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Abstract:

Despite being more meaningful and accurate to consider student technology use motivations as a set of interactive needs and expectations, the possible underlying hierarchical relationships among motivations receive little attention. Drawn from Uses and Gratifications (U&G) approach and from Means-End Chain (MEC) theory, this study investigates how student technology use motivations can be represented as a set of interrelated and hierarchically organized elements. A set of relevant data concerning students' technology use motivations was collected by the Repertory Grid Interview Technique (RGT) and analyzed qualitatively using content analysis. Eleven identified student technology use motivations were structured by adopting interpretive structure modeling (ISM) technique. By using Multiplication Applied to Classification (MICMAC) technique, eleven identified factors were further classified into three different types of variables: means, consequences, and ends. The findings of this study have significant theoretical and practical implications to both researchers and managers.

**Keywords:** motivations, technology mediated learning (TML), Means-End Chain (MEC), Uses and Gratifications (U&G), Interpretive Structural Modeling (ISM), Repertory Grid Technique (RGT)

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## I. INTRODUCTION

Given the significant benefits that Web 2.0 technologies may bring to personal life, school life, and the workplace , it is not surprising that research regarding the various psychological and social motivations of people for using technologies has emerged as one of the key topics of contemporary communication research (e.g., Guo et al., 2011; Kaye and Johnson, 2004; Korgaonkar and Wolin, 1999; Ledbetter et al., 2011; Madell and Muncer, 2007; Sheldon, 2008; Sun, 2008). A motivation is defined as a desire, need, or process that influences an individual's goal-directed behavior [Smith et al., 1982]. At universities, such an understanding of these influences is essential, because current university students are perceived as digital natives [Prensky, 2001], and various information technologies to specifically enhance learning are implemented within universities. This knowledge is important, as student's needs regarding the use of technologies in a technology mediated learning (TML) environment are determinants of their behavior; hence, we can only maximize our students services if we know WHAT and HOW we should offer to meet their goals [Dobos, 1992; Orsingher et al., 2011; Steel and Konig, 2006]. As previous studies show, a thorough understanding of student motivations for using technologies plays a vital role in ensuring the successful implementation of such technologies in the TML environment [Guo et al., 2010; Shroff et al., 2007].

The Uses and Gratifications (U&G) perspective is one of the dominant paradigms for explaining media use in the field of communication studies [Katz et al., 1973], and has been successfully applied in previous studies that examined people's motivations for using media [Ruggiero, 2000]. This type of research has been very successful in providing guidelines of understanding "why" people use different technologies. However, these studies consider motivations in isolation [Guo et al., 2011; Rubin and Rubin, 1985], whereas people's needs are hierarchical in nature [Maslow, 1943]. When examining consumer goal-directed behavior, Gutman [1997] argued that goals, which provide the primary motivating and directing factor for consumer behavior, are organized in hierarchies to facilitate their accomplishment. Although research in psychology, organizational behavior, and consumer behavior have long recognized and investigated the hierarchical nature of human motivation (e.g., Bagozzi et al., 2003; Pieters et al., 1995; Wagner, 2007), this phenomenon has been widely overlooked in the literature regarding human communication and technology-use behavior [Guo et al., 2011]. Given that technology users are goal-directed in their behavior and that their use of technologies is an active choice made to satisfy their needs [Katz et al., 1973], it is highly relevant to investigate the hierarchical structure of the motivations for using technologies in learning by university students to generate additional insights into both theory and practice. As Reynolds and Gutman [1984, p. 30] stated, "the lack of a model reflecting the relational linkages tends to make the interpretation highly subjective."

In this regard, one of the most popular theoretical perspectives in Marketing, namely Means-End Chain (MEC) theory [Gutman, 1982], provides a useful way to integrate these motivations into a single hierarchical framework. Generally speaking, MEC is focused on obtaining insight into consumer buying motivations by viewing consumers as goal-oriented decision makers who choose to perform behaviors that seem most likely to lead to desired goals [Grunert and Grunert, 1995; Reynolds and Olson, 2001]. Specifically, MEC focuses on the cognitive linkages between the relative concrete attributes of technologies (the "means"), the more abstract consequences these attributes provide people, and the highly abstract personal values or goals (the "ends") these consequences help reinforce [Reynolds and Olson, 2001]. In determining marketing strategies, the significant increase in the number of competing brands in most product categories is the major reason for most marketers to look beyond merely product attributes for the benefits that these attributes symbolize to the consumer and the higher levels of personal needs that consumers aim to satisfy [Geneler and Reynolds, 2001]. Considering the increasing number of technologies that students can select in their learning, we extend the notion of the MEC theory, whereby the consumption of information technologies is ultimately a means to achieving important values in the domain of goal-oriented technology-use behavior. The framework of such an inter-relationship could provide a guide for understanding why students select (or reject) a specific technology and help direct actions taken to motivate students to use technologies more effectively to enhance their learning. This type of analysis complements other more-established research approaches and holds important implications for researchers, educators, and practitioners that are interested in understanding how and why students select different Internet-based technologies in learning. Ultimately, we can only teach our students well if we know what they actually want.

U&G is a popular approach in communication and technology adoption research and is used to identify the technology-use motivations [Guo et al., 2010; Lim, 2009; Papacharissi and Mendelson, 2007; Shao, 2009; Stafford et al., 2004]. The MEC perspective has been used widely in marketing research for examining consumer shopping motivation hierarchies [Bagozzi et al., 2003; Claeys et al., 1995; Wagner, 2007]. In addition, both U&G and MEC hold very similar assumptions about consumer behavior. With respect to this high theoretical and practical relevance, it seems logical to integrate both theoretical perspectives toward understanding the motivations for technology use by students. However, no empirical research has integrated these two approaches in the context of understanding the structure of technology-use motivations. Hence, the current study is designed to address this gap.

Our objective was to uncover the hierarchical structure of the motivations for technology use in learning by students. This was accomplished by adopting the Interpretive Structural Modeling (ISM) technique, which is a well-established methodology for identifying and developing relationships within a system of related elements [Sage, 1977; Warfield, 1974], and its related technique, termed MICMAC (a French acronym for "matrice d'impacts goises—multiplication appliqués a un classment," meaning "cross-impact matrix—multiplication applied to classification"). A large number of existing studies have combined ISM and MICMAC techniques in other disciplines to identify the pattern of inter-relationships between factors of interest and to classify them according to their dependence and driver power to arrive at an in-depth understanding of complexity. Considering the usefulness of ISM and MICMAC techniques and lack of introduction of their application in information systems (IS) research, this study also explored the utility of both ISM and MICMAC techniques within this domain.

Specifically, the primary aim of the current study was to show that the motivations of students for using technologies can be represented in a hierarchy. The secondary objective of this article was to develop a methodology for eliciting motivations and their hierarchical framework. To achieve these goals, we first briefly review the U&G approach in technology-use motivations. We then introduce the MEC theory as a theoretical framework. This is followed by an elaboration of the methodological principles and analysis processes of ISM and MICMAC data analysis techniques. The research method employed and the results of this research are then described. Finally, the article concludes with a discussion of the implications of the findings in terms of technology use in learning.

## II. THEORETICAL FOUNDATION

### Uses and Gratifications of Using Technologies

U&G is a widely accepted theoretical framework in the study of media adoption and use [Lin, 1996]. Indeed, when focusing on the motivations of the audience, particularly on why and how they use a given technology, this communication research paradigm has been very successfully applied in examining the motives or reasons of the consumers for using a particular communication medium whenever it becomes available [Elliott and Orosenberg, 1987; Ruggiero, 2000]. One basic assumption of this approach is that media users are goal-directed in their behavior, and the personal use of media is an active choice made to satisfy their needs [Katz et al., 1974]. The second assumption of this approach is that media users are aware of their needs and can select the appropriate media to gratify their needs. This approach attempts to recognize the important role that the individual brings to the use of the media by asking what people do with the media, rather than what the media does for people [Katz, 1959].

The characteristics of the active choice of technologies and user-centered nature make the U&G approach particularly useful for understanding motivations for using Internet-based technologies [Kuehn, 1994; Ruggiero, 2000]. A range of studies employing the U&G approach have investigated the motivations for using Internet technologies [Ruggiero, 2000; Yoo and Robbins, 2008], although studies incorporating student learning contexts remain scarce [Guo et al., 2010]. For instance, Papacharissi and Rubin [2000] developed a scale of Internet usage motivations that comprised five primary dimensions: interpersonal utility, pass time, information seeking, convenience, and entertainment. Ebersole [2000] found that students used the Web for research and learning, easy access to entertainment, communication and social interaction, something to do when bored, access to material otherwise unavailable, product information and technical support, games and sexually explicit sites, and consumer transactions. When examining the uses and gratifications of blog users, Kaye [2005] found that blog users were motivated to use blogs for information seeking/media checking, personal fulfillment, political surveillance, social surveillance, and expression and affiliation. Relationship maintenance, pass time, virtual community, entertainment, coolness, and companionship have also been identified as motivations of students using Facebook [Sheldon, 2008]. Guo et al. [2010] found that students used computer-mediated communication (CMC) media to fulfill the needs of information seeking, convenience, connectivity, problem solving, content management, social presence, and social context cues within the context of learning.

These studies typically develop lists or categories of discrete audience motivations; however, some investigations indicate that media-use motivations are not isolated, static traits, but are interrelated structures [Ledbetter, 2009; Rubin, 1983; Rubin and Rubin, 1985]. While considering motivations as a set of interactive needs and expectations is a more meaningful and accurate explanation of media uses and gratifications, the possible underlying hierarchical relationships among motivations have not been investigated. Such relationships contribute towards understanding the relative positioning and influences of the motivations to one another. It is important to develop a hierarchy, as this structuring would assist to categorize motivations and hence help in the formulation of strategies, while providing clarity of thought [Hasan et al., 2007].

