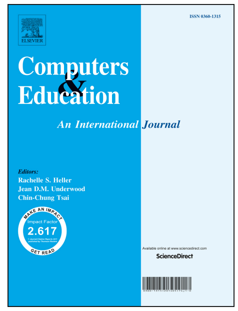
Accepted Manuscript



The influence of Gesture-based Learning System (GBLS) on Learning Outcomes

Moamer Shakroum, Kok Wai Wong, Chun Che Fung

PII: S0360-1315(17)30221-X

DOI: 10.1016/j.compedu.2017.10.002

Reference: CAE 3250

To appear in: *Computers & Education*

Received Date: 18 January 2017

Revised Date: 3 October 2017

Accepted Date: 5 October 2017

Please cite this article as: Shakroum M., Wong K.W. & Fung C.C., The influence of Gesture-based Learning System (GBLS) on Learning Outcomes, *Computers & Education* (2017), doi: 10.1016/j.compedu.2017.10.002.

The Influence of Gesture-based Learning System (GBLS) on Learning Outcomes

Moamer Shakroum, Kok Wai Wong, Chun Che Fung
Murdoch University, WA, Australia
M.Shakroum@Murdoch.edu.au, K.Wong@Murdoch.edu.au,
L.Fung@murdoch.edu.au

Corresponding author: Moamer Shakroum

Email: M.Shakroum@Murdoch.edu.au

Abstract

The effectiveness of Gesture-Based Learning System (GBLS) has been reported in some recent studies. However, not many of those studies have investigated on how GBLS mode influences the learning outcomes. The aim of this study therefore focuses on investigating how GBLS mode impacts the learning outcomes. The findings of this study revealed that GBLS's features positively affect the students' intrinsic motivation. Consequently, the increase in the intrinsic motivation leads to improving the learning outcomes; this study also showed that GBLS's features indirectly influence the learning outcomes via intrinsic motivation. In other words, this study found that the GBLS's features (interactivity and multimodality) create an instructional learning environment that positively influences the students' intrinsic motivation. The increase of the students' positive intrinsic motivation led to enhancing the learning achievements of students.

Keywords: Gesture-Based Learning System (GBLS), Technology-Mediated Learning (TML), Multimodality, Kinect sensor, learning outcomes.

1.0 Introduction

Educational technologies have been used by more and more education systems worldwide. Several studies claimed that technologies can help to foster an effective learning environment, others believe that technology only has a small Impact on learning (Buckingham, 2013; Hair Jr et al., 2016). However, the best way to determine the educational potential of a particular technology is by evaluating that technology meticulously and following that by investigating how the technology impacts the learning experience (Alavi & Leidner, 2001; Persico et al., 2014). The educational technology focus in this study is Gesture-Based Learning System (GBLS) mode. The GBLS is used by Shakroum, Wong and Fung (2016) as a general term to describe the utilisation of the Kinect or any full-body gesture-based user interface, as a teaching and learning tool. The effectiveness of the GBLS mode has been empirically demonstrated by (Shakroum et al., 2016) as they found that the GBLS mode has a higher positive effect on students learning outcomes when compared with other learning modes. Up to the time of writing this paper, none of the previous research has explained how the application of GBLS mode improves learning. Therefore, the aim of this study is to investigate how the GBLS mode positively influences the learning experience. The results of this research can help the understanding on how the GBLS mode works, which consequently will help supporting the legitimacy of the GBLS mode as an adequate learning technology. This study addressed the research question of how does GBLS mode positively influence learning outcomes?

2.0 Literature Review

2.1 The effect of Gesturing on Learning

People usually use gestures when they speak to express some information that cannot revealed in words. Novack and Goldin-Meadow (2015) indicated that learners also use gestures to point-out the unclear peace of information, and teacher can also utilise those gestures to understand the learners thought. Moreover, Alibali and GoldinMeadow (1993) claimed that students usually use gestures to indicate to their teachers that they know more than they say. Gestures in learning represent alternative resort for student to explore and express new ideas (Goldin-Meadow, 2003). Learners can benefit from gestures not only by gesturing themselves but also by seeing their teachers gesturing during the lesson (Church et al., 2004; Cook et al., 2013).

The positive role of gesturing in improving learning has been scientifically demonstrated. For example, a study by Autumn B Hostetter, Bieda, Alibali, Nathan and Knuth (2006) found that teachers can use gestures to strengthen their instructional tasks, help their students to link ideas and to simplify complicated concepts. Other studies indicate that gestures are powerful tools and can be used by instructors to communicate effectively with their students (Alibali et al., 2014; Cook et al., 2008; Autumn B Hostetter, 2011; Nathan, 2008). Furthermore, several studies have proved that using gestures during learning help students learn better, in terms of understanding the ideas and problems-solving (Autumn B. Hostetter & Alibali, 2008; Keene et al., 2012). Broaders, Cook, Mitchell, and Goldin-Meadow (2007) run an experiment to investigate the effect of gesture on learning. Their research found that those children who were allowed to use gesture added more correct problem solving methods than those children who were asked not to use their gesture. The same study reported that the children were more successful in solving math problems than those children who were asked not to use gesture in their tasks. (Cook & Goldin-Meadow, 2006) also conducted an experiment to examine the value of gestures in learning where he compared children who used gesture while learning a new concept with another group of students who were required to speak while learning. The study found that the gesturing group retained more knowledge than the speaking group. In summary, encouraging students to use gesture while learning can positively impact their learning outcomes. Gesture based technology can be effective method to stimulate students to gesture. Therefore, the following section explains the potential of GBLS mode in learning.

2.2 The Potential of GBLS mode

Hus (2011a) (2011b) claimed that GBLS mode can benefit both teachers and learners. GBLS mode can stimulate learners' motivation, as it utilizes a unique and natural interaction interface that grabs the students' attention. GBLS is a multimodal system that can facilitate kinaesthetic interactions and coordinate them with auditory and visual information. The coordinating of those three different inputs-modalities makes the GBLS mode an excellent tool to support students with various learning styles, especially kinaesthetic learners. Besides its educational benefits, a study by O'Hanlon (2007) shows that Kinect games can help children with different levels of obesity by engaging them in physical activities during class time for fitness and physical development. In addition, the cost of the Kinect can be considered as low when it compared with other learning technologies (Hsu, 2011b). In fact, most of the Kinect-based learning applications are open sourced and available for free. The next sections outline the feature of the GBLS mode that makes it as an effective learning method.

2.3 GBLS's features

2.3.1 Interactivity

The interactivity and the effectiveness of any learning method are always linked as reported by many educational researchers (Beauchamp & Kennewell, 2010; Roussou, 2004). Interactivity can be defined as the contingent responses to students' actions during lessons in the classroom (Beauchamp & Kennewell, 2010). Interactivity in classrooms can be measured by the level of control that teachers have over the classroom activities. In other words, the interactivity in the classrooms depends on the pedagogy of learning; whether it is teacher-centred learning or student-centred learning (Burns & Myhill, 2004; Hsu, 2011b). Teacher-centred pedagogy represents the conventional learning method where teachers talk for a long time with a little or none students' participation or feedback. In contrast, student-centred learning gives learners more opportunities to participate, analyse and organise the knowledge content (Kain, 2003). According to (Hsu, 2011b), promoting interactivity between learners and knowledge content requires some thoughts on giving students sufficient chance to participate in the classroom activities. Burns & Myhill (2004) has identified the characteristics of interactive learning as follows; 1) students get a chance to talk and participate; 2) provides a proper participation environment; and 3) leverages of the level of student-centred learning. It has been proven that student-centred learning positively improves students' skills such as problem-solving and critical thinking (Saye & Brush, 2001). Student-centred learning is derived from constructivism learning theory, which argues that students learn from the interaction between their experience and the new idea (Kain, 2003). However, technologies can be used in classrooms to promote student-centred learning and to support interactivity. According to Beauchamp & Kennewell (2010), technologies itself cannot achieve the desired interactivity in the classroom, but it can be used by teachers and learners to orchestrate the learning recourses and facilitate an interactive environment to achieve the desired learning goals. GBLS mode can promote the interactivity in the classroom (Homer et al., 2014). For example, GBLS mode can accommodate more than one user, which enables teachers to share the interaction with their students. A teacher can work with students in a one-to-one mode. This will encourage group work and cooperation within the classroom (Hsu, 2011a, 2011b).

2.3.2 Multimodality

Multimodality in learning field refers to the learning environment that facilitates the presentation of instructional elements in more than single-sensory method (visual, audible, aural, writing and kinaesthetic) (Sankey et al., 2010). The presentation of the learning materials in various ways usually results in grabbing the learners' attention as the variety of material's presentation matches different of learning styles (Chen & Fu, 2003; Moreno & Mayer, 2007; Sankey et al., 2010). According to Megowan (2007), conventional learning system supports only conceptual structure which represents knowledge as symbols, words, and equations. Megowan (2007) further explains that many students with different learning styles struggle with learning with conventional learning mode, as some of them prefer learning using images, others prefer learning by doing, etc. However, many educational organisations have adopted a mix of multimodal and hypermedia technologies to create a multimodal learning environment that serves all learners with different learning styles (Sankey et al., 2010). The primary benefit of multimodal learning environment is that it allows the students to experience learning in the way that suits them (Picciano, 2009). In short, multimodal learning environment provides an optimal learning environment for different people as it presents the learning materials in various ways that meet different needs (Pashler et al., 2008). The GBLS mode provides a multimodal learning environment that facilitates almost all learning styles. Unlike other learning technologies that ignore kinaesthetic learning style, GBLS enables users to interact with the learning materials using their body movements (Hsu, 2011b).

2.4 Related work

In recent years several studies were conducted to investigate the effectiveness of GBLS mode. However, this section will summarise the previous related studies that used gesture based interfaces as a learning method. Chang et al. (2013) tested the effect of gesturing and body motions on learning using the Kinect, the results of this study indicated that participants showed better understanding and higher information's retaintion with the Kinect-based learning method. Moreover, Chao et al. (2013) found that students who used Kinect-enhanced learning method recall more information comparing with students who used desktop-based learning system. In addition, Meng et al. (2013) compared Kinect-based learning system with Augmented Reality (AR) magic mirror to teach anatomy. They found that students who used Kinect-based learning outperformed others who used AR magic mirror. Recently, Hsiao & Chen (2016) tested the learning effectiveness of gesture interactive game-based learning (GIGL) using a similar device to the Kinect called ASUS Xtion PRO. The participants in this study were pre-schoolers. The results revealed that the GIGL method positively improved the participant's learning achievements and their motor skills. Ke et al. (2016) used Kinect-based interface to create Mixed-reality Integrated Learning Environment (MILE) and tested the effect of MILE on teaching achievements of 23 university lecturers. The results showed that MILE enhanced the teaching tasks for most the participants. Shakroum et al. (2016), compared the impact of the GBLS mode on learning outcome with other two learning methods that are the conventional learning mode and Computer Simulation Learning (CSL) mode. The results of this study revealed that GBLS mode outperformed the other two learning modes in term of academic performance, satisfaction and perceived learning effectiveness. Kinect-based learning, GIGL, MILE, and GBLS are full body gesture-based learning technologies.

Table 1 summarises and compares most of the relevant previous work, despite the fact that the effectiveness of GBLS mode has been reported, none of the previous studies explained how GBLS mode influences learning outcomes. Therefore, this study will be conducted to determine and explain how GBLS mode impacts learning outcomes of students.

