Student's Perspective of eLearning and the Future of Education with MOOCs

Dr. Akashdeep Bhardwaj
School of Computer Science (SoCS)
University of Petroleum & Energy Studies, Dehradun, India
Email: bhrdwh@yahoo.com

Dr. Sam Goundar
The University of the South Pacific, Suva, Fiji
sam.goundar@gmail.com

Abstract-The number of students enrolling in e-Learning courses at institutions is increasing exponentially. One would hardly ever find a course of study in an institution that has not blended Information Communications Technology (ICT) or Electronic and Web based resources in some form or the other. Institutions offering Massive Open Online Courses (MOOCs) are claiming millions of students enrolled in their courses. One institution claimed to have at least onestudent enrolled from every country in the world. Students are the main stakeholders in e-Learning courses. Students were asked about their perceptions of e-Learning courses in an effort to improve its delivery and student success.

Problems with technology are the main reason that student's dropout from e-Learning courses. Research shows that novice e-Learner's underestimate the amount of ICT skills that are required for success. The researchers used a mix of research design methods andcollected qualitative data to triangulate with quantitative data from 185 participants. The research hypotheses were then tested by applying the results to the Decomposed Theory of Planned Behaviour (DTPB) model to further inform the findings. Resultsindicate that the ease of use and its perceived usefulness creates a positive attitude towards e-Learning and further reinforces student's intention to continue. The teachers have a strong influence on students to use e-Learning and so do their peers. Most students are quite confident with using e-Learning platforms (32% of them were IT students). However, the rest are not happy with the resources and technologies of their current e-Learning platforms. The researchers conclude that the e-Learning platform at the institution of study needs immediateattention to attract and retain more students. This study has implications for the institution and every other institution that intends to provide more e-Learning courses and possibly follow the MOOCs development pathway and offer MOOCs courses.

Keywords-eLearning; MOOCs; DTBP;eLearning adoption;eLearning behaviour; Education

I. INTRODUCTION

Of the many changes in our lives during the 21st century, the advent of the Internet and its cyber-offspring, the World Wide Web, has been responsible for invoking the most change. Of these changes one major aspect is that through the Internet and the World Wide Web people are finding new ways of getting educated and employment. Apart from these, the Internet and the World Wide Web are enabling people to remain connected regardless of their geographical distances, socialise, shop and entertain themselves. This study discusses the perceptions of students who are using the e-Learning technology in their courses of study. Online survey questionnaires and face-to-face interviews were conducted to gather data for this study. The data was then analysed using qualitative and quantitative methodologies. The findings are reported with the required narratives in the results section. This is followed by discussions, conclusions and guidance for future research.

Education landscape and student population is changing because of rapid technology developments, (Jeffrey 2006) with most institutions making course content and course work assessment available to students via some sort of CMS (course management system). Almost all students now own a personal computing device, while laptops, notebooks and tablets have become a standard stationery item for today's student. But using e-Learning platforms requires more than basic computer skills. It is a three tier learning process that includes:

- Acquiring basic computer skills
- Realising the use of e-Learning platforms
- Learning the course subjects

Problems with technology is premiere reason that students dropout from online courses (Frankola, 2001). Research shows that novice online learners frequently underestimate the amount of technical skill needed to be successful in online courses (Carr, 2000; Kumar, et. al., 2006). E-Learning courses using a best practice CMS with appropriate instructional design, user friendly interface and simple instructions will compensate for the technology problems encountered by e-Learning students. The first step in this study is to find out what those problems are via student perceptions as well as take on board their relevant suggestions.

II. OBJECTIVES, LIMITATIONS AND SCOPE

This study is centred on finding information regarding what students at an institution think of their e-Learning courses. It will survey and interview students on the CMS (in this case Moodle) used for e-Learning and how this particular mode of learning might be improved and adapted for future offerings. Due to the large scope of this research area, this study will focus on student's computer literacy, CMS knowledge, communication options (with instructors and peers), and ease of understanding of their e-Learning course. Due to time constraints, participant's availability and other resource constraints, this study will be conducted within certain boundaries. Some of them are: surveying only one out of five schools in the institution, limiting the survey to 10 questionnaires only so as to not take too much time of the participants and interviews to 15 minutes only. This study, however, does not include the faculty's perspective of e-Learning courses. It encourages student-centred design of e-Learning courses. This research will rely on responses from students and their perspectives, so there will be a bias in which data is collected. The stage in which students are in their studies will also influence their responses as well as a host of other factors not related to this research. The participants involved in this research contain a large number of students doing information technology majors (with computing skills) and therefore the findings cannot be generally applied across all other schools of study and students. Academics might question what expertise would the students have on instructional design and pedagogy to provide relevant responses to this study.

The objective of this study is to obtain up to date information regarding the current thoughts of students using e-Learning as well as their suggestions on improvements to make it more conducive for learning. The significance of the earlier statement follows on to one of the central objectives of this study, which is to improve the instructional design, course content, delivery of e-Learning courses and student support at the institution of this study as well as any other institution.