Despite being a useful theory to understand the "content" of the motivations for technology use by students, the U&G theory fails to explain the structural nature of technology use. Our conceptualization of the student technology-use motivation hierarchical framework is similar to the notion of the MEC approach toward understanding the decision-making process of consumers [Gutman, 1982]. Within the perspective of MEC, people undertake a behavior (such as using blogs) as a means to reach an objective (or an end), such as reflecting and learning from others, which is, in turn, important for achieving learning goals.

## III. A MEANS-END CHAIN APPROACH FOR UNDERSTANDING TECHNOLOGY USE MOTIVATIONS

Using Expectancy-Value theory, Gutman [1982] developed the MEC theory to understand how consumers think about the products or services they sought. Specifically, this theory focuses on understanding the consumer decision-making process by connecting product attributes, consequences of using a product, and personal goals or values achieved by use of that product [Reynolds and Olson, 2001].

The major assumption of this theory is that consumers are likely to select products that are more relevant for achieving their personal goals or values. In other words, people do not use products for the sake of the product, but for the positive consequence (called *benefits*) that their consumption can provide, which is, in turn, important for the fulfillment of their personal goals [Costa et al., 2004]. Hence, using a particular information technology in learning should not be seen as a student goal of technology use, but rather as a means of fulfilling their needs, thereby facilitating the realization of their values or goals. The second assumption of the MEC theory is that consumers make voluntary and conscious choices between alternative products [Gutman, 1982]. In the case of TML, there is a free choice of the technologies. In other words, students can decide which technology (of those available) they want to use to meet their specific goals.

Attributes are physical features or observable characteristics of products that may be preferred or sought by consumers. For example, an information technology, such as Instant Messaging (IM), may be described in terms of "convenience" or "real time conversation" features. Consequences, which may be desired or undesired, accrue to the consumers from their consuming behaviors [Gutman, 1982]. It is consequences, rather than attributes, of a product that represent the reasons why an attribute is important to consumers. The nature of the consequences resulting from consumer consumption may be physiological (e.g., food, air, or other physiological needs), psychological (e.g., self-esteem, belonging), or sociological (e.g., enhanced status, accomplishment). Benefits are the advantages that consumers enjoy from the consumption of products or services. Consequences have more abstract meanings that reflect the perceived benefits that people receive from a specific attribute of a product [Costa et al., 2004; Gutman, 1982]. For instance, "real time conversation" of IM might lead to the consequence of quick "interaction," which is the benefit of using IM. Personal values, which are a powerful force in governing individual behaviors for all aspects of people's lives [Rokeach, 1968], are the ultimate factors that drive consumer preference and choice behavior [Claeys et al., 1995]. Furthermore, a technology with a "real time conversation" attribute might allow students to "interact" quickly during the learning process, which, in turn, might achieve the value of improved "communication quality" or "learning capability."

Overall, MEC perceives consumers as goal-directed decision makers, choosing products that seem most likely to lead to desired outcomes [Costa et al., 2004; Reynolds and Gutman, 1988]. The attribute–consequence–value sequence explains how and why product attributes are important. Consumers select products that generate desired consequences and minimize undesired consequences [Gutman, 1982]. Values provide the overall direction, consequences select specific behaviors in specific situations, while attributes are those features of the actual product that generates the consequences [Costa et al., 2004]. Students are goal directed when they use various technologies by actively selecting the more suitable option.

The literature provides the rationale when applying the MEC approach to investigate the technology use motivations of students. As Reynolds and Gutman [1988] point out, an understanding of the structure of attributes, consequences, and personal values depicted in MEC facilitates a "motivational perspective." This is because it uncovers the underlying reasons why certain attributes or expected consequences are desired. From a "motivational view," MEC and its associated data collection technique, namely laddering, are concerned with obtaining insights into consumer product buying or using motives [Grunert and Grunert, 1995]. Cohen and Warlop [2001] also define the hierarchical levels inherent in an MEC as "motivational layers." Collectively, by uncovering the way that attributes, consequences, and values are linked in the technology-use decision-making processes of students, MEC can provide insights into understanding the structure underlying the different motivational layers of technology use by students [Wagner, 2007].

## IV. ISM AND MICMAC: DATA ANALYSIS TECHNIQUES ADOPTED IN THIS STUDY

### ISM Methodology

Warfield [1973] developed the interactive learning process ISM, in which a set of unique, interrelated variables that affect the system that is under consideration are structured into a comprehensive systemic model [Sage, 1977; Warfield, 1974]. The objective of this methodology 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]. This method is considered interpretive, because discerning which variables are related, and how strongly, is left to the judgment of the coder [Sage, 1977]. The system is also structural, because an overall structure is extracted from a complex set of variables based on relationships. Furthermore, the process is iterative, because coders can continuously refine early aspects of the model until they are satisfied with the resulting structural model [Mandal and Deshmukh, 1994; Sage, 1977]. The resulting specific relationships and overall structures are portrayed in digraph models for easier analysis.

By using the practical experience and knowledge of individuals or groups, ISM provides a means by which people can impose order and direction on the complex relationships among elements of a system [Sage, 1977]. For complex issues, such as the one considered in this study, a number of factors may affect student choices in using technologies for learning purposes. Taken in conjunction, the direct and oft-hidden indirect relationships between motivations describe the situation far more accurately than individual motives taken in isolation [Singh and Garg, 2007]. Because people are limited in their ability to address complex issues involving a significant number of variables at one time [Waller, 1975; Warfield, 1976], the use of ISM can advance the collective understanding of such relationships by providing a comprehensive model of an inherently complex and usually impenetrable system [Anantatmua, 2008; Singh and Kant, 2008]. ISM is also easy to use, and its results are easy to convey to a wide audience. The fact that it is readily understood by a variety of users in interdisciplinary groups, provides a means of integrating the diverse viewpoints of participating groups [Vivek et al., 2008; Warfield, 1990]. Even though this tool is primarily used as a group-learning tool, it can also be used individually to investigate relationships among variables of a system [Janes, 1988]. The overall potential of the methodology is best realized in a group context with a computer [Janes, 1988].

Since its inception, various researchers have applied ISM to develop a better understanding of complex systems. Table 1 lists a selection of studies on the application of ISM in various areas. The review clearly illustrates the versatility of ISM as a tool capable of modeling a diverse range of complex issues. ISM provides structural clarity and establishes a hierarchical order for prioritization and consequent action. This study explores its applicability and usefulness in analyzing the dynamics of direct and indirect relationships between various motives of technology use by students for learning.

Building an ISM involves a number of steps [Farris and Sage, 1975; Janes, 1988; Malone, 1975; Sage, 1977; Warfield, 1974; Warfield, 1976; Watson, 1978]. The general process of ISM development is described here. It contains eight steps, as described in turn below. Since this study adopted a new data collection technique (Repertory Grid Technique), step 3 of the process was unnecessary in this study (see the Results Section for explanation).

#### Step 1: Defining a set of variables that affect the system

A structural model is a collection of variables and their relationships [Sharma et al., 1995]. Clearly, a set of variables affecting the system must first be defined before any structuring begins. General variable groups include objectives, enablers, barriers, problems, criteria, motives, and the like. These variables can be generated by using previous literature, brainstorming, interviews, or other research methods [Arcade et al., 1999; Janes, 1988]. In this study, student technology-use motivations are the variables of interest, which were generated through interviews.

#### Step 2: Establishing a contextual relationship among variables

Identifying contextual relationships is the second fundamental concept of ISM methodology [Malone, 1975]. In general, a group of people are asked to specify a relationship between each variable pair (pair-wise comparison). Examples of relationships include "cause," "lead to," "assist," and "is more important." Warfield [1994] provides a detailed discussion of the various relationship structures. Taking "Intent structure" as an example, participants may use the following words to express the fact that motivation "A" influences motivation "B": Attaining motivation "A" helps to achieve motivation "B."

| Table 1: Applications of ISM and MICMAC | | | |
|---|---|---|---|
| No. | Researchers | Area in which ISM has been applied | MICMAC technique adopted |
| 1. | Hawthorne and Sage [1975] | Higher education program planning | No |
| 2. | Malone [1975] | Capturing and communicating individual and group perceptions regarding complex issues | No |
| 3. | Saxena et al. [1992] | Hierarchy and classification of program plan elements | Yes |
| 4. | Mandal and Deshmukh [1994] | Vendor selection criteria | Yes |
| 5. | Sharma et al. [1995] | The objectives of waste management in India | Yes |
| 6. | Kanungo et al. [1999] | Evaluating IS effectiveness | Yes |
| 7. | Arya and Abbasi [2001] | Key variables in environmental impact assessment | Yes |
| 8. | Singh et al. [2003] | Developed interdependence among KM variables | Yes |
| 9. | Jharkharia and Shankar [2004] | Mutual relationships among IT based enablers of supply chain management | Yes |
| 10. | Bolanos et al. [2005] | Strategic decision-making groups | No |
| 11. | Hsiao and Liu [2005] | Hierarchical interaction among exterior drivers of product design | Yes |
| 12. | Sahney et al. [2006] | Interrelationships of design characteristics of a high-quality education system | No |
| 13. | Hasan et al. [2007] | Barriers to agile manufacturing | Yes |
| 14. | Anantatmua (2008) | IT and KM role in project management performance | Yes |
| 15. | Vivek et al. [2008] | Interactions among core, transaction and relationship-specific investments in offshoring | Yes |
| 16. | Kanungo [2009] | IT-enabled value creation process | Yes |
| 17. | Anantatmua and Kanungo [2010] | Enablers for successful IM implementation | Yes |
| 18. | Lee et al. [2010] | Structural approach to design website user interface | Yes |
| 19. | Guo et al. [2011] | A framework of students' CMC use motivations | Yes |

The literature documents a number of ways to seek opinions from experts about the contextual relationships of variables, such as brainstorming and nominal group technique [Barve et al., 2007]. This study identified the contextual relationships between each pair of variables through in-depth interviews, which are described in the Results Section.

