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A TYPOLOGY AND HIERIERARCHICAL FRAMEWORK OF TECHNOLOGY USE IN DIGITAL NATIVES' LEARNING

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Abstract

The technological capability of digital natives is thought to have considerable implications on the way they communicate, socialize, think and learn. Some researchers have even suggested that fundamental changes to the educational system are required to cater for the needs of this new cohort of learner, although such claims have little empirical support. In this study, we adopt a structural approach to the investigation of the digital natives' motivations for using technologies in learning. Based on in-depth interviews with 16 digital natives, a cluster analysis was used to segment respondents into two distinct groups: independent learners and traditional learners. Interpretive Structural Modelling (ISM) was used to develop a hierarchical structural model of technology use motivations for each group. The results show that these two groups are driven to achieve the same learning goals by different paths. Implications are drawn for both educators and managers from both research and practical perspectives.

Keywords: Digital Natives, Technology Use Motivations, Hierarchical Framework, Technology Mediated Learning

1 INTRODUCTION

Compared with their predecessors, today's students have been described as 'digital natives' (Prensky, 2001), 'net generation' (Tapscott, 1998), and 'millennials' (Howe & Strauss, 2000), a generation that has grown up with digital technologies, operating at 'twitch speed', performing multiple tasks simultaneously, accessing information in a nonlinear way, having visual rather than textual skills, and functioning best when networked (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 digital natives 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).

These claims have, however, been criticized for their lack of theoretical and empirical support (Bennett et al., 2008; Hargittai, 2010; Rikhye et al., 2009; Selwyn, 2009), with some recent studies suggesting that 'digital nativeness' is far from universal among young people (Bennett et al., 2008). In addition, Bennettet et al. (2008) and Spires (2008) suggest that, no matter how net-savvy today's generation may be, their technology skills may not be directly applicable to their academic tasks, suggesting a division between technology use for 'living' and technology use for 'learning' (Jones et al., 2010; Waycott et al., 2010). Furthermore, there is only weak empirical and theoretical foundation supporting the notion that digital natives prefer discovery-based learning (Bennett et al., 2008).

At present, a number of critical questions remain unanswered about digital natives and their use of technology in learning. Specifically, this paper seeks to address the following issue: even if today's students are, in fact, all digital natives, does it necessarily mean that all of them prefer discovery-based learning and are motivated to use technology to enable such learning? Given that the call for changes to the education system depends upon the assumption that digital natives will prefer discovery-based learning, it is important then to establish whether what motivates digital natives to use technologies in learning warrants such assumptions.

We attempt to address this issue by identifying groupings of digital natives and understanding the differences between those groupings in terms of their motivation for using technology in learning. Through examining the motivations for using technology, the underlying approach to the learning of the digital natives can be established. Should this approach differ between groups then it can be concluded that the preference for discovery-based learning is not a universal trait of digital natives and calls for fundamental changes to the education system are perhaps not well founded. In pursing these objectives, the following two questions were asked:

(1) Are there different groups or 'profiles' of digital natives in regard to their motivations for using technologies in learning?

(2) If such 'profiles' exist, what factors characterize those profiles and what are inter-relationships among these factors?

In regard to the first question, there has been limited academic attention on investigating the existence of a discernible typology for digital natives in terms of their reasons 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 et al., 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 minimize the resistance of some learners towards using technologies in learning and encourage collaborative and innovative learning.

In regard to the second question, if we expect that there might be heterogeneity among digital natives in terms of their reasons for using technologies in learning, it is important to understand the hierarchical structure of the factors that influence their use of those technologies. The construction of these factors for each group is useful for illustrating the different drivers which influence the way digital natives use technologies in learning (Ledbetter, 2009; Roberts et al., 2006). Such an inter-relationship framework may serve as a guide for taking appropriate actions to motivate digital natives to use technologies more effectively in their learning.

As the literature on information systems (IS) provided few insights to these questions, an empirical study was undertaken to (1) identify a typology of digital natives based on their reasons for using technologies in learning, and (2) develop a hierarchical structural framework of those factors for each group of digital natives. To achieve these goals, we first identified the reasons why digital natives use technologies in learning through interviews of 16 technically competent digital natives. Based on their technology use perceptions in learning, we segmented the participants into two distinct groups. We used Interpretive Structural Modelling (ISM) technique (Sage, 1977; Warfield, 1974) to structure each group's technology use hierarchy.

