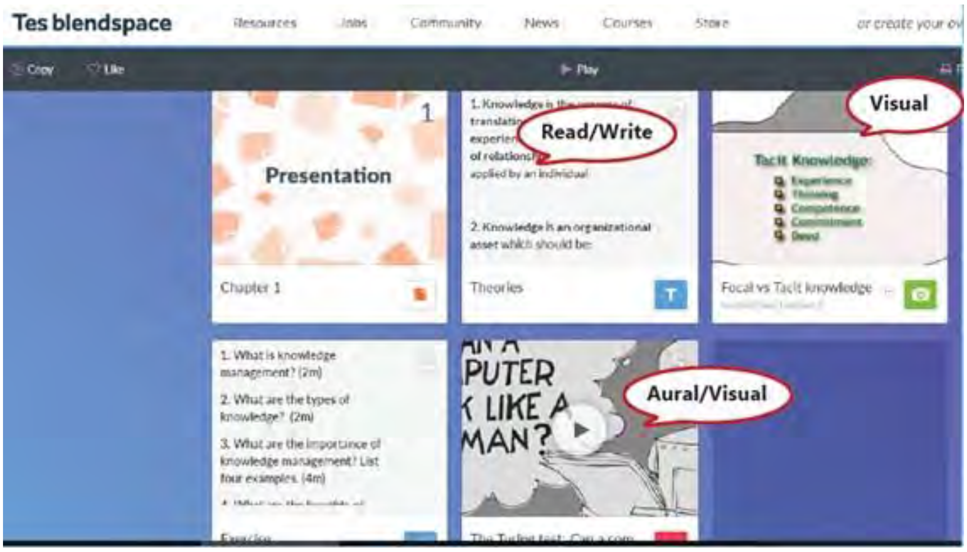

Fig. 2. Compilation of learning content in different modes

The assignment feature in Google Classroom makes use of Google Drive allows lecturers to create and share the assignments and enables students to submit their assignments in a paperless way. Collaborative learning can be effortlessly achieved via G Suite. Students can collaboratively work on the same word document from different devices at the same time via Google Docs. Collaborative learning can be similarly achieved via Google Sheets, Google Slides, etc.

The development of Cloud e-learning module makes full use of educational accessibility and the characteristics of Cloud Computing such as flexibility, reusability, shareability, scalability and availability (Gong et al., 2010; El-Sofany et al., 2013; Rajput & Deora, 2017) which leads to optimised resource utilisation. The previous e-learning modules for KM and DCN subjects were not as flexible, sharable and personalised. It was a conventional learning management system that allows only downloading of lecture notes, announcement and conventional quiz feature. With the newly developed Cloud e-learning module, learning becomes more student-centred, personalised and interactive. The Cloud e-learning objects in different formats accommodate different types of learners. Most importantly, Cloud e-learning module is less expensive and less complex in terms of infrastructure.

3.4. Survey instrument (questionnaire) design and development

A set of seventy-two-question Likert-scale questionnaire was formulated. Likert scale was adopted in this study due to the fact that it is the most universal method for survey collection and the responses are easily quantifiable. Likert scale has been widely used in the educational and social science research (Joshi et al., 2015). All the constructs in the survey were quantified by means of a five-point Likert scale labelled from “Strongly Disagree”, “Disagree”, “Neutral”, “Agree” and “Strongly Agree”, ranging from 1 to 5, respectively. Five-point Likert scale was selected for its low complexity (Sekaran & Bougie, 2016). The standard five-point Likert scale is simple and thus allows students to answer with ease and without confusion. The English written questionnaire was set for self-perceived characteristics. Therefore, the questions were phrased to be of self-understanding of the students. Since the Cloud e-learning module was designed for IT students, the questions were expressed in the context of IT relevance.

Fig. 3. An example of a complete cloud e-learning module

There are four sections in the survey instrument. First section gathers personal and academic information of students. Second section gathers the students' use of digital technology for learning. Third section gathers information on students' experience with e-learning such as average time spent, purpose of using e-learning, etc. Fourth section consists of twelve groups of questions to measure twelve constructs that aims to gather perceptions of students on Cloud e-learning.