### Step 3: Developing a Structural Self-Interaction Matrix (SSIM)

The pair-wise relationships of variables identified are now ready to be developed into a matrix. To develop a structural self-interaction matrix (SSIM), the following four symbols have been used to denote the direction of the relationship between any two variables (i and j, i < j) of the system:

- V—Variable i assists variable j.
- A—Variable j assists variable i.
- X—Variables i and j assist each other.
- O— Variables i and j are unrelated.

### Step 4: Developing a Reachability Matrix from the SSIM, and checking the matrix for transitivity

The transitivity of the contextual relationship in ISM states that if variable "A" is related to variable "B," and "B" is related to variable "C," then "A" is necessarily related to "C." The Reachability Matrix indicates whether a column variable can be "reached" from a row variable along a continuous, directed path [Watson, 1978]. To determine this, we first need to convert SSIM into a binary matrix, *A*, called an Adjacency Matrix, by substituting V, A, X, and O with 1 or 0, accordingly. The rules for substitution are as follows:

- If the (i, j) entry in the SSIM is V, then the (i, j) entry in the Adjacency Matrix becomes 1 and the (j, i) entry becomes 0.
- If the (i, j) entry in the SSIM is A, then the (i, j) entry in the Adjacency Matrix becomes 0 and the (j, i) entry becomes 1.
- If the (i, j) entry in the SSIM is X, then the (i, j) entry in the Adjacency Matrix becomes 1 and the ( j, i) entry also becomes 1.

- If the (i, j) entry in the SSIM is O, then the (i, j) entry in the Adjacency Matrix becomes 0 and the (j, i) entry also becomes 0.

For completeness, we define the (i, i) entry in the Adjacency Matrix as 0.

The Reachability Matrix is then obtained by incorporating transitivity, which is an algorithm-based process. If we add the identity matrix, *I*, to *A*, we obtain the matrix that describes reachability for all paths of length 0 and length 1. We then multiply *(A+I)* by itself, where all the operations are Boolean, until successive powers produce identical matrices (that is, until the longest path length has been reached). Stated explicitly, $(A+I) \neq (A+I)^2 \neq \ldots \neq (A+I)^{r-1} = (A+I)^r = M$, where *M* is defined as the Reachability Matrix. The power, *r*, in the equation, is defined as less than or equal to the number of points in the set, *S*. The matrix, *M*, describes a transitive reflexive relation, according to the definition of reachability.

The Reachability Matrix may be obtained by using the method described above. However, its complexity inhibits manual calculation [Farris and Sage, 1975]. Fortunately, ISM software is available to generate Reachability Matrices [Warfield, 1976]. In this study, Matlab was used to calculate the Reachability Matrix.

### Step 5: Partitioning the Reachability Matrix into different levels

Once the Reachability Matrix has been obtained, it must be "future-processed" to form different levels to develop the structural model. From the final Reachability Matrix, *M*, the reachability and antecedent set [Warfield, 1974] for each motivation category can be found. The reachability set for a particular variable consists of the variable itself and the other variables it may reach. In comparison, the antecedent set consists of the variable itself and the other variables that may reach it. Then, the intersection of these sets, $R \cap A$, is derived for all variables. The variable for which the reachability and intersection sets are the same is the top-level variable in the ISM hierarchy. Once the top-level variable is determined, it is separated out from the other variables. The same process is then repeated to identify the variables in the next level. This process is continued until the level of each variable is found. In the Results Section, we describe the first level in detail for demonstration purposes.

### Step 6: Forming a canonical form of the matrix

A canonical form of the matrix is achieved by rearranging the variables from the Reachability Matrix according to their level [Farris and Sage, 1975]. The resultant matrix has most of its upper triangular entries as 0, and the lower triangular entries as 1. This matrix helps to generate the structural model.

### Step 7: Drawing a directed graph (DIGRAPH) and removing the transitive links

A canonical matrix is not an easy format to interpret. A digraph is useful for pictorially interpreting the contextual relationships between each pair of variables and their hierarchies [Iyer and Sagheer, 2010].

Warfield [1974] presented an algorithm for producing the structural model that is too complex to be completed manually. In this study, we adopted the method of Farris and Sage [1975] to develop the structural model, from the canonical form of the matrix obtained in Step 6, whereby:

1. Place the Level 1 variables at the top of the hierarchy.
2. Place the Level 2 variables just below the top level.
3. Repeat this process until all variables are placed at different levels.
4. The inter-relationships between variables can be obtained from the corresponding entries in the canonical matrix. According to Farris and Sage [1975], a different set of sub-matrices may be defined by grouping the variables of the same level in the index sets, and using these level groups as follows:

$$M' = \begin{array}{c} \\ L_1\{ \\ L_2\{ \\ \\ L_i\{ \end{array} \begin{array}{c} \begin{array}{ccccc} \overbrace{\phantom{N_{11}}}^{L_1} & \overbrace{\phantom{N_{22}}}^{L_2} & \overbrace{\phantom{N_{i3}}}^{L_3} & \phantom{\cdots} & \overbrace{\phantom{N_{ii}}}^{L_i} \end{array} \\ \begin{bmatrix} N_{11} & 0 & 0 & \cdots & 0 \\ N_{21} & N_{22} & 0 & \cdots & 0 \\ \vdots & & & & \\ N_{i1} & N_{i2} & N_{i3} & \cdots & N_{ii} \end{bmatrix} \end{array}$$

The diagonal sub-matrices, $N_{11}$, $N_{22}$, $N_{33}$, etc. display the reachability among the variables of levels $L_1$, $L_2$, $L_3$ etc., respectively. These diagonal sub-matrices become identity matrices when there are no cycles remaining. The sub-matrices to the right of the main diagonal are always zero, since there is no reachability from a higher level to a lower level. The reachability of the structural model is organized from lower-level items to higher-level items, and the sub-matrices to the left of the main diagonal contain the interconnection information. For instance, sub-matrix $N_{21}$ contains information concerning the reachability of variables in level $L_2$ to variables in level $L_1$. Similar comments apply to $N_{31}$, $N_{32}$, and so on. The lines between each pair of variables are drawn based on the following steps:

(a) Sub-matrices of the form, $N_{i+1,\, i}$, indicate reachability between adjacent levels, and all lines indicated by the sub-matrices should be drawn.

(b) If a line between the two non-adjacent levels of sub-matrices of the form, $N_{i+2,\, i}$, is indicated, first check to see if a line was drawn in step (a), which would infer the line in question. If there is a line, do not draw the line; if not, it should be indicated.

(c) In subsequent steps, consider sub-matrices of the form $N_{i+3,\, i}$, $N_{i+4,\, i}$, etc. In each case, check whether the lines drawn earlier infer the line in question. If they do, do not draw the line; otherwise, draw the line. Continue this procedure until all possible sub-matrices are exhausted.

### Step 8: Converting the resultant digraph into an ISM by replacing variable nodes with statements

You replace $S_i$ with corresponding motivation categories.

## MICMAC

The Cross Impact Matrix Multiplication Applied to Classification (MICMAC) tool was developed by Duperrin and Godet [1973]. It is a systematic analysis tool for categorizing variables based on hidden and indirect relationships, as well as for assessing the extent to which they influence each other [Hu et al., 2009; Kanungo et al., 1999; Sharma et al., 1995].

The MICMAC principle, which is based on the multiplication properties of matrices, states that, in binary matrix ***A***, which identifies the existence of an arrow of influence (path of length 1), if variable X directly influences variable Y, and Y directly influences variable Z, then any change affecting X may have repercussions on Z. In other words, there is an indirect connection between X and Z. However, when matrix A is squared using Boolean algebra, second-order relationships between X and Z are revealed. Likewise, the $3^{rd}$, $4^{th}$, $5^{th}$, … $n^{th}$ powers of the direct relationship matrix reveal $3^{rd}$, $4^{th}$, $5^{th}$, …, $n^{th}$ order indirect relationships among all variables. Each time the process is repeated, a new, more indirect, set of influences among variables may be produced. When, finally, the next stage of a multiplication of the set repeats itself, the matrix is said to be in a “stable stage” [Sharma et al., 1995]. This stable matrix is then used for MICMAC classification.

Both ISM and MICMAC have similar calculating processes [Lee et al., 2010]. However, the ISM approach can only help us understand the direct relationships between variables of the system since the DIGRAPH only shows the direct relationships among variables [Kanungo et al., 1999; Lee et al., 2010; Sharma et al., 1995]. Therefore, to have a better understanding of the complicated and indirect relationships among all variables, MICMAC was adopted in this study. The use of combined ISM and MICMAC techniques has been successfully applied in a wide range of areas (Table 1). In this study, the ISM technique was used to develop the interpretive structural model of the variables, as a way to provide insights about the direct relationships between variables, and MICMAC was then used to map and understand the indirect and hidden relationships between variables.

Mandal and Deshmukh [1994] claim that the primary goal of MICMAC analysis is to analyze the driver power and dependence of each variable. “Driver power” refers to the degree of influence that one variable has over another, and “dependence” is defined as the extent to which one variable is influenced by others [Arcade et al., 1999]. The driver power and dependence of each variable can be obtained from the stable matrix by the summation of 1s in the corresponding rows and columns, respectively. Next, based on driver power and dependence, we can create a two dimensional graph, called a driver-dependence diagram, with the horizontal axis representing the extent of dependence and the vertical axis representing the extent of driver power. The means of the driver power and dependence can then be used to divide the driver-dependence diagram into four clusters for variable classification into Independent, Linkage, Dependent, and Autonomous variables [Hu et al., 2009].

