Typology and Hierarchy of Students' Motivations to Use Technology in Learning

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Abstract

Considerable discussion has taken place in practice and academe regarding the need for changes to the educational system to better suit current student's approaches and preferences for technology use in learning. Much of this discussion involves assumptions about the current students (referred to by some as 'digital natives') preference for independent learning and that students are motivated in similar ways to use technology to achieve and support their preferred learning style. This study sought to better understand student's motivations for technology use in learning and whether assumptions about the homogeneity of motivations are warranted. We sought to identify students' motivation typology and any groupings within these typologies, and understand the inter-relationship between motivations. Using data collected from 16 Information Systems (IS) students via the Repertory Grid Interview technique (RGT), a cluster analysis segmented respondents into two distinct groups: 'Independent Learners' and 'Traditional Learners'. A hierarchical framework of technology use motivations was developed for each group using Interpretive Structural Modelling (ISM) and Cross-impact Matrix Multiplication Applied to Classification (MICMAC) was used to categorise each group's motivation factors. Results show that the two groups were driven to achieve the same learning goals by different paths and hence questioning the assumption of homogeneity in technology use motivations among the current student cohort.

Keywords: digital technology enabled learning; motivations; digital natives; typology; hierarchical framework.

1 Introduction

Worldwide, educational systems have undergone revolutionary changes at a meteoric rate, with widespread implementation and adoption of advanced new technologies, changing curriculum, but also so-called transformation of today's student study habits (Brown, 2005). Growing up and surrounded by digital technologies, today's students are seen by some commentators as having fundamental differences to previous generations of students and have been given new labels, such as digital natives (Prensky, 2001) or net generations (Tapscott, 1998). These students are seen to have different thinking and learning styles, preferring experimental and discovery learning (Prensky, 2001). The difference between these students and their predecessors is perceived as sufficiently significant and has given rise to calls for changes to the education system to accommodate the needs of this new cohort of learners (Helsper & Eynon, 2010; Prensky, 2001; Selwyn, 2009; Tapscott, 1999). The widespread adoption of Web 2.0 technologies in learning environments has added strength to these calls as the learning and information processing capabilities of today's students are considered to have been transformed by Web 2.0 technologies (Selwyn, 2009) and it is argued by some that "the old approach [of didactic teaching] is ill-suited to the intellectual, social, motivational, and emotional needs of the new generation" (Tapscott, 1998, p.131).

Although superficially compelling and persuasive, the claimed need for fundamental change to educational systems has come under quite some critical scrutiny (Bennett & Maton, 2010; Bennett, Maton, & Kervin, 2008; Lai & Hong, 2015; Parkes, Stein, & Reading, 2015; Smith *et al*., 2012). The notions of a homogenous generation with technical expertise and a distinctive learning style have been challenged in regard to both the lack of empirical support and theoretical justification (Bennett & Maton, 2010; Lai & Hong). Over the last decade, a growing body of evidence provides a very mixed picture with heterogeneous views in terms of students access to various technologies, the technology-based activities they engaged in, their technological skills, their learning characteristics, and even the needs that were fulfilled by use of the technologies in learning (Bennett & Maton, 2010; Bennett *et al*., 2008; Kennedy, Judd, Churchward, Gray, & Krause, 2008). As literature has indicated that human behaviour is affected by various factors, such as gender, culture, motivations, it is problematic to claim that today's generation has homogeneous characteristics in technology use (Lai & Hong, 2015). Parkes *et al*. (2015) found that students were not well prepared for the university e-learning environment, in particular in skills required for discovery-based learning, such as analysing and evaluating, which were claimed by digital native proponents to be the key learning styles of today's digital native students (Lai & Hong, 2015). At present a number of pressing questions remain unanswered about digital natives and the use of technology in learning. In particular, two research gaps have been identified.

First, there has been limited academic attention on investigating the existence of a discernible typology for digital natives in terms of their motivations for technology use in learning. Vodanovich *et al*. (2010) called for empirical research to identify and differentiate the various segments of technology users with a view to better understand the profiles of different types of digital natives. Such research would address the concern that, no matter how technologically competent today's generation is, there is no guarantee that they will have the same motivation for using technologies in the learning context as they do in other contexts, since effective learning is not only impacted by their technological skills, but also by their learning approaches and preferences (Bennett *et al*., 2008; Jonassen, Hernandez-Serrano, & Choi, 2000). Understanding the profiles of different groups of digital natives would assist educators in incorporating technologies in teaching in a more responsive manner. It may help minimise the resistance of some learners towards using technologies in learning and encourage collaborative and innovative learning. In addition, these profiles would also help organisations understand the technology use and learning motivations of their future workforce, since these digital natives may bring their technology use preferences into the workplace (Vodanovich *et al*., 2010). This understanding is crucial to better comprehend their attitudes, perceptions, and patterns of technology use, and it is only through developing an understanding of these factors that educators and managers will be able to develop strategies and tactics to engage digital natives' in learning via technologies.

Second, if we expect that there might be heterogeneity among students in terms of their motivations for using technologies in learning, it is important to understand the hierarchical structure of the factors that influence their use of those technologies for each group of the students, considering people's needs are hierarchical in nature (Maslow, 1943). Although research in psychology, organisational behaviour, and consumer behaviour have long recognised and investigated the hierarchical nature of human motivation (e.g.,Bagozzi, Bergami, & Leone, 2003; Pieters, Baumgartner, & Allen, 1995; Wagner, 2007), this phenomenon has been widely overlooked in the literature regarding human communication and technology use behaviour (Guo, Lu, Li, & Li, 2011). The construction of these factors into an inter-related framework for each group is useful for illustrating the different drivers which influence the way students use technologies in learning (Ledbetter, 2009; Roberts, Hann, & Slaughter, 2006). Such information would allow us to assess the relative importance of the factors and their direct and indirect hierarchical relationship so that we might predict the influence of each factor (Hasan, Shankar, & Sarkis, 2007). Such an inter-relationship framework may serve as a guide for taking appropriate actions to motivate each group of students to use technologies more responsively and effectively in their learning. The framework will also allow us to categorise factors based on their driver power and dependence power, enabling us to focus on the most significant factors influencing learning. As Reynolds and Gutman (1984, p.30) stated, "the lack of a model reflecting the relational linkages tends to make the interpretation highly subjective."

Overall, this study is designed to fill these two research gaps and to advance our understanding of today's student technology use motivations by investigating the following three specific questions:

- Are there different groups of students in regard to their motivations for using technologies in learning?
- If such 'student technology use typology' exists, what are inter-relationships among these motivations for each group to use technology in learning?
- What is the relative importance of each motivation in achieving each group students' learning goals?

An empirical study was undertaken to (1) identify a typology of students based on their reasons for using technologies in learning, (2) develop a hierarchical structural framework of those factors for each group of students identified, and (3) classify those factors based on their relative importance. To achieve these goals, the reasons why students use technologies in learning were identified through interviews of 16 technically competent students. Using these technology use perceptions in learning, a cluster analysis was conducted to segment the cohort into two distinct groups. Interpretive Structural Modelling (ISM) technique (Sage, 1977; Warfield, 1974) was used to structure each of these group's technology use hierarchy, and the MICMAC (a French acronym for "matrice d'impacts goises – multiplication appliqués a un classment", meaning "cross-impact matrix – multiplication) (Duperrin & Godet, 1973) technique was used to classify the factors found into different categories.

The remainder of this paper is organised as follows. First, the extant literature regarding the reasons for technology use by young people and use typologies and hierarchy frameworks are discussed. Then the research method is introduced, the participants described and the data collection method and data analysis techniques explained. The findings are then presented, focusing on describing the characteristics of each group of students and its hierarchical framework of technology use motivations. Finally, the theoretical and practical implications of this study are discussed.