Table 1: previous work summary

Study	Variable examined	Key findings	Knowledge gap
(Chang et al., 2013)	The direct impact of gesture based presentation on cognitive learning outcomes.	participants showed better understanding and higher information retention with the Kinect-based learning method	Most of the previous studies did not consider the underlying learning process when explaining the effect of the gesture based technology
(Chao et al., 2013)	The impact of the body motion interface to information retention.	students who used Kinect enhanced learning method recall more information comparing with students who used desktop-based learning system	
(Meng et al., 2013)	The impact of Kinect-based learning system on cognitive learning outcomes.	Students who used Kinect-based learning outperformed others who used AR magic mirror	
(Hsiao & Chen,	The impact of gesture based technology on	The GIGL method positively improved the	

2016)	learning performance and motor skills (namely, coordination and agility)	participant's learning achievement and their motor skills.
(Ke et al., 2016)	The effect of MILE on the participation, engagement, and perceptions of teaching staff.	MILE enhanced the teaching tasks for most the participants

3.0 Research Framework:

Error! Reference source not found. shows the research framework used in this paper. This framework is developed based on Alavi and Leidner framework (Alavi & Leidner, 2001). Alavi and Leidner have called for broader and deeper research approach in investigating the effectiveness of learning-mediated technologies. They claimed that the research questions should not only ask whether the technology helps to improve learning, it should also ask how does the technology help to improve learning (Alavi & Leidner, 2001). This research framework (**Error! Reference source not found.**) has been developed along the line of what Alavi and Leidner have proposed. The research framework is developed to answer the main research question of how does GBLS mode positively influence learning outcomes? The research framework and the variables used are discussed as follows.

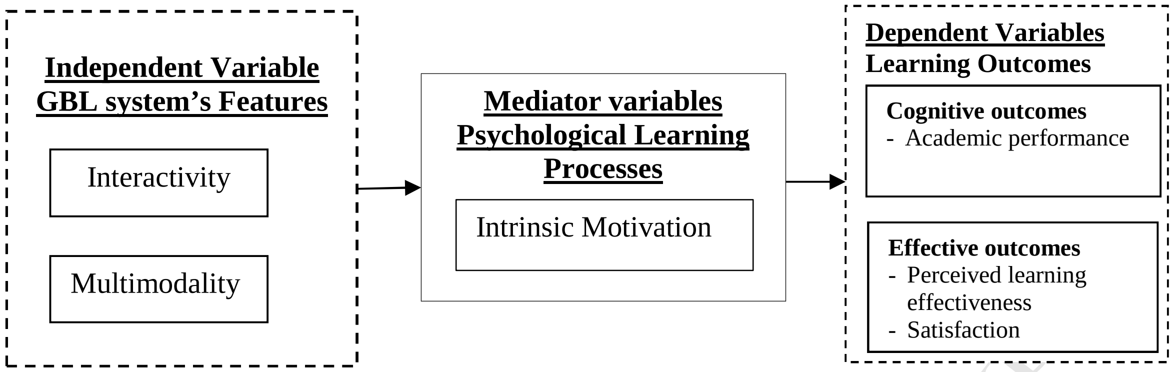


Figure 1: The Research framework

3.1 Independent variables: GBLS's Features

Technology has been used in the classroom for many years as an assistive tool to support the instructional strategy. Technology can benefit classroom instructions in several ways, for example, presenting the learning content in different ways, promotes interaction between students and instructors in the classroom. However, Alavi and Leidner (2001) believe that technology features can influence learning by impacting the psychological learning processes that consequently leads to improvement in the learning outcomes. Therefore, to understand how the technology influences the learning outcomes, it is necessary to define the technology's features that may influence the psychological learning processes. As this study is aiming to investigate how the GBLS mode influences learning outcomes, it is crucial to define the main features of this technology. In this research, two features of the GBLS mode are tested. These features are interactivity and multimodality.

3.1.1 Interactivity

Interactivity will be measure using three-item scale borrowed from Pituch and Lee (2006), the items were modified to suit the purpose of this study. For all items, participants were asked to rate themselves on five-point Likert scale ranging from (1) strongly agree to (5) strongly disagree.

3.1.2 Multimodality

Three-item scle was developed for the purpose of this study to measure the multimodality. For all items, participants were asked to rate themselves on five-point Likert scale ranging from (1) strongly agree to (5) strongly disagree.

3.2 Mediated variable: Psychological Learning Processes (PLP)

Alavi and Leidner (2001) have defined the PLP as "*states within the learner that are involved in learning*." These states include motivation, information processing activities, memory, and interest. Alavi and Leidner (2001) affirmed that learning occurs through psychological learning processes. Therefore, understanding how a particular technology affects learning requires studying the impact of that technology's features on the psychological learning processes. As this study is aiming to understand how GBLS influence learning, this study will test the impact of the GBLS's features on one example of PLP that is Intrinsic Motivation.

3.2.1 Intrinsic motivation

Intrinsic motivation can be defined as what people are willing to do without any external stimulator. In other words, intrinsically motivated person engages in an activity for no reward but the enjoyment and interest that accompanies it (Malone & Lepper, 1987). Intrinsic motivation has been studied widely in the field of education, and there is no doubt about the value that the intrinsic motivation can bring about to the learners (Shia, 2000). Students who are intrinsically motivated will be able to maintain interest in the learning subject, acquire knowledge and have more chance to apply and retain that knowledge, show better academic achievement, and have self-competency (Pintrich et al., 2008; Ryan & Deci, 2000a). However, classroom environment plays an important role in facilitating and promoting motivation (Stefanou & Salisbury-Glennon, 2002). According to Deci & Ryan (1985), classroom environment can help stimulating learners' motivation by providing a learning experience that considers all students with different needs and individual characteristics. For example, Alfassi (2004) found that interactive students-centred learning environment increases learners' intrinsic motivation. In the current study, students' intrinsic motivation will be measured using Intrinsic Motivation Inventory (IMI), four subclasses have been chosen from IMI to evaluate students' intrinsic motivation. These subclasses are 1) Interest and enjoyment, 2) Perceived competence, 3) Value/ usefulness, 4) Tension and pressure (Ryan, 1982; Ryan & Deci, 2000b).

3.3 Dependent variables: Learning Outcomes

According to Sharda et al. (2004), learning outcomes can be divided into three components that are cognitive outcomes, affective outcomes, and psychomotor outcomes.

Cognitive outcomes represent analysis, knowledge, cognition and application of the learning content. Affective outcomes include learners' satisfaction, attitude, and appreciation toward the learning experience. Psychomotor Outcomes includes response magnitude, accuracy, and efficacy. Only the cognitive and affective outcomes are in the interest of this study. However, this research will measure the cognitive outcomes using pre-test and post-test scores and the affective outcomes through measuring the students' perception of learning effectiveness and satisfaction.

3.4 Developing research hypotheses:

According to Alavi & Leidner (2001), understanding how the technology improves learning requires determining the effect of the technology's features on the learners Psychological Learning Processes, which, subsequently influence the learning outcome. As shown in (Figure 2), twelve hypotheses were developed to answer the research question on how does the GBLS influence the learning outcomes?

H1: Intrinsic Motivation is affected by the GBLS' features.

H2: Learning Outcomes are affected by Intrinsic Motivation.

H3: The influence of GBLS's features on Learning Outcomes is mediated by Intrinsic Motivation.

H4: Interactivity is a first-order factor of GBLS's features.

H5: Multimodality is a first-order factor of GBLS's features.

H6: Interest/Enjoyment is a first-order factor of intrinsic motivation.

H7: Perceived competence is a first-order factor of Intrinsic Motivation.

H8: Pressure/Tension is first-order factor of Intrinsic Motivation.

H9: Value/Usefulness is a first-order factor of Intrinsic Motivation.

H10: Academic Performance is a first-order factor of Learning Ooutcomes.

H11: Perceived Learning Effectiveness is a first-order factor of Learning Outcomes.

H12: Satisfaction is a first-order factor of Learning Outcomes.

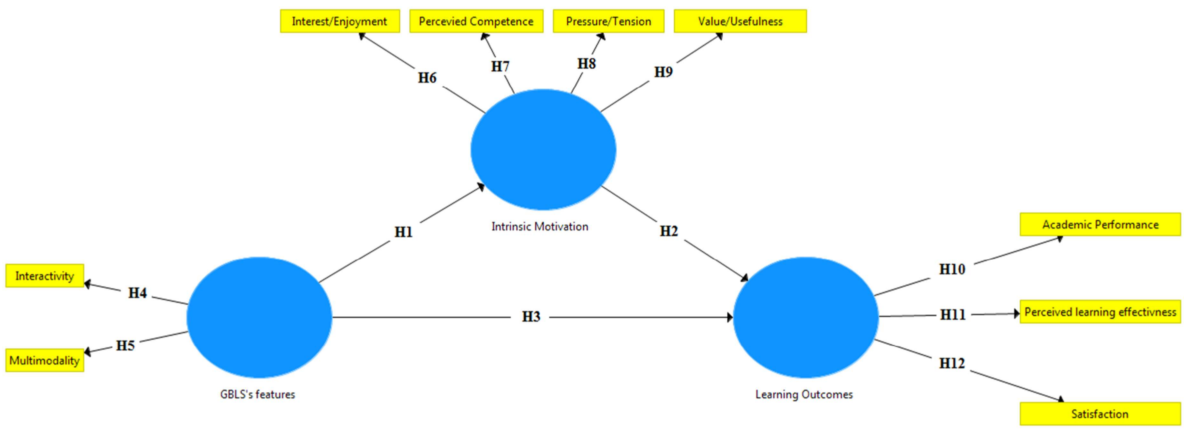


Figure 2: Hybothesis

4.0 Research Methodology

4.1 Research Design

This study uses the quantitative explanatory research methodology. To achieve the research's objectives, a Quasi-experiment was employed to create a causal relationship between GBLS mode and Learning Outcomes.

4.2 The Quasi-experiment design

The GBLS mode was setup by attaching Microsoft Kinect sensor to a formal classroom computer. To enable the computer in using the Kinect sensor, OpenNI driver was installed on the classroom PC. Kinect-based application that called K-Solar system was installed to the classroom computer. The k-solar system was developed by the *Juan de Lanuza School and the BIFI- Biocomputation and Physics of Complex Systems Institute of the University of Zaragoza*. (http://www.k-solarsystem.org/home/servlet/). The researcher was granted a license from the developer of the k-Solar System to use it in this study.

4.3 K- Solar System

The K-Solar System is a Kinect-based application. The application was developed by Juan de Lanuza School and BIFI- Biocomputation and Physics of Complex Systems Institute of the University of Zaragoza ("K-Solar System ", 2012). The K-Solar System's developers have granted a license to the researcher to use it in this experiment. The K-Solar System can be described as an interactive 3-D software for learning the solar system: planetary and satellite movements, and the phenomena they create (such as eclipses, the seasons and lunar phases). The interaction is carried out through the Kinect device, which recognises the students' body movements and reproduces them in the 3-D virtual models that are visualised on the classroom board. This way of interaction offers the students a new and motivating experience (See Figure 3).

