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A LONGITUDINAL STUDY ON THE EFFECT OF HYPERMEDIA ON LEARNING DIMENSIONS, CULTURE AND TEACHING EVALUATION

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Abstract. Earlier studies have found the effectiveness of hypermedia systems as learning tools heavily depend on their compatibility with the cognitive processes by which students perceive, understand and learn from complex information sources. Hence, a learner's cognitive style plays a significant role in determining how much is learned from a hypermedia learning system. A longitudinal study of Australian and Malaysian students was conducted over two semesters in 2008. Five types of predictor variables were investigated with cognitive style: (i) learning dimensions (nonlinear learning, learner control, multiple tools); (ii) culture dimensions (power distance, uncertainty avoidance, individualism/ collectivism, masculinity/femininity, long/short term orientation); (iii) evaluation of units; (iv) student demographics; and (v) country in which students studied. This study uses both multiple linear regression and linear mixed effects to model the relationships among the variables. The results from this study support the findings of a cross-sectional study conducted by Lee et al. (2010); in particular, the predictor variables are significant to determine students' cognitive style.

1. Introduction

The adoption of hypermedia technologies as tools in supporting teaching and learning has become widespread in the education environment as it provides learners and educators with convenient access to information that had been traditionally imparted through face-to-face contact. Online instruction is typically delivered via dedicated hypermedia (web-based hypertext) systems that are used to store and manage a variety of relevant course information, such as student assignments, lecture notes, tutorial materials and announcements. Online instruction as a delivery paradigm is viewed as either an alternative or a complement to traditional classroom instruction, particularly for students who are geographically and temporally dispersed or when physical classroom space may be limited. It is also recognized as a convenient delivery method for learners by extensively reducing the time for them to travel to campus. Hypermedia literature extends across a number of different but related fields; for example, educational technology, cognitive psychology, computer science, and geography (Eveland & Dunwoody, 1999). Hence, this research incorporates multiple factors and is cross-disciplinary. This paper attempts to portray multiple factors that determine students' cognitive style (CS) and presents the connections in a research model. The relationship is further tested using advanced statistical models such as multiple linear regression and linear mixed effect. The purpose of this research is to attain greater comprehension of the cognitive mechanisms underpinning hypermedia learning. Earlier research (Lee, Cheng, Rai & Depickere, 2005; Lee, Sudweeks, Cheng & Tang, 2010) revealed that learning dimensions (characteristics and learning patterns) such as non-linear learning, learner control and multiple tools, have significant effects on students' cognitive style in a hypermedia learning system.

In addition, rapid advancements in technologies have resulted in increasing numbers of people of different cultures working together and communicating more. Understanding cultural differences is essential in order to comprehend that what works in one location may not work elsewhere. Thus, culture may be viewed as an important source of an individual's values, expectations and needs (Markus & Kitayama, 1991). On the other hand, evaluation in education has long been used to determine the worth or value of the continuation of a course. Feedback from evaluations provides quality control over the design and delivery of teaching and learning activities (Newby, 1992). Unit evaluation is important as it provides an overall picture of teaching performance.

2. Literature Review

2.1. HYPERMEDIA SYSTEMS

The features of hypermedia systems have great appeal to educators. An attribute of hypermedia is that it parallels the way the human brain and memory work. Hypermedia imitates how the human mind gathers knowledge by association, jumping from one concept to another in a complex web of connections. A hypermedia-based learning system is a form of web-based educational system. It is deemed a valuable educational tool because it presents information in multiple modes; it provides learners with easy and nonlinear access to large amounts of information. In addition, it provides students with greater autonomy and responsibility in their quest for learning (Gracia & Gracia, 2005; Konradt, 2004). Several studies (Gracia & Gracia, 2005; Greene, 2007) have indicated that students play a more active role in the educational process with the use of hypermedia learning systems. It is suggested that the hypermedia learning system's rich content encourages learning in a task-driven process, where learners are motivated to explore alternative navigational paths through domain knowledge and different resources, and subsequently promotes effective learning as it allows students to construct their own learning goals and plans. Furthermore, hypermedia-based learning systems demonstrate the capability of facilitating multiple forms of communication such as chat rooms, forums, email, and video conferencing.