2 Literature Review

2.1 Students' motivations for using technologies in learning

Numerous studies across a broad range of contexts have investigated the factors influencing people's use of technologies (e.g., Ledbetter *et al*., 2011; Lim, 2009; Wakefield, Wakefield, Baker, & Wang, 2011; Yates, Wagner, & Majchrzak, 2010). A number of these studies have focused identifying the various factors that explain the use of digital technologies by young people. For example, employing a Uses & Gratifications approach to investigate the media habits of college students in the context of the new media, Parker and Plank (2000) found that students did not abandon traditional forms of communication media for the Internet, with relaxation and escape being the key drivers of use. Similarly, Stafford (2005) found that distance education students used the Internet to satisfy their content, social and information needs. In investigating Facebook's popularity with young adults, Sheldon (2008) found that they use Facebook for relationship maintenance, passing time, virtual community, entertainment, 'coolness', and companionship. In a survey conducted to determine why college students use Wikipedia, Lim (2009) found that it is used for quickly checking facts and finding background information.

Overall, these identified motivations were very similar to the motivations found in mass media and interpersonal communication studies (Stafford, Stafford, & Schkade, 2004). However, when examining the motivations for using technologies within learning contexts, some new and distinct learning related factors have been identified. For instance, Pena-Shafe *et al*. (2005) found the key motivations for students' participating in online discussions were meeting course requirements and gaining feedback from other students. Lonn and Teasley (2009) found that most students said saving time was the most important benefit of technology-mediated learning systems. Chou *et al*. (2010) found that the four most important motivations for students to use course management systems were (1) registering for a course, (2) monitoring their current status, (3) receiving and giving course-related messages/materials, and (4) communicating with instructors and students. In examining students' motivations for using Internet-based communication media in their learning context, Cavus and Kanbul (2010) found that students' most important expectations from learning technologies were (1) accessing materials without time and place constraints, (2) having a secured system, (3) showing their assessment results, (4) getting prompt assessment feedback, and (5) interacting more with instructors. Guo *et al*. (2011) found that students used computer mediated media for reasons such as accessibility, communication mode, content management, communication goals, interaction, information seeking, problem solving, and self-disclosure. Collectively, these studies demonstrate that there is a very broad range of reasons why students use technologies in learning contexts and suggests that there is no consistent and cohesive understanding of those motivations in the literature, indicating that further work is required to improve this understanding.

2.2 Motivation-based student technology use typology

Another way to study the use of technologies in learning by students is by examining their typology. Typology is a means of categorising them into a limited number of groups or types based on various orientations (Westbrook & Black, 1985). This approach is common in the

Marketing discipline, and while many Marketing studies seem to be preoccupied with the typology of the online shopper (Kau, Tang, & Ghose, 2003), some research has examined the typologies of students (who are treated as customers of education products offered by educational institutions) in a technology mediated learning environment (Tao, 2008). In a study of British children (the *Go Online* project), Livingstone *et al*. (2005) identified three groups of teenagers: 'interactors', the 'civic-minded', and the 'disengaged', each of which was distinctive in its social context and approach to the Internet. A survey of Dutch 10–23 year olds (Van den Beemt, Akkerman, & Simons, 2010) found four different clusters of interactive media users: 'traditionalists', 'gamers', 'networkers', and 'producers', each of which had specific uses and opinions about interactive media. Similar findings arose in a survey of 1000 young Brits, in which four Internet use groups were identified: 'peripherals', 'normative', 'all-rounders', and 'active participants', which were differentiated by individual characteristics and contextual features (Eynon & Malmberg, 2011). Tao (2008) examined the typologies of students based on their perceptions toward e-learning and identified two very distinct groups of students: 'sceptics' and 'optimists', who were seen to require different online approaches. Viewed together, these studies paint a picture of considerable diversity among today's generation in terms of computer skills, the kind of technologies they use in both their everyday life and in their learning. This diversity also extends to their attitudes toward technology use in learning.

Since the needs for using technologies should presumably account for students' technology use behaviour, directly focusing on these needs represents a potentially illuminative approach to identifying the distinctive characteristics of students (Westbrook & Black, 1985). Few studies, have however, examined the typology of students based on their motivations for using technologies in learning (Vodanovich *et al*., 2010). This study aims to close this gap, and attempts to provide a holistic view of students, in terms of their social and psychological needs to be fulfilled when using technologies in learning.

2.3 Hierarchical frameworks of technology use motivations

Previous studies of the motivations for technology use have found that the motivations are not isolated, static traits, but interrelated structures (Ledbetter, 2009; Markus, Manville, & Agres, 2000; Rubin, 1983; Vodanovich *et al*., 2010), suggesting that people select a technology for interrelated reasons. For instance, Ledbetter (2009) speculated about a possible structural model among five online communication attitude variables that indicated their direct and indirect relationships, after identifying strong correlations among the variables. While the premise of considering these factors as a set of interrelated needs and expectations is a more meaningful and accurate explanation of technology use, the possible underlying hierarchical relationships among factors has not been addressed. As Phang *et al*. (2010, p.345) stated: "studying the effect of the variables in isolation may not allow for the inter-relations to be uncovered and may result in ambiguous findings". Understanding the influences of the factors on each other and the hierarchy in which the factors sit is important, as it helps classify and categorise the factors, and thereby formulate their respective strategies, while also providing clarity of thought (Hasan *et al*., 2007). More recently Guo *et al*. (2011) developed a hierarchical framework of the reasons for media use by students. The framework identified the relative importance of each 'reason', thus assisting course instructors to identify those aspects related to the most important motivations, hence improving media use within the course. Drawing from input-process-output framework and constructivist paradigm, Eom (2016) proposed a system view of e-learning systems, demonstrating the interrelationships among input variables (students, instructors, and e-learning system characteristics), process (learning cognitive process, student self-regulation, and dialogues between students and instructors), and output variables (learning outcomes and student satisfaction). Eom (2016) found a significant impact of the dialogue (interaction) on improved student learning outcomes, suggesting that interaction can be a significant factor leading to students' improved learning.

This study seeks to explore the inter-relationship of technology use motivations for each identified segment of students. Such a hierarchical framework of motivations would inform our understanding of not only what students want to achieve via technology (various motivations) but also the direct and indirect relationships among all motivations, hence provide insight as to the relative importance of each motivation in the students' technology mediated learning, and how students higher level motivations can be fulfilled.

3 Research Method

This study adopted a structural approach in order to (1) develop a student typology based on their motivations for using technologies in learning, (2) develop an inter-related framework of motivations for each group of students, and (3) classify the motivations into different categories based on their relative importance for each group of students.

Data for the study was collected using RGT from 16 university students. From these interviews, 646 raw constructs where elicited and consolidated into 11 factors using qualitative data analysis, from which a RepGrid was constructed. Cluster analysis was performed on the RepGrid and the data generated from the analysis being analysed via ISM and MICMAC, from which a hierarchical framework was produced and classification of motivations was achieved.

3.1 Data collection method—RGT

RGT is a structured interview process, involving the generation/selection of a list of concepts ('elements') about things and/or events to be studied and the forming of attributes ('constructs') based on the list of concepts and the linkages which exist among those concepts (Latta & Swigger, 1992). As the RGT process allows for uncovering the cognitive constructs of individuals (Tan & Hunter, 2002), without the use of a prior adoption of a theoretical framework, thus producing less biased results. In addition, RGT allows participants to express their own views in their own words and yet, due to its systematic nature, allows researchers to probe deeper into the responses to derive rich information. It has been widely used in organisational and Information Systems (IS) research. In IS research, the RGT technique has been used to elicit the qualities of excellent system analysts (Hunter, 1997), explore the cognitive thinking processes of business and IS executives (Tan & Gallupe, 2006), examine the skills of successful IT project managers (Napier, Keil, & Tan, 2009), understand website usability (Tung, Xu, & Tan, 2009), and the most recent study of exploring analytical capabilities for combating e-commerce fraud identify (Tan, Guo, Cahalane, & Cheng, 2016). Within the study of technology in learning, RGT has been used to identify students' motivations for using information and communication technologies in learning (Guo *et al.*, 2011; Guo, Tan, & Cheung, 2010).