- The first goal of this study is to improve and enhance the delivery of e-Learning courses for students at the institution of study as well as in other institutions. By researching either a student is a full time student or part time student (Guiney, 2011) and the type of course(s) that the student population are studying in an e-Learning environment, educational institutions might be able to re-design and better target e-Learning delivery to students (Guiney, 2013).
- The second goal is to enable faculty at the institution of study to customise e-Learning courses based on student perceptions and expectations for higher acceptance of e-Learning as a medium of teaching and learning that ensures greater student success. As (Bently, 2010) points out "the creation and implementation of effective quality assurance for e-Learning process has been identified as one of the most challenging tasks that face higher education providers today. Nichols (2008) suggests "whenever possible, the choice of e-Learning tools should reflect rather than determine the pedagogy of a course.

The lessons learnt from this study will assist the institution involved to fulfil one of its objectives, which is to move from the current blended (face-to-face plus online supplement) learning courses to totally online courses. This will remove the resources constraint faced at the moment to cap student enrolment numbers for its more popular courses and the ability to enrol students regardless of their physical location. This study intends to improve the instructional design, course content, delivery of e-Learning courses and student support at the institution of this study. It would enable faculty to customise e-Learning courses based on student perceptions and expectations for higher acceptance of e-Learning as a medium of teaching and learning. It will provide information for institutions that are ready to move from the current blended (face-to-face plus online supplement) learning courses to totally online courses. Apart from providing information to researchers in the area of e-Learning course design, this study will provide students intending to enrol in e-Learning courses a perspective on what their predecessor have experienced. Future research on faculty's perspective might come up with a balanced (of students and faculty) framework for delivering e-Learning courses.

III. LITERATURE REVIEW

Technology is the enabler of e-Learning platforms. Without the use of computers, networks and other associated information communication technologies (ICT), such as Web 2.0 and Course Management Systems, there would be no e-Learning know today. But what type of technologies should or should not be used for e-Learning? How should these technologies be evaluated, selected and used? What should be the criteria for such evaluation and selection? How should course materials for e-Learning platforms be written? Where does instructional design and pedagogy fit into e-Learning? These are some of the questions that have been investigated by earlier researchers in this field. This study focuses on students.

Song et al. (2018) proposed developing and accessing MATLAB exercises for active concept learning. A systematic approach to MATLAB problem design and automated assessment is described, based on the experience working with the MATLAB server provided by MathWorks and integrated with the edX massive online open class (MOOC) platform. Background: New technologies, such as MOOCs, provide innovative methods to tackle new challenges in teaching and learning. However, they also bring challenges in course delivery and assessment, due to factors such as less direct student-instructor interaction. These challenges are especially severe in engineering education, which relies heavily on experiential learning, such as laboratory exercises and computer simulations, to assist students in understanding concepts. As a result, effective design of experiential learning components is extremely critical for engineering MOOCs. Intended Outcomes: This paper shares the experience gained through developing and offering an MOOC on communication systems, with special focus on the development and the automated assessment of MATLAB exercises for active concept learning. Application Design: The proposed approach introduced students to concepts by using learning components commonly provided by many MOOC platforms (e.g., online lectures and quizzes), and augmented the student experience with MATLAB-based computer simulations and exercises to enable more concrete and detailed understanding of the material. Findings: The effectiveness of the instructional methods was supported by evaluation of students' learning performance.

Rajab Khaniran (2018) compared the effectiveness of e-Learning and face-to-face education in the previously neglected context of Saudi Arabia. This was done by examining Najran University’s e-Learning experience after the institution suspended traditional course delivery due to the ongoing war between Saudi Arabia, the Arab Coalition, and Yemeni rebel groups. The analysis also considers the potential benefits offered by e-Learning in crisis zones such as the southern border region of Najran, Saudi Arabia. The results indicate that there is no statistical or practical difference between online and face-to-face learning with respect to student performance. This paper also demonstrated that e-Learning is capable of delivering the educational goals of higher learning institutions to areas wrecked by wars. E-Learning offers students a safe learning environment, engaging platforms, and most importantly a quality education. The findings of this paper contribute to a growing body of scholarship on the effectiveness and implementation of e-Learning in the Middle East.

Chen et al. (2018) studied thelearning outcome prediction for online courses. Whereas prior work has focused on semester-long courses with frequent student assessments, we focus on short-courses that have single outcomes assigned by instructors at the end. The lack of performance data and generally small enrolments makes the behaviour of learners, captured as they interact with course content and with one another in Social Learning Networks (SLN), essential for prediction. Our method defines several (machine) learning features based on the processing of behaviours collected on the modes of (human) learning in a course, and uses them in appropriate classifiers. Through evaluation on data captured from three two-week courses hosted through our delivery platforms, we make three key observations: (i) behavioural data contains signals predictive of learning outcomes in short-courses (with classifiers achieving AUCs $\geq$ 0.8 after the two weeks), (ii) early detection is possible within the first week (AUCs $\geq$ 0.7 with the first week of data), and (iii) the content features have an "earliest" detection capability (with higher AUC in the first few days), while the SLN features become the more predictive set over time as the network matures. We also discuss how our method can generate behavioural analytics.