Hypermedia tangibly stimulates learners to filter, link and search for new or existing information. These features have made hypermedia an ideal tool for supporting multilineal thinking and facilitating self-directed learning (Schwen, Goodrum & Dorsey, 1993). This has been deemed a pragmatic way to empower learners in meeting today's educational needs, particularly in offering an innovative learning and teaching instructional delivery system that connects learners with educational resources. Nevertheless, there are potential risks that can impede learning based on hypermedia system. First, there is spatial disorientation, also known as the ‘‘lost in hyperspace” phenomenon. This disorientation occurs due to a high degree of learner control in a nonlinear space and can be disastrous, given the lack of appropriate instructional support, as students may find it difficult to get ‘a good grasp’ of the learning material in a hypermedia system. Second, cognitive load will impede learning if not carefully managed. This overload can occur due to constantly assimilating and referring to previous hyperlinks while trying to understand the next link (Chandler, 2009; Chen & Dwyer, 2003).

2.2. COGNITIVE STYLES

The effectiveness of hypermedia systems as learning tools depends to a large extent on their compatibility with the students’ cognitive style; in other words, the psychological processes by which students perceive, understand and learn from complex information sources. Witkin, Moore, Goodenough & Cox’s (1977) concept of cognitive style, specifically field dependence-independence (FDI), is the central framework used in this research to study the cognitive styles of individual learners and their characteristics when interacting in hypermedia systems. The reason for choosing the FDI concept is that it has a profound influence on learning performance in a nonlinear hypermedia environment, where the ability to structure and to restructure data is of central importance (Chen & Macredie, 2002; Chen, 2010; Lee & Boling, 2008; Lee et al. 2005; Lee et al. 2010; Mampadi, Chen, Ghinea & Chen, 2011; Thomas & McKay, 2010). Specifically, FDI implicitly conditions the development of operative schemata as well as learners’ overall cognitive structuring (Robertson, 1990; Fitzgerald & Semrau, 1998). FDI differentiates the tendency of an individual to structure and analyze incoming information.

According to Witkin, the concept of FDI has important implications for cognitive and interpersonal behaviors. While most learners fall on a continuum between these two cognitive processing approaches, each style is defined by certain characteristics. Specifically, field independent people tend to be more autonomous in relation to the development of cognitive restructuring skills and less autonomous in relation to the development of interpersonal skills. Conversely, field dependent people tend to be more autonomous in the development of interpersonal skills and less autonomous in the development of cognitive restructuring skills. Field-dependent learners might adopt a global strategy and demand information with more explicit cues whereas field-independent learners tend to employ an analytical approach (Chen & Macredie, 2002; Antonietti, Ignazi & Perego, 2000). In other words, field dependent learners are likely to process information passively by operating an external reference, as opposed to the “inner directedness” of field-independent learners who might prefer to actively impose their own structure (Ford, Wilson, Foster, Ellis & Spink, 2002). As a result, compared to field-independent learners, field dependent individuals are more likely to have greater difficulty when required to provide organization as an aid to learning, as is required in a nonlinear environment. Hence, information systems should be designed to accommodate the different preferences of learners with different cognitive styles (Chen, Czerwinski, & Macredie, 2000; Leader & Klein, 1996).

2.3. LEARNING DIMENSIONS

According to Chen & Macredie (2002), an individual's cognitive style in a hypermedia-based learning environment can be determined according to three main categories of learning dimensions: (i) nonlinear; (ii) learner control; and (iii) multiple tools.

(i) Nonlinear

Individuals who prefer a linear learning approach are considered field dependent. They generally demonstrate greater social orientation, which means they enjoy working in groups. Furthermore, they are more likely to face difficulties in unstructured environments or when they have to restructure new information and forge links with prior knowledge. In other words, they prefer guided navigation or a linear format representation and tend to demonstrate more syllabus-bound characteristics. These individuals fear failure but focus on a minimum pass as they often show little interest in the course content. They also demonstrate heavy reliance on memory and are strongly dependent on external sources, such as their tutors who dictate the information to be learnt. These characteristics are often due to their lack of understanding of the purpose and objectives of the course. In contrast, individuals who adopt a non-linear learning approach are categorised as field independent individuals. They are characterised as individuals who enjoy working alone and prefer free navigation or the use of a discovery approach to explore the topic of interest as well as to generate ideas. They tend to seek meaning in order to understand the course content. In addition, they attempt to relate ideas between courses and make use of evidence to draw conclusions.