Key steps in this interview process include (1) element selection, and (2) construct elicitation.

3.1.1 Element selection:

Element selection aims to identify subjects within the domain of the investigation. The relevant elements for this study are information technologies used by the students in learning. A minimum of six elements are required to permit construct elicitation (Tan & Hunter, 2002).

In this study the six elements used by the interviewees were supplied. The six elements used were the most commonly used technologies identified from the literature for learning (conventional websites, Learning Management Systems, Discussion Forums, Wikis and Blogs) (Ioannou, Brown, & Artino, 2015) and traditional face-to-face teaching (for comparison purposes). These predefined elements were used so that every participant elicited constructs based on the same set of elements (Siau, Tan, & Sheng, 2010), with the constructs being the motivations for using technologies in learning, to be identified in the interviews. The names of each of the six technologies were then written on individual index cards.

3.1.2 Construct elicitation: select triad, elicit raw constructs, and ladder

Constructs are the qualities that people attribute to the elements. Constructs are bipolar in nature. They describe how some elements are alike and yet different from others (Tan & Hunter, 2002). Two interviewing methods, "triading" and "laddering", are employed to elicit constructs. First, each participant was asked to randomly select three index cards (Select Triad) from the stack. Based on the three elements on the cards, the participant was asked: How are two technologies similar and yet different from the third in terms of your motivations for using these in your learning? To complete the processing of each triad, the participant was encouraged to provide a brief label that best described the motivation and its contrast. The labels for similarity and difference that were identified formed a bipolar construct, e.g., easy to use - difficult to use. Based on the construct identified, the researcher probed the participants with a series of "how" and "why" questions to clarify the meaning and uncover the underlying meanings (laddering process). The participant then placed the three cards back in the stack, shuffled the deck of index cards, selected another three cards, and the exercise was repeated. The construct elicitation process was then repeated to identify more constructs until either no new constructs were elicited from a triad or the participant became noticeably tired.

3.2 Sample and data collection

Given the intensive and comprehensive nature of the RGT, sample sizes of fifteen to twenty five participants are considered to be more than adequate (Tan & Hunter, 2002). In this study, sixteen university students (13 males, 3 females), enrolled in two advanced IS courses, were interviewed, with each interview ranging from 50 to 110 minutes in length. The participants ranged in age (yrs.) from 20 to 26, and all had been at university for at least 2.5 years (average of 3 years). The majority of students (94%) were studying Information Systems or Software Engineering at either undergraduate (88%) or masters (12%) level. All participants reported having used the Internet for at least 7 years. All participants had used Discussion Forums and Wikis extensively for online discussions, group assignments, personal journal reflections and other class communications. Twelve participants had used Wikis for at least 3 years in their university courses. All participants had made use of blogs while at University, with 11 participants using blogs as part of a formal, compulsory activity in one or more of their university classes. All students indicated that they had used blogs in their private life and had used Facebook for more than 4 years.

3.3 Data consolidation and categorisation

The data collected comprised statements of the motivating factors (constructs) for using technology and statements regarding the relationships between those factors. By design, the RGT process allows participants to freely voice their opinions so to permit the best construct elicitation. As a result, a total of 646 raw constructs were provided by the 16 participants. The initial coding was undertaken by one researcher. A second researcher coded two interview transcripts for which a cross-coder reliability of 81.1% was reached, above the 80% acceptable level of cross-coder agreement for exploratory studies (Krippendorff, 1980), suggesting that the coding schema was valid. A data reduction process consolidated similar constructs and removed insignificant constructs (those with less than 3 occurrences) (Guo *et al*., 2010; Siau *et al*., 2010). The consolidation resulted in 77 unique constructs. These 77 constructs were then categorised via an adjusted core-categorisation procedure (Jankowicz, 2004) with the aim of maximising the similarity of meaning within the category and dissimilarity between categories. The 77 unique constructs were consolidated into 11 dimensions, as shown in Table 1, in which each dimension is denoted as Si, in sequence. The categorisation process was examined independently by two researchers with an initial agreement level of just over 80% agreement being achieved, with all remaining discrepancies being resolved via discussion and consensus between the researchers.

Motivation Dimension	Code	Description
Access and Content Control	S1	The security aspects of accessing the technology and the content maintained by the technology.
Accessibility	S2	Both the physical access to the technology and subsequent use of the technology (Culnan, 1984).
Communication Efficiency	S3	The extent to which communication can be done conveniently, easily, frequently, and quickly.
Communication Mode	S4	The way in which the technology assists the learners to communicate, such as audio, video, or multimedia.
Communication Quality	S5	The extent to which communication is clear, in depth, effective, specific, and focused.
Course Management	S6	Involves the ability of learning technologies to take an administrative role in learner's learning.
Information Seeking	S7	The "purposive seeking for information as a consequence of a need to satisfy some goals." (Wilson, 2000 p.49)
Interaction	S8	The exchangeability of sources and receivers, including interactions between students and learning contents, students and instructors, students and students, and students and technology itself (Bouhnik & Marcus, 2006; Rice, 1987).
Learning Capability	S9	The ability to create a learning environment to develop learners' critical thinking skills, to be independent, active and reflective, to collaborate and cooperate, and to be constructive (Miers, 2004).
Managing Contents	S10	The ways people want to manage their data with technologies.
Self-Disclosure	S11	The extent to which any message about the self a person communicates to another (Wheeless & Grotz, 1976).

Table 1: Summary of digital native's technology use motivations

The richness of data allowed the researchers to also distinguish a total of 504 unique relationship nodes among the 646 raw constructs, where each node was in the form of one motivation construct being influenced by another, with the relationship type being defined as 'influences', where attaining factor 'A' influences achieving factor 'B' (Warfield, 1994). As with the constructs, a data reduction process was undertaken on the relationship nodes, which resulted in 328 unique relationships. These relationships were then categorised using the motivation categories (Table 1), giving rise the matrix of influence between the 11 categories, as shown in Table 2. The relationships identified in this matrix represented the relation between any two unique constructs from any two factors for any participant. A total of 65 unique relationships between the various constructs were identified.

3.4 Data analysis techniques

The study sought to understand whether differences existed in the motivations for using technology in learning between different typologies of students. Thus, a two-stage approach to clustering (Hair, Anderson, Tatham, & Black, 1998; Punj & Stewart, 1983) was used. Initial solutions, using the Average-Linkage hierarchical method, with squared Euclidean distance as a measure of similarity, provided a preliminary indication of the total number of clusters. Following Phang *et al*. (2010), the final cluster solution was then identified using the Quick Cluster K-means procedure. Details of the analysis undertaken and clusters found are set in the Results section.