Figure 3: K- Solar System ("K-Solar System ", 2012)

4.4 Participants

Fifty-six undergraduate students were recruited to voluntarily participate in the research from a total of about 500 first year undergraduate students at Almergib University. Recruiting a larger number of students was not achievable in this research due to the nature of the experiment as the students have other classes and lab-work to attend. However, 56 participants is an adequate sample size in this research. Partial Least Square – Structural Equation Modelling (PLS-SEM) tool will be used to analyse the research model. PLS is recommended to be used with small sample size (Hair et al., 2012; Wong, 2013). Almrgib University is located in the city of Msellath, Libya. Convenience sampling was used to choose Almergib University as the researcher has access to the university, which assisted him to recruit participants. To ensure that the knowledge and experience's of the participants are consistent, only first-year students were recruited. All participants are Libyans. Out of 66 participants recruited, only 56 participants completed all stages of the experiment with a response rate of 86.3%.

4.5 Instruments to collect data

The major part of the instruments that used to measure the variables was adopted from past related research, some of the instruments were built for the purpose of this study. (Table 2) indicates all the instruments that were used in this study.

Table 2: Research instrument

NO	Variable	Type of variable	Instrument	Source
1	Academic Performance	Dependent	Pre-test and post-test	27 Questions were extracted from test-bank, (Pearson Education, 2014), the questions are a mix of true/ false and multi-choice. All the questions were checked and edited by a lecturer in the subject area.
2	Perceived Learning Effectiveness	Dependent	Questionnaire	Eleven items were adapted from previous studies (Benbunan-Fich & Hiltz, 2003; E. A. L. Lee, 2011; Marks et al., 2005)
3	Satisfaction	Dependent	Questionnaire	Seven items were adopted from previous studies (Chou & Liu, 2005; E. A. L. Lee, 2011).
4	Interactivity	Dependent	Questionnaire	3 items were adopted from Pituch and Lee (2006)
5	Multimodality	Dependent	Questionnaire	Three items were built from the theory of multimodality.
6	IMI	mediator	Questionnaire	intrinsic motivation was measured using Intrinsic Motivation Inventory (IMI) (Ryan, 1982; Ryan & Deci, 2000b).

4.6 Experimental procedures:

1. Participants were requested to sit for the pre-test and to complete the initial questionnaire. The initial questionnaire consists of background information.
2. Participants received 10 minutes' introduction to the GBLS mode before the lecture to ensure all participants are familiar with the use of the technology.
3. Participants received a lecture using GBLS mode. The learning topic title was (An Introduction to the solar system and time measurement). Arabic language, the mother tongue of the students was used to deliver the lecture. Although The K-solar system is in

English language, the students were capable to understand all the terms as all the expression used in K-solar are basic English vocabulary; the researcher was also there to support if needed.

4. After having receiving the treatment, all students were requested to sit for the post-test and to complete the final questionnaire. The final questionnaire consists of five parts, Multimodality, Interactivity, Intrinsic Motivation, Perceived Learning Effectiveness and Satisfaction.

4.7 Data analysis

Smart-PLS V2 and V3 were employed to analyse the research model to answer the research question.

4.7.1 Smart-PLS

Smart-PLS is a tool for Partial Least Square – Structural Equation Modelling (PLS-SEM). PLS-SEM is an ordinary least square regression-based approach. PLS-SEM uses the data to derive the path relationships in the model with the aim of minimizing the error terms of the endogenous constructs (Hair Jr et al., 2013). PLS-SEM was chosen to analyse this research model among other SEM techniques for the following reasons. First, PLS-SEM has no issues with small sample size and achieve a high level of statistical power with small sample size. Second, PLS-SEM does not require distributional assumptions. Third, PLS-SEM is robust in case of a few missing values. Forth, PLS-SEM works with different scales of measurement including, metric data, ordinal scaled data, and binary coded data. On the other hand, PLS-SEM model can handle constructs measured with single or multi-item measures. PLS-SEM model can incorporate reflective and formative constructs. PLS-SEM can handle a complex model with a large number of indicators (Hair et al., 2012; Hair Jr et al., 2013; Tenenhaus et al., 2005). Therefore, Smart-PLS was used to assess the model's validity and to examine the relationships between the constructs of the proposed research model.

According to Hair Jr et al., (2013), analysing the model in Smart-PLS is usually performed in two steps, in the first step, the validity of the measurement model is assessed, then the assessment of the structural model is performed in the second step.

4.7.1.1 Assessing the measurement model

Assessing the reflective measurement model includes evaluating internal consistency, indicator reliability, convergent validity and discriminant validity. Below is a description of each criterion for the reflective measurement model.

1. **Internal consistency reliability**

   Internal consistency reliability can be evaluated using composite reliability values. According to Hair Jr et al. (2013).

2. **Convergent validity:**

   Convergent validity can be evaluated using either by outer loading of the indicators or the Average Variance Extracted (AVE).

3. **Discriminant Validity:**

   Establishing discriminant validity means that a construct is truly distinguished from other constructs. In other words, a construct should capture a specific phenomenal that is not explained by any other construct in the model. There are two criterions that can be used to evaluate the discriminant validity, namely, cross-loading of indicators and Fornell-Larcker criterion.

4.7.1.2 Assessing the Structural Model

The assessment of the structural model can be done in five steps that are, checking the model for collinearity issues, Assessing Path coefficients, Assessing the level of R^2, Assess the effect sizes F^2, Assess the predictive relevance $Q^2$and q^2 effect sizes. They are elaborated as follows.

1. **Assess structural model for collinearity issues**.

   Prior interpreting the structural model results, it is important to check for collinearity issues.

2. **Path Coefficients**

   In Smart-PLS software, the analysis of the structural model relations can be done by examining the paths coefficient to check whether they are positive or negative. The path coefficient values can be obtained from bootstrapping calculation results (Wong, 2013).

3. **Coefficient of determination (R^2 Value)**

   R^2 value is a common way to evaluate the structural model, R^2 value is a measure of the model predictive accuracy.

4. **Assess the effect sizes f^2**

   The effect size f^2 is the change in the value of R^2 when a certain exogenous construct is excluded from the model.

4.7.1.3 Assessing the Blindfolding and predictive relevance Q2

Q^2 is an indicator of the model's predictive relevance. Q^2 measure only applies to reflective constructs and single item constructs, not to formative constructs.

4.7.1.4 Effect size q2

q2 effect size cannot be obtained from Smart-PLS, but, it can be calculated manually from the following equation:

$$q^2 = \frac{Q^2 included - Q^2\ excluded}{1 - Q^2 included}$$

The rule of thumb of the q2 value are as follows, the values of 0.02, 0.15 and 0.35 represent that a certain exogenous variable has small, medium or large predictive relevance respectively for a specific endogenous latent variable.

4.7.1.5 Analysing for mediation.

Mediator construct is a variable that captures part of the relationship between an exogenous construct and an endogenous construct in the PLS path model through the indirect effect. The indirect effect is the relationship between the exogenous construct and the mediator, and between the mediator and the endogenous construct. The mediator helps to explain the relationship between the independent and the dependent constructs. In other words, the mediator detects the true relationship between the exogenous and the endogenous constructs. The significant mediation effect can be partially or fully capture the direct relationship between the exogenous and the endogenous constructs, and in some cases, it changes the direction of the relationship, which called suppressor effect. Analysing mediation in Smart-PLS requires series of steps as can be seen in (Figure 4) (Hair Jr et al., 2016)

.

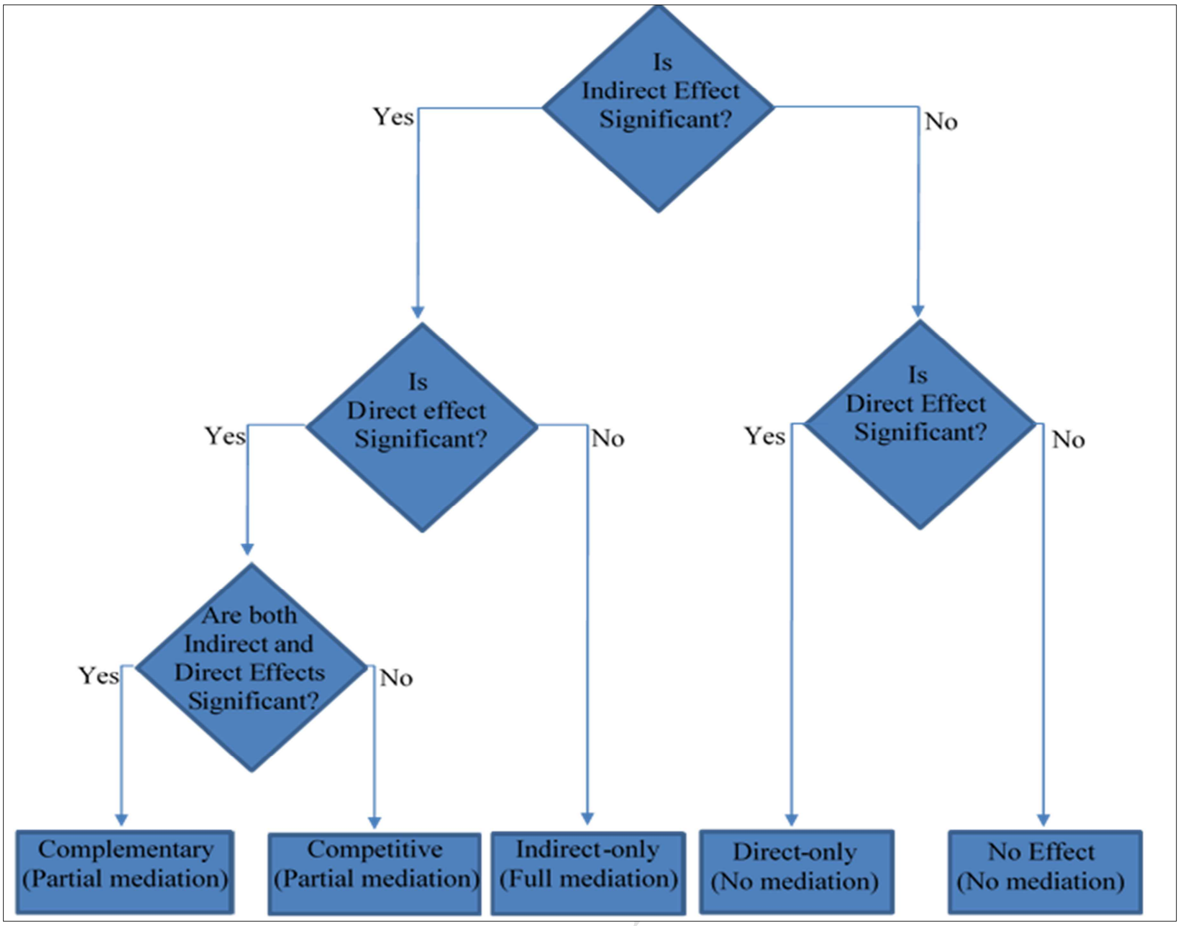


Figure 4: Mediation analysis steps (Hair Jr et al., 2016)

4.7.1.6 Dealing with second-order constructs.

Hierarchical Component Model (HCM) consists Higher-order component (HOC) and Lower-order Components (LOC). However, depending on the relationship between HOC and LOC, there are four types of HCM, namely, Reflective-Reflective type, Reflective-Formative type, Formative-Reflective type and Formative-Formative type (Becker et al., 2012), (See Figure 5).