Choen et al. (2017) proposed considering the importance of social and collaborative learning, this research aims to explore the characteristics of the discourse in forums in order to have insight into learners' needs and interests in massive open online courses. This will help in developing an instructional strategy that will increase the learners' participation in forums, and their involvement in the creation of knowledge; consequently, improving learning processes. An innovative approach was taken in this study, using the Natural Language Processing (NLP) tool and Henri's content analysis model in order to analyse the learners' discourse in forums and identify their types of interactions. We hope that this approach will lead to additional understanding and shed light on the ability to create effective online learning communities, through the learners' behaviour.

Kappas et al. (2017) suggested a way to create Greek MOOCs for Greek Arts making use of digitalized resources of cultural material, mainly DARIA-GR. In this proposal we use University Open Courses so that the described platform will be able to form, on the one hand, a basis for the training of SE teachers who teach the relevant disciplines and on the other hand an area of enriched material aiding them in the teaching process. Finally, we recommend that TraMOOC be used for the creation of complete foreign-language MOOC for Digital Humanities.

In recent years, online learning course has been drawn much attention from educators and researchers through the world. Nowadays, some popular Massive Open Online Courses (MOOCs) in the world provide video courses for learning various subjects and have been successfully applied to many subjects. On the other hand, there are some researchers have indicated that attention state and learning are strongly correlated. However, despite their importance, it is a complicated procedure that when educators want to observe the attention state of each student in online learning course. To help educators effectively observe students' attention state in online learning environments, Cheng et al. (2017) designed and implemented a real-time attention recognition and feedback system, for measuring changes in learner attention state. Finally, to achieve the goals as mentioned above, this study carried out the stability testing, usability testing, and expert evaluation of the real-time attention recognition and feedback system.

In recent years, Massive Open Online Courses (MOOCs) have a widespread and became one of the future trends to help people from different places to learn online and study courses in different majors. One of the most interesting subjects on MOOCs platforms is Language Learning. The lack of motivation to complete the course after enrolling, and completion rates still real problems need to find an innovative solution. Gamification can increase learner motivation to continue studying through MOOCs and can reduce drop-out rates. Ahmed et al. (2017) proposed theoretical and practical framework for connecting Gamification in Massive Open Online Chinese Courses and applying Gamification mechanics to support Chinese Language learning through focusing on different perspectives for applying: gamification and instructional design, gamification and course elements, gamifying course interface.

Although Massive Open Online Courses (MOOCs) have become a way of online study used by millions of people across the world, so many websites and courses often confuse people that they can't choose the suitable courses quickly and accurately. Zheng et al. (2017) constructed a knowledge graph of courses by using machine learning methods, and then provide three scenes to study easily from MOOC courses. The authors crawled courses information from several MOOC websites, and carry out entity extraction and relation extraction to construct a high educational knowledge graph. The experiment results show the correctness of the knowledge graph, and which can be applied into our real life.

Development of Information and Communication Technology has heavily influenced many life aspects including educational practices scheme. The development has brought new and diverse learning methods to support the conventional learning ones. Massive Open Online Courses (MOOC) is a scheme of open access e-Learning methods using Internet and possible to deliver in a real time virtual classroom for any participant. Rahayu et al. (2017) conducted research to evaluate effectiveness of using MOOC platform for Numerical Method subject which is one of the most common subject in engineering. The course was conducted interactively and real time. The evaluation was taken through 3 aspects which were measurability, satisfaction, and engagement. From 34 tested participants in the numerical method class through this MOOC scheme, the evaluation of this learning process shows that the MOOC is effective for such mathematical subject based on respondent interpretation 60.1%. The effectiveness are mostly influenced by satisfaction, followed with measurement and engagement parameters.

In an article titled Design and Evaluation of Student-Focused e-Learning, Bently (2010) discussed the use of technology in relation to how technologies are causing new educational paradigms and models that challenge conventional assumptions and indicators of quality. These insights are becoming possible with the help of the increasing sophistication in information technology. While this study focussed on e-Learning design and evaluation in England, in New Zealand similar technological frameworks have also been created, for example e-Learning Maturity Model Version 2.0 by Marshall (2006).

Marshall (2006) presents an overview of e-Learning performance framed in a methodology designed to assess process capability. The approach used is designed to be independent of technology and pedagogy decisions, focusing rather on the ability of an institution to deliver e-Learning in a high-quality and sustainable way. The success of any e-Learning course is in its instructional design and delivery, which leads to higher student satisfaction and acceptance (Freeze, et. al. 2010; Lee, et. al. 2011; Paechter, et. al. 2010; Jasper, et. al. 2012).

In education sector this is usually either Blackboard or Moodle. The importance of free source VLEs, such as Moodle has been described by Wyles (2004) as being the area in which “the open educational resources movement holds great promise for delivering cost effective e-Learning infrastructure, increased innovation in our education and greater levels of collaboration in its delivery, at a system-wide level”. Although an open-source e-Learning is financially beneficial to the institution, questions have to be asked regarding what is the students’ perception towards e-Learning courses and their ability to efficiently use course management systems for effective learning outcomes.