		To										
		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
From	S1: Access and Content Control		4	5		5	1	9	11	13	8	5
	S2: Accessibility	2		8		3		1	3	4		1
	S3: Communication Efficiency					1		1		2		
	S4: Communication Mode		1	3		11			4	2	2	7
	S5: Communication Quality			1				1			1	
	S6: Course Management		4	2		1			3	3		
	S7: Information Seeking			2		5			1	2		
	S8: Interaction		1	7		7	1	8		15	1	2
	S9: Learning Capability			2		1		1			1	1
	S10: Managing Contents	1		3		2	1	7	7	10		1
	S11: Self-Disclosure		1			3		3	4	2	2	

Table 2: Contextual relationships between factors

Interpretive Structural Modelling (ISM) was used to generate hierarchical frameworks of motivations. ISM is an interactive learning process, whereby a set of different interrelated variables affecting the system under consideration is structured into a comprehensive systemic model (Sage, 1977; Warfield, 1974). ISM is considered as one of the best approaches to use to develop the models of the factors and their direct relationships (Sage, 1977). Its objective is "to expedite the process of creating a digraph, which can be converted to a structural model, and then inspected and revised to capture the user's best perceptions of the situation" (Malone, 1975, p. 399).

By using the practical experience and knowledge of individuals and groups, ISM provides a means by which order and direction can be imposed on the complex relationships among the elements of a system (Sage, 1977) and the limitations that individuals have in dealing with complex issues involving a significant number of variables at one time can be overcome (Waller, 1975; Warfield, 1976). ISM provides both a comprehensible model of an inherently complex and usually impenetrable system (Kanungo & Anantatmula, 2008) and a means of integrating diverse viewpoints (Vivek, Banwet, & Shankar, 2008). ISM has been applied across a range of relevant areas including developing a better understanding of higher education program planning (Hawthorne & Sage, 1975), evaluating IS effectiveness (Kanungo, Duda, & Srinivas, 1999), determining information technology (IT) enablers and barriers for knowledge management (Bhattacharyya & Momaya, 2009; S. Kanungo & Anantatmula, 2008), and understanding students' motivations for using computer mediated communication (CMC) technologies in their learning contexts (Guo *et al*., 2011).

MICMAC (a French acronym for "matrice d'impacts goises – multiplication appliqués a un classment," meaning "cross-impact matrix – multiplication applied to classification") was used to classify the motivations into different categories for each group identified in cluster analysis. MICMAC is a data analysis technique related to ISM and is a systematic analysis tool for categorising variables based on hidden and indirect relationships, as well as for assessing the extent to which they influence each other. Consideration of the indirect relations in a hierarchical framework is important in a complex system, since indirect relations may have a great impact on the system behaviour, through influencing chains or reaction loops. Many researchers have integrated ISM and MICMAC techniques in a wide range of areas (e.g., Guo, Li, & Stevens, 2012; Guo *et al*., 2011; S. Kanungo & Anantatmula, 2008; Lee, Chao, & Lin, 2010).

Mandal and Deshmukh (1994) claim that the primary goal of MICMAC analysis is to evaluate the 'driver power' and dependence of the variables. Driver power refers to the degree of influence that one variable has over another, while 'dependence' is defined as the extent to which one variable is influenced by others (Hu, Chiu, & Yen, 2009). Based on driver power and dependence, variables can be classified into four major types: independent, dependent, linkage, and autonomous.

'Independent variables' have high driver power and relatively low dependence and have an important influence on the elements above them in the hierarchy. 'Dependent variables' have high degree of dependence, but relative low driver power, forming the upper-most level in the ISM hierarchy, often the final outcomes of the influence of all the other elements. 'Linkage variables' possess relatively high dependence and driver power and are therefore strong linkage variables in the hierarchy. Finally, 'Autonomous variables' have lower driver power as well as low dependence, and turn out to be a set of relatively low-influence, stand-alone variables.

In this study, the ISM technique was used to develop the interpretive structural model of the variables for each identified group, as a way to shed light on the direct relationships between motivations. MICMAC was then used to map and understand the indirect and hidden relationships between the variables. Table 3 presents the logical flow of both ISM and MICMAC techniques adopted in this study (e.g., Guo *et al*., 2012; Guo *et al*., 2011; Kanungo & Anantatmula, 2008; Lee *et al*., 2010). Guo *et al*. (2011) provide a concise overview of the analysis procedures involved.

Step	*Description*
1)	Identifying a set of factors affecting students' use of technologies through interviews (11 factors were identified, see Table 1).
2)	Establishing a pair-wise contextual relationship between factors through analysing interview data (see Table 2).
3)	Developing an Adjacency Matrix (See Appendix B Tables A1 & A2).
4)	Developing a Reachability Matrix, and checking the matrix for transitivity (See Tables 4 & 5).
5)	Partitioning the Reachability Matrix into different levels (see Appendix B Tables B1 & B2).
6)	Forming a canonical form of matrix (see Appendix C Tables C1 & C2).
7)	Drawing a directed graph (DIGRAPH) and removing the transitive links.
8)	Converting the resultant digraph into an ISM by replacing variable nodes with statements (see Figures 2 & 3).
9)	Conducting MICMAC analysis to classify factors into various categories based on their driver power and dependence (see Figures 4 & 5).

Table 3: Modelling approach

4 Results

4.1 A typology of students based on the motivations for using technologies in learning

To develop the typology of students based on their motivations, a matrix of the 11 motivations (rows) and the 16 participants (columns) was created, in which the cells were populated by the total number of times each motivation was mentioned by each participant. The matrix was duplicated, substituting the counts with the relative percentage that a participant mentioned each motivation. Application of the K-means clustering method to the 11 motivation percentage scores for each participant indicated that a solution with two distinct clusters produced both the most efficient and interpretable result, with the exception of one outlier. Based on the data indicating cluster centroids for the two-cluster solution, a radar diagram (Figure 1) was generated to depict the factors that influence the use of technologies in these two clusters. The labelling for each cluster, namely cluster 1 as Independent Learners and cluster 2 as Traditional Learners, was determined by examining the centroid means of the factor score obtained from cluster analysis.

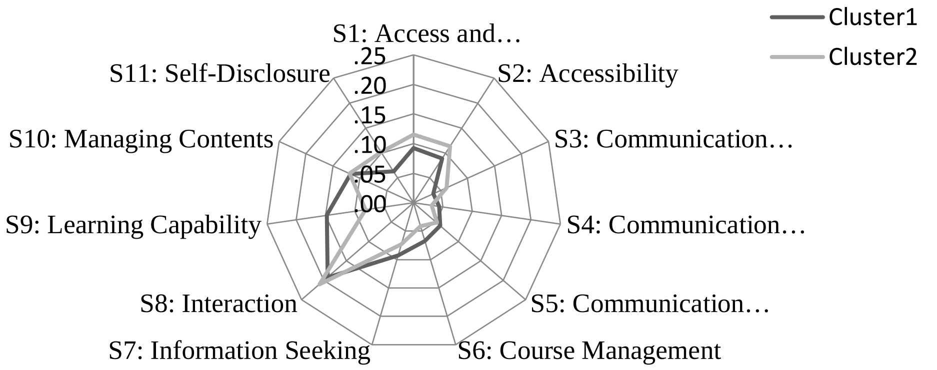

Figure 1: Radar diagram of clusters

Cluster 1 consisted of 6 males and 2 females, being 53.3% of all participants. This group scored significantly higher on Learning Capability, while scoring lower on Accessibility, Communication Efficiency, and Self-Disclosure. They were all undergraduates, majoring in IS or Software Engineering.

Cluster 2 consisted of 6 males and 1 female, being 46.7% of all participants. This group had a weaker belief that using technologies for learning improved their learning capabilities. However, they scored significantly higher in regard to Accessibility, Communication Efficiency, and Self-Disclosure. This group consisted of 2 postgraduates (IS majors) and 5 undergraduates (1 business major and 4 IS majors).

4.2 Hierarchical frameworks developed using ISM

The ISM analysis used in the study required two key elements: (1) a set of variables considered for model development and (2) pair-wise contextual relationships among this set of variables. Both Table 1 and Table 2 show the set of variables identified in this study and the contextual relationships among them.