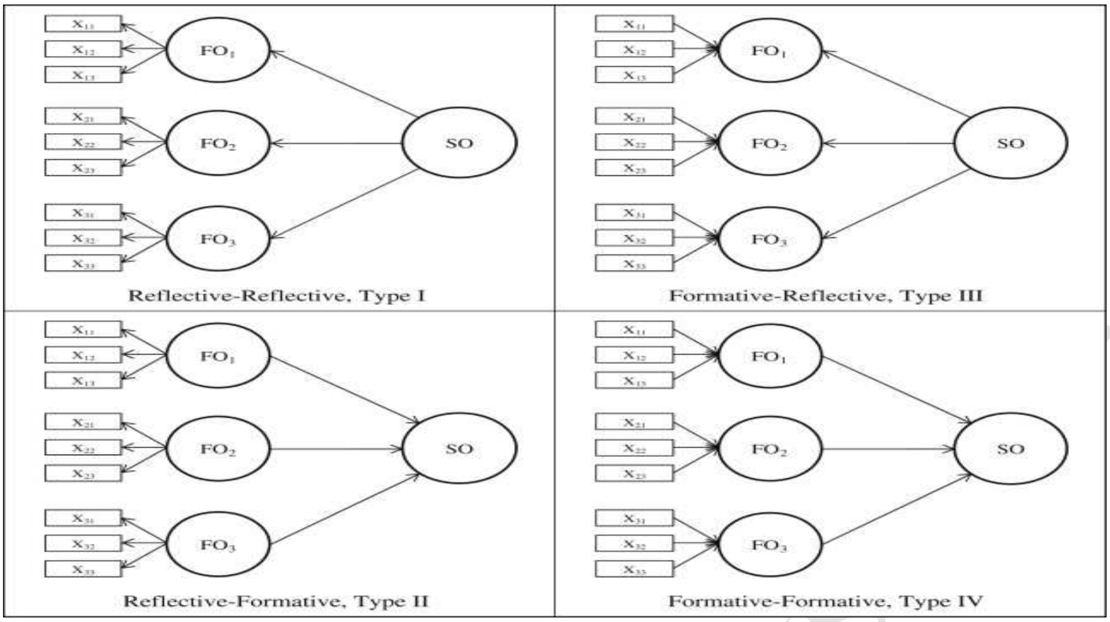


Figure 5: The four types Hierarchical Component Model (Becker et al., 2012)

According to Hair Jr et al. (2013), analysing HCM is different from analysing ordinary models. Analysing HCM can be done using one of the of the following approaches:

4.7.1.6.1 The repeated measurement approach:

In this approach, the researcher assigns all indicators from LOCs to the HOC, (See Figure 6) (Becker et al., 2012). Despite the fact that the repeated indicator approach is the most used approach and easy to implement, it has some requirements that should be considered. First, the number of indicators across the LOCs should be similar. Second, all the model's evaluation criteria that apply to LOCs should be applied to HOC as well.

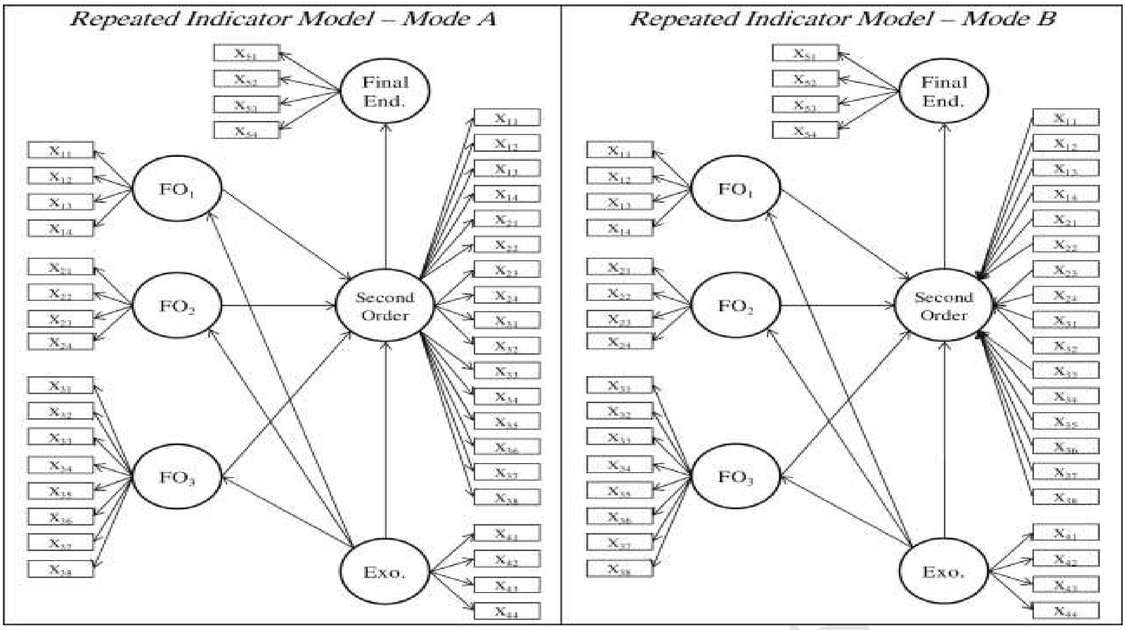


Figure 6: Repeated Measurement Approach (Becker et al., 2012)

4.7.1.6.2 Two-stage approach:

In this approach, the latent variable scores are estimated without the present of the HOCs, but with all LOCs only in the model, the measurement model is evaluated at this stage. The saved latent variable scores are then used as indicators for the HOCs in a separate high order structural analysis, (See figure 7) (Becker et al., 2012).

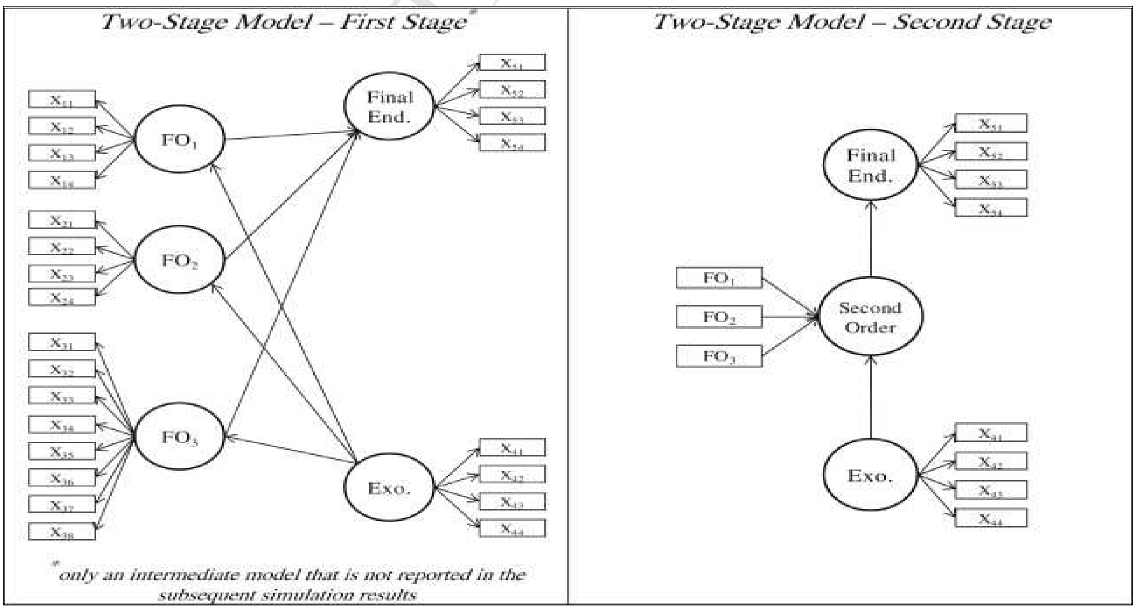


Figure 7: Two-stage approach (Becker et al., 2012)

5.0 Results

5.1 Descriptive statistics of the participants

A total of 56 first-year students have completed the experiment to the last stage, which satisfied the data collection stage. Tables (3,and 5) show descriptive statistics for participants which include gender, age group and the area of study. Table 6 shows the variables' means and standard deviations.

Table 3: Age Group

		Frequency
Valid	(18 - 22)	42
	(23-26)	13
	(over 26)	1
	Total	56

Table 4: Gender

		Frequency
Valid	Male	9
	Female	47
	Total	56

Table 5: Area of Study

		Frequency
Valid	Computer science	23
	Pathology	15
	Civil engineering	8
	Management	6
	Nursing	3
	Community Medicine	1
	Total	56

Table 6: Means and Standard Deviation for the variables

		Interactivity	Multimodality	Intrinsic Motivation	Academic performance	Perceived learning effectiveness	Satisfaction
N	Valid	56	56	56	56	56	56
	Missing	0	0	0	0	0	0
Mean		13.4286	13.5000	77.1964	34.3254	81.5260	80.3061
Std. Deviation		1.85724	1.59545	6.56830	14.11638	9.95724	7.44411

5.2 Description of the research model:

The research model is HCM type, as shown in (Figure 8) the model consists of 3 HOCs reflective-reflective constructs, namely, GBLS's features, Intrinsic Motivation and Learning outcomes. The GBLS's Features construct composed of 2 reflective LOCs that are Multimodality and Interactivity. The Intrinsic Motivation composed of 4 reflective LOCs namely Perceived Competence, Pressure/Tension, Value/Usefulness and Interest/Enjoyment. The Learning Outcome construct composed of 3 LOCs that are Academic Performance, Perceived Learning Effectiveness, and Satisfaction. Intrinsic Motivation is proposed to mediate the relationship between the GBLS's Features and the Learning outcomes.

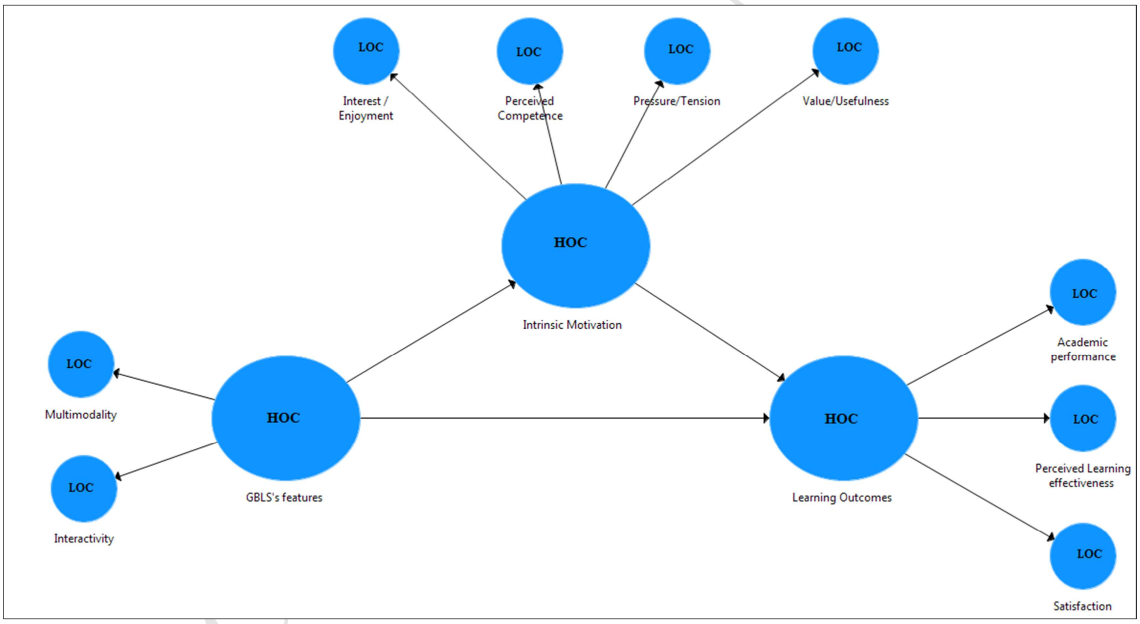


Figure 8: Model description

As described above, HCM should be analysed in a special way using either repeated indicator approach or Two-stage approach. As a result of reviewing some literature on dealing with HCM using Smart-PLS, the Two-stage approach was found to be preferable to analyse this research model, as the number of indicators across the LOCs are not similar.