(ii) Learner Control

Field dependent individuals perform better with a program control version of computer-based instruction as they are relatively passive and less capable of learning independently (i.e. externally directed). These individuals can be characterised as using less control features in hypermedia programs. On the other hand, field independent individuals use greater control features in hypermedia programs as they possess a higher ability to engage in independent learning with analytical thought (i.e. internally directed) and perform better in a learner-control version of computer-based instruction (Yoon, 1994; Chen & Macredie, 2002). Hence, field independent individuals are likely to perform significantly better and learn more effectively than field dependent individuals in a hypermedia-based learning environment.

(iii) Multiple Tools

A hypermedia environment is usually designed with nonlinear multidimensional paths traversing the subject matter to provide multiple perspectives of the content to guide students' acquisition of the subject matter. Generally, individual learners are able to control their own paths through complex subject matter independently of the guidance provided by the course tutor. However, learners can quickly and easily get lost in cyberspace given the links and multiple tools available. In such a situation, field dependent individuals tend to desire greater navigation support as they are relatively passive whereas field independent individuals tend to be more analytical when confronted with a problem. According to Chou (2001), field dependent individuals are better at recalling social information, such as conversations and relationships, approaching a problem in a more global way and perceiving the total picture in a situation. Conversely, field independent individuals are better with numbers, science and problem solving tasks as they apply an analytical approach (Chou, 2001).

2.4. CULTURE DIMENSIONS

There is a need to ensure flexibility and access to learners of diverse cultural background because culture and learning are interwoven and inseparable (Downey, Wentling, Wentling & Wadsworth, 2005). Moreover, hypermedia is a relatively new medium of learning delivery; the relationship between users' cultural backgrounds and cognitive style in hypermedia systems is not clear. As a result, the educator's tasks have become more complex since individuals who are fostered by different cultures may have different cognitive styles. Although some research has been conducted in relation to different aspects of culture and technology (Downey, et al. 2005; Gaspy, Dard & Legorreta, 2008; Gevorgyan & Porter, 2008) very little is known about the ramifications of cultural influences on students' cognitive style in educational hypermedia learning systems. This calls for further research in incorporating culture dimensions as one of the factors to be examined in this study. It is important to understand different cultural backgrounds, characteristics and learning patterns as cultural differences may play an important role in defining, conceptualizing, inventing, adapting and distributing teaching and learning materials through hypermedia learning systems.

There are several well-known researchers who have contributed to the field of culture, such as Edward Hall, Kluckhohn and Strodtbeck, Trompenaars and Hampden-Turner, Schwartz, and Geert Hofstede (Gaspy, et al., 2008; Zakour, 2003). However, there have been mixed reviews of Hofstede's research (e.g. McSweeney, 2002; Ess & Sudweeks, 2006). Nevertheless, Hofstede's cultural framework is adapted as a cultural theoretical framework in this study based on the following grounds:

(i) Hofstede's work still remains the most influential in cultural classification due to the research-based validation and the widespread acceptance by research scholars (Downey, et al., 2005; Gaspy, et al., 2008; Reisinger & Crotts, 2010; Zakour, 2003).
(ii) Hofstede's cultural theory has consistently proven to help explain the complexities of the impact national culture has on various areas of IT research (Gaspy, et al. 2008; Gevorgyan & Porter, 2008).
(iii) Hofstede's theory has many similarities with the cultural dimensions of Schwartz (1994) and Trompenaars & Hampden-Turner (1998); that is, a belief that culture consists of values and preferred behaviour related to the values (Pors, 2007; Zakour, 2003).
(iv) Hofstede's cultural framework has not yet been applied in explaining to what extent national culture influences students' CS in hypermedia system.

Hofstede (2001, p. 9) defined culture as "the collective programming of the mind". He further explains that, "culture in this sense includes values; systems of values are a core element of culture" (p. 10). Hofstede (1980) identified cultures at three different levels: individual, collective, and universal. The individual level represents an individual's personality that is unique. However, both collective and universal mental programs are shared with others. The collective level represents a group's culture (based on specific values); the universal level is the programming necessary to survive and therefore shared by all human beings. Hofstede's five cultural dimensions are summarised in Table 1.