This paper is organized as follows. First, the reasons for technology use by today's generation and their technology use typologies are discussed. Next, the research method is described. The findings are then presented and discussed. The paper concludes with an outline of the theoretical and practical implications of the study.

2 BACKGROUND

2.1 Factors Influencing Digital Natives' Use of Technologies

Various factors have been identified to explain today students' use of digital technologies. For example, Kaye (1998) investigated university students' use of the World Wide Web and found that the major motivations for going online included entertainment, social interaction, passing time, escape, and information seeking. Employing the Uses & Gratifications (U&G) 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 why Facebook has become so popular with today's young adults, Sheldon (2008) found that they use Facebook for relationship maintenance, passing time, virtual community, entertainment, coolness, and companionship. A survey of college students' use of Wikipedia, Lim (2009) found that it was primarily used for quickly checking facts and finding background information.

Overall, these identified factors are very similar to the reasons found in mass and interpersonal communication studies (Stafford et al. 2004). However, when examining the reasons for using technologies within learning contexts, some new and distinct learning related factors have been identified. For instance, Pena-Shafeet al. (2005) found the key reasons that students participated in online discussions were to meet course requirements and gain feedback from other students. Lonn and Teasley (2009) found that most students gave 'saving time' as the most important benefit of technology-mediated learning systems. Chou et al. (2010) found that the four most important reasons 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. These studies demonstrate the very broad range of motivations behind young people's use of technologies in learning contexts and suggest that we do not have a consistent or cohesive understanding of these motivations, indicating that further work is required to consolidate this understanding.

2.2 Digital Native Typologies Based on Technology Use Factors

Typology is a means of categorizing a cohort into a limited number of groups or types based on various orientations (Westbrook & Black, 1985). This approach is common in the marketing and advertising domain, and while most studies appear to be preoccupied with the topology of the online shopper (Kau et al., 2003), some research has examined the typologies of digital natives (who are treated as customers of education institutions within that context), 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 et al., 2010) found four clusters of interactive media users: traditionalists, gamers, networkers, and producers, each of which had specific uses and opinions about interactive media. A similar finding arose in a survey of 1000 UK young people which identified four types of internet use groups: peripherals, normative, all-rounders, and active participants, that were differentiated by individual characteristics and contextual features (Eynon & Malmberg, 2011). Tao et al. (2008) examined the typologies of students based on their perceptions toward e-learning and identified two very distinct groups of students: skeptics and optimists, who were seen to require different online approaches. Seen 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 learning, and their attitudes toward technology use in learning.

Since the reasons for using technologies presumably account for digital natives' technology use behaviour, directly focusing on their reasons for technology use represents a potentially illuminative approach to identify the distinctive characteristics of this group (Westbrook & Black, 1985). Despite this group having become increasingly important in the adoption and use of technology, few studies have examined the typology of digital natives based on their reasons for using technologies in learning (Vodanovich et al. 2010). Therefore, this study aims to close this gap, and attempt to provide a holistic view of digital natives, in terms of their social and psychological reasons for using technologies in learning.

2.3 Structural Frameworks of Technology Use Factors

Factors influencing technology use are not isolated, static traits, but interrelated structures (Ledbetter, 2009; Markus et al., 2000; Rubin, 1983; Vodanovich et al., 2010) suggesting that people select a technology for interrelated reasons. For instance, in a study of motivations for watching television, Robin (1983) found five unique, but interrelated, motivations: pass time, information, entertainment, companionship, and escape. More recently, Ledbetter (2009) speculated about a possible theoretical structural model among five online communication attitude variables that indicated their direct and indirect relationships, after identifying strong correlations among them. While the premise of considering these factors as a set of interactive needs and expectations is a more meaningful and accurate explanation of technology use, the possible underlying hierarchical relationships among factors has not been addressed, although examining the effect of the factors in isolation may not allow for the inter-relations to be uncovered and may result in ambiguous findings (Phang et al. (2010). Understanding the influences of the factors on each other and the hierarchy in which they sit is important as it helps classify and categorize the factors, and thereby formulate plans and actions, while also providing clarity of thought (Hasan et al., 2007), as demonstrated by Guo et al. (2011), where a structural framework of the reasons for media use by students was developed, and the relative importance of each factor was identified.