5.3 Two stage-approach

As explained in the data analysis section, the model analysis is done throughout two stages:

5.3.1 Stage-one:

The latent variable scores are saved without the present of the HOCs, but with all LOCs only in the model. The measurement model is also evaluated at this stage. (See Figure 9).

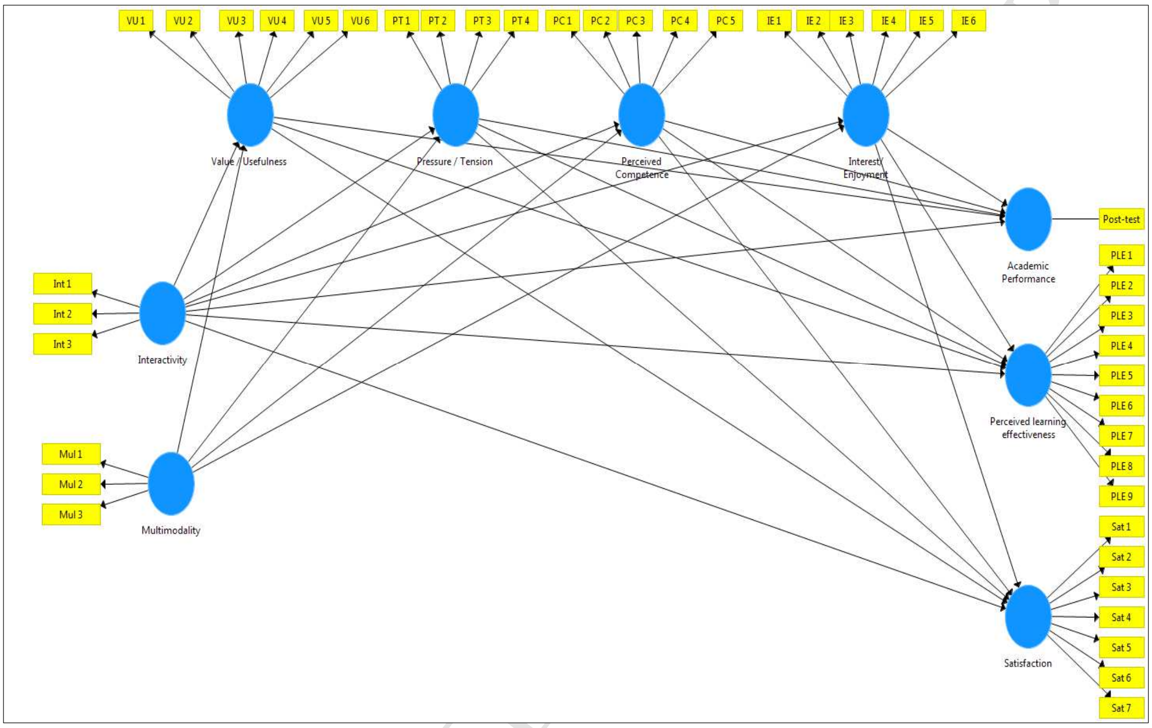


Figure 9: Stage one of the tow Stage approach

5.3.1.1 Evaluating the measurement model:

As it can be seen in (Figure 9), all constructs are reflective. Assessing the reflective measurement model includes evaluating the convergent validity, discriminant validity, and internal consistency reliability. The assessment of each criterion has been explained in details under data analysis section. Below are the results of the assessment of each criterion for the reflective measurement model.

1. Convergent validity:

Convergent validity can be evaluated using one of the following criterions, the outer loading of the indicators and, the Average Variance Extracted (AVE).

a. The indicator's outer loading.

As shown in (Figure 10) and (Figure 11)**,** any indicator has not met the rule of thumb was dropped from the model. The remaining indicators are shown in (Table 3). All the remaining indicators in the nine reflective constructs are way higher than the minimum acceptable threshold.

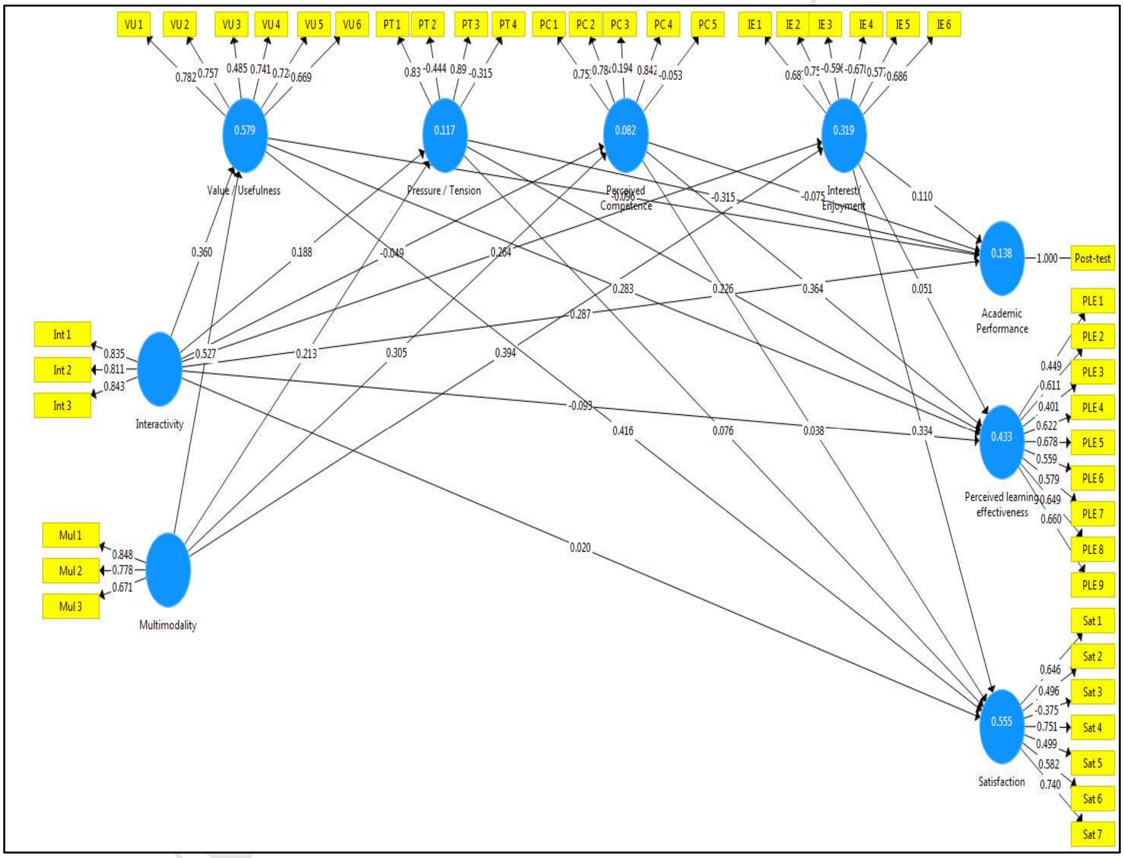


Figure 10: Initial measurement model before dropping the unsatisfactory indicators

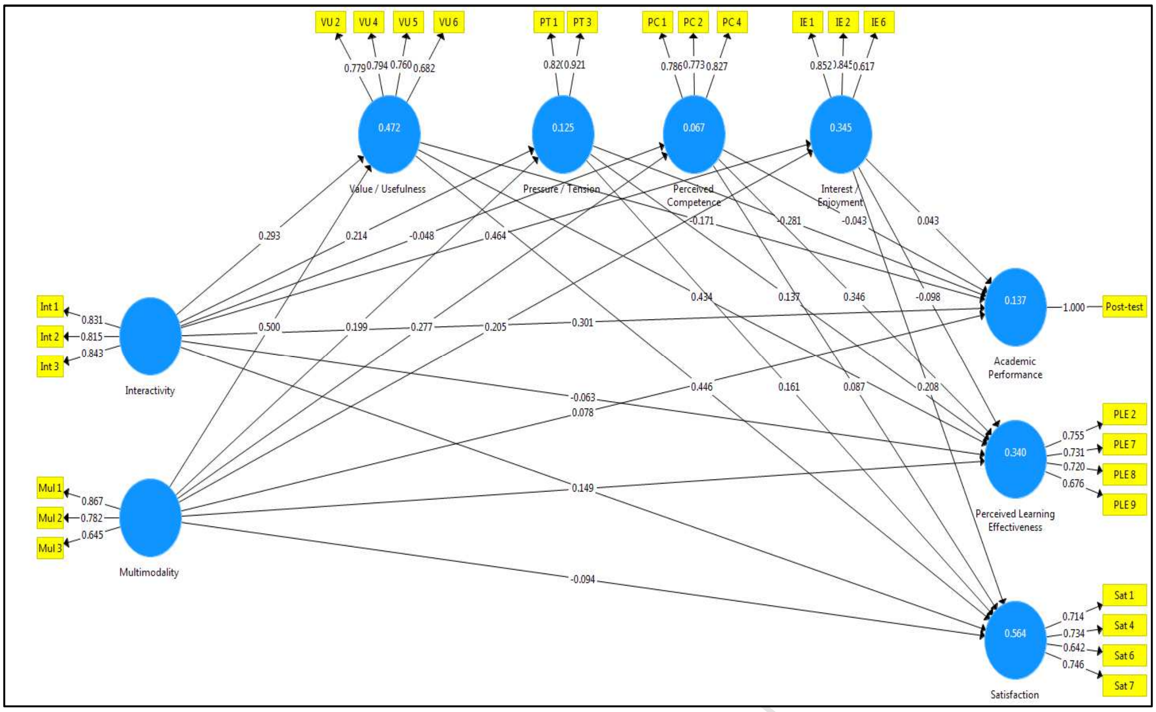


Figure 11 Initial measurement model after dropping the unsatisfactory indicators

b. Average Variance Extracted (AVE)

As indicated in (Table 9), Convergent validity can be established based on the AVE values for the nine reflective constructs. All the AVE values of the nine reflective constructs are above the threshold of AVE that is 0.50.

2. Discriminant Validity:

There are two criterions that can be used to evaluate discriminant validity, which are cross-loading of indicators and Fornell-Larcker criterion.

a. Cross loading: (Table 7) shows the results of the cross-loading. The discriminant validity can be established for all nine reflective constructs as the outer loading of each indicator on its associated construct is greater than its loadings on the other constructs.