An earlier study conducted by Lee et al. (2010) revealed multiple factors such as unit evaluation, learning dimensions and culture dimensions are interrelated and these factors have varying degrees of significance on the effect of CS. Hence, it is suggested the quality of education can be enriched in the development of hypermedia system when these factors are considered.

Table 1. Hofstede's Dimensions of Culture

Cultural Dimension	*Definition*
Power Distance	The extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally.
Uncertainty Avoidance	The extent to which the members of a culture feel threatened by ambiguous or unknown situations.
Individualism/ Collectivism	Individualism refers to societies in which individuals are expected to look after themselves and their immediate family; collectivism refers to societies in which individuals integrate into strong, cohesive in-groups.
Masculinity/ Femininity	A society is referred to as masculine when emotional gender roles are clearly distinct and feminine when emotional gender roles overlap.
Long-term/ short-term orientation	Long-term orientation refers to the fostering of virtues oriented toward future rewards; short-term orientation refers to the fostering of virtues related to the past and present.

(Source: Hofstede and Hofstede, 2005)

2.5. UNIT EVALUATION

The literature on teaching evaluation is abundant and well researched, particularly on ways that teachers can present content and skills to enhance the opportunities for students to learn. It is equally filled with suggestions of what not to do in the classroom. However**,** there is no consensus on which teaching methods match best to which skills and/or content being taught. Students often have little expertise in knowing if the method selected by an individual instructor was the best teaching method, or just "a method", or simply the method with which the teacher was most comfortable. The use of students' ratings for evaluating teacher effectiveness is the most researched issue in higher education (Ory, 2001). The most accepted criterion for measuring good teaching is the amount of student learning that occurs. There are consistently high correlations between students' ratings of the "amount learned" in the course and their overall ratings of the teacher and the course. Those who learned more gave their teachers higher ratings (Cohen, 1981; Marsh & Overall, 1980; Theall and Franklin, 2001). In other words, it is a process that detects any differences between present achievement, intended goals and, if necessary, finding solutions to narrow down the difference.

There have only been a few studies using student evaluations to predict student cognitive style. For instance, Prosser and Trigwell (1990) showed that Australian university students taught by highly rated teachers tended to approach their learning through the use of deep rather than surface study strategies. Similar findings were found by Diseth (2007) who suggested that students' evaluation and perception of the learning environment are important predictors of students' approaches to learning as they affect examination performance. Miller (2007) explored the effect of cognitive style and expected evaluation on creativity with the assumption that individuals classified as field independent are more likely to have higher creativity scores, which was partially supported. On the other hand, expectations of evaluation as well as interactions between evaluation condition and cognitive style had no significant effect. Findings from Kember, Jenkins, & Ng (2004) suggest that students faced with a teaching style that is incompatible with their conception of learning are likely to give poor ratings in student evaluations.

3. Hypotheses

This study is an extension of previous research by Lee et al. (2005) and Lee et al. (2010). The results derived from Lee et al.'s research may not apply in other countries and therefore must be treated with caution as cognitive styles may vary with different cultures. Numerous studies (Chen, 2010; Diseth, 2007; Miller, 2007) have shown consistently high correlations between students' ratings of the amount learned in the course and their overall ratings of the teacher and the course. Therefore, factors such as culture and unit evaluation were taken into consideration for the purpose of this study.

H1: Students' cognitive style changes over time in hypermedia systems.
H2: Students' learning dimensions, culture dimensions or unit evaluation change over time in hypermedia systems.
H3: Students' cognitive style varies with changes in their learning dimensions, culture dimensions or unit evaluation in hypermedia systems.
H4: Each student's cognitive style varies with changes in their learning dimensions, culture dimensions or unit evaluation in hypermedia systems.

4. Methodology

A review of the multiple factors that influence students' cognitive style identified the interrelationships and connections among the factors. Based on the literature, Figure 1 is a representation of the research model for this study.