3 RESEARCH METHOD

The following approach was undertaken to address the research questions. Data for the study was collected via structured interviews of students using Repertory Grid Interview Technique (RGT). Thematic analysis was applied to the interview data to identify constructs and relationships between constructs. A data consolidation process was undertaken on the identified constructs which resulted in 11 categories of motivations and 65 relationships between these motivations. Cluster Analysis was used to differentiate groups within the cohort and ISM was used to model the relationship between the various motivations for the groups identified in the cluster analysis.

3.1 Data Collection, Consolidation and Categorisation

The data for this study was collected via structured interviews of 16 university students (13 males, 3 females) using the RGT (Tan & Hunter, 2002). The age of participants ranged from 20–26 years, and all had been at university for at least 2.5 years (average of 3 years). The majority of students were studying IS or Software Engineering (15 out of 16) at either undergraduate (14) or coursework master's (2) level. All participants reported having used the Internet for at least 7 years and all had extensive experience using popular Web 2.0 technologies (such as Wikis, Blogs, and Facebook) and considered themselves to be digital natives (as described by Prensky 2001).

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 allowed participants to freely voice their opinions as this permits the best construct elicitation. As a result, a total of 646 raw constructs and 504 unique relationship nodes were provided by the 16 participants. 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 and 328 relationship nodes. These 77 constructs were then categorized via an adjusted core-categorization procedure (Jankowicz, 2004) with the aim of maximizing the similarity of meaning within the category and dissimilarity among categories. The 77 unique constructs were consolidated into 11 categories, as shown in Table 1, in which each factor was denoted as Si, in sequence.

Motivation Factor	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 (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 us to also distinguish a total of 504 unique relationship nodes among 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. The relationships identified 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.

3.2 Data Analysis Approach

3.2.1 Cluster Analysis to Identify Groups within the Participants

The study needed to understand whether differences existed in the motivations for using technology in learning between different topologies of students. To determine the different types of typology of students, a two-stage approach to clustering (Hair et al., 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.

3.2.2 Model Development Technique: ISM

Interpretive Structural Modelling (ISM) was considered the best approach to use to develop the models of the factors (and their relationships) for each of the groups identified in cluster analysis. 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). 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 limitations individuals have in dealing with complex issues involving a significant number of variables at a time can be overcome (Waller, 1975; Warfield, 1976). As the use of ISM provides a comprehensible model of an inherently complex and usually impenetrable system (Anantatmua, 2008; Singh & Kant, 2008), ISM provides a means of integrating diverse viewpoints (Vivek et al., 2008; Warfield, 1990). ISM has been extensively applied in various disciplines (Guo et al., 2011).

Building an ISM involves a number of steps, which are well documented in the literature (e.g., Farris & Sage, 1975; Janes, 1988):

Step 1: Defining a set of variables affecting the system (identified via interviews, as shown in Table 1);
Step 2: Establishing a contextual relationship between variables (identified via content analysis);
Step 3: Developing a Reachability Matrix, and checking the matrix for transitivity

(shown in Tables 2 and 3);

Step 4: Partitioning the Reachability Matrix into different levels (shown in Appendix B, Tables B1 and B2);

Step 5: Forming a conical form of matrix (shown in Appendix C, Tables C1 and C2);

Step 6: Drawing a directed graph (DIGRAPH) and removing the transitive links; and

Step 7: Converting the resultant digraph into an ISM by replacing variable nodes with statements (Figures 2 and 3)

Details of the development of the structural models for each of the clusters are set out in the results section.

4 RESULTS

4.1 A Typology of Digital Natives

The typology of students was developed using a cluster analysis (Punj & Stewart 1983). A matrix of the 11 factors (rows) and the 16 participants (columns) was created, in which the cells were populated by the total number of times each factor was mentioned by each participant. The matrix was duplicated, substituting the counts with the relative percentage that a participant mentioned each factor. Application of the K-means clustering method to the 11 factor percentage scores for each participant indicated that a two distinct cluster solution produced both the most efficient result and the most interpretable solution, 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.

Cluster 1 consisted of 6 males and 2 females, being 53.3% of all participants. This group scored significantly higher on Learning Capability factor, 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).