Table 7: Table of cross-loadings

	Interest / Enjoyment	Interactivity	Multimodality	Perceived Competence	Perceived Learning Effectiveness	Pressure / Tension	Academic Performance	Satisfaction	Value / Usefulness
IE 1	**0.852**	0.582	0.292	0.196	0.106	0.311	-0.087	0.590	0.468
IE 2	**0.845**	0.346	0.291	0.144	0.159	0.316	0.049	0.476	0.499
IE 6	**0.617**	0.330	0.431	0.346	0.277	0.351	0.133	0.267	0.329
Int 1	0.315	**0.831**	0.364	-0.017	0.063	0.287	0.115	0.384	0.335
Int 2	0.483	**0.815**	0.327	0.077	0.193	0.167	0.149	0.49	0.354
Int 3	0.550	**0.843**	0.445	0.116	0.060	0.305	0.177	0.399	0.575
Mul 1	0.364	0.446	**0.867**	0.200	0.214	0.215	-0.022	0.431	0.584
Mul 2	0.274	0.550	**0.782**	0.059	0.125	0.256	0.097	0.284	0.48
Mul 3	0.322	0.049	**0.645**	0.334	0.161	0.224	0.013	0.218	0.384
PC 1	0.202	-0.019	0.132	**0.786**	0.483	0.039	-0.059	0.239	0.329
PC 2	0.179	0.113	0.221	**0.773**	0.241	0.178	-0.167	0.216	0.248
PC 4	0.278	0.112	0.264	**0.827**	0.353	0.315	-0.053	0.308	0.240
PLE 2	0.174	0.093	0.232	0.421	**0.755**	0.313	-0.092	0.283	0.320
PLE 7	0.098	0.152	0.102	0.273	**0.731**	0.231	-0.104	0.377	0.380
PLE 8	0.165	0.049	0.103	0.253	**0.720**	0.076	0.033	0.166	0.350
PLE 9	0.192	0.060	0.194	0.385	**0.676**	0.188	-0.165	0.269	0.230
PT 1	0.234	0.285	0.270	0.102	0.222	**0.820**	-0.034	0.298	0.271
PT 3	0.449	0.258	0.256	0.257	0.279	**0.921**	-0.31	0.475	0.397
Post-test	0.020	0.182	0.032	-0.108	-0.115	-0.225	**1.000**	0.031	-0.065
Sat 1	0.400	0.488	0.122	0.032	0.229	0.332	0.094	**0.714**	0.418
Sat 4	0.435	0.251	0.366	0.435	0.377	0.368	-0.126	**0.734**	0.577
Sat 6	0.280	0.359	0.307	0.345	0.251	0.297	-0.109	**0.642**	0.467
Sat 7	0.561	0.376	0.377	0.077	0.222	0.298	0.245	**0.746**	0.439
VU 2	0.513	0.320	0.475	0.387	0.351	0.291	-0.141	0.601	**0.779**
VU 4	0.286	0.327	0.438	0.299	0.508	0.230	0.001	0.506	**0.794**
VU 5	0.515	0.470	0.499	0.221	0.337	0.240	0.119	0.499	**0.760**
VU 6	0.373	0.485	0.517	0.111	0.123	0.450	-0.193	0.419	**0.682**

b. The Fornell-Larckercriterion

(Table 8) Shows the results of the Fornell-Larcker criterion. The discriminant validity can be established for all nine reflective constructs.

Table 8: Fornell-Larcker Results

	Interactivity	Interest/Enjoyment	Multimodality	Perceived learning effectiveness	Perceived Competence	Performance	Pressure/Tension	Value/Usefulness	Satisfaction
Interactivity	0.830								
Interest/Enjoyment	0.539	0.780							
Multimodality	0.458	0.428	0.770						
Perceived learning effectiveness	0.125	0.229	0.223	0.721					
Perceived Competence	0.087	0.284	0.261	0.453	0.798				
Performance	0.181	0.035	0.030	-0.114	-0.113	1.000			
Pressure/Tension	0.303	0.416	0.297	0.287	0.229	-0.225	0.872		
Value/Usefulness	0.520	0.566	0.638	0.438	0.342	-0.070	0.396	0.754	
satisfaction	0.512	0.578	0.420	0.381	0.328	0.026	0.459	0.679	0.710

3. Internal consistency reliability

As shown in (Table 9), the composite reliability values of all latent variables are in the satisfactory limit between 0.70 and 0.90. Therefore, all the nine reflective constructs demonstrated a high level of internal consistency reliability.

Table 9: Results summary of the measurement model analysis

Latent Variable	Indicators	Loading	Composite Reliability	AVE	Discriminant Validity
Interactivity	Int 1	0.831	0.870	0.689	Yes
	Int 2	0.815			
	Int 3	0.843			
Multimodality	Mul 1	0.873	0.812	0.594	Yes
	Mul 2	0.795			
	Mul 3	0.623			
Value / Usefulness	VU 2	0.799	0.841	0.570	Yes
	VU 4	0.794			
	VU 5	0.760			
	VU 6	0.682			
Pressure / Tension	PT 1	0.820	0.863	0.760	Yes
	PT 3	0.921			
Perceived Competence	PC 1	0.786	0.837	0.632	Yes
	PC 2	0.773			
	PC 4	0.827			
Interest/Enjoyment	IE 1	0.852	0.819	0.607	Yes

	IE 2	0.845			
	IE 6	0.617			
Academic Performance	Post-test	1.000	Single-item construct	Single-item construct	Yes
Perceived learning effectiveness	PLE 2	0.755	0.812	0.520	Yes
	PLE 7	0.731			
	PLE 8	0.720			
	PLE 9	0.676			
Satisfaction	Sat 1	0.714	0.802	0.504	Yes
	Sat 4	0.734			
	Sat 6	0.642			
	Sat 7	0.746			

5.3.2 Stage-Two:

The saved latent variable scores are used as indicators for the HOCs in a separate high order structural analysis, see (Figure 12).

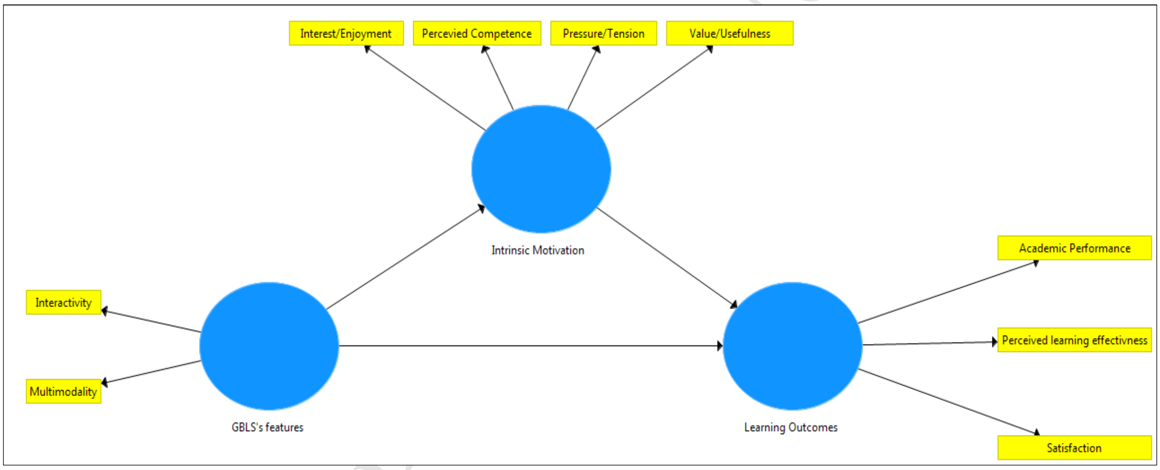


Figure 12: Stage-tow of the Tow-stages approach

5.3.2.1 Evaluating Structural Model:

The assessment of the structural model can be done in five steps as follows, Checking the model for collinearity issues, Assessing Path coefficients, Assessing the level of R^2, Assess the effect sizes f^2, Assess the predictive relevance Q^2 and q^2 effect sizes. Below are the results of the structural model analysis for each step:

Step 1: Assess structural model for collinearity issues.

The collinearity issue was assessed for the following sets of predictor contracts:

a. *Interactivity* and *Multimodality* as Predictors of *Interest/ Enjoyment, Perceived competence, Pressure/ Tension* and *Value / Usefulness*.
b. *Interactivity, Multimodality, Interest/ Enjoyment, Perceived competence, Pressure/ Tension* and *Value / Usefulness* as Predictors of *Academic performance, Perceived Learning Effectiveness*, and *Satisfaction*.

The (Table 10) shows the VIF values of the collinearity assessment; the VIF values are below the threshold of 5.0. Accordingly, there is no collinearity issue among the predictor constructs in the research model.

Table 10: collinearity issue assessment

First set		Second Set	
Construct	**VIF**	**Construct**	**VIF**
Interactivity	1.271	Interactivity	1.720
Multimodality	1.271	Multimodality	1.758
		Interest/ Enjoyment	1.825
		Perceived competence	1.203
		Pressure/ Tension	1.274
		Value / Usefulness	2.248

Step 2: Path coefficients

To obtain the T-statistics value for the structural model relationships, bootstrapping with 5000 subsamples procedure was conducted. (Figure 13) shows the T-statistics value for the structural model relationships resulting from bootstrapping calculation. With 5% significance level, all relationships in the model are significant, except the relationship between GBLs features → Learning outcomes with a T-Statistic value of 0.396. More details are provided under Hypothesis testing section.

(Figure 13) shows the results of each construct's indicators outer Weight, which can help identifying the specific elements of each construct. A summary of the results can be found in (Table 13).

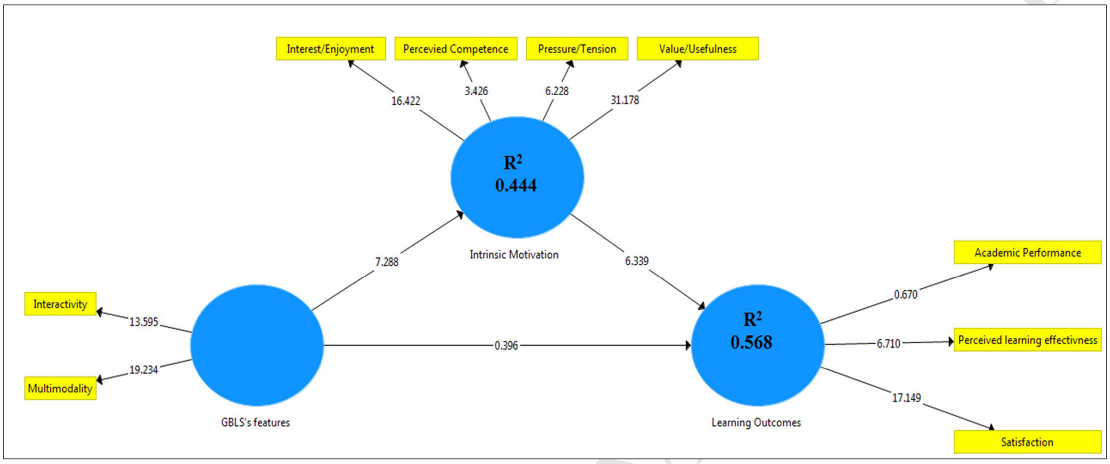


Figure 13: Bootstrapping results

Step 3: Assessing the level of R^2

R^2 has been used to test whether the model is able to explain the variance in the dependent variables. 44.4% of the variance in the intrinsic motivation was explained by GBLS's features. The research model explained 56.8% of the variability in the learning outcomes.

Step 4: Assess the effect sizes f^2

(Table 1) indicates the results of the f^2 value of the exogenous latent variables on endogenous latent variables. GBLS's Features have a large effect size of (0.799) on Intrinsic Motivation, Intrinsic Motivation also has a large effect size of (0.816) on Learning Outcome. On the other hand, GBLS's Features have no direct effect (0.006) on Learning Outcomes.

Table 11: *f*2 Results

Constructs	f^2
GBLS's features on intrinsic motivation	0.799
GBLS's features on Learning outcomes	0.006
Intrinsic Motivation on Learning outcome	0.816

Step 5: Assess the predictive relevance Q^2

As it shown in (Figure 14), the Q^2 values of both endogenous variables are bigger than zero. These Q^2 value can be considered as evidence of the model's predictive relevance regarding the latent endogenous constructs.