Eleven exogenous constructs (system quality, content quality and pedagogical quality, perceived usefulness and perceived ease of use, social influence and facilitating conditions, attainment value and utility value, computer self efficacy and enjoyment) that are mapped against five different aspects of technology acceptance factors along with the hypotheses to investigate their associations with the endogenous construct (Intention to Use). System Quality, Content Quality and Pedagogical Quality constructs are adopted to investigate the impact of features and characteristics of Cloud eLearning towards its usage Perceived Usefulness and Perceived Ease of Use constructs are adopted to investigate how students' perceptions affect its usage. Social Influence and Facilitating Conditions constructs are adopted to investigate the impact of supporting roles towards the usage of Cloud e-learning among students. Attainment Value and Utility Value constructs are adopted to investigate how students' subjective values affect the usage of Cloud e-learning. Computer Self Efficacy and Enjoyment constructs are adopted to investigate the impact of students' personal motivations towards the usage of Cloud e-learning among students in higher education. Table 1 shows the constructs mapped to acceptance factors.

System quality aims to obtain students' perception on the technical attributes of the developed Cloud e-learning module, specifically the frequency of errors encountered (Gable et al., 2008; Hamilton & Chervany, 1981), accessibility (Gable et al., 2008; McKinney et al., 2002), controllability (McKinney et al., 2002), flexibility (Bailey & Pearson, 1983; Gable et al., 2008; Hamilton & Chervany, 1981; Iivari, 2005), interoperability (Bailey & Pearson, 1983; Iivari, 2005) and functionality (Gable et al., 2008). It is a crucial implicit expectation that supports the usability of Cloud e-learning module. Content Quality aims to obtain students' perception on the subject matter of Cloud e-learning module. It is related to how well the developed module is tailored to the students' needs. The main attributes of content quality include flow of content, understandability, shareability, searchability, content format and relevancy. Pedagogical Quality aims to obtain students' perception on the impacts of Cloud e-learning strategies and instructional design. The principle of pedagogical quality is the potential effectiveness of Cloud e-learning in fitting and fulfilling goals of learning. The pedagogical attributes include coherence and pedagogy richness, learning context, and support for learning goal.

Table 1
Constructs mapped to acceptance factors

Acceptance factors	Constructs
Features and characteristics of Cloud e-learning	System quality
	Content quality
	Pedagogical quality
Students' perceptions	Perceived usefulness
	Perceived ease of use
Supporting roles	Social influence
	Facilitating conditions
Subjective values	Attainment value
	Utility value
Personal motivations	Computer self-efficacy
	Enjoyment

System quality aims to obtain students' perception on the technical attributes of the developed Cloud e-learning module, specifically the frequency of errors encountered (Gable et al., 2008; Hamilton & Chervany, 1981), accessibility (Gable et al., 2008; McKinney et al., 2002), controllability (McKinney et al., 2002), flexibility (Bailey & Pearson, 1983; Gable et al., 2008; Hamilton & Chervany, 1981; Iivari, 2005), interoperability (Bailey & Pearson, 1983; Iivari, 2005) and functionality (Gable et al., 2008). It is a crucial implicit expectation that supports the usability of Cloud e-learning module. Content quality aims to obtain students' perception on the subject matter of Cloud e-learning module. It is related to how well the developed module is tailored to the students' needs. The main attributes of content quality include flow of content, understandability, shareability, searchability, content format and relevancy. Pedagogical quality aims to obtain students' perception on the impacts of Cloud e-learning strategies and instructional design. The principle of pedagogical quality is the potential effectiveness of Cloud e-learning in fitting and fulfilling goals of learning. The pedagogical attributes include coherence and pedagogy richness, learning context, and support for learning goal.

Perceived usefulness aims to obtain students' perception on the degree to which they believe that using Cloud e-learning would improve their learning productivity. It is relevant to the practicality of Cloud e-learning and its usefulness in students' learning processes. Perceived ease of use, on the other hand, aims to obtain students' perception on the degree which they believe that using Cloud e-learning would be free of cognitive effort, particularly in the learning-how-to-use and human-computer-interaction aspects.

Social influence aims to obtain students' perception on the extent to which they believe that important others think they should use Cloud e-learning. In this context of study, social influence primarily takes form in peer pressure (course mates and friends) and obedience (lecturers) (Colman, 2009). Facilitating conditions aims to obtain students' perception on the degree to which they believe that the university or surroundings provide enough supports and resources to use Cloud e-learning. In this study, facilitating conditions was refined to include resources and supports such as internet access, digital devices and guidelines from lecturers.