Who are studying online, what are they studying and how are they studying? These three questions are important in any investigation regarding any institutions e-Learning programme delivery. In the case of this paper and because of the survey case-study methodology used in this research, the survey questionnaires used have been adapted and modified from Voce’s (2007) study in England. For a New Zealand perspective, reports by Guiney (2013) for the Ministry of Education, detailing the demographics of the e-Learning students currently (2013) studying online for NZQA qualifications has been referenced.

Reports on Education sector written by Guiney titled e-Learning Provision and Participation (2011) and e-Learning Achievement: (2013) are good references for this study as well. Both of these reports are important since they offer a glimpse into who are studying online through emphasis on demographical studies and also what students are actually studying for in an online environment. At the same time the Guiney reports (2011 &

2013) may be of benefit to institutions who may wish to use this information in other areas, such as forecasting the future demographics of education students and for marketing their e-Learning courses.

The proliferation of access and use of information communication technologies (ICTs) have had a positive impact on education delivery strategies. Across the globe, schools and universities have extended their delivery modes to include fully online, and blended to support the traditional face-to-face approach. Studies have shown that e-Learning has emerged as a new paradigm of modern education (Sun, et al., 2008 and Martins et al., 2004). This evolution has not only occurred in the education sector, many organizations have also adopted technology-based classroom instructions to enhance learning and knowledge development (Yoo et al, 2012). Some of the key benefits include improved flexibility in education delivery, improved focus on learner centeredness, greater access to knowledge, improved archival capability of knowledge and general improvements in knowledge management, and potential for increased global audience (Zhang, et al., 2004). As a result, there is a growing emphasis by local institutions to increase the number of blended and fully online modules and e-Learning courses (Paechter & Maier, 2010; Zhang, 2003).

Some of the main reasons why students drop-out of e-Learning courses is because of the students' perceived ability of using ICT as compared to the actual level of ICT skills required with e-Learning courses (Masrom, 2007; Levy 2007; Park & Choi, 2009). In many cases, being computer literate and being able to use the Internet and play computer games does not provide enough skills to tackle many e-Learning platforms. This misconception is common amongst students enrolling in e-Learning courses and faculty designing e-Learning courses (Phillips, et. al., 2004; Rovai, 2003; Martinez, 2003). Understanding this misconception should produce better e-Learning course design, delivery, acceptance and success.

Decomposed Theory of Planned Behaviour has already been used by researchers (Sadaf, et. al., 2012; Chen, 2011; Roca, et. al., 2006; Ndubisi, 2006) to investigate adoption, intention to use, continued usage, and acceptance of e-Learning courses in institutions. Studies by (Ajjan & Hartshorne, 2008; Ajjan & Hartshorne, 2009; Smorkola, 2008; Taylor & Todd, 1995) have proved the power of DTPB to predict usage intention and usage behaviour.

Other similar studies, such as (Teo, Lee & Chai, 2008; Park, 2009; Teo, 2009; Chen, 2010; Paechter et. al., 2011; Shroff, et. al. 2011; Sadaf, et. al. 2012; Al-Adwan, et. al. 2013; Sharma & Chandel, 2013) used both qualitative and quantitative methods in their survey. In most of the studies, the qualitative data collected online described aspects of learning and teaching students consider important and desirable from the fields of instructions The quantitative data was collected from an evaluation of students' expectations of e-learning. This study has done something similar.

By using the Technological Acceptance Model (TAM), (Park, 2009; Rashid, 2013), Theory of Planned Behaviour (TPB), (Venkatesh, et. al. 2003; Pavlou, 2006) and its extension, the Decomposed Theory of Planned Behaviour (DTPB), (Ndubisi, 2004; Kummer, 2013) offer sound measuring tools to ascertain the differences between students perceived thoughts to that of actual reality. Some references about these two measuring modelling tools can be found in Masrom (2007) "where TAM proposes that perceived ease of use and perceived usefulness of technology are predictors of user attitude towards using the technology, subsequent behavioural intentions and actual usage. Perceived ease of use was also considered to influence perceived usefulness of technology" (Masrom, 2007, p.3). "The DTPB extends the TPB by adding further influence factors on attitude and perceived behavioural control, resulting in more explanatory power (Taylor & Todd, 1995)". (Kummer, 2013, p.3 in Harris, 2011) uses the expectancy theory. Expectancy theory provides a framework for explaining "how future actions are predicated on the degree to which expected outcomes are met (Isaac, Zerbe, & Pitt, 2001 in Harris, 2011, p.3).

As an online student survey, some of the questions were adapted from previous online student surveys that covered the same topic as this paper, but customised towards the school of study and institution. As a result, we ended up with ten (10) questions based on a mixture of methodologies that was put up on Survey Monkey. We found it important to have students write their own thoughts and perceptions about various issues concerning their e-Learning platform and e-Learning courses within the school of study. Each section of the survey contained more than one (1) open-ended question in order to obtain a rich data. These open ended questions offered students an opportunity to critique their e-Learning platform and e-Learning courses. An analysis of the responses to the open ended questions might give us insight into further research areas and to information that we might otherwise have missed. By knowing the critical issues faced students doing e-Learning courses through their thoughts and suggestions, this study is a first step towards collating information for further action.

