“KNOWLEDGE VISUALIZATION AND KNOWLEDGE MANAGEMENT IN E-LEARNING”

Instructional Design and Technology Dissertation

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Students' Perceived Learning Outcomes and Satisfaction in e-learning:

An Observed Investigation

Abstract

In this study, structural equation modelling is applied to examine the determinants of students' satisfaction and their perceived learning outcomes in the context of Botswana college of Distance and Open Learning (BOCODOL) online courses. Independent variables included in the study are course structure, instructor feedback, self-motivation, learning style, interaction, and instructor facilitation as potential determinants of online learning. A total of 250 valid unduplicated responses from students who have completed at least one online course at Botswana College of Distance and Open Learning in Botswana were used to examine the structural model. The results indicated that all of the antecedent variables significantly affect students' satisfaction. Of the six originator variables hypothesized to affect the perceived learning outcomes, only instructor feedback and learning style are significant. The structural model results also reveal that user satisfaction is a significant predictor of learning outcomes. The findings suggest online education can be a superior mode of instruction if it is targeted to learners with specific learning styles (visual and read/write learning styles) and with timely, meaningful instructor feedback of various types.

Key focus areas: Asynchronous Learning, Correlation Analysis, Distance Education/Distance Learning, Learning Effectiveness, Perceived Learning Outcomes, Structural Equation Modelling, Student Satisfaction, and User-Satisfaction.

INTRODUCTION

An e-learning system is a system that provides services that are necessary for handling all aspects of a course through a single, intuitive and consistent web interface. Such services are, for example: (1) course content management, (2) synchronous and asynchronous communication, (3) the uploading of content, (4) the return of students' work, (5) peer assessment, (6) student administration, (7) the collection and organization of students' grades, (8) online questionnaires, (9) online quizzes, (10) tracking tools, etc. With the advent of Web 2.0 technologies and services (like wikis, blogs, RSS, 3D virtual learning spaces, etc) e-learning systems will provide services that enable students to shift from passive to active learners where they can actively participate in the on-line learning process. E-learning environments that provide access to synchronous and asynchronous learning resources and activities are going to continue growing. In addition to educational organizations, business organizations are also using e-learning technologies and services for cost-effective online training for their employees. In spite of the fact that educational and/or business institutions are investing a lot of money and resources in implementing e-learning systems, such systems will not be fully utilized if the users fail to use the system. When a new e-learning environment is presented, it needs to be adopted by its users. User's perceptions regarding the use and acceptance of an eLearning system can be affected by different factors, which can be combined into two main groups: (a) technological characteristics (like reliability, responsiveness, efficiency, security, etc.) and (b) individual characteristics (like age, gender, e-learning experience, etc.). The main challenge for e-learning system developers is to provide an e-learning system with appropriate services that will positively affect a user's experience. E-learning content providers must attract learners with appropriate e-learning content and they have to adequately incorporate e-learning services and technologies in the e-learning process. For these reasons, developers, designers and purchasers of eLearning systems must carefully consider the needs, trends and values of e-learning users and ensure that the system will meet their demands. This study aimed to investigate the factors that affect the acceptance and use of an e-learning system, namely Moodle. Moodle provides different activity modules (like Assignments, Forums, Wikis, Blogs, Quizzes, Tracking, etc.), and can therefore be applied in different ways. Moodle can be used as a tool for delivering content to students and assess learning using assignments or quizzes and, more interestingly, it can be used to build rich collaborative learning communities.

To understand students' perceptions about using Moodle, the technology acceptance (TAM) research model and hypothesized relationships between TAM constructs were empirically tested using the structural equation modelling (SEM) approach.

One may emphasise that the landscape of distance education is changing. This change is being driven by the growing acceptance and popularity of online course offered at colleges and universities worldwide. The distance learning system can be viewed as having several human or nonhuman entities interacting together via computer-based instructional systems to achieve the goals of education, including perceived learning outcomes and student satisfaction. These two outcomes can be perceived as some of the measures of the effectiveness of online education systems.

The primary objective of this study is to investigate the determinants of students' perceived learning outcomes and satisfaction in university online education using e-learning systems. Using the extant literature, we begin by introducing and discussing a research model illustrating factors affecting e-learning systems outcomes. We follow this with a description of the cross-sectional survey that was used to collect data and the results from a Partial Least Squares (PLS) analysis of the research model.

The landscape of distance education is changing. This change is being driven by the growing acceptance and popularity of online course offerings and complete online degree programs at colleges and universities worldwide. The distance learning system can be viewed as having several human/nonhuman entities interacting together via computer-based instructional systems to achieve the goals of education, including perceived learning outcomes and student satisfaction. These two outcomes are widely cited as measures of the effectiveness of online education systems.

Theoretical backgrounds

The theory of reasoned action (TRA), developed by Martin Fishbein and Icek Ajzen, posits that individual behaviour is driven by behavioural intentions. The theory received particular attention in the field of consumer behaviour as it provides a simple tool to identify possibilities to change customers' behaviour when using an innovation. To this regard, the actual use of an innovation is determined by the individual's behavioural intention to use it. The model resulting from their research is visualised in and consist of the following components:

Starting from the behavioural intentions, these include the functions of an individual's attitude towards the behaviour and the subjective norm surrounding the performance of the behaviour. Accordingly, the actual use of an innovation is determined by the individual's behavioural intention to use it. The Attitude towards an act or behaviour is the individual's positive or negative feelings about performing a behaviour, determined through an assessment of one's beliefs. Subjective norm is defined as an individual's perception of whether people important to the individual think the behaviours should be performed. "To put the definition into simple terms: a person's volitional (voluntary) behaviour is predicted by his/her attitude toward that behaviour and how he/she thinks other people would view them if they performed the behaviour. A person's attitude, combined with subjective norms, forms his/her behavioural intention".

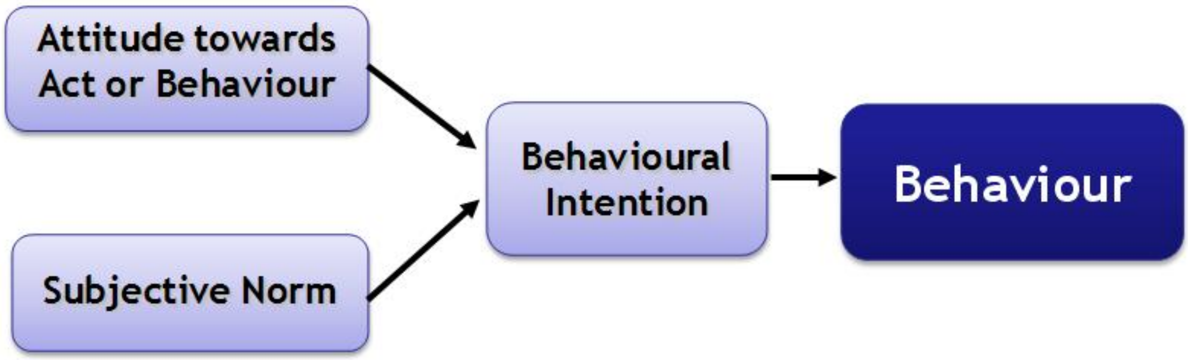

Figure 1: Schematic of the theory of reasoned action (TRA)

However, the TRA has some limitations on explaining all mechanisms of the actual use of an innovation and the role of the individual's behavioural intent, which are discussed in the relevant scientific literature. One limitation is the significant risk of confounding between attitudes and norms since attitudes can often be reframed as norms and vice versa. Furthermore, the assumption that when someone forms an intention to act, they will be free to act without limitation, is often unfounded. Lastly, in practice, constraints such as limited ability, time, environmental or organisational limits, and unconscious habits will limit the freedom to act.