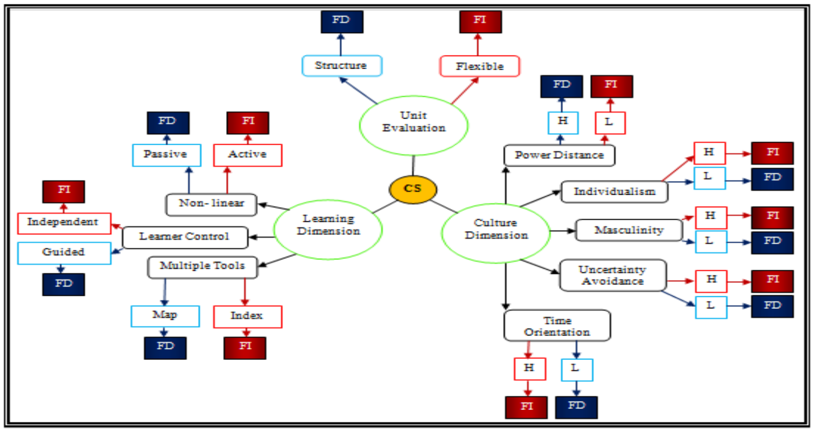

*Figure 1.*Relationships between cognitive style, learning dimensions, culture dimensions and unit evaluation.

4.1. PARTICIPANTS

This longitudinal study was conducted over two semesters in 2008. In semester 1, 40 Australian and 41 Malaysian students participated in the first survey. In semester 2, 47 Australian and 30 Malaysian students participated in the second survey.

The Australian students were enrolled in four different units in the School of Information Technology, Murdoch University, Australia, and were invited to participate in the study. Of the four units, two were first-year units (ICT105 Introduction to Information Technology and ICT108 Introduction to Multimedia and the Internet), one was a second-year unit (ICT231 Systems Analysis and Design), and one was a Masters level unit in which students in their fourth year (Honours) could also enrol (ICT650 Information Technology Research Methodologies). Murdoch University is a multicultural institution and the cohorts in each unit comprised approximately 50% Australian born students with the other 50% a cultural mix of international students.

The Malaysian students were enrolled in Software Technology 151 and Engineering Programming 100 units offered by the school of Engineering at Curtin Sarawak, Malaysia, and were also invited to participate. Both units are first-year units within the Bachelor of Technology (Computer Science) and Bachelor of Engineering programs. Students in both programs consist mostly of Malaysians, with a small number of international students. For entry into both programs, students would have completed the Foundation Studies programs in Engineering and Science, delivered by Curtin University, or other matriculation studies such as General Certificate of Education (GCE) Advance Levels from other institutions.

4.2. REPEATED MEASUREMENT DESIGN

The data collected from repeated measures design of each subject is called longitudinal data. A *repeated measures design* refers to studies in which the same measures are collected multiple times for each subject but under different conditions; for instance, repeated measures are collected in a longitudinal study in which change over time is assessed. This survey method is ideal when only a few participants are available. The repeated measures design can reduce the variance of estimates of treatment-effect; that is, allowing statistical inferences to be made with fewer students. It also allows the investigation of the changes in students' behaviours or responses over time.

Longitudinal data are highly valued in all areas of social science research. In education research, in particular, the rapidly growing availability of data that tracks student achievement over time has made longitudinal data analysis increasingly prominent (Lockwood and McCaffrey, 2007). The reason for this is that, unlike cross-sectional studies, longitudinal studies track the same people, and therefore the differences observed in those people are less likely to be the result of cultural differences across generations. The changes observed in longitudinal studies, therefore, are more accurate. Because longitudinal studies are observational, in the sense that they observe the state of the world without manipulating it, it has been argued that they may have less power to detect causal relationships than do experiments (Awé & Bauman, 2010). But because of repeated observations at the individual level, they have more power than cross-sectional observational studies (Shepard et al., 2003).

4.3. SURVEY

The survey used in this study was based on survey design used in earlier research (Lee et al. 2010). Participants were asked to respond to all questions on a Likert scale of 1 to 5. There were a number of questions for each variable (Table 2) and the responses were classified as high (>3) or low (<3). A cluster sampling approach was chosen to accelerate the sample collection as well as to ensure that the required sample size for both groups was met, given the project time constraints.

Table 2. Number of survey questions for each variable.