IV. PROPOSED FRAMEWORK AND HYPOTHESIS

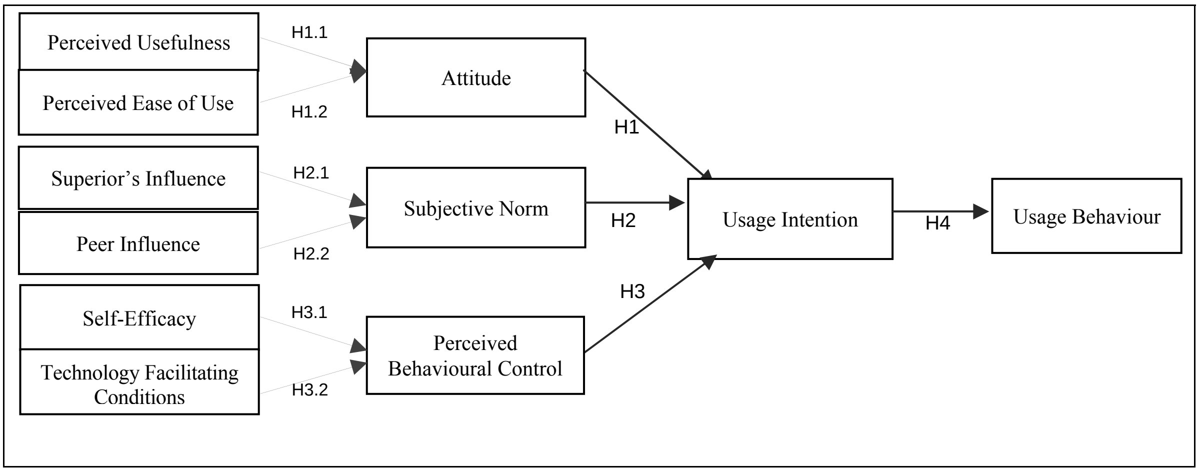
As a case study or pilot study research, the intention is for the findings to be focussed on 'future developments' for both the school of study used and the institution. With such findings, it is possible to take an insight into a possible future of e-Learning and MOOC for the school of study, the institution and other schools and institutions. This research study also used the methods of 'sampling procedures' and 'expectancy theory'.

Sampling procedure is better explained by (Harris, 2011) in which he depicts how case studies on a single chosen group of people or sample can be used to obtain specific information about the rest by using the sampling procedure. This sampling procedure is used when a researcher has a specific purpose for the research and is interested in specific groups (Trochim, 2007). According to (Oliver, 1974), expectancy theory proposes that an individual will decide to behave or act in a certain way because they are motivated to select a specific behaviour over other behaviour due to what they expect the result of that selected behaviour will be.

Based on (Taylor & Todd, 1995) paper on Understanding Information Technology Usage: A Test of Competing Models, the authors chose the Decomposed Theory of Planned Behaviour as our theoretical framework (DTPB) DTPB provides a better explanation of behavioural intention by focusing on the factors that are likely to influence systems (in our case e-Learning systems) use through the application of design and implementation strategies. The DTPB extends the theory of planned behaviour (TPB), which focuses on the direct measures of attitude, subjective norms, and perceived behaviour control to predict intention and in turn predict one's behaviour.

Technology Acceptance Model (TAM; Davis, 1989) has been used by a number of studies (Park, 2009; Shroff, et. al., 2011; Al-Adwan, et. al., 2013; Sharma & Chandel, 2013)to investigate student's use and acceptance of e-Learning. Other theoretical frameworks, such as the Theory of Planned Behaviour (TPB; Ajzen, 1985; 1988; 1991) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh, et. al., 2003)have also been used. This study draws on the Decomposed Theory of Planned Behaviour as a guiding framework (Taylor & Todd, 1995) derived by deconstructing TPB and adding TAM.

Table 1: Theoretical Framework - Decomposed Theory of Planned Behaviour



According to (Taylor & Todd, 1995), in this (DTPB) model, attitudinal, normative and control beliefs are decomposed into multi-dimensional belief constructs. This decomposition approach provides several advantages. First, it has been noted that it is unlikely that monolithic belief structures, representing a variety of dimensions will be consistently related to the antecedents of intention. By decomposing beliefs, those relationships should become clearer and more readily understood. In addition, the decomposition can provide a stable set of beliefs which can be applied across a variety of settings. This overcomes some of the disadvantages in operationalization that have been noted in other the traditional models. Finally, by focusing on specific beliefs, the DTPB model becomes more managerially relevant, pointing to specific factors that may influence adoption and usage.

In this way, the DTPB shares many of the same advantages associated with Technology Acceptance Model (TAM). It differs in that it is more complex because it introduces a larger number of factors that may influence usage. Because of this, the DTPB should provide a more complete understanding of IT usage relative to the more parsimonious TAM (Taylor & Todd, 1995). The DTPB model is a widely used and validated model for predicting behaviour intentions from attitudes, subjective norms, and perceived behavioural control in both information technology and education studies (Taylor & Todd, 1995) as illustrated in Table 1 below.

This study tests the following hypotheses as illustrated in Table 2 below.