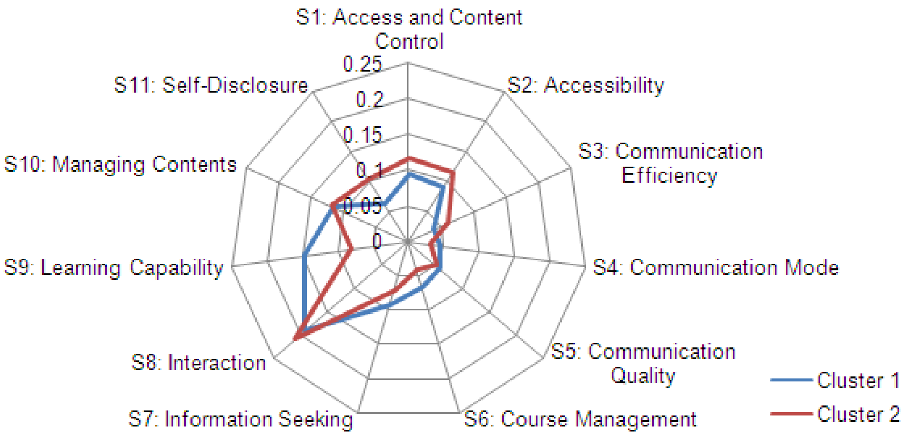

Figure 1. Radar diagram of clusters

4.2 Structural Frameworks Developed Using ISM

Based on overall contextual relationships, we obtained contextual relationships for each cluster of students, as shown in Appendix A, Tables A1 and A2, in which cells were populated by 1s and 0s, whereby ‘1’ indicates a relationship and ‘0’ indicates otherwise. These binary matrixes, which describe whether there is a direct relationship between the row and column variables, are termed Adjacency Matrixes and are used for ISM analysis. Using the Adjacency Matrix, Reachability Matrix (Tables 2 and 3), level partitions (Appendix B, Tables B1 and B2), and Conical Matrix (Appendix C Tables C1 and C2) for both two clusters were calculated. Figures 2 and 3 show ISM models for Clusters 1 and 2 respectively. These two diagrams represent the structural linkages among factors that influence students to use technologies in their learning.

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

Table 2. Cluster 1 reachability matrix

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

Table 3. Cluster 2 reachability matrix

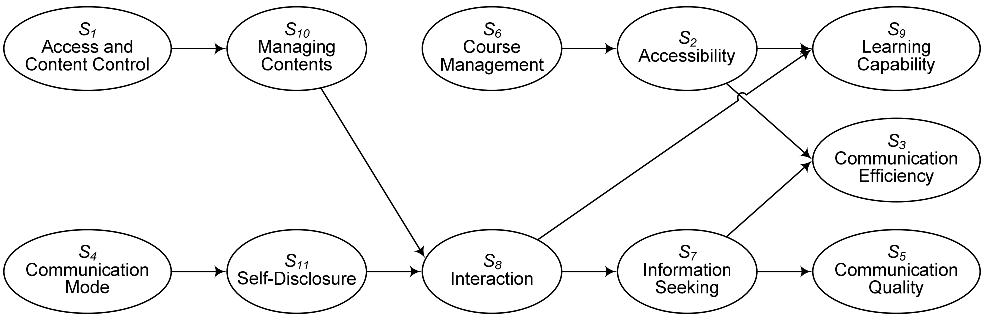

Figure 2. Cluster 1 ISM

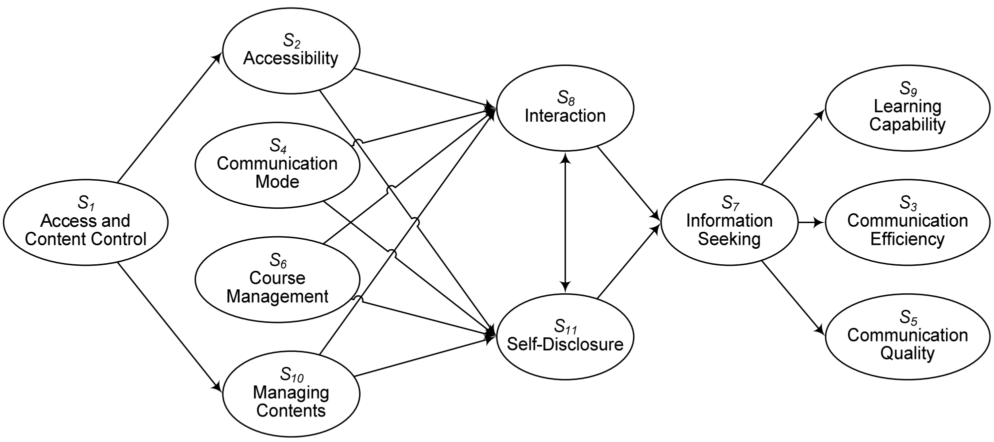

Figure 3. Cluster 2 ISM

For Independent Learners (Figure 2), the driver variable of Access and Content Control enabled Managing Contents and various Communication Modes of technologies to give digital natives 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 (Figure 3), 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. Interaction and Self-Disclosure influenced each other, as well as Information Seeking, which was the only route for developing students' communication and learning capabilities.