## V. RESEARCH METHODOLOGY

A structured approach was used to develop the motivation hierarchical model. The modeling technique involves two steps. First, a list of all possible factors pertinent to the issue is generated. Second, these factors are ranked, and meaningful relationships among the factors are obtained.

To create a list of pertinent factors, rather than reusing motivations for technologies from the extant literature, a series of one-to-one face-to-face in-depth interviews using the Repertory Grid Interview Technique (RGT) were conducted to elicit distinctions consumers make among various technologies [Kelly, 1955; Reynolds and Gutman, 1984; Tan and Hunter, 2002]. RGT was employed to develop a set of context-specific motivations, rather than general ones presumed to apply universally across contexts [Bagozzi et al., 2003]. This step was necessary, due to the absence of comprehensive, student-specific technology-use motive scales for university students in the TML environment. Prior research may not have reflected factors specific to current, digital native students. In addition, ISM was selected as the tool to portray the underlying structure among these motivations, as it provides an efficient means to aid individuals or groups in identifying and structuring complex problems [Malone, 1975]. MICMAC was then used to classify motivations depending on their driver power and dependence, based on the model derived from ISM. Table 2 outlines the research methods used to develop the model.

**Table 2: Research Process**

| Stage | Step | Technique adopted | Output |
|---|---|---|---|
| 1. Identifying categories of students' motivations for using technologies in learning | (1) Interviewing university students in order to identify their motivations for using technologies in learning | RGT | Interviewed 16 university students |
| | (2) Analyzing interview data to identify typologies of students' technology-use motivations | Content analysis | Identified 11 motivation categories |
| 2. Developing motivation category interrelationship model | (1) Developing technology-use motivation hierarchical framework | ISM | Generated a 5-level relationship model |
| | (2) Identifying driven-dependence relationship of technology-use motivations | MICMAC | Motivation categories were classified into three types of variables |

## Sample

Given the intensive nature of RGT, a relatively small sample size of about fifteen to twenty-five participants is capable of eliciting a comprehensive list of constructs [Tan and Hunter, 2002]. In total, sixteen university students (thirteen males, three females) were interviewed, in interviews ranging from 50–110 minutes in length. The age of the participants ranged from twenty to twenty-six years, and all had been at university for at least two and a half years (average of three years). All were studying at the Business School, with majors in IS, Business, or Software Engineering at an undergraduate (fourteen) or masters (two) coursework level. All participants reported using the Internet for at least seven years, had experience using popular Web 2.0 technologies (such as wikis, blogs, and Facebook), and considered themselves highly computer literate.

## Data Collection Procedure

Following the recommendations of prior research, one-to-one in-depth interviews, termed RGT, was used to collect data. By incorporating both "triadic sorting task" and "laddering" [Reynolds and Gutman, 1988], this interview technique allowed us to elicit both the "conceptual content embodied in the respondent's mental model and the linkages that exist among these concepts" [Latta and Swigger, 1992, p. 116].

RGT involves presenting participants with a sequence of technologies, namely "elements," for comparison. In this research, the researcher provided a list of five most commonly used technologies identified in the literature (conventional websites, Learning Management Systems (LMS), discussion forums, wikis, and blogs), plus face-to-face teaching (for comparison purposes), as elements, since this allowed every participant to elicit constructs based on the same set of elements [Siau et al., 2010]. The interviews involved construct elicitation, a process to identify the constructs when the research participant interprets the elements [Siau et al., 2010]. Constructs, which are bipolar in nature, are the qualities that people attribute to elements. The constructs describe how some elements are alike and yet different from others [Tan and Hunter, 2002].

The "triadic sorting task" involved the participants randomly selecting three elements each time. Each element was written on a separate index card. Then the interviewer asked the participant to think of any way in which two of the three elements were similar to each other but different from the third, in terms of his/her reasons for using them in learning. Usually, the distinction provided by the participant tended to be at the product attribute level; for instance, video or text feature would be used to differentiate face-to-face and wikis, etc. [Reynolds and Gutman, 1984; Reynolds and Gutman, 1988]. To provide higher-level interpretations of the more abstract concepts, a series of "how" and "why" questions are required to probe the participant. This is termed the "laddering" interview technique, which is a widely used technique to uncover linkages connecting lower-level concepts to higher-level concepts [Gutman, 1982]. 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 no new constructs could be elicited from a triad or the participant wearied [Tan and Hunter, 2002]. The interviews conducted using RGT allowed us to collect each participant's idiographic responses regarding technology use motivations, as well as their connections in learning, which is a requirement for representing an individual's cognitive structures [Grunert and Grunert, 1995].

## VI. RESULTS

The first step in analyzing the large number of responses to the triadic sorting and laddering tasks was to conduct a content analysis of transcribed interviews to allow for the creation of a limited number of thematic categories from the constructs described in the interviews [Neuendorf, 2002; Reynolds and Gutman, 1988]. The thorough analysis of interview data generated a summary table showing the contextual relationships between each pair of identified motivation categories, which are the focus of interest. The hierarchical framework and classification of motivation categories were then derived from this summary table, through the use of ISM and MICMAC analysis techniques.

### Content Analysis

The interview transcripts were imported into NVivo 8, and open coding was used to code the data. Whenever an "entity" appeared, it was coded as a construct. If a statement about "relationships" between constructs appeared, a relationship "from" construct "A" and the "to" construct "B" was created. The Relationship Type was defined as "influences," and shown as a one-way arrow, indicating that attaining motive "A" influences achieving motive "B." The initial coding was undertaken by one researcher. A second researcher coded two of the transcripts for which a cross-coder reliability of 81.1 percent was obtained, which was above the 80 percent acceptable level of cross-coder agreement for exploratory studies [Krippendorff, 1980]. Any points of disagreement between researchers was subsequently resolved by discussion.

By design, the "laddering" process allows participants to freely voice their opinions and, hence, achieve the greatest possible construct elicitation effect. As a result, the sixteen interviewees produced a total of 646 raw constructs and 504 unique relationship nodes. Since there was considerable overlap between constructs across all participants, a data reduction process was conducted to consolidate similar constructs and remove insignificant constructs (less than three occurrences) [Guo et al., 2010; Siau et al., 2010]. For example, "cheap," "low cost," and "free" were coded under the label of "cost." The consolidation of raw constructs ultimately yielded 77 unique constructs and 328 relationship nodes.

After data reduction, further content analysis was performed by two researchers on the identified unique constructs, to categorize the elicited constructs. For the categorization of constructs, an adjusted core-categorization procedure outlined by Jankowicz [2004] was used, with the aim of maximizing the similarity of meaning within the category and dissimilarity among categories. The categorization process was examined independently by two researchers, and over 80 percent agreement was initially achieved, with all remaining discrepancies being resolved via discussion between the researchers. The process resulted in the 77 unique constructs being consolidated into eleven large categories, as shown in Table 3.

Since the relationships identified in NVivo represented the relationship between any two unique constructs from any two categories for any participant, it allowed the researchers to determine the relationship for each pair, resulting in sixty-five pair-wised relationships in total, which are shown in Appendix A. The weak relationships (those mentioned by less than three participants) were then removed, to avoid the hierarchy becoming too cluttered and difficult to interpret [Grunert and Grunert, 1995]. Table 4 shows the final relationships between each pair of motivation categories, in which the cells were populated by 1s and 0s, whereby "1" indicated the relationship and "0" indicated otherwise. This binary matrix, which describes whether there is a direct relation between the row and column variables, is called the Adjacency Matrix, and is used for ISM analysis. Since the contextual relationships identified from the interview data allowed us to establish the adjacency matrix directly, we omitted the step of establishing SSIM, as described in ISM development procedure.

### Constructing a Hierarchical Framework of Technology Use Motivations

Based on the ISM development procedure, the set of variables considered for ISM development were the eleven motivation categories presented in Table 3, denoted as Si, in sequence, where i = 1,2,3,4,5,6,7,8,9,10,11.