No. of questions	*Variable*	*Variable Code*
4	Cognitive style	CS
7	Nonlinear	NL
7	Learner control	LC
9	Multiple tools	MT
3	Power distance	PD
3	Individualism/collectivism	IC
3	Masculine/feminine	MF
3	Uncertainty avoidance	UA
3	Short/long term orientation	TO
6	Evaluation of units	EU
18	Demographics	

4.4. STATISTICAL METHODS

A paired t-test was used to compare the mean of two groups. This study uses both multiple linear regression (MLR) and linear mixed effects models (LME) to model the relationships among CS and four groups of variables: learning styles, culture dimensions, unit evaluation, and time. These variables are assigned in both models as presented in Table 3. Students' t-tests are used to test the significant of all estimated parameters, e.g. slope and intercept, in all MLR and LME.

Table 3.Variable assignment in MLR and LME models

MRL Model Variables	*LME Model Variables*
y_i response variable of student i	y_{ij} response variable of student i at year j
x_i predicted variable of student i	x_{ij} predicted variable of student i at year j
z_i covariate of student i (z_i 0 (Malaysia) or 1 (Australia))	z_i covariate of student i (z_i 0 (Malaysia) or 1 (Australia))

In the MLR model, y_i is the CS. x_i can be one of the five culture dimensions, one of the three learning styles, the unit evaluation, or the time the survey was conducted. The process errors are assumed normally independently distributed. In the LME model, y_{ij} is the CS. x_{ij} can be one of the five culture dimensions, one of the three learning styles, the unit evaluation, or the time the survey was conducted. The process errors are assumed normally independently distributed. The estimated individual intercept and slope of each student is assessed by a bivariate normal distribution. There is no serial correlation of each measured CS with time.

Both Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Akaike, 1974; Schwarz, 1978) were used to select the best LME model. The best sub-model can be determined when all the estimated coefficients are significant ($P<0.05$) with the minimum information value from all above information criteria. In addition, a comparison of the fitting results of both LME and MLR models with the information criteria is essential to determine the best model in representing the data.

5. Results

The results of the first survey (Semester 1) reveal that there is a significant difference ($P=0.043$) between the means score of Australian and Malaysian students' CS (2.70 and 2.93 respectively). The results of the second survey (Semester 2) are similar, with a significant difference ($P=0.02$) between the means score of Australian and Malaysian students' CS (2.56 and 2.87 respectively). Based on this observation pattern, it is shown that Malaysian students tend to be FD whereas Australian students tend to be FI. There is no significant difference in Malaysian students' CS ($P=0.38$) and Australian students' CS ($P=0.43$) between the two surveys. This result supports that a cognitive style is a characteristic that does not change but may vary over time (Biggs & Moore, 1993; Goldstein & Blackman, 1978; Peterson et al, 2009). In other words, the finding does not support H1. The duration of the two semesters study showed no significant linear relationship ($P>0.20$) between CS and time. However, this study has detected small variation of individual students' CS over time but with no overall significant ($P=0.43$). A possible reason of this variation is due to measurement errors.

The findings based on the estimated LME revealed that response variables, such as learning dimensions ($P> 0.20$), culture dimensions ($P >0.20$) and unit evaluation ($P>0.10$), and the predictor variable (time) of each student are not significant. This indicates that the outcome does not support H2. Another test was carried out on combination of all variables (CS, learning dimensions, culture dimensions and unit evaluation) from first and second hypotheses and results revealed that all variables do not change over time. Nevertheless, it is possible to encounter measurement errors and process errors although the means of these variables do not change over time.

Both MLR and LME models were used to investigate learning dimensions, culture dimensions and unit evaluation to determine direct linear relationships with CS. Comparing both models, MLR models presented a better fit of all students in a linear regression, which supported H3. On the other hand, LME models presented a better fit of individual students in linear regressions with two replicates in different times, which support H4. Of all the predictor variables fitted in both LME and MLR models, only the predictor variables EU, LC, PD and TO displayed significant slopes ($P<0.05$) and intercepts. However, the LME models outperformed the MLR models when modeling the relationship of the predictor variables based on both AIC and BIC information criteria (Table 3). Moreover, the outcomes of analyses based on the LME model have generated smaller residual standard errors (sigma values in Table 3) compared with the MLR model. Nevertheless, all estimated parameters, including both slope and intercepts of MLR and LME models, are highly significant ($P<0.01$). The estimated slope and intercepts of MLR are similar in values to the estimated of slope and intercept of LME model.