Consequently, extended theories were needed to better describe the mechanisms that actually explain the use of an innovation and the role of the individual's behavioural intent. A selection of these theories is described in the following sections.

The Technology Acceptance Model (TAM) by Davis is based on TRA and tailored towards the acceptance of information technology (IT). A key purpose of TAM is to provide a basis for tracing the impact of external variables on internal beliefs, attitudes and intentions. The resulting hypothesis framework of Davis is visualised in . In his research, two main factors are of prime relevance in explaining system usage. Namely these are:

- "Perceived ease of use": The degree to which a person believes that using a particular system would be free from effort.
- "Perceived usefulness": The degree to which a person believes that using a particular system would enhance his or her job performance.

Various researchers have simplified TAM by removing the attitude construct found in TRA from the current specification (e.g. Venkatesh et al.). Moreover, there are several attempts to extend TAM, which generally have taken one of three approaches:

- Introducing factors from related models
- Introducing additional or alternative belief factors (risk, emotion, etc.)
- Examining antecedents and moderators of perceived usefulness and perceived ease of use

Also when TAM extends TRA, some limitations can also be found:

- Both TRA and TAM have strong behavioural elements, assuming that when someone forms an intention to act, they will be free to act without limitation.
- However, in practice constraints such as limited ability, time, environmental or organisational limits, and unconscious habits will limit the freedom to act.

Adoption of an e-learning system by learners may be treated as technology adoption. The most common theory in the field of IT/IS (information technology/information system) adoption is the Technology Acceptance Model – TAM. Davis proposed TAM to explain the potential user's behavioural intentions when using a technological innovation, because it explains the causal links between beliefs (the usefulness of a system and ease of use of a system) and users' attitudes, intentions, and the actual usage of the system. The principal TAM concepts are:

- Perceived ease of use (PEOU) – the degree to which a person believes that using a particular system would be free of effort,
- perceived usefulness (PU) – the degree to which a person believes that using a particular system would enhance his or her job performance, and
- The dependent variable behavioural intention (BI) – the degree to which a person has formulated conscious plans to perform or not perform some specified future behaviour.

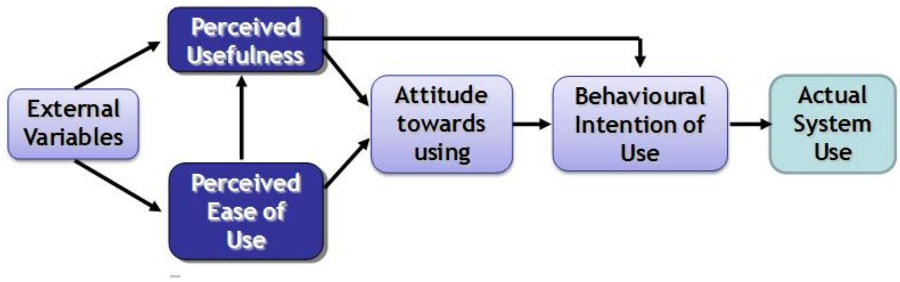

Figure 2: Hypothesis Framework of the TAM

The theory itself describes the process by which an innovation is communicated through certain channels over time among the members of a social system. In other words, the study of the diffusion of innovation is the study of how, why, and at what rate new ideas and technology spread through cultures. To this regard, the theory of Rogers is an excellent resource to develop strategies in order to enable the diffusion of complex and controversial technologies in society.

Adoption is similar to diffusion, except that it deals with the psychological processes an individual goes through, rather than an aggregate market process, which is described by the process of diffusion.

The Diffusion of Innovation (DoI) theory especially focuses on the following core topics, which will be described in the following sections:

- Adopters
- Key innovation characteristics
- Stages of adoption

Adopters

In his research, Rogers proposed that adopters of any new innovation or idea could be categorised as innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%). Looking at the two extremes of the described groups, “early adopters” tend to adopt new innovations very fast, as they embrace change and are usually educated in the relevant field of the innovation being looked at. On the other hand, the adoption group of the “laggards” will adapt very late, as they tend to be resistant to change. Using the market for mobile services as an example, the early adopters tend to be educated, technology accepting people, who can afford to use such newly introduced mobile services. Furthermore, this group has the ability to understand the complexity of mobile services and their value added, even though the level of uncertainty of the success of an innovation could be quite high (higher risk propensity). For the group of laggards however, this is ultimately turned to the opposite. The characteristics for the remaining adopter groups can be found in the following:

Innovators (2.5%):

- Characteristics: Venturesome, educated, multiple info sources, greater propensity to take risk
- Has the ability to understand and apply complex technical knowledge and can cope with a high level of uncertainty of an innovation.
- The innovator is a catalyst who brings about the use and adoption of new ideas.

Early adopters (13.5%):

- Characteristics: Social leaders, popular, educated
- Other members of the group look to these individuals for advice and knowledge about the innovation.

Early majority (34.0%):

- Characteristics: Deliberate, many informal social contacts
- Tend to adopt the innovation just prior to time the average individual adopts it (link between early adopters and later majority).

Late majority (34.0)%:

- Characteristics: Sceptical, traditional, lower socio-economic status
- Acceptance comes after the average person accepts

Laggards (16.0%):

- Characteristics: Neighbours and friends are main info sources, fear of debt
- Laggards are those who are consistent or even adamant in resistance to change.

Characteristics of adopter groups

Moreover, the adopter groups can be placed into a bell curve based on standard deviations from the mean of the normal curve, provided a common language for innovation researchers. Each adopter's willingness and ability to adopt an innovation would depend on their awareness, interest, evaluation, trial, and adoption. People could therefore fall into different categories for different innovations.

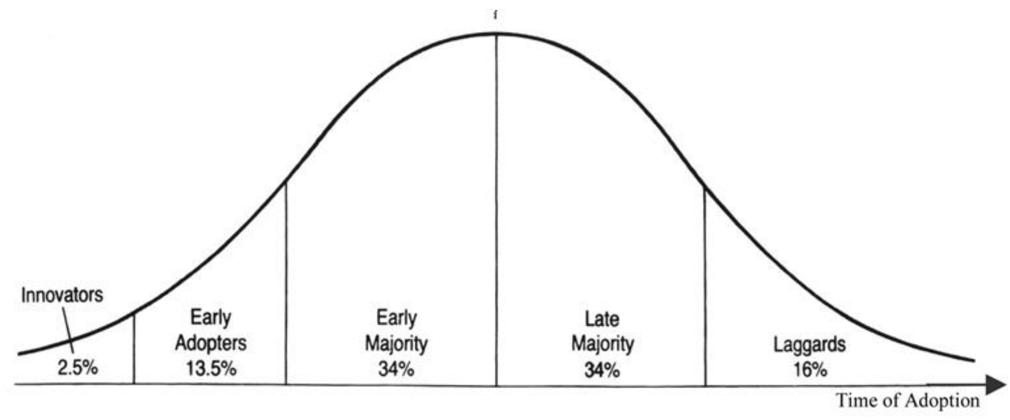

Figure 3: Adopters Bell Curve

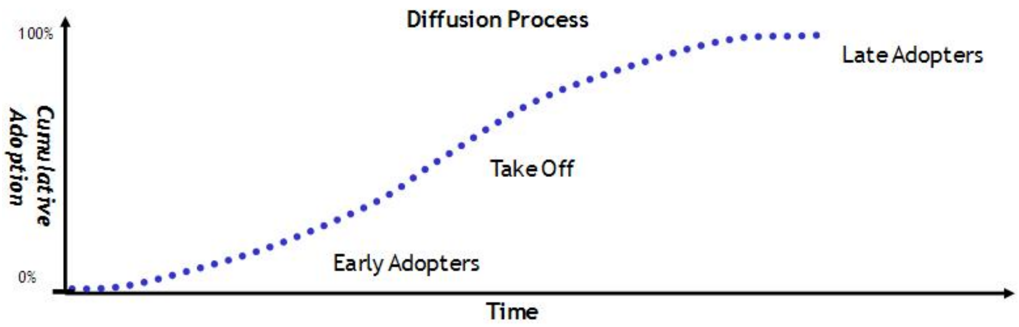

Figure 4: Cumulative adoption of an innovation overtime, resulting in the S-shaped adoption curve