After obtaining the adjacency matrix of the variables from content analysis, we used Matlab to obtain the Reachability Matrix, *M*, and obtained the result $(A+I)^2 = (A+I)^3$, indicating 3 as the power, *r.* Table 5 presents the Reachability Matrix. Table 5 clearly shows that the Reachability Matrix provides both direct and indirect relationships

| Table 3: Summary of Motivation Categories | |
|---|---|
| Motivation | Description |
| $S_1$: Access and Content Control | 1. Access control (12); Content control (15); Data security (9); and Multiple-user editing (16); Privilege (13)<br>2. The Access and Content Control factor is concerned with the security aspects of accessing the application and the content maintained by the application. |
| $S_2$: Accessibility | 1. Cost (3); Easy access (12); Ease of use (14); Familiarity (5); Place independence (10); Quick access (10); and Time independence (14)<br>2. Accessibility refers to both the physical access to the technology and subsequent use of the technology [Culnan, 1984]. |
| $S_3$: Communication Efficiency | 1. Convenience (7); Ease (6); Frequency (4); and Speed (12)<br>2. Communication efficiency refers to the extent to which communication can be done conveniently, easily, frequently, and quickly. |
| $S_4$: Communication Mode | 1. Audibility (7); Multimedia (7); and Visibility (12)<br>2. Communication mode relates to the way in which the application assists the students communicate. |
| $S_5$: Communication Quality | 1. Clarity (14); Depth (4); Effectiveness (8); Specificity (5); and Topic focusing (6)<br>2. Communication quality refers to the extent to which communication is clear, in depth, effective, specific, and focused. |
| $S_6$: Course Management | 1. Assessment function (3); Compulsion (6); Control for assignments submission (3); Grading (4); Integrative systems (14); Subscription(4); and virtual class (5)<br>2. Course Management involves the ability of learning technologies to take an administrative in student learning. |
| $S_7$: Information Seeking | 1. Accuracy (10); Amount of information (9); Currency (7); Granularity (5); Trustworthiness (12); and Various sources (7)<br>2. Information Seeking refers to the “purposive seeking for information as a consequence of a need to satisfy some goal” [Wilson, 2000, p. 49]. |
| $S_8$: Interaction | 1. Communication direction (16); Communication flow (8); Communication format (9); Guarantee response (5); Intensity (13); Participation (16); Pattern (11); Range (5); Seniority (9); Sharability (11); Speed (12); and Synchronicity (12)<br>2. Interaction refers to the exchangeability of sources and receivers [Rice, 1987]. |
| $S_9$: Learning Capability | 1. Collaborative learning (15); Critical thinking (3); Group work efficiency (12); Independent thinking (3); Internalization (3); Learning at your own pace (4); Learning from others (10); Learning guidance (7); Reflection (5); Suitable learning style (5); Taking initiative (7); and Teaching effect examination (4)<br>2. Technologies with Learning Capability have the ability to create a learning environment to develop students’ critical thinking skills, to be independent, active and reflective, to collaborate and cooperate, and to be constructive [Miers, 2004]. |
| $S_{10}$: Managing Contents | 1. Add files (9); Electronic trail (5); Information index (13); Keep notes (10); Put citations/references/page links (7); Reprocessibility (16); Storage (3); Traceability (5); and Versioning capability (8)<br>2. Managing contents refers to the ways people want to manage their data with media. |
| $S_{11}$: Self-Disclosure | 1. Anonymity (6); Belonging (7); Courtesy (10); Formality (3); Homophily (3); Self-expression (13); and Social cues (7)<br>2. Self-disclosure refers to the extent to which any message about the self a person communicates to another [Wheeless and Grotz, 1976]. |
| Note: for each category, the first row provides unique constructs as well as the number of participants mentioning it; and the second row provides description of the category. | |

| Table 4: Adjacency Matrix | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ | $S_8$ | $S_9$ | $S_{10}$ | $S_{11}$ |
| $S_1$ | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 |
| $S_2$ | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| $S_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_4$ | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 |
| $S_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_6$ | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| $S_7$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_8$ | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| $S_9$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_{10}$ | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 |
| $S_{11}$ | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |

among motivations. For example, in the Adjacency Matrix, the cell entry ($S_{2,7}$) is 0, indicating that there is no direct relationship between $S_2$ and $S_7$. However, in the final Reachability Matrix, the cell entry ($S_{2,7}$) is 1, due to transitive links from $S_2$ to $S_8$, and $S_8$ to $S_7$. The Matlab program codes required for this analysis are provided in Appendix B.

| Table 5: Reachability Matrix | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| M | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ | $S_8$ | $S_9$ | $S_{10}$ | $S_{11}$ | Driver power |
| $S_1$ | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 9 |
| $S_2$ | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 6 |
| $S_3$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $S_4$ | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 7 |
| $S_5$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $S_6$ | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 7 |
| $S_7$ | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 2 |
| $S_8$ | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 5 |
| $S_9$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| $S_{10}$ | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 6 |
| $S_{11}$ | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 6 |
| Dependence | 1 | 3 | 8 | 1 | 9 | 1 | 8 | 7 | 8 | 2 | 3 | 51/51 |

Level partition was then conducted on the Reachability Matrix, to determine the ISM hierarchy of all variables. For example, the first row of the Reachability Matrix shows that digit 1 occurs for all variables except $S_4$ and $S_6$, indicating that $S_1$ can reach all variables except $S_4$ and $S_6$. Therefore, in this case, the reachability set $R(S_1)$ = {1, 2, 3, 5, 7, 8, 9, 10, 11}. Similarly, in the first column, all variables are 0, except in the first row, indicating that variable $S_1$ can only be reached by itself. Thus, the antecedent set of variable $S_1$ $A(S_i)$ = {1}. The intersection of the reachability set, and the antecedent set (the common variables in both sets), results in $R \cap A$ = {1}. This process was repeated for all other variables to complete the first iteration of the partitioning process, as shown in Table 6. This table includes the reachability set, antecedent set, and intersection set for all variables. According to this table, the variables of $S_3$, $S_5$, and $S_9$, have the same reachability and intersection sets; therefore, forming the first hierarchy. Hence, $S_3$, $S_5$, and $S_9$ would be positioned at the top of the ISM hierarchy. In successive iterations, the variables identified as “level variables” in the previous iterations were deleted, and new variables were selected for successive levels using the process, until the level of each variable was found. The results for iterations 2–5 are also summarized in Table 6.

The canonical form of the matrix is obtained from the Reachability Matrix by combining variables that are in the same level across rows and columns [Kanungo et al., 1999]. The resultant matrix is also known as a lower triangular matrix, because most of the upper triangular entries are 0, while the lower triangular entries are 1.

So far, this article has focused on the detailed procedures of creating Adjacency and Reachability matrices, partitioning a Reachability Matrix into different levels, and creating a canonical form from the Reachability Matrix. Now, the structural model will be built. A digraph is useful to interpret the contextual relationships between all motivation categories and hierarchies pictorially, as derived by modeling [Iyer and Sagheer, 2010]. We followed the procedures described for Step 7 of the ISM development process to construct the ISM model. Since sub-step 4 is critical and nontrivial, each level and the sub-matrices of first three levels of variables are described in detail, so that the structure development process is evident. Figure 1 shows the data.

| Table 6: Level Partition of Reachability Matrix | | | | | |
|---|---|---|---|---|---|
| Iteration | Motivation ($S_i$) | Reachability Set $R(S_i)$ | Antecedent Set $A(S_i)$ | Intersection Set R∩A | Level |
| 1 | 1 | 1, 2, 3, 5, 7, 8, 9, 10, 11 | 1 | 1 | $L_1=\{S_3, S_5, S_9\}$ |
| | 2 | 2, 3, 5, 7, 8, 9 | 1, 2, 6 | 2 | |
| | 3 | 3 | 1, 2, 3, 4, 6, 8, 10, 11 | 3 | |
| | 4 | 3, 4, 5, 7, 8, 9, | 4 | 4 | |
| | 5 | 5 | 1, 2, 4, 5, 6, 7, 8, 10, 11 | 5 | |
| | 6 | 2, 3, 5, 6, 7, 8, 9 | 6 | 6 | |
| | 7 | 5, 7 | 1, 2, 4, 6, 7, 8, 10, 11 | 7 | |
| | 8 | 3, 5, 7, 8, 9 | 1, 2, 4, 6, 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 | 1, 4, 11 | 11 | |
| 2 | 1 | 1, 2, 7, 8, 10, 11 | 1 | 1 | $L_2=\{S_7\}$ |
| | 2 | 2, 7, 8 | 1, 2, 6 | 2 | |
| | 4 | 4, 7, 8, 11 | 4 | 4 | |
| | 6 | 2, 6, 7, 8 | 6 | 6 | |
| | 7 | 7 | 1, 2, 4, 6, 7, 8, 10, 11 | 7 | |
| | 8 | 7, 8 | 1, 2, 4, 6, 8, 10, 11 | 8 | |
| | 10 | 7, 8, 10 | 1, 10 | 10 | |
| | 11 | 7, 8, 11 | 1, 4, 11 | 11 | |
| 3 | 1 | 1, 2, 8, 10, 11 | 1 | 1 | $L_3=\{S_8\}$ |
| | 2 | 2, 8 | 1, 2, 6 | 2 | |
| | 4 | 4, 8, 11 | 4 | 4 | |
| | 6 | 2, 6, 8 | 6 | 6 | |
| | 8 | 8 | 1, 2, 4, 6, 8, 10, 11 | 8 | |
| | 10 | 8, 10 | 1, 10 | 10 | |
| | 11 | 8, 11 | 1, 4, 11 | 11 | |
| 4 | 1 | 1, 2, 10, 11 | 1 | 1 | $L_4=\{S_2, S_{10}, S_{11}\}$ |
| | 2 | 2 | 1, 2, 6 | 2 | |
| | 4 | 4, 11 | 4 | 4 | |
| | 6 | 2, 6 | 6 | 6 | |
| | 10 | 10 | 1, 10 | 10 | |
| | 11 | 11 | 1, 4, 11 | 11 | |
| 5 | 1 | 1 | 1 | 1 | $L_5=\{S_1, S_4, S_6\}$ |
| | 4 | 4 | 4 | 4 | |
| | 6 | 6 | 6 | 6 | |

| Table 7: Canonical Form of Matrix | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| M | $S_3$ | $S_5$ | $S_9$ | $S_7$ | $S_8$ | $S_2$ | $S_{10}$ | $S_{11}$ | $S_1$ | $S_4$ | $S_6$ |
| $S_3$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_5$ | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_9$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_7$ | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_8$ | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| $S_2$ | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| $S_1$ | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| $S_1$ | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| $S_1$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| $S_4$ | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 |
| $S_6$ | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |

$N_{11}$

| Level | | $S_3$ | $S_5$ | $S_9$ |
|---|---|---|---|---|
| L1 | $S_3$ | 1 | 0 | 0 |
| | $S_5$ | 0 | 1 | 0 |
| | $S_9$ | 0 | 0 | 1 |