5 DISCUSSION

5.1 Typology of Digital Natives

Two distinct groups of digital natives, labelled Independent and Traditional Learners, were identified in this study, in terms of their different reasons for using technologies in learning.

The first finding is that these two groups have very strong views regarding the use of technology for 'Interaction', which was given the highest ranking on average by all interviewees. The claims of digital native proponents that digital natives are collaborative and interactive do, in fact, appear to be borne out in this finding. The second important finding of this analysis was that Learning Capability was the distinguishing factor between the two groups, which suggests that it is only the Independent Learner group that carries the attributes claimed by digital native proponents: "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 the traditional way of learning with technologies. This finding is consistent with findings 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.

Using technology to manage their learning content appears to have become standard fare expected by all digital natives. 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). Since digital natives are constantly using a range of the technology features to communicate (i.e., being connected), it is not surprising to find that these digital natives have similar views regarding communication and information seeking.

5.2 Comparison of Independent and Traditional Learners

Among the factors constituting the hierarchical frameworks depicted in Figures 2 and 3, there are three key groups of variables: givens, means and ends. The variables at the left hand side of the ISM model can be considered as a set of givens. These 'entry variables' often behave as non-negotiable inputs in the systems because they are exogenous to the system and cannot be readily controlled or manipulated (Kanungo 2009). These variables can be considered as aspects that are necessary, though not sufficient, to achieving the desired ends, which tend to be variables located at the right hand side of the ISM model. On the other hand, the ends represent the factors that are the end-states of digital natives in technology mediated learning environment. They are, therefore, important, since they form the basis of the outcome matrix for technology mediated learning goal evaluation. Without these givens, digital native's learning goals are difficult to achieve. Means appear between the given and end variables. They are the variables that can be controlled, manipulated, or developed to form a link between the given and end variables (Anantatmua & Kanungo 2010), ensuring a smooth transformation from the beginning to the desired ends.

A review of the two structural models reveals both significant differences and similarities between them. The first similarity is that both groups have the same end variables indicating that the groups had similar learning goals in technology mediated learning environments. The second similarity is that Interaction was the key means for both groups, which was related to both given variables and learning outcomes. Interaction is the key activity that most digital natives perform online; thus, it is not surprising to find that both groups enjoy engaging with technologies. Any change in this variable would result in significant changes to other variables. The third similarity is that both groups considered Access and Content Control, Communication Mode, and Managing Contents as the key givens that explain their use of technologies to enhance learning outcomes. These variables are all considered as technology related product attributes and without these technological attributes as given conditions, the interaction of digital natives with other variables cannot be ensured. If such were the case, the goals of technology-enabled learning would be difficult to achieve. This suggests that the attributes of the technologies used in learning should be continuously and consciously improved, since they have an overarching effect on all other variables.

The key difference between these two groups is the inter-relationships identified among all variables. For example, Information Seeking emerged as the only route that drives the Traditional Learner group to use technologies to enhance their communication and learning capabilities. In contrast, Independent Learners can improve their learning capability via Interaction, whereby Information Seeking can only result in Improved Communication Efficiency and Communication Quality. In addition, both Self-Disclosure and Interaction influenced each other, causing Information Seeking behaviour in the Traditional Learner group. In comparison, Self-Disclosure led to Interaction, which was linked to Information Seeking and Learning Capability in the case of Independent Learners. Furthermore, the level of system security access and content was the pre-condition linking Accessibility and Managing Contents in the Traditional Learning group, determining whether they accessed and used these technologies in learning. However, the Independent Learner group was not concerned with Accessibility.

6 IMPLICATIONS AND CONCLUSIONS

This study provides a significant contribution to both research and practice. From a research perspective, the identification of two distinct digital native groups based on their attitudes towards the use of learning technologies provides a foundation for future research on digital natives. Our findings indicate that digital natives are heterogeneous in terms of using technologies in learning, whereby not everyone prefers independent learning styles, as has been claimed by some digital native proponents. Future research examining digital natives should be aware of the heterogeneous nature of today’s generation. One interesting avenue for future research would be to explore whether there is a significant difference between these two groups of digital natives in terms of their approaches to learning. These digital natives may not learn differently from digital immigrants; instead, they may only use different tools to learn and have different learning preferences.