Based on overall contextual relationships, a pair-wise contextual relationship for each of the clusters was identified. After removing the weak relations (those mentioned by less than two participants), the final contextual relationships between each pair of variable categories for clusters 1 & 2 were created (Appendix A Tables A1 & A2), in which cells were populated by 1s and 0s, whereby '1' indicates the relationship and '0' indicates otherwise. These binary matrices, which describe whether there is a direct relationship between the row and column variables, are termed Adjacency Matrices.

Based on each cluster's Adjacency Matrix, Reachability Matrix (Tables 3 & 4), level partitions (Appendix B Tables B1&B2), and Canonical Matrix (Appendix C Tables C1&C2) for both two clusters were calculated. Then an ISM was formed for Clusters 1 & 2 respectively based on its own Canonical Matrix, as shown in Figures 2 & 3. These two diagrams represent the structural linkages among factors that motivate students to use technologies in their learning. Tables 4 & 5 also include each motivation's driver power and dependence, which can be obtained from the Reachability Matrix by the summation of 1s in the corresponding rows and columns respectively (Hu *et al*., 2009).

M	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	*Driver power*
S1	1	0	1	0	1	0	1	1	1	1	0	7
S2	0	1	1	0	0	0	0	0	1	0	0	3
S3	0	0	1	0	0	0	0	0	0	0	0	1
S4	0	0	1	1	1	0	1	1	1	0	1	7
S5	0	0	0	0	1	0	0	0	0	0	0	1
S6	0	1	1	0	0	1	0	0	1	0	0	4
S7	0	0	1	0	1	0	1	0	0	0	0	3
S8	0	0	1	0	1	0	1	1	1	0	0	5
S9	0	0	0	0	0	0	0	0	1	0	0	1
S10	0	0	1	0	1	0	1	1	1	1	0	6
S11	0	0	1	0	1	0	1	1	1	0	1	6
Dependence	1	2	9	1	7	1	6	5	8	2	2	44/44

Table 4: Cluster 1 reachability matrix

M	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	*Driver power*
S1	1	1	1	0	1	0	1	1	1	1	1	9
S2	0	1	1	0	1	0	1	1	1	0	1	7
S3	0	0	1	0	0	0	0	0	0	0	0	1
S4	0	0	1	1	1	0	1	1	1	0	1	7
S5	0	0	0	0	1	0	0	0	0	0	0	1
S6	0	0	1	0	1	1	1	1	1	0	1	7
S7	0	0	0	0	1	0	1	0	0	0	0	2
S8	0	0	1	0	1	0	1	1	1	0	1	6
S9	0	0	0	0	0	0	0	0	1	0	0	1
S10	0	0	1	0	1	0	1	1	1	1	1	7
S11	0	0	1	0	1	0	1	1	1	0	1	6
Dependence	1	2	8	1	9	1	8	7	8	2	7	54/54

Table 5: Cluster 2 reachability matrix

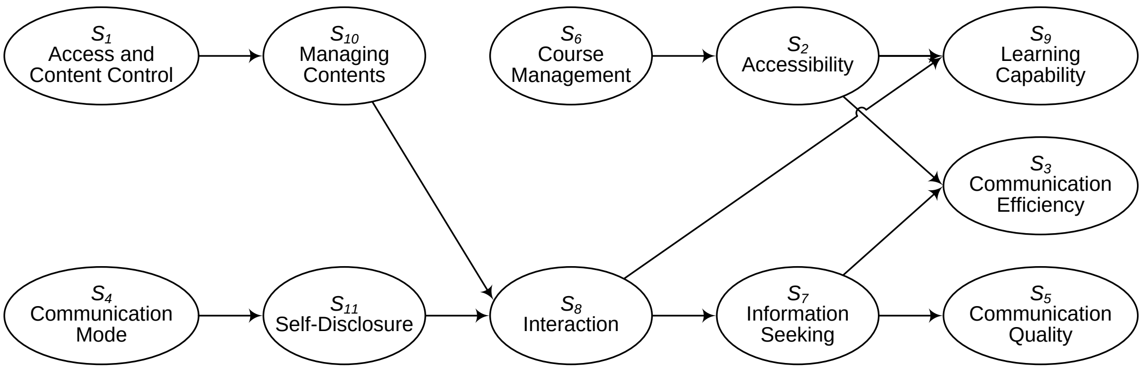

Figure 2: Independent Learners' ISM

From each cluster's hierarchical framework, the direct relationships among all motivations can be identified. For Independent Learners, the driver variable of Access and Content Control enabled Managing Contents and various Communication Modes of technologies to give students freedom in terms of the ways they express themselves in technology mediated learning environment. Then, both Managing Contents and Self-Disclosure variables resulted in Interaction, which influenced both Information Seeking and Learning Capability. Course Management determined Accessibility. Communication Efficiency was dependent on both Accessibility and Information Seeking. Information Seeking also influenced Communication Quality. In contrast, for Traditional Learners, Access and Content Control was identified as the main driver of Accessibility and Managing Contents, which also co-determined, along with Communication Mode and Course Management, Interactions and Self-Disclosure. Interactions and Self-Disclosure influenced each other, as well as Information Seeking, which was the only route for developing students' communication and learning capabilities.

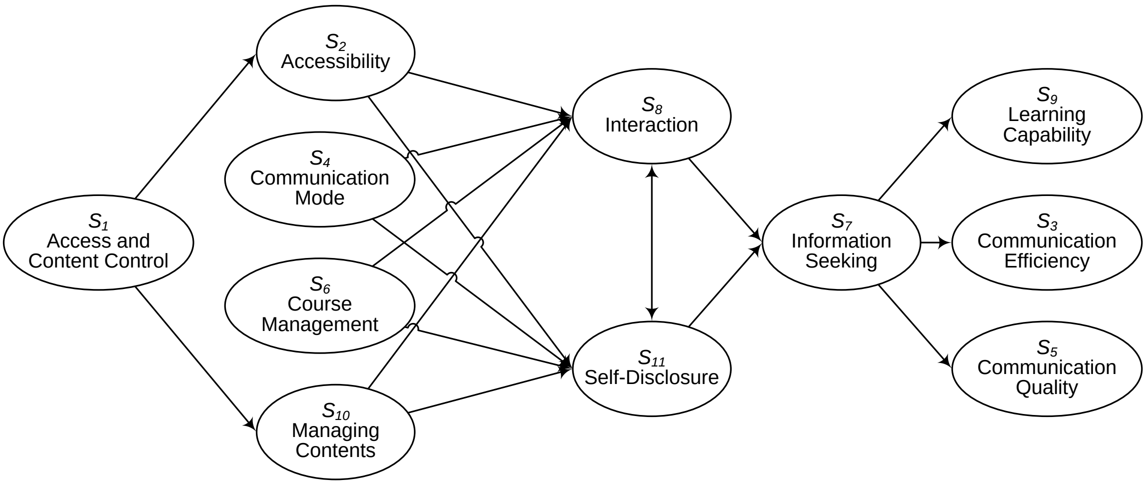

Figure 3: Traditional Learners' ISM

4.3 Classifications of motivations generated using MICMAC

To understand the nature of these motivations in depth, the development of structural models with a MICMAC analysis is followed to identify both the direct and indirect relationships among all variables, and demonstrate the complete role of each motivation by classifying motivations into four different categories based on their driver power and dependence provided, as shown in Tables 4 & 5 (Guo *et al*., 2011). Figures 4 & 5 show the categorisation results, in which quadrants I, II, III and IV represent Independent, Linkage, Dependent, and Autonomous variables respectively. The means of the driver power and dependence were used to divide the driver power and dependence diagram into the four quadrants.