**a: Sub-matrix *$N_{11}$***

$N_{22}$

| Level | | $S_7$ |
|---|---|---|
| L2 | $S_7$ | 1 |

**b: Sub-matrix *$N_{22}$***

$N_{33}$

| Level | | $S_8$ |
|---|---|---|
| L3 | $S_8$ | 1 |

**c: Sub-matrix *$N_{33}$***

$N_{21}$

| Level | | $S_3$ | $S_5$ | $S_9$ |
|---|---|---|---|---|
| L2 | $S_7$ | 0 | 1 | 0 |

**d: Sub-matrix *$N_{21}$***

$N_{31}$

| Level | | $S_3$ | $S_5$ | $S_9$ |
|---|---|---|---|---|
| L3 | $S_8$ | 1 | 1 | 1 |

**e: Sub-matrix *$N_{31}$***

$N_{32}$

| Level | | $S_7$ |
|---|---|---|
| L3 | $S_8$ | 1 |

**f: Sub-matrix *$N_{32}$***

**Figure 1. Sub-matrices of Reachability Matrix**

First, we followed the first three sub-steps to place all variables to the corresponding levels, whereby $S_3$, $S_5$, and $S_9$ were placed at Level 1; $S_7$ at level 2; $S_8$ at level 3; $S_2$, $S_{10}$, and $S_{11}$ at level 4; and $S_1$, $S_4$, and $S_6$ at level 5. The sub-matrix $N_{21}$, which indicated reachability from $S_7$ (Level 2) to $S_3$, $S_5$, and $S_9$ (Level 1), showed that there was a line between $S_7$ to only $S_5$ in Level 1. Hence, a line was drawn between $S_7$ to $S_5$ only. Sub-matrix $N_{31}$**,** which indicated reachability from $S_8$ (Level 3) to $S_3$, $S_5$, and $S_9$ (Level 1), showed there was a line between Level 3 variable $S_8$ to each of the variables in Level 1. However, a line had already been drawn for $S_5$ in Step 1. Therefore, only a line between $S_8$ to $S_3$, and a line between $S_8$ to $S_9$ were required. Of course, a line between $S_8$ to $S_7$ was required according to $N_{32}$**.** Other links were drawn based on the same principles.

Figure 2 shows the structural model for this study. The digraph illustrates the direct relations among all motivation categories, with arrows indicating the direction of each impact.

After obtaining the structural model, each point was followed by a description for interpretive purposes. Figure 3 shows the interpretive structural model, which provides a clear picture of student's motives and the corresponding flow of relationships.

Figure 3 shows that Access and Content Control is the key for Accessibility, Managing Contents, and Self-Disclosure, while Course Management impacts Accessibility, and Communication Mode impacts Self-Disclosure. Interaction, which affects Communication Efficiency, Information Seeking, and Learning Capability, is influenced by Accessibility, Managing Contents, and Self-Disclosure. The model shows that Information Seeking behaviors promote higher quality communication.

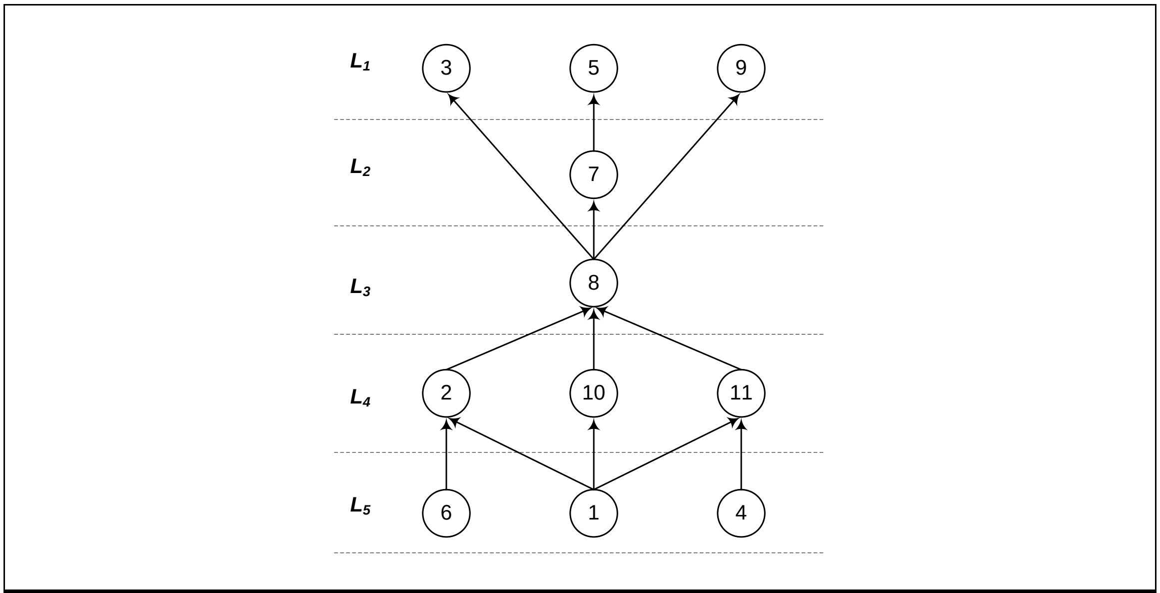


**Figure 2. Interpretive Structural Model**

## Classification of Motivation Categories

According to Arcade et al. [1999], the driver power and dependence of each variable can be obtained from the Reachability Matrix by the summation of 1s in the corresponding rows and columns, respectively, as shown in Table 5. The driver power and dependence indicate the corresponding influence and of dependence of the variable, respectively, taking into account both direct and indirect relationships [Arcade et al., 1999]. By summing up the driver power and dependence and then dividing them by 11 (the total number of variables considered), we obtained an average of 4.63 for both parameters. This value was used to separate the driver and dependence diagram into the four quadrants shown in Figure 4, which is a plot of the nature of the interrelations of motivation categories. Consequently, these motivations were classified into four clusters, which are different to one another depending on the specific role they play in the dynamic technology use process of students.

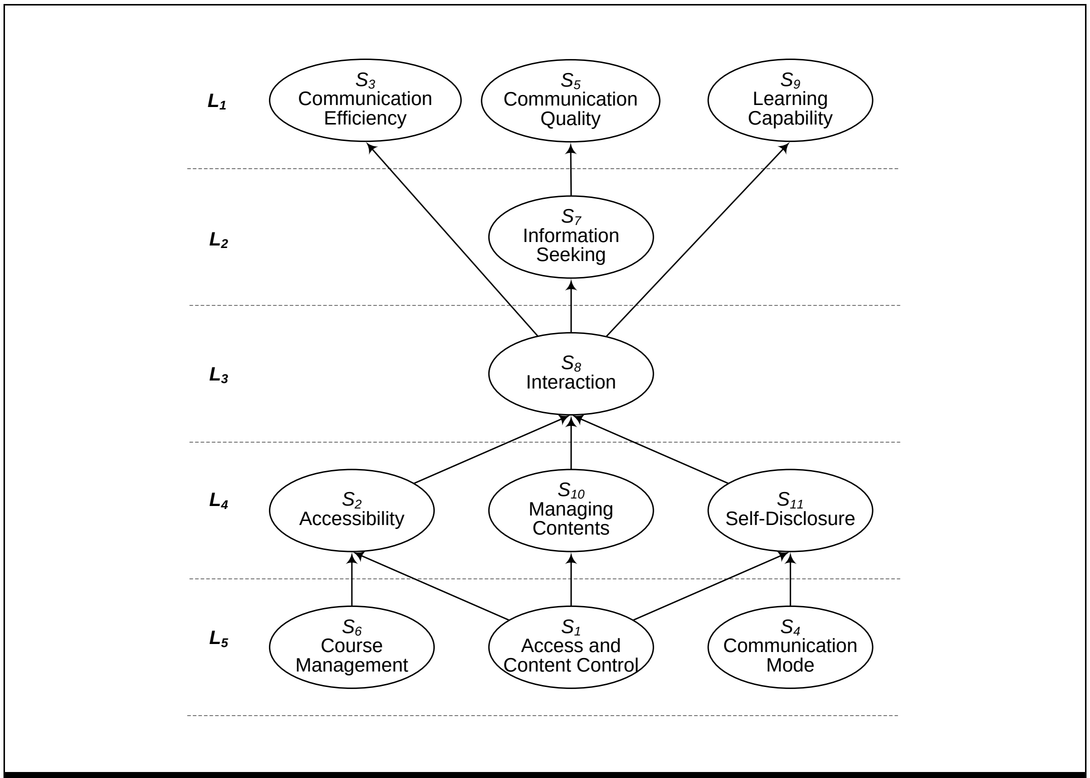


**Figure 3. Student Technology Use Hierarchical Framework**

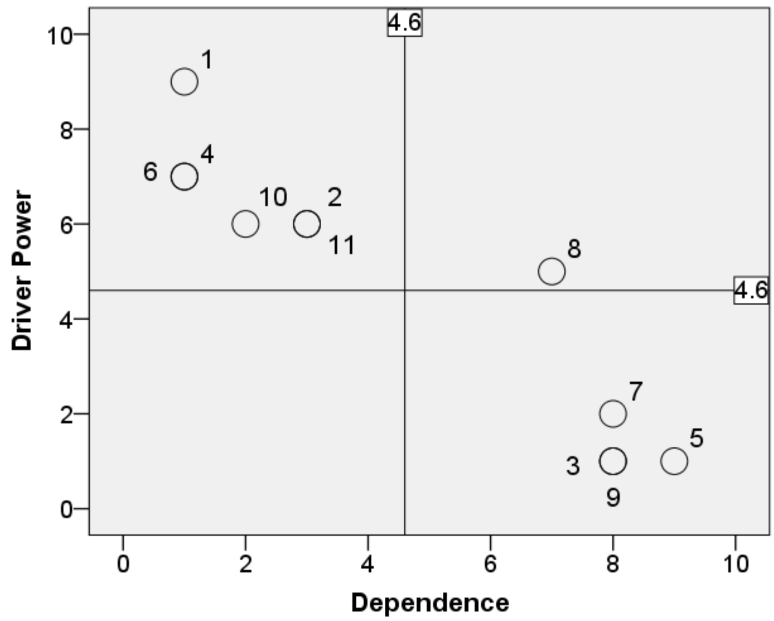


Figure 4. Driver-Dependence Plot

Independent Variables are variables with high driver power, but low dependence, and are considered "independent" or "influencing" variables. They have an important influence on the variables above them in the hierarchy [Kanungo et al., 1999]. Therefore, most systems are dictated by them. These "entry variables" are crucial, since they seem to explain, or affect, system behavior [Kanungo, 2009]. Independent variables often behave as non-negotiable inputs to the systems, because they are exogenous to the system and, thus, cannot be easily manipulated [Kanungo, 2009]. Based on our analysis, the categories of Access and Content Control, Accessibility, Communication Mode, Course Management, Managing Contents, and Self-Disclosure, which lie towards the bottom of our ISM hierarchy, belonged to this cluster.