Attainment value aims to obtain students' perception on the impacts or importance of doing well in Cloud e-learning, particularly their sense of achievement, sense of confidence and sense of independence. Utility value aims to obtain students' perception on how Cloud e-learning fulfils their current or future goals, such as reduced exam preparation time, improved exam performance, increased learning productivity, etc.

Computer self-efficacy aims to obtain students' perception on their confidence level to use Cloud e-learning based on their skilfulness in handling technology. A review of literature discovered that instruments pertaining various aspects of general computer skills and students' efficacy beliefs with particular software application have been developed and validated (Lau & Woods, 2008b). Besides that, a recent study by Phan (2023) has shown the importance and impact on self-efficacy on online learning, indicating computer self-efficacy for online and e-learning is worth exploring. Lastly, enjoyment aims to obtain students' perception on the degree to which they experience joy when using Cloud e-learning. Enjoyment is believed to be an intrinsic motivation that drives students to use Cloud e-learning when they enjoy exploring the content and features at their own pace and time.

3.5. Pretest-posttest experiment

Students' behavioural intentions were examined via a pretest-posttest experimentation. Initial views of Cloud e-learning were collected in the beginning of the trimester before the pretest-posttest experiment was commenced in KM and DCN subjects (pretest). Experiment involving students from two subjects using the Cloud e-learning module was then commenced for a period of twelve weeks. An assessment of the students' perceptions after using Cloud e-learning module was conducted at the end of the trimester (posttest). Data obtained after the pretest-posttest experiment was then analysed and reported. Paired sample *t*-test was performed to determine substantial differences of the pretest and posttest evaluation.

3.6. Students' performance analysis

To examine the effects of the use of Cloud e-learning module, students' academic performance of two batches of students for KM and DCN subjects were statistically analysed. The independent samples *t*-test was used to determine if there is a significant difference in academic performance between the experimental group and the control group.

Prior to the independent samples *t*-test analysis, an assumption where the variances in the two groups must be similar, i.e., a condition known as homogeneity must be met (Chinna & Choo, 2016). Therefore, the *p*-value of Levene's test for equality of variance is examined at 5% significance level to verify the homogeneity of the two groups.

4. Data analysis and results

Prior to inferential analysis, issues of missing data, straight lining responses, outliers and data normality were addressed. An in-depth examination of the responses exposed a total of 21 responses with missing values and 42 responses with straight lining answers. The remaining 222 responses were then subjected to further examination to detect extreme responses.

4.1. Demographic analysis

Out of the 222 respondents, 157 (70.72%) were males and 65 (29.28%) were females. It is common that male to female ratio is higher in technical courses such as IT and Engineering in higher education. The age of respondents was at the average of 21 years old. Majority of the students were in their first year of study (54.05%), followed by second year (33.33%), third year (11.71%) and fourth year (0.90%). All the respondents were from the IT field, having five different majors, namely Security Technology (ST), Artificial Intelligence (AI), Data Communication and Networking (DCN), Information Technology Management (ITM), and Bioinformatics with the percentage of 38.74%, 31.08%, 14.41%, 11.71% and 4.05%, respectively. Table 2 shows the summary of respondents' demographic profile.

Table 2
Demographic profile of respondents (*n* = 222)

		Count	Percentage
Gender	Male	157	70.72
	Female	65	29.28
Age (years old)	18 and below	1	0.45
	19	17	7.66
	20	74	33.33
	21	51	22.97
	22	34	15.32
	23 and above	45	20.27
Year of study	1st Year	120	54.05
	2nd Year	74	33.33
	3rd Year	26	11.71
	4th Year	2	0.90
IT major	Artificial Intelligence	69	31.08
	Bioinformatics	9	4.05
	Data Communications	32	14.41
	IT Management	26	11.71
	Security Technology	86	38.74

Table 3 presents the e-learning experience of respondents. Out of 222 respondents, 220 (99.10%) had experience in e-learning via Internet-enabled digital devices, indicating that the sample consists of high numbers of technology savvy students. Majority of the respondents (59.01%) spent 1-2 hours a week on e-learning, 27.93% of them spent 3-4 hours per week, and minority (13.06%) spent more than 5 hours per week. Most of the respondents (91.89%) agreed that they had good experience with e-learning, while 8.11% of them felt otherwise.