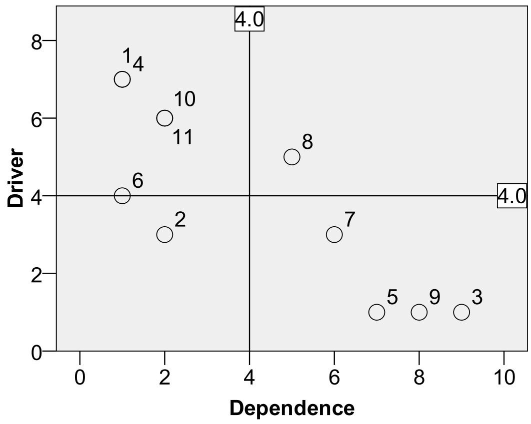

Figure 4: Independent Learners' driver power and dependence plot

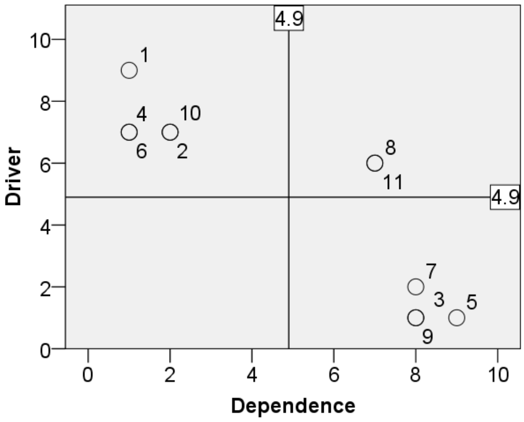

Figure 5: Traditional Learners' driver power and dependence plot

The driver power and dependence diagram shows the nature of how the identified motivations interact and play, and how the four types of variables differ from each other depending on the specific role they play in today's students' dynamic technology use process in learning. For comparison purposes, Table 6 shows both groups' technology use motivation roles in their corresponding hierarchical framework. It is clear that both groups had the same Dependent variables, but differed in the other three categories, indicating the different underlying mechanism taken by each of the groups to achieve their learning goals.

Variable Role	*Independent Learners^*	*Traditional Learners^*
Independent Variables	**Access and Content Control**	**Access and Content Control**
	Communication Mode	Accessibility
	Managing Contents	**Communication Mode**
	Self-Disclosure	Course Management
		Managing Contents
Linkage Variables	**Interaction**	**Interaction**
		Self-Disclosure
Dependent Variables	**Communication Efficiency**	**Communication Efficiency**
	Communication Quality	**Communication Quality**
	Information Seeking	**Information Seeking**
	Learning Capability	**Learning Capability**
Autonomics Variables	Accessibility	
	Course Management	

^ Variables that are common to both groups are highlighted in bold

Table 6: Different roles of motivations in each group's technology use

5 Discussion

This study yields four important findings. First, two groups of students, namely Independent Learners and Traditional Learners, were identified based on students' motivations for using technology in learning. Second, this study captured the hierarchical structure of these factors and their functional dependencies among each other for each group respectively. Third, despite the similarity of learning goals between the groups, their individual paths toward their learning goals were different when it comes to learning with technologies. Finally, it was found that Interaction is the key activity that leads to student learning goals for both groups. Each of these key findings is discussed in detail below.

5.1 Independent vs. traditional learners

Two distinct groups of students, labelled as Independent Learners and Traditional Learners, were found. The groupings were based on the different motivation preferences for using technologies in learning, in which the 'Learning Capability' factor was the main distinguishing factor between the two groups.

The Independent Learners had significantly stronger preferences than Traditional Learners in terms of using technologies for improving Learning Capability. This suggests that it is only the Independent Learner group that carries the distinctive learning attributes claimed by some studies to be universal across today's students. These distinctive attributes are summed up by Selwyn, who describes students as "as being no longer a passive recipient of educational instruction, but instead cast into an active role of (re)constructing the nature, place, pace and timing of learning events as they wish" (Selwyn, 2009, p. 367). The other group of learners retained a more traditional view of learning with technologies. This finding is consistent with those of Spires *et al*. (2008), in which students' technology use in schoolwork was found to be less creative and meaningful than their use of technology outside of school. The differences between the two groups in regard to Learning Capability are not reflected in differences in their technology experience (for which there was none), nor are the differences reflected in the demographics of the participants. The lack of differentiation between the groups in both of these aspects suggests that the explanation of differences between the groups lies elsewhere.

The different approaches toward using learning technology may well be the underlying source of this difference as the Learning Capability pursued by the Independent Learner group was observed to be in line with constructive learning paradigm (Biggs, 2003).

This finding has considerable implications for the proponents of the 'digital natives' / 'net generation' / 'millennial' (Conklin, 2013; Jones, Ramanau, Cross, & Healing, 2010) view of students, as our findings demonstrate the attributes that are often ascribed to all students are not in fact universal, as is discussed later.

5.2 Hierarchical frameworks of independent and traditional learners

Analysis of the two structural models (Figures 2 & 3) and the driver power and dependence diagrams (Figures 4 & 5) for each group reveals a number of similarities as well as differences between the two groups in terms of the hierarchy and relative importance of the motivations.

Both groups had some common independent variables for their technology use in learning, although the driver powers varied across the variables, hence indicating differences in their relative importance. The Traditional Learner group had two additional independent variables, Accessibility, and Course Management, whereas the Independent Learners had only Self-Disclosure. The Access and Content Control variable, having maximum driver power in the Traditional Learner group, was the key enabler influencing Traditional Learners' technology use. Hence, the security of the system and the extent of control the student has over content appear to have a direct impact on how they use the technology to manage their learning content, which may ultimately impact their learning outcomes. These independent variables, appearing at the bottom (left hand side, in this case) of the ISM, are all considered technology related product attributes. Without these technological attributes as given conditions, the interaction of students with the other aspects of the technology cannot be assured and, hence, the goals of technology-enabled learning would be difficult to achieve. These 'givens', from a technology mediated learning process perspective, can be considered as aspects that are necessary, though not sufficient, to achieve the desired ends (Guo *et al.*, 2011). In practical terms this suggests that these technological features should be properly maintained, and continuously and consciously improved.

The Linkage variable 'Interaction', sits in the middle of the hierarchy and is imperative for both groups in translating technology features into effective use to enhance communication performance and learning capabilities, although the relationship between this linkage variable and others differs between the two different groups. This finding is not only consistent with Eom's (2016) empirical finding of the significant impacts of the interaction on student learning outcomes and satisfaction, but also support Eom's argument of considering "Interaction" as a process (linkage variable) through which students can enhance their learning in e-learning systems.

The key difference between these two group's hierarchical frameworks, was the role of the Self-Disclosure variable. For Traditional Learners, this variable was a linkage variable which interacted with "Interaction", while for Independent Learners, Self-Disclosure was a 'given' (independent) variable. This suggests that Independent Learners believe that it is important for them to have more control over the technologies they use in learning in terms of their extent to self-disclose. This is consistent with previous findings, such as, Ledbetter (2009) identified self-disclosure as an important motivation for people who communicated online. Interestingly, Denker *et al.* (2017) found a negative impact of self-disclosure on students' willingness to participate in social media (Twitter) discussions as part of their coursework because of fears that the University instructors would learn about their personal life. This study was, however, conducted in learning systems which were only used for class learning (so-called walled garden), which may explain why our participants showed a positive relationship between self-disclosure and interaction.

In the ISM hierarchy, linkage variables are considered as 'means' to achieve individual eventual goals since they are related to both independent ('given') variables and dependent ('end') variables (Guo *et al.*, 2011). By their nature, these 'means' variables are 'factors of instability', since any action towards them would result in significant changes on other variables (Hu *et al.*, 2009). Thus, finding a way to control, manipulate, or develop students' interaction skills is critical to fulfil their learning goals.