Table 3: Summary of LME and MLR fits with CS as the response variable and EU, LC, PD and TO as the predictor variables.

Predictor variable	**Model** (P-value of likelihood ratio test between LME and MLR results)	**Estimated**							
		Intercept (st.error)	Slope (st.error)	SD of intercept	SD of slope	Correlation between random slopes and random intercepts	AIC	BIC	Sigma
EU	LME (P=0.01)	1.83 (0.40)	0.46 (0.16)	1.19	0.45	-1	72.17	82.59	0.38
	MLR	1.99 (0.31)	0.40 (0.14)				78.42	83.64	0.53
LC	LME (P=0.003)		0.86 (0.03)		0.13		79.67	90.09	0.41
	MLR		0.85 (0.03)				87.61	91.13	0.60
PD	LME (P=0.02)	1.76 (0.50)	0.36 (0.16)	1.52	0.47	-1	79.45	89.87	0.42
	MLR	2.24 (0.41)	0.21 (0.14)				83.70	88.91	0.56
TO	LME (P=0.009)	1.50 (0.59)	0.49 (0.23)	1.64	0.66	-0.986	79.67	90.09	0.34
	MLR	2.60 (0.48)	0.08 (0.17)				85.20	90.41	0.58

5.1. THE EFFECT OF *EU* ON *CS*

Figure 2 illustrates the plots of observed data and fitted results of the LME models on 22 students based on both surveys. The assigned response variable is CS and the predictor variable is EU. The estimated linear regression relationship indicates that students with no expectation of course materials (low EU score) are FI students (low CS score). Students with a high expectation of well prepared lectures are FD students (high CS score). The estimated correlation between the random effects of slope and intercept is -1. This indicates that the estimated individual student regression line with a smaller intercept will have a bigger slope. In other words, FD students are not likely to change in their expectations in EU, even though there is a random change in the course preparation from the first to the second semester. In contrast, FI students are likely to change in their expectations in EU when there is a random change in the course materials from the first semester to the second semester.

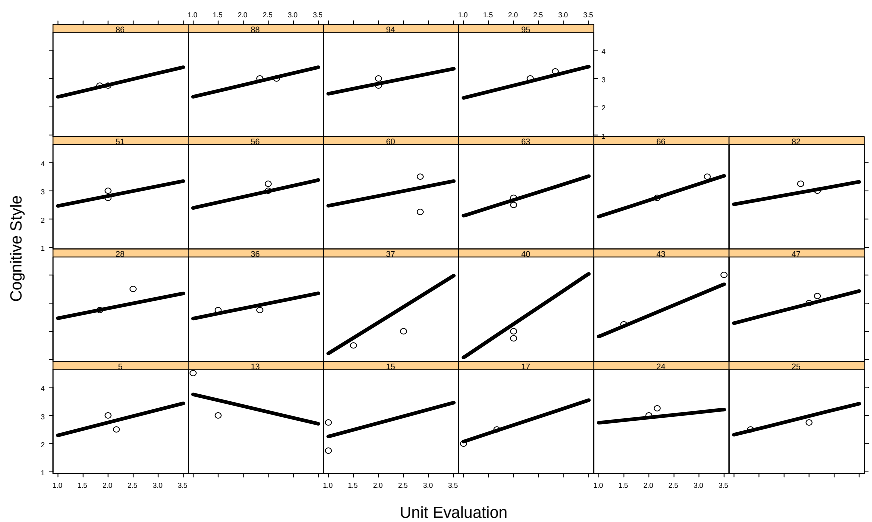

Figure 2: Plots of the linear mixed effect models predicted results of 22 students in both Semester 1 and 2 surveys with response variable CS and predictor variable EU.