Linkage Variables are variables with higher driver power and dependence and are considered as "linkage" variables because they are the strong linkage elements in the hierarchy. These variables, by nature, are factors of instability, since any action towards them has consequences not only on them but also on other variables [Hu et al., 2009; Iyer and Sagheer, 2010; Kanungo, 2009]. One variable, Interaction, which was located in the middle of our ISM hierarchy, belonged to this cluster.

Dependent Variables are variables that have low driver power and high dependence, and are considered "dependent" or "end/result" variables, since they are the final product of the influence of other variables in the system. In our study, Communication Efficiency, Communication Quality, Information Seeking, and Learning Capability, which were positioned towards the top of our ISM hierarchy, were the dependent variables.

Autonomous Variables are variables with low driver power and low dependence. They have relatively few connections to the system. They are usually excluded from the system, since they are highly autonomous and may develop in their own way. Moreover, they do not determine the future of the system; thus, they receive limited focus. In our study, there were no autonomous variables.

## VII. DISCUSSION

Among a wide spectrum of motivations for using technologies in learning, some have a more direct role compared to others. Motivations of Access and Content Control, Accessibility, Communication Mode, Managing Contents, Course Management, and Self-Disclosure, which were located at the bottom of the model, are highly important but interrelated technology attributes. These variables help students achieve their desired learning outcomes. In particular, as one of the most influencing variables, Access and Content Control had direct impacts on three variables, indicating that secured and controlled technologies and the contents they provided on the Web were identified as being critical in influencing student use of technologies in learning. These technological attributes should be continuously and consciously improved, since they have an overarching effect on all other variables. Accessibility, Managing Contents, and Self-Disclosure, were next in the hierarchy and are imperative for translating technology Access and Content Control, Communication Mode, and Course Management into effective use among students. The variable Interaction is higher up the ISM, and indicates that, for students to use technologies in a learning context, they must learn how to use the technologies to interact well. Any shortcomings in the entire technology use process could have a negative impact on fulfilling top-level technology use needs. At the top of the ISM model, there were four variables with the highest dependence. In other words, they were influenced by lower level motivations. Any action on any other variable has an impact on them, due to the higher dependence [Hasan et al., 2007]. In particular, Intensive Interaction is critical for fulfilling student technology use needs, as it has direct impacts on improving student learning capabilities and communication efficiency.

Figure 4 shows that no autonomous variables were identified in this study. This indicates that all the variables considered here have relevance to the system and serious attention should be paid to all identified variables [Bhattacharyya and Momaya, 2009].

From a MEC perspective, both Figure 3 (ISM model) and Figure 4 (Driver and Dependence Plot) can also be interpreted in terms of “Means,” “Consequences,” and “Ends” in TML environments. The variables at the bottom of Figure 3, including Access and Content Control, Communication Mode, Course Management, Managing Contents, Accessibility, and Self-Disclosure, can be considered as the set of means, which are also considered as independent variables from Figure 4. From a technology-mediated behavior perspective, these “Means” can be considered as aspects that are necessary (though not sufficient) to achieve the desired ends. In other words, without these technology attributes, student-learning goals are impossible to achieve in TML environments.

“Ends” tend to be variables at the top of the model (Figure 3), which are dependent variables (Figure 4). Four motivation categories are the ends in the TML process, which are determined by all other variables identified in the model. These four motivation categories represent the variables that are the resultant action for effective technology use in student learning. However, they are important, as they form the basis for perceptions that govern the technology use behavior of students. These “Ends” variables provide the ultimate motivations for students to select a technology with certain attributes in learning.

The “Consequences” are variables that appear between the “Means” and the “Ends” and can be considered as the linkage variables (Figure 4). “Consequences” are the reason why students use a technology. Although “Consequences” are not the end state, their ability to move students towards their learning end state (Ends) is what gives “Consequences” a meaningful role in this model [Gutman, 1982]. In this study, “Interaction” was the only reason students use technologies, and it plays a significant role in assisting students to achieve their learning goals.

In summary, this study shows that various technology attributes are important for discriminating among all technologies. However, these important technology attributes are only the first important step to lead to “Interaction” among students, which is the desired consequence or called benefit students seek in the TML environment. What actually impels students to interact with other students is their desired learning goals, namely, improved information seeking, effective and efficient communication, and enhanced learning capabilities.

## VIII. IMPLICATIONS

From a research perspective, this study has three key contributions. First, the combination of Uses & Gratifications (U&G) and Means-End Chain (MEC) as theoretical perspectives, Repertory Grid Technique (RGT) as a data collection method, and Interpretive Structural Modeling (ISM) and cross-impact matrix—multiplication applied to classification (MICMAC) as data analysis techniques has proved to be an effective way of understanding people’s motivations in areas where empirical studies are scarce. The integration of U&G and MEC approaches provides a conceptual framework of goal-directed consumer behaviors. The data obtained from RGT is rich enough to enable a thorough examination of content elicited by every individual’s construct system and linkages [Hunter and Beck, 2000]. The combination of ISM and MICMAC allows researchers to reveal both direct and indirect relationships among variables and to ascertain the chain of influences, as well as the most fundamental factors that drive the system. Future studies could use U&G and MEC as conceptual frameworks for understanding people’s motivations and their linkages in product purchasing or usage behaviors. Subsequently, RGT is used to elicit relevant data, while ISM/MICMAC are adopted to identify the structural framework of motivations and classify them into different categories. One potential research area is to adopt this approach to understand why so many people use social media and what technological attributes of social media are preferred by consumers, in other words, for what benefits and goals, although the proposed approach could be applied to many other aspects of any other product, e.g., why are people so addicted to online games, why is online group-buying behavior popular in American and China , but not in Australia, why are smartphones so popular, etc.?

Second, by adopting the ISM/MICMAC techniques, the motivation linkages for technology use by students were developed through a single, systemic framework. In this study, the identified hierarchical structure model indicates that motivations are related and influence one another. Such a hierarchy also helps in the classification and categorization of motivations into “Means,” “Consequences,” and “Ends,” allowing researchers to better formulate their views and disseminate them to others. Since technology-use behavior is often depicted as goal directed, understanding the structure of motivations for consumer technology use can provide insights into consumer behavior. By interpreting the motivational structure of their behaviors, researchers would be able to understand not only the concrete technology attributes consumers prefer, but also the desired benefits they expect from the technology, ultimately their goals to be fulfilled. The key is that it is not technology attributes that matter, but the benefits that they provide, which are in turn important for the realization of consumer goals and values [Reynolds and Olson, 2001]. For example, most people use the very tangible attribute of “smartphone face-time” for the benefit of “keep in touch with family and friends,” which is, in turn, important for them to have a good “social life” and, eventually, a “better lifestyle,” In the case of this study, students preferred to use technologies with a “multimedia” (one of the “Communication Mode” items) function, since it made “Interaction” more effective and efficient, which was important for improved communication (“Communication Efficiency” and “Communication Quality”). However, we must be aware that these tangible technology attributes are necessary, but not sufficient, to achieve the goals.

Finally, both ISM and MEC are useful for developing a motivational hierarchical framework of consumers with different emphasis. With ISM and the associated MICMAC technique, we can develop a motivational hierarchy that reflects the direct and indirect relationships among variables. This approach also allows us to categorize the variables into different clusters based on their dependence and driver power, from which the relative importance of each variable can be identified. The integration of ISM and MICMAC provides a means by which a group can impose order and direction on the complexity of the variables (arrows in the digraph). The development of the hierarchy helps in the classification and categorization of the motivations and helps towards understanding the relative position and influence of the motivations to each other, thereby efficiently focusing attention on the most significant motivations [Hasan et al., 2007]. In contrast, the MEC model focuses on the connections among product attributes, consumer consequences, and personal values, which are a chain of hierarchically related variables, called the Hierarchical Value Map (HVM) [Reynolds and Olson, 2001]. The HVM represents the most important motivational variables and the links that are most frequently established among them [Costa et al., 2004; Gengler et al., 1995], from which we can identify the chain from the attribute–consequence–value that is more important, based on the linkage frequency. Although the developed hierarchical models from both methods convey slightly different information, they can all be used as a framework to improve our understanding of why people look for certain product attributes and what goals they aim to achieve, thus complementing each other [Thompson and Chen, 1998]. The great potential to provide an increasingly better understanding of consumer product knowledge and its behavioral implications has made both approaches valuable tools in information technologies, in general, particularly social media, planning, design, and promotional strategies [Costa et al., 2004; Gutman, 1982]. Since both approaches adopt the same data collection procedure of RGT, it would be interesting to develop research that compares the results of both techniques to show the advantages of each technique.