Table 3
e-Learning experience of respondents (n = 222)

		Count	Percentage
Use digital technology for e-learning	Yes	220	99.10
	No	2	0.90
Average time spent on	0	5	2.25
e-Learning (hours per week)	1-2	131	59.01
	3-4	62	27.93
	5-6	16	7.21
	7 and more	8	3.60
e-Learning experience	Good	204	91.89
	Bad	18	8.11

4.2. Pretest-posttest analysis

To investigate the students' post adoption behaviour and continuance usage of Cloud e-learning in higher education, the paired sample *t*-test procedure was used to test the difference between the pretest and posttest evaluations. The pretest-posttest analysis aims to confirm whether the diffusion of Cloud e-learning has caused a change in students' perceptions.

Data collected from pretest-posttest experiment was first examined to ensure that they do not violate the assumption for conducting paired sample *t*-test. The crucial assumption prior to paired sample *t*-test analysis has to be verified to ensure the data is approximately normal (Chinna & Choo, 2016). After ensuring that no assumptions have been violated, descriptive statistics of means and standard deviations for pretest-posttest constructs were calculated. Lastly, academic performance was measured to strengthen the pretest-posttest analysis.

4.2.1. Descriptive statistics

Table 4 presents the means and standard deviations of constructs from the pretest-posttest evaluations. It is observed that the standard deviation values of all the constructs were less than one for both pretest and posttest scores, inferring that the respondents have consistently rated all the constructs before and after using Cloud e-learning.

From pretest to posttest, the mean values of enjoyment and social influence constructs are higher while the mean values for the remaining constructs are lower. Overall, the mean values showed a slight decrease after using Cloud e-learning. However, since the mean differences are very small and the standard deviations are all less than 1, it should not be of big concern until the paired sample *t*-test is run.

4.2.2. Paired sample t-test

The mean values of pretest-posttest constructs were subjected to paired sample *t*-test to determine the significant differences between the pretest and posttest evaluations. Mean differences are considered significant at $p < 0.05$. Table 5 presents the results of paired sample *t*-test to compare the mean values of pretest-posttest constructs.

Table 4
Means and standard deviations of constructs for pretest-posttest

	Mean		Standard deviation	
Construct	Pretest	Posttest	Pretest	Posttest
System quality	3.813	3.573	0.837	0.885
Content quality	3.780	3.757	0.845	0.786
Pedagogical quality	3.980	3.752	0.819	0.822
Perceived usefulness	3.822	3.690	0.832	0.819
Perceived ease of use	3.892	3.765	0.815	0.793
Enjoyment	3.855	3.926	0.932	0.840
Computer self-efficacy	3.920	3.691	0.819	0.845
Social influence	3.495	3.568	0.956	0.863
Facilitating condition	3.962	3.715	0.877	0.880
Attainment value	3.830	3.658	0.810	0.843
Utility value	3.867	3.675	0.802	0.856
Intention to use	3.830	3.640	0.889	0.924

Table 5
Paired sample *t*-test results

	Paired Differences			
Construct	Mean	SD	*t*-value	*p*-value
System quality*	0.240	0.167	3.518	0.017
Content quality	0.022	0.111	0.480	0.651
Pedagogical quality*	0.227	0.186	2.979	0.031
Perceived usefulness*	0.132	0.102	3.148	0.025
Perceived ease of use	0.127	0.147	2.114	0.088
Enjoyment*	-0.072	0.052	-3.380	0.020
Computer self-efficacy*	0.230	0.147	3.833	0.012
Social influence*	-0.073	0.050	-3.617	0.015
Facilitating condition*	0.247	0.219	2.765	0.040
Attainment value**	0.172	0.095	4.409	0.007
Utility value*	0.193	0.150	3.151	0.025
Intention to use**	0.190	0.078	5.969	0.002

Note. $^{**}p < 0.01$, $^{*}p < 0.05$

4.2.3. T-test results and discussion

The reason for examining the practical significance is to help with more informed and solid decision making regarding an intervention. Paired sample *t*-tests revealed the mean differences to be significant for ten constructs, namely system quality (t = 3.518; p = 0.017), pedagogical quality (t = 2.979; p = 0.031), perceived usefulness (t = 3.148; p = 0.025), enjoyment (t = -3.380; p = 0.020), computer self-efficacy (t = 3.833; p = 0.012), social influence (t = -3.617; p = 0.015), facilitating condition (t = 2.765; p = 0.040), attainment value (t = 4.409; p = 0.007), utility value (t = 3.151; p = 0.025), and intention to use (t = 5.969; p = 0.002).