5.2. THE EFFECT OF LC ON CS

The assigned response variable is CS and the predictor variable is LC. The estimated intercepts of the LME model are not significant (P>0.20). The best fitted model of LME illustrates a slope that only began from the origin. The estimated slope of the LME model is 0.86 (Table 3). In addition, it is similar to the estimated slope of the MLR model which is 0.85. Thus, it is apparent that the LME model resulted in a better fit compared with the MLR model. The coefficient of variation of random effects is 0.13/0.86=15%. A lower LC score relates to a lower CS score. This implies that students with a lower LC score are likely to be FI as they tend to have a higher ability to engage in independent learning with analytical thought. On the other hand, a higher LC score relates to a higher CS score. This implies that the students with a higher LC score are likely to be FD as they tend to be relatively passive and less capable of learning independently. Students' LC is likely to change with time. This change will affect the variation of individual CS too.

5.3. THE EFFECT OF *PD* ON *CS*

The assigned response variable is CS and the predictor variable is PD. The estimated slope and intercept from the LME model are highly significant ($P<0.01$). The estimated slope from the MLR model is not significant ($P >0.05$). When comparing the standard residual errors of both models, it is apparent that the LME model resulted in a better fit. Based on the fitted results from the LME model, students who prefer equal distribution of power (low PD score) are likely to be FI students. On the other hand, students who prefer unequal distribution of power (high PD score) are likely to be FD students. The estimated correlation between the random effects of the slope and the intercept is -1. This indicates that the estimated individual student regression line with a smaller intercept will have a bigger slope or a bigger change in CS. Therefore, FD students are not likely to change their view of power distance randomly with time, whereas FI students are likely to change.

5.4. THE EFFECT OF *TO* ON *CS*

The assigned response variable is CS and the predictor variable is TO. The estimated linear regression relationship suggests that students with long-term orientation (low TO score) are FI students (low CS score). However, students with short-term orientation (high TO score) are FD students (high CS score). The estimated correlation between the random effects of the slope and intercept is -0.986. The estimated individual student regression line with a smaller intercept will have a bigger slope or a bigger change in CS. Therefore, FD students are unlikely to change their orientation randomly with time, whereas FI students are likely to change.

5.4. SUMMARY OF RESULTS

The predictor variables of EU, LC, PD and TO are significant to determine students' CS. These results correspond with the findings of the cross-sectional study conducted by Lee et al. (2010). This previous study had used tree-based regression to model the relationships of CS with EU, LC, NL, IC, PD and TO as well as determining their higher order interaction. The longitudinal study has provided further findings that facilitate educators to understand that variation of individual CS is affected by changes of EU, LC, PD and TO with time. Nevertheless, one of the limitations of this study is that it can only investigate one predictor variable with CS in the LME model. This limitation was caused by the data; that is, having only one repeated measure of 22 students. If the data contain more repeated measures, it would allow the LME model to investigate the correlation of the estimated random slopes and random intercept among the predictor variables (Cheng and Kuk, 2002). The use of the LME model with repeated measures data enables us to understand the variation of CS with time. This variation is a combination of measurement errors, sampling errors and random errors. It is distributed with a constant mean and unknown variation. This implies that the measurement of student CS should be conducted several times instead of just one time due to variation errors. However, the variation of CS can also be understood with the predictor variables, EU, LC, PD and TO.

6. Conclusions

This study has undertaken rigorous advanced statistical analysis to identify the interdisciplinary connections between cognitive style, learning dimensions in hypermedia, culture dimensions, unit evaluation and time effect. A particularly important outcome from this study suggests that unit evaluation is the key variable in predicting students' cognitive style. To some extent, as observed in this longitudinal study, learning dimensions and culture dimensions have an influence on students' ability to structure a cognitive overview in a hypermedia learning system. These factors have strong connections with learning effectiveness and are essential when designing and developing effective hypermedia materials that match the style of teaching with students' cognitive style.

Typically, a unit evaluation is only conducted at the end of each semester for each unit and may not provide educators with the necessary information to modify and develop effective teaching and learning materials in a hypermedia learning environment. From the results of this study, it is suggested that educators should conduct an evaluation at the beginning and at the end of each unit. The pre- and post-unit evaluations would provide information about students' particular needs and preferences according to their various learning characteristics. The evaluations would also guide educators in providing teaching and learning materials in the hypermedia system that cater to different cognitive styles. Hence, effective learning, retention and retrieval of information can be attained through an adaptable hypermedia learning system.

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