As a real life example for the cumulative adoption of an innovation over time, the growth of the Internet is analysed in:

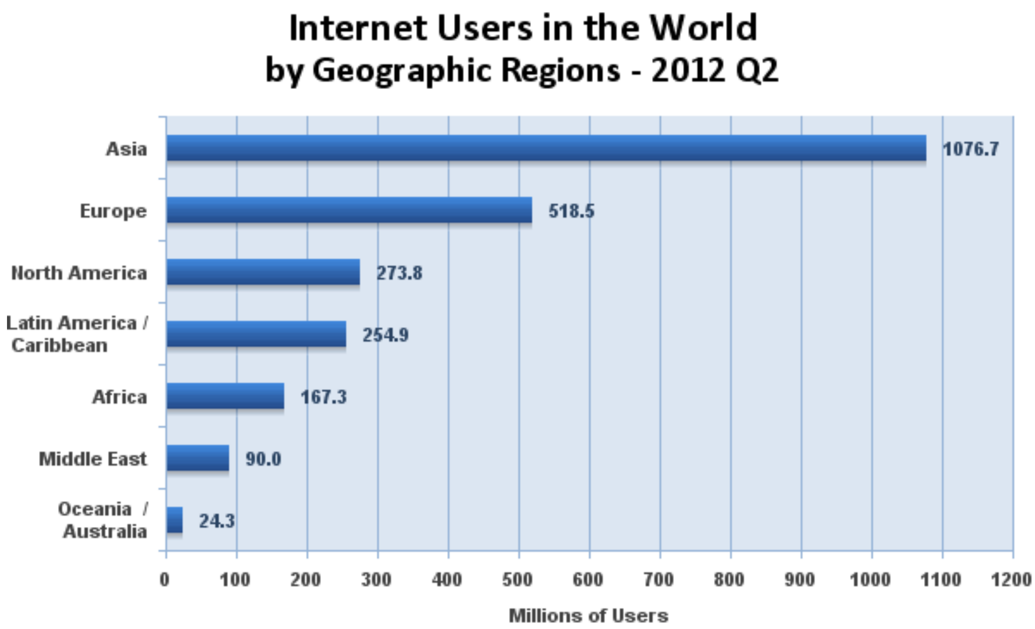

Figure 5: Cumulative growth Internet users in the world as at June 2012 (www.internetworldstats.com/stats.htm)

Key Innovation Characteristics

For the adoption itself, certain characteristics can be observed:

- **Relative Advantage**: The degree to which the innovation is perceived as being better than the practice it supersedes
- **Compatibility**: The extent to which adopting the innovation is compatible with what people do
- **Complexity**: The degree to which an innovation is perceived as relatively difficult to understand and use
- **Trialability**: The degree to which an innovation may be experimented with on a limited basis before making an adoption (or rejection) decision
- **Observability**: The degree to which the results of an innovation are visible to others

Following, the presented innovation characteristics are applied to the case of mobile telecommunications and its behaviour to adoption:

1. Relative Advantage:
    a. Availability/reachability of the subscriber
    b. Communicate (almost) anywhere / anytime
    c. Personal device(s)
2. Compatibility:
    a. High compatibility in society, as flexibility and reachability become more important.

3. Complexity:
    a. Low to medium:
        i. Basic functionality (e.g. telephony) can be used by everyone being capable of using a standard, fixed-line telephone.
        ii. Advanced features (e.g. SMS) need further training to use them.
4. Trialability:
    a. High: A potential customer can subscribe to a prepaid contract for testing the technology and later on switch to a "normal" subscription based contract.
5. Observability:
    a. Reachability of the customers anytime and anywhere.
    b. More and more people are using mobile phones and services.
    c. People using mobile phones can easily be observed by non-users.
    d. The concept and benefit of mobile telephony is easily observable by non-
    e. users.

LITERATURE REVIEW

Due to its flexibility in delivery and just-time access, e-learning has been widely adopted in recent years. In eLearning applications, learners are encouraged to learn through interacting with a wide range of resources to acquire and build their knowledge. While such a resource-abundant and self-regulated learning environment allows learners a great deal of freedom and flexibility in searching for, selecting, and assembling information, learners may suffer from cognitive overload and conceptual and navigational disorientation when faced with massive information online (Tergan, 2005; Kayama & Okamoto, 2001; Miller & Miller, 1999). The challenge is even greater when learning contents are scattered under disparate topics and complex knowledge structures. When faced with this problem, many learners are unable to figure out features and meaningful patterns of various kinds of information, and are easily hampered by limited working memory. This is mainly because novices lack sufficient knowledge and a deep understanding of the subject domain, which is crucial to organizing information and knowledge for retention in long-term memory. Also, traditional education breaks wholes into parts, and focuses separately on each part, and learners are often unable to create the big picture before all the parts are presented. As a result, most online learners, especially novices, become “lost-in-hyperspace”.

This study aims to improve the design of current e-learning systems by dealing with the aforesaid problem. To facilitate cognitive processing and self-regulated learning, learners should be supported with appropriate learning strategies, among which cognitive and meta-cognitive strategies have been well identified (Bransford, 2000, Zimmerman, 2000; Winne, 2001). Learners are helped in their independent learning if they have conceptual knowledge, and learners can become more independent if they have awareness of their own knowledge and ability to understand, control, and manipulate individual learning processes. While these strategies have been found to be effective, few studies have examined how these strategies can be implemented in instructional design, especially in online learning environments. While learning theories or strategies offer guidelines of improving the design of current e-learning systems, it is far more difficult and additional effort is needed to explore effective instructional methods (Reigeluth, 1999). This study investigates knowledge visualization (KV) approach to support resource-abundant and self-regulated online learning, which consists of three components. First, an explicit representation of conceptual knowledge structure is constructed by capturing key knowledge concepts and their relationships in a visual format. This visualized knowledge structure serves as a cognitive roadmap to facilitate the knowledge construction and high level thinking of online learners. Second, abstract concepts are connected with concrete contents by linking knowledge concepts with learning resources. In this way, information processing and knowledge construction, the two key aspects of the learning process, are well integrated. Learners can easily navigate throughout the resource-abundant, non-linear knowledge space aided by the visualized cognitive roadmap. Third, meta-cognitive learning support is provided for learners to regulate and plan their learning process. Assessment materials associated with knowledge concepts are provided for self-evaluation of learning outcomes in granular knowledge components, from which the system generates feedback and guides individuals throughout their learning process.

To implement the proposed approach, an online learning system was developed using computer and Web-based technologies. The system has been designed to help learners transcend the limitations of their minds, not only in cognitive processing, but also in high level thinking and knowledge construction. In doing so, computers are used as electronic pools for reflecting human cognitive processes through visual representations on the screen. These visual representations provide more effective use of learners' mental effort by amplifying, extending, and enhancing human cognitive functions, and engaging learners in representing, manipulating, and reflecting on what they know.

Compared with other related work, this study is unique in the following aspects. First, while traditional education breaks wholes into parts and focuses separately on each part, this study aims to help learners see the "whole" before they are able to make sense of the parts. Second, instead of asking learners to construct knowledge maps by themselves, this study utilizes expert knowledge structure to help novices build up their thinking and understanding on a solid foundation. This may reduce novices' cognitive overload in advanced thinking. Third, instead of using visualized knowledge structure as an isolated instructional instrument, this study uses it as infrastructure and integrates it with curriculum design, learning resources, learning assessment, intellectual processes, and social learning.