Construct Crossvalidated Redundancy

Total | Case1 | Case2 | Case3 | Case4 | Case5 | Case6 | Case7 | Case8 | Case9

	SSO	SSE	Q^2 (=1-SSE/SSO)
GBLS's features	112.000	112.000	
Intrinsic Motivation	224.000	176.025	0.214
Learning Outcomes	168.000	133.888	0.203

Figure 14 : Q^2 values including all constructs of the model

Step 6: Effect sizes q^2

To complete the last step of assessing the structural model, the q2 effect size was calculated manually using the following formula: $q^2 = \frac{Q^2 included - Q^2\ excluded}{1 - Q^2 included}$

$Q^2_{included}$ are the Q2 value that are shown in (Figure). The $Q^2_{excluded}$ values were obtained from re-estimating the research model after dropping a specific construct each time. For example, the construct (Intrinsic Motivation) was dropped to get the first value in (Table 12) and construct (GBLS's Features) was deleted to obtain the second value in (Table 12) . identical omission distance D of 9 was used when computing the results of $Q^2_{excluded}$ and $Q^2_{included}$.

Table 12: $Q^2_{excluded\ values}$

1	Q2 value when Intrinsic motivation is excluded	0.208
2	Q2 value when GBLS's features is excluded	0.072

$$q^2_{\text{Intrinsic Motivation} \rightarrow \text{learning Outcomes}} = \frac{0.203-0.072}{1-0.203} = 0.164.$$

$$q^2_{\text{GBLS's Features} \rightarrow \text{Intrinsic Motivation}} = \frac{0.214-0.208}{1-0.214} = 0.007.$$

Based on the rule of thumb, the q^2 effect size indicates that Intrinsic Motivation has large predictive relevance for Learning Outcomes. And the GBLS's Features have small predictive relevance for the Intrinsic Motivation.

5.3.3 Testing for mediation:

The research model assumed that Intrinsic Motivation mediates the relationship between GBLS's Features and learning outcomes. The method of testing mediation in Smart-PLS was explained under the data analysis section.

The first step is to test the indirect effect. The indirect effect from GBLS's Feature via Intrinsic Motivation to Learning Outcomes is significant with β = 0.530 and t = 5.115 (p-value < 0.001) which indicate that there is mediation. As the indirect relationship is significant, the second step will be testing the significance of the direct effect, the direct effect from GBLS' Features to Learning Outcomes is weak and not significant with β = -0.067 and t = 0.399 (p-value = 0.690). Following the meditation analysis procedure, it can be concluded that Intrinsic Motivation fully mediates the relationship between GBLS's Features and Learning Outcomes.

5.4 Hypothesis testing

This section will show the hypothesised paths to answer the research question of how does GBLS mode influence learning outcomes?

H1: Intrinsic Motivation is affected by the GBLS' features.

The relationship between GBLS's Features and Intrinsic Motivation was significant with β = 0.666 and t = 7.242 (p-value < 0.001) indicating that the GBLS's Features has a direct positive influence on the Intrinsic Motivation. On other words, 100-point change in GBLS's Features will bring 66.6-point change in the Intrinsic Motivation.

H2: Learning Outcomes are affected by Intrinsic Motivation.

The relationship between Intrinsic Motivation and Learning Outcomes was significant with β = 0.797 and t = 6.278 (p-value < 0.001) indicating that the Intrinsic Motivation has a direct positive influence on the Learning Outcomes. It also can be interpreted that 100-point change in Intrinsic Motivation will bring 79.7 change in the Learning Outcomes.

H3: The influence of GBLS's features on Learning Outcomes is mediated by Intrinsic Motivation.

The Intrinsic Motivation fully mediate the effect between GBLS's Features and Learning Outcomes with β = 0.531 and t = 5.088 (p-value < 0.001)

H4: Interactivity is a first-order factor of GBLS's Features.

Interactivity is a first-order factor of GBLS's Features with β = 0.848 and t = 13.616 (p-value < 0.001)

H5: Multimodality is a first-order factor of GBLS's Features.

Multimodality is a first-order factor of GBLS's Features with β = 0.861 and t = 18.945 (p-value < 0.001)

H6: Interest/Enjoyment is a first-order factor of Intrinsic Motivation.

Interest/enjoyment is a first-order factor of Intrinsic Motivation with β = 0.803 and t = 16.508 (p-value < 0.001)

H7: Perceived Competence is a first-order factor of Intrinsic Motivation.

Perceived Competence is a first-order factor of Intrinsic Motivation with β = 0.551 and t = 3.382 (p-value < 0.001)

H8: Pressure/Tension is a first-order factor of Intrinsic Motivation.

Pressure/Tension is a first-order factor of Intrinsic Motivation with β = 0.666 and t = 6.297 (p-value < 0.001)

H9: Value/Usefulness is a first-order factor of Intrinsic Motivation.

Value/usefulness is a first-order factor of Intrinsic Motivation with β = 0.855 and t = 30.770 (p-value < 0.001)

H10: Academic Performance is a first-order factor of Learning Outcomes.

Academic Performance is not a first-order factor of Learning Outcomes with β = - 0.158 and t = 0.664 (p-value > 0.05)

H11: Perceived Learning Effectiveness is a first-order factor of Learning Outcomes.

Perceived Learning Effectiveness is a first-order factor of Learning Outcomes with β = 0.757 and t = 7.029 (p-value < 0.001)

H12: Satisfaction is a first-order factor of Learning Outcomes.

Satisfaction is a first-order factor of Learning Outcomes with β = 0.884 and t = 17.399 (p-value < 0.001).

Table 13: Summary of Structural model assessment results

	Hypothesis	**Path Coefficient**	**T Statistics values**	**P values**	**Significance level**	**Results**
H1	Intrinsic Motivation is affected by the GBLS' features	0.666	7.242	0.000	***	Supported
H2	Learning Outcomes are affected by Intrinsic Motivation.	0.797	6.278	0.000	***	Supported
H3	The influence of GBLS's features on Learning Outcomes is mediated by Intrinsic Motivation.	0.531	5.088	0.000	***	Supported: Full mediation
H4	Interactivity is a first-order factor of	0.484	13.258	0.000	***	Supported

	GBLS's features.					
H5	Multimodality is a first-order factor of GBLS's Features.	0.861	18.873	0.000	***	Supported
H6	Interest/enjoyment is a first-order factor of Intrinsic Motivation.	0.803	16.998	0.000	***	Supported
H7	Perceived competence is a first-order factor of Intrinsic Motivation.	0.550	3.433	0.001	***	Supported
H8	Pressure/Tension is a first-order factor of Intrinsic Motivation.	0.666	6.234	0.000	***	Supported
H9	Value/Usefulness is a first-order factor of Intrinsic Motivation.	0.855	30.883	0.000	***	Supported
H10	Academic Performance is a first-order factor of Learning Outcomes.	-0.158	0.679	0.497	NS	Not Supported
H11	Perceived Learning Effectiveness is a first-order factor of Learning Outcomes.	0.756	6.884	0.000	***	Supported
H12	Satisfaction is a first-order factor of Learning Outcomes.	0.884	17.687	0.000	***	Supported

Path significance Level:
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$
(e.g. $t > 1.96$ at $p < 0.05$, $t > 2.576$ at $p < 0.01$, $t > 3.29$ at $p < 0.001$ for two-tailed tests)

6.0 Discussion and Conclusion

This study investigated how the GBLS mode influences the learning outcomes by identifying the relevant latent variables and examining the relationship between those variables. A research model of the three high-order constructs was introduced and analysed. The data that used to run the research model was obtained from quasi-experiment with 56 participants. The causal relationships were tested between GBLS's Features and Intrinsic Motivation, and between Intrinsic Motivation and the Learning Outcomes. The mediating effect of Intrinsic

Motivation between the GBLS's Feature and the Learning Outcome was examined. The research model explained 56.8% of the variability in the Learning Outcome. (Table 13) presents a summary of the results of the hypothesised relations.

The results of the model analysis indicated that GBLS's Features positively influence the students' intrinsic motivation. These results are consistent with the finding of W.-J. Lee, Huang, Wu, Huang, & Chen (2012) whose Kinect-enhanced Digital Learning Playground was found to have a high positive impact on students' intrinsic motivation. These results also supported the findings the of previous studies in the Technology Mediated Learning (TML) field, for example, Lawlor, Marshall, and Tangney (2013) found that team-based, technology-mediated model that called Bridge21 has a direct positive influence on students' intrinsic motivation. However, the positive influence of GBLS's Features on the Intrinsic Motivation can be explained through interactivity and multimodality. According to (Homer et al., 2014) boosting the intrinsic motivation can be achieved by giving students chances to participate and have control over the learning experience. As explained above, Kinect promotes an interactive learning environment that encourages students to participate and lead the learning experience. Multimodality has also been proven as an influencer of the intrinsic motivation. Valerio (2014) indicated that intrinsic motivation could be increased by delivering the learning content in different ways to grab the attention of learners.

The results of this study also showed that Intrinsic Motivation is positively related to the Learning Outcomes. These results supported the models that introduced by (Alavi & Leidner, 2001; Benbunan-Fich & Hiltz, 2003). These results also matched the findings of previous intrinsic motivation studies, for example, Pintrich et al. (2008) indicated that intrinsically motivated learners are more committed to achieving their learning goals. Other studies showed that student with high intrinsic motivation engage deeply in the learning materials, curious, have more self-regulation, have less avoidance behaviour and they are also less likely to drop out from the school (Hair et al., 2012; Tenenhaus et al., 2005; Wong, 2013).

On the other hand, this study showed that the GBLS's Feature has no direct effect on the Learning Outcomes, but it indirectly influences the Learning Outcomes via increasing the Intrinsic Motivation of students. To put it in another way, this study indicated that Intrinsic Motivation mediates the effect of GBLS's Features on Learning Outcomes. These results supported Alavi and Leidner (2001) findings who claimed that technology does not influence the learning outcomes but the features of that technology provide a unique instructional environment that influences the intrinsic motivation of students, which in turn positively influence the learning outcomes. These results also provide an answer to the research question of how does GBLS mode positively influence learning outcomes? This study found that the GBLS's Features, which are Interactivity and Multimodality, provide an instructional learning environment that positively influences the psychological learning process (Intrinsic motivation) of students. The improvement of the students' intrinsic motivation, leads to improvement in the Learning Outcomes. These findings also matched the claims of the Integrated Model of Multimedia Interactivity (INTERACT), which believes that motivating students is not an end product of learning interactive multimedia. Motivation plays an important roles by being part of the learning process loop and influencing the cognitive and the metacognitive activities (Domagk et al., 2010). The findings of this study are important as they provided a scientific explanation of how GBLS mode positively influences the learning outcomes. Long-term experimentation (for example, one-semester) and with larger number of participants is highly recommended in future studies, so as to perceive whether the GBLS mode will generate the same learning outcomes. In addition, this study only focused on the influence of GBLs on intrinsic motivation, however, there are many other psychological learning processes such as (cognitive offloading, mental effort) that are as important as intrinsic motivation. Therefore, those factors should be investigated individually and eventually as a whole to understand the interaction of the factors in future work.