As the structural relationships of the ISM move toward the top of the models, the same four dependent variables for both groups were found. Information Seeking emerged as the only route that drove the Traditional Learner group to use technologies to enhance their communication and learning capabilities. In contrast, Independent Learners' learning capabilities can be directly influenced through Interactions, whereby Information Seeking can only result in Improved Communication Efficiency and Communication Quality. This suggests that Traditional Learners see that learning is about instructors creating content and students being passive recipients of that content. This group sees the role of technology as enabling them to retrieve course materials and learning content. Conversely, Independent Learners see that learning is about interaction, engagement, peering learning, collaboration, and improving their learning capabilities (Shih, Feng, & Tsai, 2008). Despite being the 'end' variables, and not driving any other variables, the high dependence of these variables means that they are important as action on any other variable will have an impact on them (Hasan *et al*., 2007).

Finally, Accessibility and Course Management, which were the 'givens' for the Traditional Learner group, were considered as autonomous variables for the Independent Learner group, which suggests for this group, that these two factors can be seen as disconnected and needing little attention. The Traditional Learner group however, these factors are important variables that do require attention. The differences in the importance of these two variables would seem to further support the notion that Traditional Learners see the technology as providing a means to access content, whereas Independent Learners are less concerned about these more administrative aspects of technology.

5.3 Importance of Interaction and the use of technology to manage learning content

All students had very strong views regarding the use of technology for 'Interaction' as this was the highest ranked factor by all interviewees. This result supports those of other studies and confirms that today's students are collaborative and interactive (Chen, 2014). This finding is also consistent with previous technology mediated learning literature, in which interaction is one of the most important elements in improving the value of the e-learning experience (Laer & Elen, 2017). However, Parkes *et al*. (2015) reported that students perceived themselves to be less competent in Interaction with the learning content and less prepared to seek interactions with other members of the learning community (especially instructors), hence challenging the notion of social constructivist principles. Our findings provides a means of reconciling these different view by indicating that although students appreciate the benefits of interaction in e-learning, they may have difficulties fully realising interaction because they lack the skills needed for effective interactions with others.

The use of technology to manage learning content appears to have become a standard practice by all students. This finding is consistent with previous studies in which students were found to use computer mediated communication media for file management, storage, and database repository (e.g., Guo *et al*., 2010; Pena-Shafe *et al*., 2005). However, a recent study examining student's preparedness for e-learning environment (Parkes *et al*., 2015) shows that students perceived themselves less competent in terms of knowledge and use of e-learning systems. As both groups of students demonstrated the direct impact of the skills required to manage learning content in e-learning systems on Interaction, it is crucial to find a way of enhancing student's ability of managing their e-learning systems in order to promote high quality interaction and enhance their learning goals.

6 Implications

6.1 Implications for research

This study makes a number of significant contributions to research about today's students technology use in learning. First, by using students motivations towards the use of learning technologies, two distinct grouping of students have been identified, hence indicating today's students are heterogeneous in terms of these motivations and not all students prefer an independent learning style, as has been claimed by some recent studies (Buchanan & James, 2014; Cheng, 2014; Marriott, 2010). Future research examining students' technology use should take this heterogeneity into account when considering how technology should be implemented, and avoid assumptions as to how technology can be used in learning as our findings suggest that the current cohort of students may not learn differently from previous generations; instead, they may only use different tools in that learning and have different learning preferences.

The second contribution of the study is the identification of the hierarchical framework and classification of the motivations for using technologies in learning for the two groups identified in the study. This finding further demonstrates the heterogeneity of students in terms of not only their motivations, but also the inter-relationships among those motivations. Since the inter-relationships identified in this study will aid in our understanding of the relative position and influence of the motivations to each other, the results of this study reveal that different groups of students may have different underlying mechanisms to achieve their learning goals in regard to technology mediated learning, as driven by the different factors, and, as such, a universal teaching approach would not seem appropriate. Although our data was obtained from a small group of technological competent students, our results were based on rigorous data collection and analysis, and show that there was a set of inter-related factors that influenced students' technology use in learning. In addition to the theoretical desirability of such a linkage, this study reaffirmed the value of the integration of ISM and MICMAC methodologies in exploring structure and inter-relationships among variables.

6.2 Implications for practice

From a practical perspective, this study offers insights for university policy-makers and instructors who shape the policies and strategies on the use of information technologies for educational purposes, and for practitioners who wish to understand the new technologies today's generations are using, and will use, in learning and future work. First, Learning Capability is the most distinct factor differentiating the two groups of students, indicating that there is heterogeneity among today's students, in terms of their motivations toward learning with technologies. This suggests that calls for fundamental change to the existing education systems to cater for the needs of this new cohort of learners may in fact be somewhat premature as our data shows that not every student prefers discovery-based learning (Bennett *et al.*, 2008). This is not to say that radical change of current educational systems is unnecessary, but does suggest that whatever changes are required, they are unlikely to be captured in a single approach. University policy makers and instructors should differentiate and tailor their technology related business strategies, policies, and/or actions to accommodate the different learning approaches of the different types of students or risk student dissatisfaction and less-than-effective learning performance. In addition, even though the current generation of students seem to enjoy an 'engage and collaborate' rather than a 'command and control' model within organisations (Vodanovich *et al.*, 2010), our findings suggests that this may not be the case for all students.

Second, the development of a hierarchical framework of motivations for each group helps in understanding how different motivations drive students' technology use in learning. The classification of the motivations also allows us to understand their relative importance in the technology use process, i.e. which technological attributes are required for achieving their eventual learning goals. This integrated model is important, since it can assist identify why students want to use technologies (dependent variables) and what are the fundamental drivers to achieve those goals (independent variables). Although both groups showed the importance of the linkage variable "Interaction" in enhancing learning goals, it appears that some students, (notably the traditional learners) would benefit from training that helped them develop a learning culture so that they can make full use of e-learning systems for interaction and collaboration (Parkes *et al*., 2015). More importantly, it was found that there is a different flow of causal influence for each group, i.e., different mechanisms to achieve the learning goals, indicating that technological features favourable to one group may not be popular with the other group. Instructors should be aware that intensive and high-quality interactions among the Independent Learners are key enablers leading to improved learning capabilities, whereas for Traditional Learners, Information Seeking has a more direct impact than Interaction on improving learners' learning outcomes. In addition, since the identified independent variables could have an overarching effect on the overall performance, if instructors fail to introduce the right technologies with appropriate attributes into their teaching, they may in fact demotivate students and inhibit technology use. This may be especially the case for traditional learners, given their attitudes toward e-learning systems. Some suitable orientation that focuses on knowledge and use of learning management systems may be needed in order to make the students realize the full potential of the systems. Furthermore, differences in the relationships between the variables means that the impact of the de-motivators may be different. For example, based on Figures 2 & 3, if security (Access and Content Control) is less than ideal, which discourages systems use, then the Independent Learners are likely to make less use of the content management aspects of the system, but continue other use, whereas Traditional Learners are likely to access the system less, hence making less use of all aspects of the system.

Finally, technology application developers may find that by accommodating the technological attributes that are more important for each of these different groups of students into their designs will result in better acceptance of the their software across the student popular. Similarly Marketing functions may also consider incorporating these ideas into their customized campaigns so that they take all current students along a series of steps leading from technology specific attributes to their desired learning goals, by the paths that they understand and appreciate (Thompson & Chen, 1998). Without a better understanding of the technology use mechanisms of digital users, all organisations investing in training efforts for newly hired graduates might find that their strategies are misdirected or less than effective.