Table 2: Research Hypothesis

H1: Attitudes of students for e-Learning positively affects their usage intention and behaviour
- ➔ **H1.1**: Perceived usefulness positively affects students attitude to use e-Learning
- ➔ **H1.2**: Perceived ease of use positively affects students attitude to use e-Learning

H2: Subjective norm of students for e-Learning positively affects their behavioural intentions
- ➔ **H2.1**: Superiors influence to use e-Learning positively affects subjective norms of students
- ➔ **H2.2**: Peers influence to use e-Learning positively affects subjective norms of students

H3: Perceived behavioural control of students to use e-Learning positively affects their usage
- ➔ **H3.1**: Student's self-efficacy to use e-Learning positively affects their perceived behaviour
- ➔ **H3.2**: Technology facilitating conditions positively affects student's perceived behaviour

H4: Students' intention to use e-Learning positively affects e-Learning usage behaviour.

V. RESEARCH PERFORMED

This study is based on the academic principles of applied research with the use of online survey questionnaires consisting of a blend of questions based on both quantitative and qualitative methods. These questions gather both quantitative data (with Likert Scale questions) and qualitative data (with open ended questions) from students, these are listed below for reference.

1). Does the use of an e-Learning platform help you learn better?

2). If yes, why, can you elaborate?

3). Is there anything missing from your current e-Learning courses?

4). How often do you access your e-Learning courses?

5). How would you describe your e-Learning experience?

6). What is your level of computer expertise – expert, intermediate or beginner?

7). Do you require technical assistance and support with your e-Learning platform?

8). Can you suggest any improvements to current e-Learning courses delivery?

9). Do you feel the courses are ready to be delivered totally online;

10). Describe yourself - Age, Gender, Ethnicity, Part-time or full-time Student, and Course of Study.

These questions were aligned to gather data that could then be applied to DTPB model to predict usage intention and behaviour. The quantitative data collected were triangulated with qualitative data for validation and checked with findings from other similar studies.

- For example, in Question 1 we asked, "Does the use of an e-Learning platform help you learn more?" The participants were required to choose from a Likert scale of: Strongly Agree, Agree, Neither Agree or Disagree; Disagree, Strongly Disagree. This quantitative data could then be reported as the percentage of students who agree that e-Learning helps them learn more.
- In Question 2, complementary question (an open ended question) based on their responses from Question 1, which is "why do they agree or disagree?" This qualitative data was then cross verified with quantitative data and gave a better understanding of the responses to Question 1. This is what (Creswell & Clark, 2007) did in their study.

The sample for this study included 185 students which is illustrated in detailed format below.

Table 3: Gender Percentage

Genders	Percentage
Male	45%
Female	51%
Did not specify	04%

Table 4: Age grouping Percentage

Age Groups	Percentage
Under 20 years	23%
21-30 years	31%
31-40 years	18%
41-50 years	16%
Over 50 years	8%

Table 5: Ethnicity Percentage

Ethnicity	Percentage
NZ European	35%
Australian	21%
Indian	18%
Spanish	16%
Chinese	10%

Table 6: Gender Percentage Table 7: Gender Percentage

Genders	Percentage
Male	45%
Female	51%
Did not specify	04%

Age Groups	Percentage
Under 20 years	23%
21-30 years	31%
31-40 years	18%
41-50 years	16%
Over 50 years	8%

- 66% identified themselves as full time students and 28% as part time students, others did not specify their student status.
- Regarding programmes of studies – it was found that 38% were doing Information Technology, 26% Business, 12% Travel & Tourism, 7 % Immigration, 4% Legal Studies, 4% Conveyancing, and 2% Real Estate. The others did not specify.
- For Quantitative analysis - response to questions from Survey Monkey was analysed. This data provide response percentages to Likert scale questions, response counts, number of questions answered, number of questions skipped and created charts.
- For Qualitative analysis – use of Miles & Huberman's (1994) Constant Comparative method is adopted. Data was exported to an Excel spreadsheet, coded, and categorised according to DTPB determining factors and developed into themes.

Using an e-Learning platform to learn a subject was found useful by 76% of the participants, overall. More than 2/3 of the participants believe that using an e-Learning platform helps them learn more, reinforce their learning and can be used to review/clarify what they couldn't understand during the live class. Being able to achieve their learning goals with e-Learning would result in the participants continued use of e-Learning platforms. Past research by (Smarkola, 2007) and (Teo, et. al., 2008) shows the same.

Other things that students found useful when using the e-Learning platform were: being able to catch up on what they missed, being able to access the learning materials at leisure, work at their own pace, and follow up on anything they did not understand during the live class.