Visualization of Knowledge Structure

In facilitating learners' cognitive processing and retaining knowledge in long-term memory, clustering or chunking (i.e., organizing disparate pieces of information into meaningful units) is regarded as a pervasive approach (Bransford, 2000). According to psychology theories, knowledge in memory is organized semantically in networks, built piece by piece with small units of interacting concepts and propositional frameworks. These mental semantic networks represent a cognitive structure, which can be used as a learning tool for constructive learning processes (Jonassen, 2000). More importantly, the cognitive structure should be represented in an external format with explicit description. This is because visual methods help externalize and elicit the abstract structure of knowledge (Jacobson & Archodidou, 2000), and human brains have rapid processing capabilities to acquire and retain visual images (Paige & Simon, 1966). Computer-based technologies help further by making it easy for learners to construct, recall, and modify visual representations, and keep them for a long period of time (Jonassen, 2000; Novak & Cañas, 2008).

The Knowledge Visualization approach proposed in this study is to incorporate visualized representations of domain knowledge structure into e-learning systems. Relevant functions are developed for creation, storage, display, and revision of knowledge maps. Rather than memorizing the content, learners can use knowledge maps to identify important concepts and their relationships, and generate semantic networks for review and reflection. Moreover, a knowledge map displays intellectual processes involved in the acquisition and construction of knowledge. These become the basis for systemic inquiry, knowledge construction, and high level thinking (Wang et al., 2010).

Integration of Information Processing and Knowledge Construction

Information processing and knowledge construction are closely intertwined in the learning process. Learners need to access information to acquire content knowledge and formulate hypotheses (Jonassen, 1999). Knowledge is constructed through meaningful learning, which takes place when learners deliberately seek to relate (new) information to, and incorporate it into, relevant knowledge that he/she has already possessed (Mayer, 2001).

Facilitation of Self-Regulated Learning

Advanced learning acquires over years of experiences and derives from activities of thinking, action, and reflection. Experts have acquired a great deal of well-organized content knowledge, and their organization reflects a deep understanding of the subject matter (Bransford, 2000). Although peer models have been used to guide self-regulated learning, the creation of well-developed and stable cognitive structures for scaffolding advanced learning is noted as a primary instructional goal (Zimmerman, 2000; Reigeluth, 1999). The recognition of expert knowledge has been reflected in both objectivist and constructivist learning theories. Information processing, which is based on objectivist learning theory, requires effective and efficient processing of information and indicates that experts' knowledge structures help learners acquire information accurately. At the same time, constructivism suggests that guidance and strategies (e.g., modelling, coaching, and scaffolding) from experts provide the necessary support for learners to construct knowledge (Miller & Miller, 1999).

This study utilizes expert knowledge structures for guiding and scaffolding novices' understanding, thinking, and inquiry in their self-regulated learning. Conceptual understanding of a domain is often not fully expressed in books or learning materials, and knowledge maps can be used to articulate and manipulate such tacit knowledge more effectively. Using the expert knowledge map as the foundation may reduce the chance of misconception and faulty ideas. Although highly structured graphs may seem constraining at times, these templates are good starting points for novices, who have trouble organizing their understanding and are confused in their self-regulated learning (Hyerle, 2000).

In addition to facilitating learners' cognitive processes, knowledge maps provide meta-cognitive support. As mentioned, learners can become more independent if they are aware of their learning process and have the ability to regulate it. Visual representations are forms of metacognition that graphically display the thinking process (Costa & Garmston, 2002). Knowledge maps display intellectual processes by representing sequences, alternatives, branches, choice points, and pathways that involved in the acquisition and construction of knowledge (Wang et al., in press).

To utilize this metacognitive feature, additional functions based on knowledge maps were developed in this study to help learners plan and oversee their learning process. In doing so, assessment materials were collected and associated with knowledge concepts for evaluation of learning outcomes in granular knowledge components, with feedback to learners for correct answers and detailed explanations. At the same time, the system can monitor individual learning progress, based on which learning guidance is provided to individuals such as what to learn in the next step, further effort required for a specific knowledge concept, reminder of prerequisite knowledge to learn before moving on, etc. Individual learning progress can also be reflected in the knowledge map to indicate the knowledge that has been learnt, ready to be learnt, or not ready to be learnt.

Support of Social Learning

To support self-regulated learning, learners are encouraged to participate in social communication, discussion, and sharing. The knowledge structure constructed in this study can also be used as the index or model to organize discussion messages and shared learning resources, with a view to facilitating and steering social communication and knowledge sharing in the social learning community.

THE IMPORTANT FACTORS THAT CONTRIBUTE TO THE SUCCESS OF E-LEARNING SYSTEMS

Our conceptual model illustrating factors potentially affecting e-learning systems outcomes is built on the conceptual frameworks of Piccoli, Ahmad, and Ives (2001). Piccoli et al. (2001) refer to human and design factors as antecedents of learning effectiveness. Human factors are concerned with students and instructors, while design factors characterize such variables as technology, learner control, course content, and interaction. The conceptual framework of online education proposed by Peltier, Drago, and Schibrowsky (2003) consists of instructor support and mentoring, instructor-to-student interaction, student-to-student interaction, course structure, course content, and information delivery technology. Our research model is illustrated in the figure below.

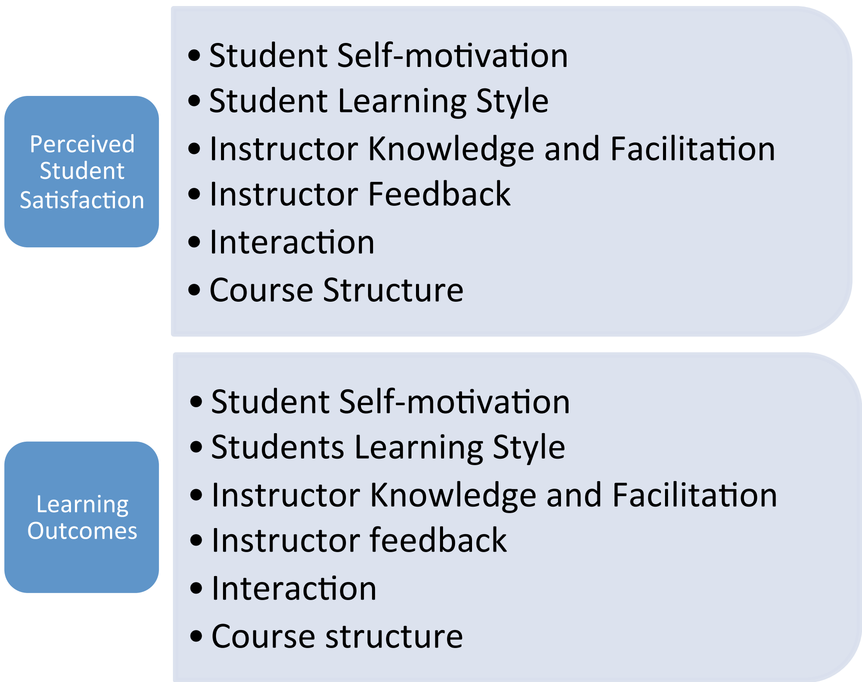

Figure 6: Research Model

Perceived Student Satisfaction

In contemporary higher education, the role of student has switched from that of passive receiver to that of an active learner, under the learning paradigm that the universities and colleges are gradually adopting. This new paradigm's constructivist approach is accompanied by the expectation that students take responsibility for their own learning by involving themselves in knowledge construction. The instructor now becomes more important than ever in the learning process, because it falls to him/her to create the environment that fully realized students learning requirements.