7.0 References

Alavi, M., & Leidner, D. E. (2001). Research commentary: Technology-mediated learning—A call for greater depth and breadth of research. *Information systems research, 12*(1), 1. doi: 10.1287/isre.12.1.1.9720

Alfassi, M. (2004). Effects of a learner-centred environment on the academic competence and motivation of students at risk. *Learning Environments Research, 7*(1), 1-22.

Alibali, M. W., & GoldinMeadow, S. (1993). Gesture-speech mismatch and mechanisms of learning: What the hands reveal about a child' s state of mind. *Cognitive psychology, 25*(4), 468-523.

Alibali, M. W., Nathan, M. J., Wolfgram, M. S., Church, R. B., Jacobs, S. A., Johnson Martinez, C., & Knuth, E. J. (2014). How teachers link ideas in mathematics instruction using speech and gesture: A corpus analysis. *Cognition and Instruction, 32*(1), 65-100.

Beauchamp, G., & Kennewell, S. (2010). Interactivity in the classroom and its impact on learning. *Computers & Education, 54*(3), 759-766. doi: http://dx.doi.org/10.1016/j.compedu.2009.09.033

Becker, J.-M., Klein, K., & Wetzels, M. (2012). Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models. *Long Range Planning, 45*(5–6), 359-394. doi: http://dx.doi.org/10.1016/j.lrp.2012.10.001

Benbunan-Fich, R., & Hiltz, S. R. (2003). Mediators of the effectiveness of online courses. *Professional Communication, IEEE Transactions on, 46*(4), 298-312.

Broaders, S. C., Cook, S. W., Mitchell, Z., & Goldin-Meadow, S. (2007). Making children gesture brings out implicit knowledge and leads to learning. *Journal of Experimental Psychology: General, 136*(4), 539.

Buckingham, D. (2013). *Beyond technology: Children's learning in the age of digital culture*: John Wiley & Sons.

Burns, C., & Myhill, D. (2004). Interactive or inactive? a consideration of the nature of interaction in whole class teaching. *Cambridge Journal of Education, 34*(1), 35-49. doi: 10.1080/0305764042000183115

Chang, C.-Y., Chien, Y.-T., Chiang, C.-Y., Lin, M.-C., & Lai, H.-C. (2013). Embodying gesture-based multimedia to improve learning. *British Journal of Educational Technology, 44*(1), E5-E9. doi: 10.1111/j.1467-8535.2012.01311.x

Chao, K.-J., Huang, H.-W., Fang, W.-C., & Chen, N.-S. (2013). Embodied play to learn: Exploring Kinect-facilitated memory performance. *British Journal of Educational Technology, 44*(5), E151-E155. doi: 10.1111/bjet.12018

Chen, G., & Fu, X. (2003). Effects of multimodal information on learning performance and judgment of learning. *Journal of Educational Computing Research, 29*(3), 349-362.

Chou, S.-W., & Liu, C.-H. (2005). Learning effectiveness in a Web-based virtual learning environment: a learner control perspective. *Journal of Computer Assisted Learning, 21*(1), 65-76. doi: 10.1111/j.1365-2729.2005.00114.x

Church, R. B., Ayman-Nolley, S., & Mahootian, S. (2004). The role of gesture in bilingual education: Does gesture enhance learning? *International Journal of Bilingual Education and Bilingualism, 7*(4), 303-319.

Cook, S. W., Duffy, R. G., & Fenn, K. M. (2013). Consolidation and transfer of learning after observing hand gesture. *Child development, 84*(6), 1863-1871.

Cook, S. W., & Goldin-Meadow, S. (2006). The role of gesture in learning: Do children use their hands to change their minds? *Journal of cognition and development, 7*(2), 211-232.

Cook, S. W., Mitchell, Z., & Goldin-Meadow, S. (2008). Gesturing makes learning last. *Cognition, 106*(2), 1047-1058.

Deci, E. L., & Ryan, R. M. (1985). Intrinsic motivation and self-determination in human behavior, 1985: Plenum, New York.

Domagk, S., Schwartz, R. N., & Plass, J. L. (2010). Interactivity in multimedia learning: An integrated model. *Computers in Human Behavior, 26*(5), 1024-1033.

Goldin-Meadow, S. (2003). Hearing gesture: How our hands help us think.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the academy of marketing science, 40*(3), 414-433.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM)*: Sage Publications.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*: Sage Publications.

Homer, B. D., Kinzer, C. K., Plass, J. L., Letourneau, S. M., Hoffman, D., Bromley, M., . . . Kornak, Y. (2014). Moved to learn: The effects of interactivity in a Kinect-based literacy game for beginning readers. *Computers & Education, 74*, 37-49.

Hostetter, A. B. (2011). When do gestures communicate? A meta-analysis. *Psychological bulletin, 137*(2), 297.

Hostetter, A. B., & Alibali, M. W. (2008). Visible embodiment: Gestures as simulated action. *Psychonomic Bulletin & Review, 15*(3), 495-514. doi: 10.3758/pbr.15.3.495

Hostetter, A. B., Bieda, K., Alibali, M. W., Nathan, M. J., & Knuth, E. J. (2006). *Don't just tell them, show them! Teachers can intentionally alter their instructional gestures.* Paper presented at the Proceedings of the 28th Annual conference of the cognitive science society.

Hsiao, H.-S., & Chen, J.-C. (2016). Using a gesture interactive game-based learning approach to improve preschool children's learning performance and motor skills. *Computers & Education, 95*, 151-162. doi: http://dx.doi.org/10.1016/j.compedu.2016.01.005

Hsu, H.-M. J. (2011a). *The potential of Kinect as Interactive Educational Techonology.* Paper presented at the 2nd International Conference on Education and Management Technology, Singapur.

Hsu, H.-M. J. (2011b). The potential of kinect in education. *International journal of information and education technology, 1*(5), 365.

. K-Solar System (2012) [Microsoft Kinect]: Juan de Lanuza School and the Faculty of Education of the University of Zaragoza. Retrieved from http://www.k-solarsystem.org/about/servlet/

Kain, D. J. (2003). Teacher-centered versus student-centered: Balancing constraint and theory in the composition classroom. *Pedagogy, 3*(1), 104-108.

Ke, F., Lee, S., & Xu, X. (2016). Teaching training in a mixed-reality integrated learning environment. *Computers in Human Behavior, 62*, 212-220. doi: http://dx.doi.org/10.1016/j.chb.2016.03.094

Keene, K. A., Rasmussen, C., & Stephan, M. (2012). Gestures and a chain of signification: the case of equilibrium solutions. *Mathematics Education Research Journal, 24*(3), 347-369. doi: 10.1007/s13394-012-0054-3

Lee, E. A. L. (2011). *An investigation into the effectiveness of virtual reality-based learning.* Murdoch University.

Lee, W.-J., Huang, C.-W., Wu, C.-J., Huang, S.-T., & Chen, G.-D. (2012). *The effects of using embodied interactions to improve learning performance.* Paper presented at the Advanced Learning Technologies (ICALT), 2012 IEEE 12th International Conference on.

Malone, T. W., & Lepper, M. R. (1987). Making learning fun: A taxonomy of intrinsic motivations for learning. *Aptitude, learning, and instruction, 3*(1987), 223-253.

Marks, R. B., Sibley, S. D., & Arbaugh, J. B. (2005). A STRUCTURAL EQUATION MODEL OF PREDICTORS FOR EFFECTIVE ONLINE LEARNING. *Journal of Management Education, 29*(4), 531-563.

Megowan, M. C. (2007). *Framing discourse for optimal learning in science and mathematics.* Arizona State University Tempe, AZ.

Meng, M., Fallavollita, P., Blum, T., Eck, U., Sandor, C., Weidert, S., . . . Navab, N. (2013). *Kinect for interactive AR anatomy learning.* Paper presented at the Mixed and Augmented Reality (ISMAR), 2013 IEEE International Symposium on.

Moreno, R., & Mayer, R. (2007). Interactive multimodal learning environments. *Educational psychology review, 19*(3), 309-326.

Nathan, M. J. (2008). An embodied cognition perspective on symbols, gesture, and grounding instruction. *Symbols and embodiment: Debates on meaning and cognition*, 375-396.

Novack, M., & Goldin-Meadow, S. (2015). Learning from gesture: how our hands change our minds. *Educational psychology review, 27*(3), 405-412.

O'Hanlon, C. (2007). Gaming: Eat Breakfast, Drink Milk, Play Xbox. *The Journal, 34*(4), 34-39.

Pashler, H., McDaniel, M., Rohrer, D., & Bjork, R. (2008). Learning styles concepts and evidence. *Psychological science in the public interest, 9*(3), 105-119.

Pearson Education. (2014) Celestial Timekeeping and Navigation.

Persico, D., Manca, S., & Pozzi, F. (2014). Adapting the Technology Acceptance Model to evaluate the innovative potential of e-learning systems. *Computers in Human Behavior, 30*, 614-622. doi: http://dx.doi.org/10.1016/j.chb.2013.07.045

Picciano, A. (2009). Blending with purpose: The multimodal model. *Journal of the Research Center for Educational Technology, 5*(1), 4-14.

Pintrich, P. R., Meece, J. L., & Pintrich, P. R. (2008). *Motivation in education : theory, research, and applications*. Upper Saddle River, N.J. : Pearson/Merrill Prentice Hall.

Pituch, K. A., & Lee, Y.-k. (2006). The influence of system characteristics on e-learning use. *Computers & Education, 47*(2), 222-244.

Roussou, M. (2004). Learning by doing and learning through play an exploration of interactivity in virtual environments for children. *Computers in entertainment CIE, 2*(1), 10. doi: 10.1145/973801.973818

Ryan, R. M. (1982). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of personality and social psychology, 43*(3), 450.

Ryan, R. M., & Deci, E. L. (2000a). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology, 25*(1), 54-67.

Ryan, R. M., & Deci, E. L. (2000b). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist, 55*(1), 68.

Sankey, M., Birch, D., & Gardiner, M. (2010). *Engaging students through multimodal learning environments: The journey continues.* Paper presented at the Proceedings ASCILITE 2010: 27th Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education: Curriculum, Technology and Transformation for an Unknown Future.

Saye, J., & Brush, T. (2001). The Use of Embedded Scaffolds with Hypermedia-Supported Student-Centered Learning. *Journal of Educational Multimedia and Hypermedia, 10*(4), 333-356.

Shakroum, M., Wong, K. W., & Fung, L. C. C. (2016). The Effectiveness of the Gesture-Based Learning System (GBLS) and Its Impact on Learning Experience.

Sharda, R., Romano Jr, N. C., Lucca, J. A., Weiser, M., Scheets, G., Chung, J.-M., & Sleezer, C. M. (2004). Foundation for the study of computer-supported collaborative learning requiring immersive presence. *Journal of Management Information Systems, 20*(4), 31-64.

Shia, R. (2000). Running Head: Academic Intrinsic And Extrinsic Motivation And Metacognition. Assessing Academic Intrinsic Motivation: A Look At Student. Goals And Personal Strategy.

Stefanou, C. R., & Salisbury-Glennon, J. D. (2002). Developing motivation and cognitive learning strategies through an undergraduate learning community. *Learning Environments Research, 5*(1), 77-97.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational statistics & data analysis, 48*(1), 159-205.

Wong, K. K.-K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24*(1), 1-32.

Highlights

- This study investigated how GBLS mode influence the Learning Outcomes
- Results showed, GBLS’s Features positively affect the students’ Intrinsic Motivation
- The increase in the Intrinsic Motivation leads to improving the Learning Outcomes
- GBLS’s Features indirectly influence the Learning Outcomes via Intrinsic Motivation