The second contribution of the study is the identification and categorization of the factors found to influence the use of technology in learning in hierarchical structure models. Such an examination of the factors related to technology use by digital natives has been absent from the literature. Although our data was obtained from a small group of digital natives, our results were based on rigorous data collection and analysis, and show that there is a set of interrelated factors that influence the use of technologies by digital natives in learning.

From a practical perspective, this study also offers insights for educators and business managers. First, Learning Capability is the most distinct factor differentiating these two groups of digital natives, indicating that there is heterogeneity among digital natives, in terms of their attitudes toward learning with technologies. This would suggest 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 digital native prefers discovery-based learning (Bennett et al. 2008). The digital native typology identified in this study may help improve educators' and organizational policy-makers' decision making, by enabling them to differentiate and tailor their technology related business strategies, policies, and/or actions according to different digital native types. For instance, as educators, we should adopt different teaching strategies when using technology in learning so to accommodate the different learning approaches of the different types of digital natives, otherwise we may not be able to meet their learning needs. This in turn would lead to dissatisfaction, and less-than-effective learning performance. Since digital natives are now moving from the education system into the workplace, we expect a similar digital native typology to be found in workplace. Thus, for managers, it would be unwise to develop rigid guidelines for organizational technology use, since all digital natives are not the same in terms of their attitudes toward technology use. Even though digital natives seem to enjoy an 'engage and collaborate' rather than a 'command and control' model within organizations (Vodanovich et al. 2010), our finding suggests that this may not be the case for all digital natives.

Second, the development of a structural model of factors also helps us understand how the factors that influence technology use in learning interact with each other. This integrated model is important, since it can assist us to identify why digital natives want to use technologies and how to achieve these goals. As educators, when we integrate technologies into our teaching, we should select technologies with attributes that digital natives want, since these attributes form the basis for them to learn well. For application developers, understanding why digital natives prefer particular features and attributes may assist in developing more effective application. More generally, these findings may assist those organizations investing in training efforts for newly hired digital natives to find the most effective means of using technology in that training.

This study has a number of limitations. First, it was assumed that all participants were digital natives, based on the participant's self-reported IT. While this assumption is considered correct, it does place limitations on the results. Second, the small number of participants may undermine the rigour of the cluster analysis, despite the clear segmentation of the data.

Future studies may wish to explore the ideas and framework presented in this study with broader and larger sample size that includes students from other institutions and degrees. Future work could also examine how digital natives differ in terms of their attitudes toward not only technologies, but also learning approaches.

7 APPENDICES

7.1 Appendix A

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

Table A2. Cluster 2 adjacency matrix

7.2 Appendix B

S_i	$R(S_i)$	$A(S_i)$	$R \cap A$
1	1,3,5,7,8,9,10	1	1
2	2,3,9	2,6	2
3	3	1,2,3,4,6,7,8,10,11	3
4	3,4,5,7,8,9,11	4	4
5	5	1,4,5,7,8,10,11	5
6	2,3,6,9	6	6
7	3,5,7	1,4,7,8,10,11	7
8	3,5,7,8,9	1,4,8,10,11	8
9	9	1,2,4,6,8,9,10,11	9
10	3,5,7,8,9,10	1,10	10
11	3,5,7,8,9,11	4,11	11

Table C1. Cluster 1 level partition

S_i	$R(S_i)$	$A(S_i)$	$R \cap A$
1	1,2,3,5,7,8,9,10,11	1	1
2	2,3,5,7,8,9,11	1,2	2
3	3	1,2,3,4,6,8,10,11	3
4	3,4,5,7,8,9,11	4	4
5	5	1,2,4,5,6,7,8,10,11	5
6	3,5,6,7,8,9,11	6	6
7	5,7	1,2,4,6,7,8,10,11	7
8	3,5,7,8,9,11	1,2,4,6,8,10,11	8,11
9	9	1,2,4,6,8,9,10,11	9
10	3,5,7,8,9,10,11	1,10	10
11	3,5,7,8,9,11	1,2,4,6,8,10,11	8,11

Table C2. Cluster 2 level partition

7.3 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 conical 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 conical matrix

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