To become effective, less-than-optimal learning environment should be redesigned to include a variety of learning activities and opportunities shown to foster achievement of the desired learning outcomes. The instructor should provide evidence of students learning by assessing student's understanding and their demonstration of the desired results.

Student's demographics have changed greatly in the recent years, as have teaching and learning technologies; because the students population is increasingly diverse – and unevenly fascinated by these technologies – instructors seeking to obtain accurate learning outcomes may need to use a variety of assessment methods, in deference to students' differential learning styles and thinking paths. Among other options are direct assessment methods evaluating how well students achieve desired outcomes and also indirect assessment methods, in particular surveys, eliciting students' opinions throughout a course? Such data collected from students sheds light on their own perceptions of learning and of the effectiveness of the learning environment created by the instructor, and they are also helpful for on-going course improvement.

Students' satisfaction is the subjective perceptions, on student's part, of how well a learning environment supports academic success. Strong students' satisfaction implies that appropriately challenging instructional methods are serving to trigger students' thinking and learning. Important elements in student satisfaction are likely to concern the role of the instructor and of the student; these elements, may be central to the students' learning.

Student Self-Motivation

Wanting something is not enough. You must hunger for it. Your motivation must be absolutely compelling in order to overcome the obstacles that will invariably come your way. - Les Brown

The students who succeed will need to be self-motivated.

Motivation is a fire from within. If someone else tries to light that fire under you, chances are it will burn very briefly. — Stephen. R. Covey

Why does some students sleep late, skip classes, do as little study as possible? I don't believe they really WANT TO make poor grades. The problem is that, for some reason they are not motivated.

Fundamentally, the process of motivation stems from stimulation, which in turn is followed by an emotional reaction that leads to a specific behavioural response. In the classroom, if a student's behavior is regarded as desirable and is rewarded, the positive reinforcement stimulates the student to repeat the desirable behavior. Conversely, if a student's behavior is regarded as undesirable and the individual receives a response with a negative undertone, demotivation results. Furthermore, anxiety and frustration often result if behavior thought to be positive does not lead to proper recognition, reinforcement and reward.

Basically, motivations stems from unsatisfied needs. However, it must be understood that individuals are motivated through a wide variety of needs. Some people are highly motivated by money, others by power, and other by praise. Since instructors are not usually in a position to offer students money or power, the focus here will be on praise. It should also be noted that some people are self-motivated and perform because they like challenge and want to perform. While educators can't make or teach students to be self-motivated, they can encourage and promote this highly desirable personal trait. Generally, students will show some self-motivation if they (1) know what is expected of them, (2) think the effort is worthwhile, and (3) feel they will benefit through effective performance.

Students are the primary participants of e-learning systems. Web-based e-learning systems placed more responsibilities on learners than traditional face-to-face learning systems. A different learning strategy, self-regulated learning, is necessary for e-learning systems to be effective. Self-regulated learning requires changing roles of students from passive learners to active learners. Learners must self-manage the learning process. The core of self-regulated learning is self-motivation. Self-motivation is defined as the self-generated energy that gives behavior direction toward a particular goal.

The strength of the learner's self-motivation is influenced by self-regulatory attributes and self-regulatory processes. The self-regulatory attributes are the learner's personal learning characteristics including self-efficacy, which is situation-specific self-confidence in one's abilities. Because self-efficacy influences choice, efforts, and volition, a survey question representing self-efficacy is used to measure the strength of self-motivation. The self-regulatory processes refer to the learner's personal learning processes such as attributions, goals, and monitoring. Attributions are views in regard to the causes of an outcome. A survey question representing a controllable attribution is used to measure the strength of self-motivation.

One of the stark contrasts between successful students is their apparent ability to motivate themselves, even when they do not have the burning desire to complete a certain task. On the other hand, less successful students tend to have difficulty in calling up self-motivation skills, like goal setting, verbal reinforcement, self-rewards, and punishment control techniques.

The extant literature suggests that students with strong motivation will be more successful and tend to learn the most in Web-based courses than those with less motivation (e.g., Frankola, 2001; LaRose & Whitten, 2000). Students' motivation is a major factor that affects the attrition and completion rates in the Web-based course and a lack of motivation is also linked to high dropout rates (Frankola, 2001; Galusha, 1997). Thus, we hypothesized:

- **H1a**: Students with a higher level of motivation will experience a higher level of user satisfaction.
- **H1b**: Students with a higher level of motivation in online courses will report higher levels of agreement that the learning outcomes equal to or better than in face-to-face courses.

Students' Learning Styles

Students learn in many ways, like seeing, hearing, and experiencing things first hand. But for most students, one of these methods stands out. Why is this important? Research has shown that students can perform better on tests if they change study habits to fit their own personal learning styles. For example, visual-learning students will sometimes struggle during essay exams, because they can't recall test material that was "heard" in a lecture. However, if the visual learner uses a visual aid when studying, like a colourful outline of test materials, he or she may retain more information. For this type of learner, visual tools improve the ability to recall information more completely. A simple explanation of learning styles is this: Some students remember best materials they've seen, some remember things they've heard, while others remember things they've experienced.

Learning is a complex process of acquiring knowledge or skills involving a learner's biological characteristics/senses (physiological dimension); personality characteristics such as attention, emotion, motivation, and curiosity (affective dimension); information processing styles such as logical analysis or gut feelings (cognitive dimension); and psychological/individual differences (psychological dimension) Due to the multiples dimensions of differences in each learner, there have been continuing research interests in learning styles. Some models of learning styles are cited in the literature (Curry, 1983) including the Kolb learning preference model (Kolb, 1984), Gardner's theory of multiple intelligence (Gardner, 1983), and the Myers-Briggs Personality Type Indicators (Myers & Briggs, 1995). The basic premise of learning style research is that different students learn differently and students experience higher level of satisfaction and learning outcomes when there is a fit between a learner's learning style and a teaching style.

This study uses the physiological dimension of the study of learning styles, which focus on what senses, are used for learning. A popular typology for the physiological dimension of the learning styles is VARK (Visual, Aural, Read/write, and Kinesthetic) (Drago & Wagner, 2004).

- Visual: visual learners like to be provided demonstrations and can learn through descriptions. They like to use lists to maintain pace and organize their thoughts. They remember faces but often forget names. They are distracted by movement or action but noise usually does not bother them.
- Aural: aural learners learn by listening. They like to be provided with aural instructions. They enjoy aural discussions and dialogues and prefer to work out problems by talking. They are easily distracted by noise.
- Read/write: read/write learners are note takers. They do best by taking notes during a lecture or reading difficult material. They often draw things to remember them. They do well with hands-on projects or tasks.
- Kinesthetic: kinesthetic learners learn best by doing. Their preference is for hands-on experiences. They are often high energy and like to make use of touching, moving, and interacting with their environment. They prefer not to watch or listen and generally do not do well in the classroom.

One can speculate that a different set of learning styles is served in an online course than in a face-to-face course. We assume that online learning systems may include less sound or oral components than traditional face-to-face course delivery systems and that online learning systems have more proportion of read/write assignment components, Students with visual learning styles and read/write learning styles may do better in online courses than their counterparts in face-to-face courses. Hence, we hypothesized:

- **H2a**: Students with visual and read/write learning styles will experience a higher level of user satisfaction.

- **H2b**: Students with visual and read/write learning styles will report higher levels of agreement that the learning outcomes of online courses are equal to or better than in face-to-face courses.

Instructor Knowledge and Facilitation

Some widely accepted learning models are objectivism, constructivism, collaborativism, cognitive information processing, and socioculturalism. Traditional face-to-face classes using primarily the lecture method, use the objectivist model of learning whose goal is transfer of knowledge from instructor to students. Even in distance learning, it is still a critical role of the instructor to transfer his/her knowledge to students, because the knowledge of the instructor is transmitted to students at different locations. Thus, we included a question to ask the perception of students in regard to the knowledge of the instructor: The instructor was very knowledgeable about the course.