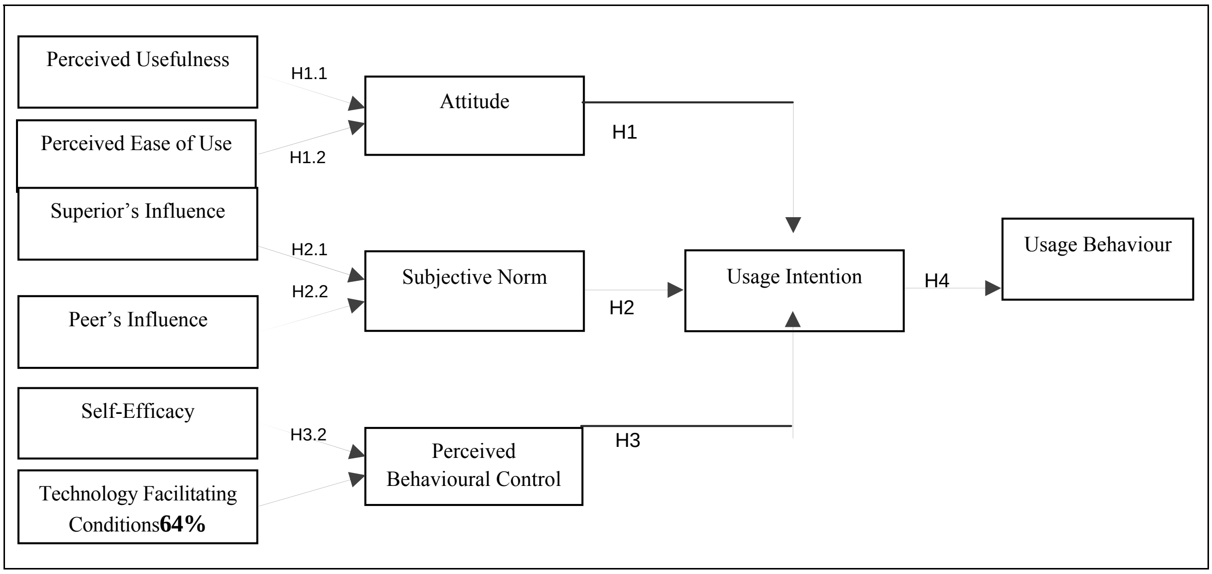
VI. RESULTS OBTAINED

43% of participants did not find their e-Learning platform easy to use. Their perceived ease of using an e-Learning platform was different and found to be rather difficult with actual use. This confirms an earlier study by (Masrom, 2007), where he states that "one of the main reasons why students drop-out of e-Learning courses is because of the differences between the students perceived ability of using ICT in comparison to the real use of ICT for e-Learning. Overall, only 57% of students agreed that their e-Learning platform was easy to use. Further breakdown and analysis reveals that only 47% of students doing information technology courses found their e-Learning platforms easy to use. If students doing information technology majors found their e-Learning platform difficult, then, it is time for the institution to check their e-Learning course design and the platform as whole. Perceived ease of use and perceived usefulness does lead to change in attitude to use e-Learning.

One of the main reasons why students drop-out of e-Learning courses is because of the differences between the students perceived ability of using ICT in comparison to the real use of ICT for e-Learning (Masrom, 2007). Using a theoretical model like the Decomposed Theory of Planned Behaviour (DTPB) enables this study to find the true perceptions of students studying e-Learning courses. According to the DTPB model, perceived usefulness refers to the degree to which the user believes that using the technology will improve his or her work performance, while perceived ease of use refers to how effortless he or she perceives using the technology will be (Masrom, 2007).Sumak (2011) writes "the main challenge for e-Learning is to provide a system with services that will positively affect a user's learning experience.

The percentages are based on the responses from participants from the online survey. These percentages have been computed from the responses to Likert scale based questions from the online survey, where participants either agreed or disagreed on statements based on the Decomposed Theory of Planned Behaviour (DTPB) determining factors as illustrated below in Table 8 below.

Table 8: Theoretical Framework based on the Decomposed Theory of Planned Behaviour



In this study, behavioural intention is concerned with motivational factors related to student’s intentions to use e-Learning. Ajzen (1991) suggested that behavioural intention is the most important factor in predicting the decision to take a specific action. Given this close relationship between intention and behaviour, past studies have used behavioural intention to predict specific behaviour (Ajjan & Hartshorne, 2008; Hartshorne & Ajjan, 2009). It is expected that there is a positive relationship between intention and the actual behaviour of students.

Therefore, the following hypothesis as proposed above is proved: **H4**: Students’ intention to use e-Learning positively affects e-Learning usage behaviour.

In order to understand the relation of independent variables with dependent variables, regression analysis of the H1to H4 data is performed as illustrated below. This analysis helped explore the relationships between the H1 to H4 variables.

Summary Output for H1:

Table 9: H1 Regression Statistical Inferences

H1 Regression Statistics	
Multiple R	0.518528252
R Square	0.268871549
Adjusted R Square	0.26083717
Standard Error	0.859745794
Observations	185

H1 ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	49.47236494	24.73618247	33.46513308	4.2017E-13
Residual	182	134.5276351	0.73916283		
Total	184	184			

H1	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	7.39104E-17	0.063209768	1.16929E-15	1	-0.124718184	0.124718184	-0.124718184	0.124718184
PU	0.505454393	0.065194127	7.753066305	6.1418E-13	0.376820901	0.634087885	0.376820901	0.634087885
EU	0.047156872	0.065194127	0.72333005	0.470405729	-0.081476621	0.175790364	-0.081476621	0.175790364

Summary Output for H2:

Table 10: H2 Regression Statistical Inferences

H2 Regression Statistics	
Multiple R	0.989301865
R Square	0.97871818
Adjusted R Square	0.978484314
Standard Error	0.146682263
Observations	185

H2 ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	180.0841451	90.04207256	4184.950079	7.0599E-153
Residual	182	3.915854883	0.021515686		
Total	184	184			

H2	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-2.98442E-18	0.010784294	-2.76738E-16	1	-0.021278319	0.021278319	-0.021278319	0.021278319
SI	0.982467061	0.011992151	81.92584076	1.3918E-145	0.958805539	1.006128583	0.958805539	1.006128583
PI	0.015578846	0.011992151	1.2990869	0.195557435	-0.008082675	0.039240368	-0.008082675	0.039240368

Summary Output for H3:

Table 11: H3 Regression Statistical Inferences

H3 Regression Statistics	
Multiple R	0.160655069
R Square	0.025810051
Adjusted R Square	0.015104667
Standard Error	0.99241893
Observations	185

H3 ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	4.74904941	2.374524705	2.410941169	0.092591612
Residual	182	179.2509506	0.984895333		
Total	184	184			

H3	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-1.00108E-16	0.072964091	-1.37201E-15	1	-0.143964283	0.143964283	-0.143964283	0.143964283
SE	-0.077539611	0.074610397	-1.039260124	0.300062459	-0.224752194	0.069672973	-0.224752194	0.069672973
FC	0.126319441	0.074610397	1.693054131	0.092156115	-0.020893142	0.273532024	-0.020893142	0.273532024

Summary Output for H1-H2-H3:

Table 12: H1 to H3 Regression Statistical Inferences

H1-H2-H3 Regression Statistics	
Multiple R	0.251687843
R Square	0.06334677
Adjusted R Square	0.047822131
Standard Error	0.975796018
Observations	185

H1-H2-H3 ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	11.65580572	3.885268573	4.080402096	0.007814805
Residual	181	172.3441943	0.952177869		
Total	184	184			

H1-H2-H3	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-1.47971E-17	0.07174195	-2.06254E-16	1	-0.141558131	0.141558131	-0.141558131	0.141558131
AT	0.129854485	0.073008839	1.778613203	0.076981743	-0.014203417	0.273912387	-0.014203417	0.273912387
SN	-0.00728715	0.072134744	-0.101021354	0.919645325	-0.149620325	0.135046026	-0.149620325	0.135046026
BC	0.195314802	0.073106702	2.671640191	0.008236712	0.051063802	0.339565803	0.051063802	0.339565803

Summary Output for 4:

Table 13: H4 Regression Statistical Inferences

H4 Regression Statistics	
Multiple R	0.730350057
R Square	0.533411205
Adjusted R Square	0.53086154
Standard Error	0.684936829
Observations	185

H4 ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	98.14766181	98.14766181	209.2083045	4.09307E-32
Residual	183	85.85233819	0.46913846		
Total	184	184			

H4	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.55162E-16	0.050357557	3.08121E-15	1	-0.099356058	0.099356058	-0.099356058	0.099356058
UI	0.730350057	0.050494213	14.46403486	4.09307E-32	0.630724375	0.829975739	0.630724375	0.829975739

VII. CONCLUSION

From the analysis it can be safely concluded that Superior's influence (80%) is a major contributing factor in forming subjective norms. Subjective norms describe a person's perceptions of whether other people believe he or she should or should not perform a particular behaviour (Ajzen, 1991). Superior's (faculty in this context) influence does push students to use e-Learning platforms and change their attitudes. Within an educational environment, student's decisions to use technology might be affected by the opinions and suggestions of other people who are important to them (Ma et al., 2005).There is influence from peers as well, although not as strong as superiors. Prior studies have found subjective norms to be a key factor affecting student's intentions to use technology (Sugar, et. al, 2004; Teo, 2009). Based on the percentages, it can be concluded that subjective norm of students are positively related to their intention to use e-Learning.

Self-efficacy is defined as the perception of how well one can perform a behaviour (Bandura, 1982). Students reported a high of 88% indicating their confidence in using technology. Technology Facilitating Conditions refer to environmental factors such as the computer lab's hardware, software, and network that influence an individual's desire to perform a task. As indicated by their many responses to open ended questions, students were not very happy about the technology facilitating conditions. Self-efficacy and technology facilitating conditions lead to perceived behavioural control. Perceived behavioural control refers to people's perception of the ease or difficulty of performing a behaviour (Ajzen, 1991). Students with self-assured computer skills and appropriate available resources are inclined to adopt innovative technologies (Ertmer, 2005; Teo, 2009; Yushua, 2006). A student's computer self-efficacy has a positive impact on technology acceptance and is the basic determinant of behavioural intentions and usage (Anderson & Maninger, 2007).

Further analysis reveals that the resources to facilitate e-Learning isn't conducive for many students at this institution. They found inconsistency amongst the online resources offered amongst different courses. Different teachers had organised their resources differently online and students wanted all teachers to follow the same pattern. Also they felt that some courses offered inadequate resources. Others were not happy with the technology, namely the Moodle learning platform as they found it confusing and had difficulty in locating where resources were. Others wanted 24/7 support when they ran into difficulties or had questions.

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