The results revealed students' mixed perceptions on the usage of Cloud e-learning module. Among the constructs with increased means in the posttest evaluation, paired sample t-tests revealed the mean difference to be significant for enjoyment (t = -3.380; p = 0.020). The mean increase in Enjoyment was 0.072 with a 95% confidence interval. Higher mean values for Enjoyment indicated students' higher levels of enjoyment after using the Cloud e-learning module. This finding reflects students' positive willingness to continue using Cloud e-learning module in future because they were enjoy using it. This is consistent with similar results reflected from recent studies that examined the significance of Enjoyment as a key factor for technology acceptance (Gan & Balakrishnan, 2018; Koo et al., 2015; Park et al., 2014). Interestingly, based on the findings from the hypotheses test, enjoyment had a small impact on students' usage of Cloud e-learning module. It was thus inferred that actual use of Cloud e-learning module may have changed students' perception on the enjoyment and increased students' willingness to use Cloud e-learning module in future.

The differences for social influence were also found to be significant (t = -3.617; p = 0.015). Higher mean score was observed for social influence in the posttest evaluations, where the mean increase was 0.073 with a 95% confidence interval. The significant higher mean score for social influence confirmed that the supporting role is crucial in students' usage of Cloud e-learning module. This is consistent with prior related studies (Tan, 2013; Thomas et al., 2013). This finding suggests that students are more likely to use Cloud e-learning module when their peers, teachers or someone important to them suggest them to use it.

System quality, pedagogical quality, perceived usefulness, computer self-efficacy, facilitating condition, attainment value, utility value and intention to use have lower mean values in the posttest evaluation. Taken all together, the results indicate that students' perceptions have changed after using the Cloud e-learning module. These findings deserve in-depth revisions and careful attention in future enhancements. Nevertheless, although the mean scores for the constructs are lower, the mean differences are very small and the standard deviations are all less than 1, indicating that there are still some potentials worth to be explored by HEIs.

4.3. Students' performance analysis

For KM subject, the composition was 170 students in the experimental group (i.e., those who experienced Cloud e-learning) and 148 students in the control group (i.e., those who did not experienced Cloud e-learning). The p-value for the Levene's test for equality of variance is 0.210. Since the p-value is more than 0.05, equality of variances is assumed (Chinna & Choo, 2016). Therefore, it was confirmed that both groups were homogenous as no significant difference was found between them.

Table 6 shows the mean scores, standard deviations, mean difference and difference of confidence interval for students' academic results in KM subject. It is observed that the experimental group recorded a mean score of 72.55, with a standard deviation of 13.13, whilst the control group recorded a mean score of 68.22, with a standard deviation of 11.45. Independent samples t-test result shows that there is a significant difference at 5% significant level (t-value = 3.108 and p-value < 0.05) in the mean score. The mean score of the experimental group is significantly higher than the control group for DCN performance. This evidently shows that the experimental group outperformed the control group. A mean difference of 4.33 is found between the groups.

Table 6
Performance analysis result for KM

Subject	Group	Mean	SD	Mean difference	95% Confidence interval of the difference	
					Lower	Upper
KM	Experimental	72.55	13.13	4.33	-7.072	-1.589
	Control	68.22	11.45			

4.3.2. *Performance analysis for DCN*

For DCN subject, the composition was 115 students in the experimental group (i.e., those who experienced Cloud e-learning) and 192 students in the control group (i.e., those who did not experienced Cloud e-learning). The *p*-value for the Levene's test for equality of variance is 0.626. Since the *p*-value is more than 0.05, equality of variances is assumed (Chinna & Choo, 2016). Therefore, it was confirmed that both groups were homogenous.

Table 7 shows the mean scores, standard deviations, mean difference and difference of confidence interval for students' academic results in DCN subject. It is observed that the experimental group recorded a mean score of 63.25, with a standard deviation of 11.91, whilst the control group recorded a mean score of 60.86, with a standard deviation of 12.81. Independent samples *t*-test result shows that there is an insignificant difference at 5% significant level (t-value = 1.593 and p-value > 0.05) in the mean score. Nevertheless, the mean score of the experimental group is higher than the control group for DCN performance. This shows that the experimental group outperformed the control group by a mean difference of 2.39.