Distance learning can easily break a major assumption of objectivism that the instructor houses all necessary knowledge. For this reason, distance learning systems can utilize many other learning models such as constructivist, collaboratism, and socioculturism. Constructivism assumes that individuals learn better when they control the pace of learning. Therefore, the instructor supports learner-centred active learning. Under the model of collaboratism, student involvement is critical to learning. The basic premise of this model of collaboratism is that students learn through shared understanding of a group of learners. Therefore, instruction becomes communication-oriented and the instructor becomes a discussion leader. Distance learning facilities promote collaborative learning across distances with facilities to enable students to communicate with each other. The socioculturism model necessitates empowering students with freedom and responsibilities because learning is individualistic.

E-learning environments demand a transition of the roles of students and the instructor. The instructor's role is to become a facilitator who stimulates, guides, and challenges his/her students via empowering students with freedom and responsibility, rather than a lecturer who focuses on the delivery of instruction (Huynh, 2005). The importance of the level of encouragement can be found in the model proposed by Lam (2005). We added two questions to assess the roles of the instructor as the facilitator and stimulator: "The instructor was actively involved in facilitating this course" and "The instructor stimulated students to intellectual effort beyond that required by face-to-face courses." Therefore, we hypothesized:

- **H3a**: A higher level of instructor knowledge and facilitation will lead to a higher level of user satisfaction.
- **H3b**: A higher level of instructor knowledge and facilitation will lead to higher levels of student agreement that the learning outcomes of online courses are equal to or better than in face-to-face courses.

Instructor Feedback

Instructor feedback to the learner is defined as information a learner receives about his/her learning process and achievement outcomes and it is "one of the most powerful component in the learning process". Instructor feedback intends to improve student performance via informing students how well they are doing and via directing students' learning efforts. Instructor feedback in the Web-based system includes the simplest cognitive feedback (e.g., examination/assignment with his/her answer marked wrong), diagnostic feedback (e.g., examination/assignment with instructor comments about why the answers are correct or incorrect), prescriptive feedback (instructor feedback suggesting how the correct responses can be constructed) via replies to student e-mails, graded work with comments, online grade books, and synchronous and asynchronous commentary.

Instructor feedback to students can improve learner affective responses, increase cognitive skills and knowledge, and activate metacognition. Metacognition refers to the awareness and control of cognition through planning, monitoring, and regulating cognitive activities. Metacognitive feedback concerning learner progress directs the learner's attention to learning outcomes (Ley, 1999). When metacognition is activated, students may become self-regulated learners. They can set specific learning outcomes and monitor the effectiveness of their learning methods or strategies (Chen, 2002). Therefore, we hypothesized:

- **H4a**: A high level of instructor feedback will lead to a high level of user satisfaction.
- **H4b**: A higher level of instructor feedback will lead to higher levels of student agreement that the learning outcomes of online courses are equal to or better than in face-to-face courses.

Interaction

The design dimension includes a wide range of constructs that affect effectiveness of e-learning systems such as technology, learner control, learning model, course contents and structure, and interaction. Of these, the research model focuses on only interaction and course structure.

Among the many frameworks/taxonomies of interaction (Northrup, 2002), this research adopts Moore's (1989) communication framework which classified engagement in learning through (a) interaction between participants and learning materials, (b) interaction between participants and tutors/experts, and (c) interactions among participants. These three forms of interaction in online courses are recognized as important and critical constructs determining the performance of Web-based course quality. Most students who reported higher levels of interaction with instructor and peers reported higher levels of satisfaction and higher levels of learning (e.g., Swan, 2001). A number of previous research studies suggested that an interactive teaching style and high levels of learner-to-instructor interaction are strongly associated with high levels of user satisfaction and learning outcomes (e.g., Arbaugh, 2000; Swan, 2001).

Swan (2001) reported student perceptions of interaction with their peers to be related to four components: actual interactions in the courses, the percentage of the course grade that was based on discussion, required participation in discussions, and the average length of discussion responses. Graham and Scarborough (2001) bolstered Swan's findings as their survey determined that 64% of students claimed that having access to a group of students was important. Furthermore, Picciano (1998) discovered that students perceive learning from online courses to be related to the amount of discussion actually taking place in them. When students actively participate in an intellectual exchange with fellow students and the instructor, students verbalize what they are learning in a course and articulate their current understanding. Therefore, we hypothesized:

- **H5a**: A high level of perceived interaction between the instructor and students and between students and students will lead to a high level of user satisfaction.

- **H5b**: A higher level of perceived interaction between the instructor and students and between students and students will lead to higher levels of student agreement that the learning outcomes of online courses are equal to or better than in face-to-face courses.

Course Structure

Course structure is seen as a crucial variable that affects the success of distance education along interaction. The course structure "expresses the rigidity or flexibility of the program's educational objectives, teaching strategies, and evaluation methods" and the course structure describes "the extent to which an education program can accommodate or be responsive to each learner's individual needs."

Course structure has two elements—course objectives/expectation and course infrastructure. Course objectives/expectation are to be specified in the course syllabus including what topical areas are to be learned, required workload in competing assignments, expected class participation in the form of online conferencing systems, group project assignments, and so on. Course infrastructure is concerned with the overall usability of the course Web site and organization of the course material into logical and understandable components. These structural elements, needless to say, affect the satisfaction level and learning outcomes of distance learners.

We theorize that course structure will be strongly correlated to user satisfaction and perceived learning outcomes, especially when the course material is organized into logical and understandable components and that the clear communication of course objectives and procedures will lead to the high levels of student satisfaction and perceived learning outcomes. Thus, we hypothesized:

- **H6a**: A good course structure will lead to a high level of user satisfaction.
- **H6b**: A good course structure will lead to higher levels of student agreement that the learning outcomes of online courses are equal to or better than in face-to-face courses.

METHODOLOGY

The six sets of hypotheses were tested using a quantitative survey of satisfaction and learning outcome perceptions of students who have taken at least one online course at Botswana College of Distance and Open Learning (BOCODOL) in Botswana. Structural equation modeling is employed to examine the determinants of these outcomes and student satisfaction. The challenge in deciding on the design of the study was to reduce the complexity of the research object without wrecking ourselves on an unjustifiable simplification or on an unmanageable research project. Details regarding the design of this research are provided in the following sections. First, the development of the survey instrument is described and a discussion of the sample subjects is provided. Next, specific measures used to assess the variables are identified and scale reliability and validity data are reported. This is followed by the presentation of the structural model results associated with the survey.

Survey Instrument

After conducting an extensive literature review, we designed a list of questions that we believed were logically associated with the factors in our model (see Appendix A).

In an effort to survey students using technology-enhanced e-learning systems, we focused on students enrolled in Web-based courses with no on campus meetings. We collected the e-mail addresses from the student data files achieved with every online course delivered through the online program of Botswana College of Distance and Open Learning. From these addresses, we generated 588 valid e-mail addresses. The 42 survey questions were generated. The survey questionnaire and instructions were sent to all valid e-mail addresses. We collected 397 valid unduplicated responses from the survey. Appendix B summarizes the characteristics of the student sample.

Research Method

The research model was tested using the structural equation model-based PLS methodology for two reasons. First, PLS is well suited to the early stages of theory building and testing. It is particularly applicable in research areas where theory is not as well developed as that demanded by linear structural relationship (LISREL) as is the case with this research study. Second, PLS is most appropriately used when the researcher is primarily concerned with prediction of the dependent variable.