This study also has practical implications for university policy makers and course instructors, in addition to technology designers and marketing people. First, the results of this study have significant implications to university policy makers and educators. The hierarchical framework identified in this study indicates that the motivations for technology use by students are linked to physical attributes related to the end goals that are important to the students. The meaning of technology attributes to a student is given by its linkage with certain consequences, which, in turn, have meaning in terms of their linkage with personal goals [Reynolds et al., 1995]. Thus, as educators, when we intend to integrate information technologies with our teaching, we cannot only focus on the lower level technology use motivations of students (i.e., what technology attributes they prefer), but must also recognize the hierarchical structure that forms the basis for connecting these attributes to higher level values. That is, what are the ultimate goals of students for using technologies in learning? In this study, for instance, we found that Access and Content Control was one of the most important attributes that students preferred when they used technologies in learning. This is because they wanted to feel more comfortable when they access and use the technologies to manage their course materials and express their opinions, with no data being leaked or revised maliciously. “Interaction” was the main reason for the students to care about these technology features, which, in turn, was necessary for them to improve their learning capabilities. This hierarchical framework helps university policy makers understand the underlying personal motivations of students for using technologies in learning. This is an important step for them to ensure that they can select the right products for the students, in addition to developing a better strategy of communication for the new products. When they communicate with the students about the new technology, they should present the technology in the perspective of students by linking all variables of the structure together to improve effectiveness, rather than presenting unconnected links in the hierarchy [Reynolds and Olson, 2001].

Second, the findings of this study also provide significant implications for the organization of new products and marketing strategy development. In the consumer-centric marketplace of today, the four key stages in the formulation of consumer-oriented new product design concept include (1) consumers' need identification, (2) idea development to fulfill the need, (3) product development to substantiate the idea and the product's market introduction, and (4) communicating the fulfillment of the need [Urban and Hauser, 1993]. In other words, the design of innovative and improved technologies should focus on the consideration of the current and future needs of consumers. The MEC model can provide a strong understanding of potential technology consumption motivations by depicting how actual product attributes are linked to self-relevant consequences of consumption and personal needs that must be fulfilled in a hierarchical structure. Such an approach would be of use to the R&D and marketing departments of technology organizations, who could gain important information and knowledge about what consumers like to use and why they use them. For instance, by developing a consumer social media use MEC model, organizations can obtain an improved understanding of what the relevant consumer needs are and which product attributes respond to those needs. As a result, the key benefits that consumers expect from using social media can be used to establish the positioning of new products in the marketplace; hence, the actual product attributes that consumers use to infer the delivery of key benefits (or the absence of negative outcomes or risks) associated with consumption can provide guidance to R&D efforts. Therefore, the values and goals establishing the relevance of the different benefits for consumers can be used to design and target advertising campaigns that communicate information about the new products [Costa et al., 2004].

Finally, from the standpoint of motivations and demotivations, the identified hierarchical model allows us to understand how each of these variables can behave as promoters or inhibitors to learning efforts in the TML environment. For example, in Figure 3, weak Accessibility would be an inhibitor while strong Accessibility would be a motivator. If it is laborious or tiresome for students to access a technology for interacting, they will not use it, and the potential of information technology as a learning tool is diminished. Conversely, an easy to access technology in the TML environment would encourage students to use it for interacting with one another, which is the reason for using such technologies in learning, since "Interaction" is critical to achieve their learning goals.

## IX. LIMITATIONS AND FUTURE DIRECTIONS

Some limitations of the study require comment. First, all interviewees were considered computer literate. Some of studies have found that there can be a lack of homogeneity in the university student population regarding their technology experience [Jones et al., 2010; Kennedy et al., 2008].Thus, caution should be taken when generalizing the findings of this study to other settings, as the innate familiarity of students with Internet technologies should not be assumed. Second, although the given sample size was appropriate for this kind of qualitative research, the subjective interpretations of the interview results did not allow for general inferences about a specific population [Wagner, 2007]. Therefore, an empirical examination is recommended to test the validity of this hypothesized model. The Structural Equation Modeling (SEM) technique is suitable for such a validation study, to confirm the structural relationships among different motivation levels [Guo et al., 2011].

Third, the "laddering" technique that we adopted in our interviews is called "soft laddering," which is a natural and unrestricted flow of speech of the interviewee and is suitable for small sample sizes or more exploratory research projects [Grunert and Grunert, 1995]. On the other hand, some researchers use "hard laddering," which "refers to interviews and data collection techniques where the respondents is forced to produce ladders one at a time and to give answers in such a way that the sequence of the answers reflects increasing levels of abstraction" [Grunert and Grunert, 1995, p. 216], to allow less freedom in the answers of respondents. One of the widely used "hard laddering" approaches is a self-administered paper and pencil method. The "soft laddering" approach is implied as a sounder steering of the interviews, thus increasing the probability of uncovering respondent's underlying reasons behind technology use with good predictive ability [Grunert and Grunert, 1995]. However, the whole data collection and analysis process is considered as complex, time-consuming, and subjective, affecting data quality. In contrast, the ease and time-saving aspects of the administration of paper and pencil questionnaires based on a "hard laddering" technique may render this approach suitable for situations where the complexity of the underlying consumption motivations is assumed to be low, or the sample size is large [Grunert and Grunert, 1995]. The exploratory nature and small sample size resulted in the adoption of "soft laddering" in this study. One interesting research avenue would be to compare the motivational hierarchies derived from data collected when using both laddering methods. If both techniques lead to similar results, we might preferentially adopt the "hard laddering" approach for data collection, as it is easier to administer and less costly, and is especially appropriate with large sample sizes.

Finally, neither ISM nor MEC can be used to identify the strength of the relationship between variables, although the HVM obtained from the MEC approach can provide the frequency of relationship occurrence. To add value to the constructed hierarchical model, future research could incorporate the strength of the relationships independently of their frequency [Gutman, 1991].

In conclusion, by uncovering the hierarchical framework defined by different student technology use motivational layers, this study demonstrates that the motivations of students for using technologies are structural in nature. This hierarchy represents the linkages between information technologies and the perceptual process of the students, yielding a more direct and useful insight into student technology use behaviors [Reynolds and Gutman, 1988]. The research approach adopted by this study also establishes a strategy for other researchers to construct hierarchical structures and to analyze variable distributions for any information system with multiple interrelated variables [Guo et al., 2011]. Academic researchers could benefit from a broader understanding and use of this approach for any given product class, to gain a deeper understanding of the underlying personal motivations of consumers. Therefore, the growth of social media indicates that we can understand customer behavior better by understanding their motivational hierarchy.

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## APPENDIX A: CONTEXTUAL RELATIONSHIPS BETWEEN MOTIVATIONS

**Table A–1: Contextual Relationships Between Motivations**

| | | To | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ | $S_8$ | $S_9$ | $S_{10}$ | $S_{11}$ |
| From | $S_1$: Access and Content Control | | 4 | 5 | | 5 | 1 | 9 | 11 | 13 | 8 | 5 |
| | $S_2$: Accessibility | 2 | | 8 | | 3 | | 1 | 3 | 4 | | 1 |
| | $S_3$: Communication Efficiency | | | | | 1 | | 1 | | 2 | | |
| | $S_4$: Communication Mode | | 1 | 3 | | 11 | | | 4 | 2 | 2 | 7 |
| | $S_5$: Communication Quality | | | 1 | | | | 1 | | | 1 | |
| | $S_6$: Course Management | | 4 | 2 | | 1 | | | 3 | 3 | | |
| | $S_7$: Information Seeking | | | 2 | | 5 | | | 1 | 2 | | |
| | $S_8$: Interaction | | 1 | 7 | | 7 | 1 | 8 | | 15 | 1 | 2 |
| | $S_9$: Learning Capability | | | 2 | | 1 | | 1 | | | 1 | 1 |
| | $S_{10}$: Managing Contents | 1 | | 3 | | 2 | 1 | 7 | 7 | 10 | | 1 |
| | $S_{11}$: Self-Disclosure | | 1 | | | 3 | | 3 | 4 | 2 | 2 | |

## APPENDIX B: MATLAB CODE FOR REACHABILITY MATRIX CALCULATION

```
% Adjusted_Adjacency.m (this is file name, it is A+I)
a=[1 1   1   0   1   0   1   1   1   1   1
0    1   1   0   1   0   0   1   1   0   0
0    0   1   0   0   0   0   0   0   0   0
0    0   1   1   1   0   0   1   0   0   1
0    0   0   0   1   0   0   0   0   0   0
0    1   0   0   0   1   0   1   1   0   0
0    0   0   0   1   0   1   0   0   0   0
0    0   1   0   1   0   1   1   1   0   0
0    0   0   0   0   0   0   0   1   0   0
0    0   1   0   0   0   1   1   1   1   0
 0   0   0   0   1   0   1   1   0   0   1];% Add the identity matrix to the Adjacency matrix

% Reachability.m
Adjusted_Adjacency; % Call the matrix (the adjacency matrix plus the identical matrix) from the
Adjusted_Adjacency.m-file
A=cast(a,'double'); % Converse data type for the Boolean operation
A1=A;
A2=logical(A^2);
i=2;
while norm(A1(:,:)-A2(:,:))>0
    A1=logical(A^i);
    A2=logical(A^(i+1));
    i=i+1;
end % Multiply A by itself where all the operations are Boolean logic until successive powers produce identical
matrices.
```

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