7 Limitations and future directions

A limitation of this study is the assumption that all participants were digitally savvy and capable. While there is no established measure of digital capability, a group of students with technical skills described by studies of recent cohorts of students was chosen deliberately, including the attributes ascribed to these students by those proposing the notion of digital natives (Helsper & Eynon, 2010; Prensky, 2001; Vodanovich *et al*., 2010). The small sample size, which may have lessened the rigour of the cluster analysis, is also another potential limitation. To increase the validity of these results, future studies need to expand on this work with a larger sample size, exploring the ideas and framework presented in this study. In addition, 11 technology use motivations and the ISM models were developed based on the opinions of 16 students from one university. The use of a larger sample size, or other groups of students might reveal additional or different factors that influence their use.

The framework developed in this study might also vary across different student cohorts as there are differences of opinion about the contextual relationships among the variables (Faisal, Banwet, & Shankar, 2006). Further research is required to provide a more robust shared mental model for current students. The ISM developed in this study was generated based on the interpretations of respondents, therefore empirical examination is needed to test the validity of this hypothesised model, with Structural Equation Modelling (SEM) technique as the recommended approach (Qureshi, Kumar, & Kumar, 2008).

In addition, while these two groups were similar in terms of their demographic factors and technological skills, one interesting avenue for future empirical research would be to explore whether there is a significant difference between these two groups in terms of their approaches to learning, challenging claims about the current generation of students distinctive and preferred independent learning style.

In conclusion, to move educational practice forward, it may be necessary to change the educational systems to meet students' learning needs as advances in technologies require societal changes in their approaches and practices to meet individuals' changing needs (Bennett & Maton, 2010). However, such changes should be designed based on theory and supported by clear research evidence (Bennett *et al.*, 2008). Drawing on current students' technology use motivation perspective, this study used both ISM and MICMAC techniques to re-assess our perceptions about students use of technologies in learning, by not only critically identifying and classifying the key factors that influence that use, but also by revealing the effects and inter-relationship of each of those factors on their technology use behaviours in learning. The differences in the technology use hierarchical structures between these two groups indicate that not all students use technologies in the same way when it comes to learning.

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Appendix A.

A	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
S1: Access and Content Control	0	0	1	0	1	0	1	1	1	1	0
S2: Accessibility	0	0	1	0	0	0	0	0	1	0	0
S3: Communication Efficiency	0	0	0	0	0	0	0	0	0	0	0
S4: Communication Mode	0	0	0	0	1	0	0	1	1	0	1
S5: Communication Quality	0	0	0	0	0	0	0	0	0	0	0
S6: Course Management	0	1	1	0	0	0	0	0	1	0	0
S7: Information Seeking	0	0	1	0	1	0	0	0	0	0	0
S8: Interaction	0	0	1	0	1	0	1	0	1	0	0
S9: Learning Capability	0	0	0	0	0	0	0	0	0	0	0
S10: Managing Contents	0	0	0	0	0	0	1	1	1	0	0
S11: Self-Disclosure	0	0	0	0	0	0	0	1	1	0	0

Table A1: Cluster 1 adjacency matrix

A	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
S1: Access and Content Control	0	1	1	0	1	0	1	1	1	1	1
S2: Accessibility	0	0	1	0	1	0	0	1	0	0	0
S3: Communication Efficiency	0	0	0	0	0	0	0	0	0	0	0
S4: Communication Mode	0	0	1	0	1	0	0	1	0	0	1
S5: Communication Quality	0	0	0	0	0	0	0	0	0	0	0
S6: Course Management	0	0	0	0	0	0	0	1	0	0	0
S7: Information Seeking	0	0	0	0	1	0	0	0	0	0	0
S8: Interaction	0	0	1	0	1	0	1	0	1	0	1
S9: Learning Capability	0	0	0	0	0	0	0	0	0	0	0
S10: Managing Contents	0	0	1	0	0	0	1	1	1	0	0
S11: Self-Disclosure	0	0	0	0	1	0	1	1	0	0	0

Table A2: Cluster 2 adjacency matrix

Appendix B.

Level	S_i	*R* (S_i)	*A* (S_i)	*R∩A*
V	1	1, 3, 5, 7, 8, 9, 10	1	1
Ⅱ	2	2, 3, 9	2, 6	2
I	3	3	1, 2, 3, 4, 6, 7, 8, 10, 11	3
V	4	3, 4, 5, 7, 8, 9, 11	4	4
I	5	5	1, 4, 5, 7, 8, 10, 11	5
Ⅲ	6	2, 3, 6, 9	6	6
Ⅱ	7	3, 5, 7	1, 4, 7, 8, 10, 11	7
Ⅲ	8	3, 5, 7, 8, 9	1, 4, 8, 10, 11	8
I	9	9	1, 2, 4, 6, 8, 9, 10, 11	9
Ⅳ	10	3, 5, 7, 8, 9, 10	1, 10	10
Ⅳ	11	3, 5, 7, 8, 9, 11	4, 11	11

Table B1: Cluster 1 level partition

Level	S_i	*R* (S_i)	*A* (S_i)	*R∩A*
V	1	1, 2, 3, 5, 7, 8, 9, 10, 11	1	1
Ⅳ	2	2, 3, 5, 7, 8, 9, 11	1, 2	2
I	3	3	1, 2, 3, 4, 6, 8, 10, 11	3
Ⅳ	4	3, 4, 5, 7, 8, 9, 11	4	4
I	5	5	1, 2, 4, 5, 6, 7, 8, 10, 11	5
Ⅳ	6	3, 5, 6, 7, 8, 9, 11	6	6
Ⅱ	7	5, 7	1, 2, 4, 6, 7, 8, 10, 11	7
Ⅲ	8	3, 5, 7, 8, 9, 11	1, 2, 4, 6, 8, 10, 11	8, 11
I	9	9	1, 2, 4, 6, 8, 9, 10, 11	9
Ⅳ	10	3, 5, 7, 8, 9, 10, 11	1, 10	10
Ⅲ	11	3, 5, 7, 8, 9, 11	1, 2, 4, 6, 8, 10, 11	8, 11

Table B2: Cluster 2 level partition

Appendix C

M	S3	S5	S9	S2	S7	S6	S8	S10	S11	S1	S4
S3	1	0	0	0	0	0	0	0	0	0	0
S5	0	1	0	0	0	0	0	0	0	0	0
S9	0	0	1	0	0	0	0	0	0	0	0
S2	1	0	1	1	0	0	0	0	0	0	0
S7	1	1	0	0	1	0	0	0	0	0	0
S6	1	0	1	1	0	1	0	0	0	0	0
S8	1	1	1	0	1	0	1	0	0	0	0
S10	1	1	1	0	1	0	1	1	0	0	0
S11	1	1	1	0	1	0	1	0	1	0	0
S1	1	1	1	0	1	0	1	1	0	1	0
S4	1	1	1	0	1	0	1	0	1	0	1

Table C1: Cluster 1 canonical matrix

M	S3	S5	S9	S7	S8	S11	S2	S4	S6	S10	S1
S3	1	0	0	0	0	0	0	0	0	0	0
S5	0	1	0	0	0	0	0	0	0	0	0
S9	0	0	1	0	0	0	0	0	0	0	0
S7	0	1	0	1	0	0	0	0	0	0	0
S8	1	1	1	1	1	1	0	0	0	0	0
S11	1	1	1	1	1	1	0	0	0	0	0
S2	1	1	1	1	1	1	1	0	0	0	0
S4	1	1	1	1	1	1	0	1	0	0	0
S6	1	1	1	1	1	1	0	0	1	0	0
S10	1	1	1	1	1	1	0	0	0	1	0
S1	1	1	1	1	1	1	1	0	0	1	1

Table C2: Cluster 2 canonical matrix