Measurement Model Estimation

The first step in data analysis involved model estimation. The test of the measurement model includes an estimation of the internal consistency and the convergent and discriminant validity of the instrument items. The composite reliability of a block of indicators measuring a construct was assessed with three measures—the composite reliability measure of internal consistency, Cronbach's alpha, and average variance extracted (AVE). The internal consistency measure is similar to Cronbach's alpha as a measure of internal consistency except the latter presumes, a priori, that each indicator of a construct contributes equally (i.e., the loadings are set to unity). Cronbach's alpha assumes parallel measures and represents a lower bound of composite reliability. The internal consistency measure, which is unaffected by scale length, is more general than Cronbach's alpha, but the interpretation of the values obtained and similar to the guidelines offered by Nunnally and Bernstein (1994) can be adopted. All reliability measures were above the recommended level of .70 (Table 1), thus indicating adequate internal consistency. The AVE was also above the minimum threshold of .5 and ranged from .616 to .783 (see Table 1). When AVE is greater than .50, the variance shared with a construct and its measures is greater than error. This level was achieved for all of the model constructs.

Table 1: Convergent and discriminant validity of the model constructs

Variable	Factor Loading
Course Structure	
IC = 0.89	
IVE = 0.73	
Struc1	0.8375
Struc2	0.8681
Struc3	0.8500
Tutor Feedback	
IC = 0.93	
AVE = 0.77	
Feed1	0.8739
Feed2	0.8295
Feed3	0.9041

Feed4	0.9017
Self-Motivation	
IC = 0.75	
AVE = 0.62	
Moti1	0.5249
Moti2	0.9783
Learning Style	
IC = 0.80	
AVE = 0.67	
Styl1	0.8876
Styl2	0.7441
Interaction	
IC = 0.77	
AVE = 0.62	
Intr1	0.8823
Intr2	0.6845
Tutor knowledge and facilitation	
IC = 0.89	
AVE = 0.73	
Inst1	0.8468
Inst2	0.9035
Inst3	0.8055
User Satisfaction	
IC = 0.90	

AVE = 0.76	
Sati1	0.8686
Sati2	0.9065
Sati3	0.8301
Learning Outcome	
IC = 0.92	
AVE = 0.78	
Outc1	0.8533
Outc2	0.8991
Outc3	0.9017
IC = Internal Consistency; AVE = Average Variance Extracted	

Convergent validity is demonstrated when items load highly (loading >.50) on their associated factors. Individual reflective measures are considered to be reliable if they correlate more than .7 with the construct they intend to measure. In the early stages of scale development, loading of .5 or .6 is considered acceptable if there are additional indicators in the block for comparative purposes. Table 1 show most of the loadings were above .7 for the eight constructs.

Discriminant validity was assessed using two methods. First, by examining the cross-loadings of the constructs and the measures and, second, by comparing the square root of the AVE for each construct with the correlation between the construct and other constructs in the model. All constructs in the estimated model fulfilled the condition of discriminant validity (see Table 2).

Table 2: Correlation among construct scores (square root of AVE in the diagonal)

	Course Structure	Tutor Feedback	Self-Motivation	Learning style	Interaction	Tutor knowledge and facilitation	User satisfaction	Learning outcome
Course Structure	**0.852**							
Tutor Feedback	0.721	**0.878**						
Self-Motivation	0.243	0.229	**0.784**					
Learning style	0.293	0.214	0.265	**0.819**				
Interaction	0.415	0.564	0.394	0.276	**0.789**			
Tutor knowledge and facilitation	0.679	0.802	0.252	0.257	0.524	**0.852**		
User satisfaction	0.740	0.695	0.393	0.406	0.531	0.708	**0.863**	
Learning outcome	0.547	0.486	0.391	0.443	0.441	0.539	0.773	**0.884**

Overall, the revised measurement model results provided support for the reliability and convergent and discriminant validities of the measures used in the study.

STRUCTURAL MODEL RESULTS

Because PLS makes no distributional assumptions in its parameter estimation procedure, traditional parameter-based techniques for significance testing and model evaluation are considered to be inappropriate. LISREL and other covariance structure analysis modeling approaches involve parameter estimation procedures, which seek to reproduce as closely as possible the observed covariance matrix. In contrast, PLS has its primary objective the minimization of error (or equivalently the maximization of variance explained) in all endogenous constructs. One consequence of this difference in objectives is that no proper overall goodness-of-fit measures exist for PLS.

Consistent with the distribution free, predictive approach of PLS, the structural model was evaluated using the R-squared for the dependent constructs, the Stone-Geisser Q^2 test for predictive relevance, and the size, t statistics, and significance level of the structural path coefficients. The t statistics were estimated using the bootstrap resampling procedure (100 resamples). The results of the structural model are summarized in Table 3.

Table 3: Structural (inner) model results

	Path coefficient	Observed *t* value	Sig level
Effect on user satisfaction (R^2 = .692)			
Course structure	+.382	+7.4497	****
Tutor feedback	+.119	+1.8467	**
Self-motivation	+.141	+4.1396	****
Learning style	+.147	+4.0405	****
Interaction	+.087	+2.0773	***
Tutor knowledge & facilitation	+.234	+4.2996	****
Effect on learning outcome (R^2 = .628)			
Course structure	-.015	+.2483	ns
Tutor feedback	+.118	+1.6713	**
Self-motivation	+.075	+1.6169	*
Learning style	+.135	+3.8166	****
Interaction	+.031	+.7687	ns
Tutor knowledge & facilitation	+.065	+1.0805	ns
User satisfaction	+.720	+12.4127	****

R^2 for Dependent Constructs

The results show that the structural model explains 69.2 percent of the variance in the user satisfaction constructs and 62.8 percent of the variance in the learning outcomes construct. The percentage of variance explained for these primary dependent variables were greater than 10 percent, implying satisfactory and substantive value and predictive power of the PLS model.

The Stone-Geisser Q^2 Test

In addition to examining the R^2, the PLS model is also evaluated by looking at the Q^2 for predictive relevance for the model constructs. Q^2 is a measure of how well the observed values are reproduced by the model and its parameter estimates. Q^2 is estimated using a blindfolding procedure that omits a part of the data for a particular block of indicators during parameter estimation. The omitted part is then estimated using the estimated parameters, and the procedure is repeated until every data point has been omitted and estimated. Two types of Q^2 can be estimated. A cross-validated communality Q^2 is obtained if prediction of the omitted data points in the blindfolded block of indicators is made by the underlying latent variable. A redundancy Q^2 is obtained if prediction of the omitted data points is made by constructs that are predictors of the blindfolded construct in the PLS model. Q^2 greater than 0 implies that the model has predictive relevance, whereas Q^2 less than 0 suggests that the model lacks predictive relevance.

The blindfolding estimates are shown in Table 4. As seen in the table, using omission distances of 10 and 25 produced identical results, indicating that the model estimates are stable. The communality Q^2 was greater than 0 for all constructs. Looking at the redundancy Q^2, both user satisfaction and learning outcomes have positive redundancy Q^2 values. Overall, the estimated model has good communality Q^2 for the model measures and good predictive relevance for the two outcomes constructs of user satisfaction and learning outcomes.

Table 4. Blindfolding results.

Construct	R^2	Omission Distance = 10		Omission Distance = 25	
		Communality Q^2	**Redundancy Q^2**	**Communality Q^2**	**Redundancy Q^2**
1. NA = not applicable.					
Course structure	NA	.7259	NA	.7259	NA
Instructor feedback	NA	.7706	NA	.7706	NA
Self-motivation	NA	.6163	NA	.6163	NA
Learning style	NA	.6708	NA	.6708	NA
Interaction	NA	.6235	NA	.6235	NA
Instructor knowledge and facilitation	NA	.7274	NA	.7274	NA
User satisfaction	.692	.7551	.5227	.7551	.5227
Learning outcomes	.628	.7832	.4920	.7832	.4920

Structural Path Coefficients

As can be seen from the results, all of the antecedent constructs hypothesized to affect user satisfaction are significant, suggesting that course structure, instructor feedback, self-motivation, personality/learning style, interaction, and instructor knowledge and facilitation affect the perceived satisfaction of students who take Web-based courses. Of the same six factors hypothesized to affect the learning outcomes construct, only two were supported at $p < .05$. These were instructor feedback and personality/learning style. The structural model results also reveal that user satisfaction is a significant predictor of learning outcomes.