Table 7
Performance analysis result for DCN

Subject	Group	Mean	SD	Mean difference	95% Confidence Interval of the Difference	
					Lower	Upper
DCN	Experimental	63.25	11.91	2.39	-5.342	0.562
	Control	60.86	12.81			

4.3.3. *Discussion*

Findings from the students' performance analysis provide evidence that the use of Cloud e-learning improved students' learning performance in KM and DCN subjects. This outcome is consistent to previous findings where the use of technology in learning improves students' academic performance (Harris et al., 2016; Olsen & Chernobilsky, 2016; Tan, 2012). This is evidently seen in the improved academic performance of the experimental group for KM and DCN subjects.

Results from the students' performance analysis also indicate that Cloud e-learning is an alternative to the conventional e-learning method to subjects that involve understanding of concepts. With Cloud e-learning, the experimental groups from KM and DCN were led into personalised and flexible learning, high pedagogical values, easy collaborations, and having fun while learning seemingly challenging subjects.

Given the advancement of Cloud Computing technology, better understanding and implementation of effective Cloud e-learning module would certainly enhance its usage and educational value of such educational technology in e-learning. With the obvious increased performance and meaningful learning found in this study, it clearly displays the fact that Cloud e-learning is worth considering as a teaching and learning method.

5. Conclusion and implications

Across literatures, there are limited studies for the adoption of Cloud e-learning approach for IT courses in higher education. This study could possibly be one of the limited studies that empirically examines the actual usage of Cloud e-learning approach. Through the use of prototyping and continuous evaluations via the developed survey instrument, the understanding towards the actual usage of Cloud e-learning module is established. Results obtained from pretest-posttest experiment in this study yield a clearer practical implication on the actual usage of Cloud e-learning module. Paired sample *t*-test results evidently show that the mean differences are significant for ten out of twelve constructs, indicating if the Cloud e-learning module has high pedagogical, subjective and enjoyment values, students are more than willing to continue using Cloud e-learning module (Rahimi et al., 2021; Shah & Barkas, 2018). Thus, Cloud e-learning module should be developed and implemented in a way that would appeal to the students. With that notation, there would be a great possibility of the actual adoption of Cloud e-learning approach by educators in higher education.

The improved academic performance in KM and DCN practically implies that Cloud e-learning approach could possibly contribute significantly to the general IT courses. In this case, the incorporation of Cloud e-learning modules in KM and DCN courses appear viable. The students' performance analysis results evidently indicate that the Cloud e-learning modules that were designed based on the principles of the Cloud e-learning framework appear to help students in improving their academic performance in those two courses. Therefore, educators or instructional designers may want to consider designing their courses based on the principles of the Cloud e-learning framework. Taking the advantages of hosting e-learning applications in the Cloud and following its virtualisation features of e-learning hardware, the Cloud e-learning framework can serve as a base framework to build a sustainable and flourishing e-learning for higher education.

Despite its benefits as discussed in this paper, Cloud e-learning also brings up privacy concerns. These concerns include data breaches, access control, and data retention. Cloud based systems can be vulnerable to data breaches, allowing for sensitive information to be exposed. Unauthorized access to Cloud based systems can lead to the exposure of sensitive information. The retention of data for extended periods also can raise concerns about potential misuse of data. To ensure the privacy of data in Cloud e-learning, a few measures can be considered. For example, strong data encryption, access controls to limit access to sensitive information, monitoring for suspicious activity, and set guidelines to data retention and deletion. By considering these aspects, privacy issues associated with Cloud e-learning can be addressed.

6. Limitations and future works

This study was conducted within one private university in southern region of Malaysia. This sample is a subset of all learners in high education. Thus, it would be interesting to expand this study across different private and public universities in Malaysia and overseas. Such efforts may provide valuable insights into how intention to use Cloud e-learning approach are evaluated in different educational settings.

Although this study has thoroughly examined the differences in student perceptions between pretest and posttest, the differences in perceptions between the experimental group and the control groups has not been examined in the posttest. The academic performances of the two groups were analysed for the posttest evaluation instead. Since evaluating the differences in perception between the experimental and control groups might be useful to gauge a more comprehensive conclusion, this aspect of data analysis will be considered in future studies.

This study examined only students' perceptions and attitudes towards the use of Cloud e-learning approach. It did not consider the educators' perceptions and attitudes towards the adoption of Cloud e-learning approach. Since educators play important role in technology adoption for teaching and learning, extended research to gauge educators' perceptions and attitudes towards the use of Cloud e-learning approach would be helpful in providing sufficient information to universities and higher education ministry for appropriate planning and implementation.

Author Statement

The author declares that there is no conflict of interest.

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