DISCUSSION

This study examined the factors that affect the perceived learning outcomes and student satisfaction in asynchronous online learning courses. The research model was tested by using a PLS analysis on the survey data. The hypotheses in this study received partial support. We found that all six factors—course structure, self-motivation, learning styles, instructor knowledge and facilitation, interaction, and instructor feedback—significantly influenced students' satisfaction. This is in accordance with the findings and conclusions discussed in the literature on student satisfaction.

Of the six factors hypothesized to affect perceived learning outcomes, only two (learning styles and instructor feedback) were supported. Contrary to previous research (LaPointe & Gunawardena, 2004), we found no support for a positive relationship between interaction and perceived learning outcomes. One possible explanation for this finding is that the study did not account for the quality or purpose of the interactions. Although a student's perception of interaction with instructors and other students is important in his/her level of satisfaction with the overall online learning experience, when the purpose of online interaction is to create a sense of personalization and customization of learning and help students overcome feelings of remoteness, it may have little effect on perceived learning outcomes. Furthermore, a well-designed online course delivery system is likely to reduce the need of interactions between instructors and students. The university under study has a very friendly online e-learning system and strong technical support system. Every class Web site follows the similar design structure which reduces the learning curve.

Another disputable point is the statistically insignificant relationship between online course structure and perceived learning outcomes. One possible explanation for this is that, for the students who visited the class Web site on a regular basis, what matters to their learning is not so much the usability of the course site as a measure of the quality of engagement in other learning activities. For instance, meaningful feedback that occurs among students or from a teacher may have a greater impact on perceived learning outcomes. As long as students received meaningful feedback about the course contents, an inadequate Web content design becomes less critical.

Contrary to other research findings, no significant relationships were found between students' self-motivation and perceived learning outcomes. We are unable to explain this deviation. Theoretically, self-motivation can lead students to go beyond the scope and requirements of an educational course because they are seeking to learn about the subject, not just fulfil a limited set of requirements. Self-motivation should also encourage learning even when there is little or no external reinforcement to learn and even in the face of obstacles and setbacks to learning. Additional work is needed to better specify the conditions under which self-motivation is likely to have a positive, negative, or neutral effect on perceived learning outcomes.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Several limitations of this study can be identified to help drive future research. First, factors examined in other studies (Peltier et al., 2003) such as course delivery technology warrant investigation. Second, future research should seek to further investigate the non-significant relationships between the remaining constructs (course structure, self-motivation, and interactions) and perceived learning outcomes. To clarify the dispute over the issue, future studies should use more sophisticated measures of course structure, self-motivation, and interactions and their engagement in learning activities, either quantitatively or qualitatively. In this study, the learning outcome variables ask students about whether they perceive the quality of online learning to be better than that of face-to-face courses or whether students learned more in one than the other. Although students are in general satisfied with online courses, they believe that they did not learn more in online courses or they believe that the quality of online courses was not better than face-to-face class. In future research, it would be interesting to know the critical success factors for improving the quality of online learning using multilevel hierarchical modeling.

PRACTICAL IMPLICATIONS

Higher educational institutions have invested heavily to constantly update their online instructional resources, computer labs, and library holdings. Unfortunately, most institutions like Botswana College of distance and Open Learning (BOCODOL) have not studied the factors that influence online student satisfaction or learning outcomes. This study is one of the first in Botswana to extend the structural equation modeling to student satisfaction and perceived learning outcomes in asynchronous online education courses. The findings from the current study have significant implications for the distance educators, students, and administrators. In this study, what we questioned is whether all the six factors will lead to higher levels of student agreement that the learning outcomes of online courses are equal to or better than that for the conventional setup. The results indicated that online education is not a universal innovation applicable to all types of instructional situations. The findings in this study suggest online education can be a superior mode of instruction if it is targeted to learners with specific learning styles (visual and read/write learning styles) and with timely, helpful instructor feedback of various types. Although cognitive and diagnostics feedbacks are all important factors that improve perceived learning outcomes, metacognitive feedback can induce students to become self-regulated learners.

More specifically, there is a clear relationship between instructor feedback and student satisfaction and perceived outcomes. Feedback is a motivator to many students and should be incorporated into the design and teaching of online courses. Although students prefer feedback from the instructor, peer feedback can also be a valuable instructional tool. As this high level of interaction becomes time consuming, faculty may want to consider efficient teaching and time management strategies. Online quizzes can provide pre-programmed feedback to learners. In addition, instructors may want to develop feedback comments and frequently asked question databases that can be used repeatedly. This study may be useful as a educational tool for instructors planning learning ventures or to justify technological expenditures at the administrative level. It is conceivable that, through this type of research, online learning will be enhanced when there is a better understanding of critical online learning factors.

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Appendices

APPENDIX A: SURVEY QUESTIONS

Instructor

Inst1 = The instructor was very knowledgeable about the course.

Inst2 = The instructor was actively involved in facilitating this course.

Inst3 = The instructor stimulated students to intellectual effort beyond that required by face-to-face courses.

Course Structure

Struc1 = The overall usability of the course Web site was good.

Struc2 = The course objectives and procedures were clearly communicated.

Struc3 = The course material was organized into logical and understandable components.

Feedback

Feed1 = The instructor was responsive to student concerns.

Feed2 = The instructor provided timely feedback on assignments, exams, or projects.

Feed3 = The instructor provided helpful timely feedback on assignments, exams, or projects.

Feed 4 = I felt as if the instructor cared about my individual learning in this course.

Self-Motivation

Moti1 = I am goal directed, if I set my sights on a result, I usually can achieve it.

Moti2 = I put forth the same effort in online courses as I would in a face-to-face course.

Learning Style

Styl1 = I prefer to express my ideas and thoughts in writing, as opposed to oral expression.

Styl2 = I understand directions better when I see a map than when I receive oral directions.

Interaction

Intr1 = I frequently interacted with the instructor in this online course.

Intr2 = I frequently interacted with other students in this online course.

OUTPUTS

User Satisfaction

Sati1 = The academic quality was on par with face-to-face courses I've taken.

Sati2 = I would recommend this course to other students.

Sati3 = I would take an online course at Southeast again in the future.

Learning Outcomes

Outc1 = I feel that I learned as much from this course as I might have from a face-to-face version of the course?

Outc2 = I feel that I learn more in online courses than in face-to-face courses.

Outc3 = The quality of the learning experience in online courses is better than in face-to-face courses.

APPENDIX B: STUDENT CHARACTERISTICS

	Number	Proportion (%)
Age		
<20	12	3.02
20–24	145	36.52
25–34	116	29.22
35–44	69	17.38
45–54	51	12.85
>54	4	1.01
Total	397	100.00
Gender		
Male	111	27.96
Female	282	71.03
Not answered	4	1.01
Total	397	100.00
Area of study		
Diploma in HIV/AIDS (DAFE)	139	35.01
Diploma in Tourism (DTS)	93	23.43
Bachelor of Information Technology (BSc-IT)	62	15.62
MBA (HR/Marketing)	18	4.53
CDEP	39	9.82
Nutrition and Child Care (CNCC)	13	3.27
Certificate in Environmental studies (CES)	11	2.77

Others	22	5.54
Total	397	100.00