The Effects of using Mobile-Augmented Reality Learning Environment with Cognitive and Affective Learning Outcomes using Structural Equation Modeling Approach

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Abstract: ***Mobile-Augmented Reality (mAR) technology enables the mobilization of a learning environment, providing greater student access to learning material, regardless of location. This study contributes to cognitive and effective learning by investigating the differences in the learning outcomes and performance achievement of mAR within a classroom-learning centered and self-centered learning environment. There are 260 students from public and private universities involved. The implementation of quantitative method has been conducted to establish mAR as an effective learning technology. In addition, a theoretical model comprising of causal factors for effective mAR-based learning was developed. This model provides insight into the relationship between the important determinants that integrate and facilitate learning in mAR-based environment. The findings confirmed that mAR could leverage and used as an optimum learning tool in educational context.***

Keywords: Affective learning; Cognitive learning; Motivation; Mobile-augmented reality

I. INTRODUCTION

Learning is a crucial process that is heavily influenced by both cognitive and social changes throughout an individual's life (Gagne, 1977). Recently, notable shifts in the pedagogical approach to teaching has been observed with the implementation of technology, particularly in secondary schools and higher education(Tondeur, 2017; Jamali et al., 2014a; Fuxin, 2012; Holzinger et al., 2005). The use of technology has been shown to assist in the delivery of information and reference material acquisition. Following this, significant learning factors, motivation and stimulation, have been attributed to the use of such technology due to the superior learning environment that is created (Chiang et al., 2014; Holzinger et al., 2005). AR technology has been previously demonstrated in higher education (Chehimi et al., 2007; Norman et al., 2012) to aid in learning and assist in revision. AR lies between the real and virtual environment with a range of digital objects such as videos, audios, images or haptic/touch can be embedded and overlaid augmented on top of a real environment and allows users to interact with them (Azuma, 1997; Carmigniani & Burko, 2011; Carmigniani, Furht, et al., 2011).

With these unique features, AR has been utilized in education to enhance the learning in a complex field. Refer to study by Jamali et al. (2014b) most AR has been presented in a computer desktop as learning aid. However, due to the downsides of bulkiness and being stationary, reliance on the desktop has been eliminated. Therefore, AR has shifted to mobile. AR technology is integrated through a handheld tablet device called mobile-Augmented Reality (mAR). MAR offers the advantage of mobility and improves the learning environment. In this respect, mobile learning is referred to as ubiquitous learning as it provides learners with information through handheld devices that are also known as learning tools (e.g. mobile phones and tablets). MAR creates a flexible learning environment that is not constrained by location and/or time. This is principal as time and location facilitation can impact learner's motivation, while prime learning conditions enhance learning outcomes (Di Serio et al., 2013; Jamali et al., 2015; Markwell, 2003). Therefore, in comparison to the restricted access in the traditional learning environment, mAR has the ability to provide unlimited access to learning materials for the student.

Recently, Antony et al. (2018), Cole et al. (2017) and Bergman et al. (2013) highlighted that the fundamental key for increasing information retention was by repetition of subject learning materials. Owing to mAR ability and mobility, satisfies the learner's requirements to access learning materials without limitation. The adoption of mAR in a teaching context is limited, although the extensive use of mAR is reported elsewhere (Ashraf et al., 2012; Chang et al., 2014; Harris, 2011; Institute, 2004), therefore research is warranted regarding mAR use to relay a more robust user experience, especially in the context of user evaluations of motivation (Azuma et al., 2011; Di Serio et al., 2013). Moreover, there is still a lack of motivation studies of mAR in education as a learning tool (Lee, 2012; Margetis et al., 2012; Rogers, 2012; Tarng et al., 2012; Ternier et al., 2011).

The comprehension of complex subjects in higher education taught through traditional methods may benefit from technology, such as mAR. For example, the anatomy of the human body is often taught through traditional lectures and combined with practical sessions, which may or may not include human cadaver or didactic models. Furthermore, the human material involves high cost and difficult to acquire, therefore, not all learners have access let alone during lab.

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This mode of pedagogy is conserved within this field as it was originally designed to facilitate long-lasting understanding of this subject. Despite this, observations have been made that students experience retention issues using this approach for some subjects that uses the physical materials to give more understanding in the lecture right up to practical learning, for instance, sketching for mechanical systems (Bergig et al., 2009), physics, mathematics, computer and electrical engineering lab equipment (Andújar et al., 2011), cultural science (Ternier et al., 2011) and many more.

Despite the support that effective learning is attributed to technology use in learning, it is important to investigate the educational effectiveness. Prior studies have concentrated on developing virtual contents for AR but largely ignored mAR, particularly with regards to measuring learners' motivation. Therefore, this research aims to investigate the effectiveness of learning through the use of mAR. This research also developed a framework to evaluate students-centered learning and motivation through mAR to contribute to higher educators understanding of mAR as an educational tool to increase learning outcomes in higher education. This research was undertaken through the use of current learning methods in learning human anatomy; 1) multimedia presentation; 2) physical human skeleton, that implemented in a higher education setting. The subject requires the learning of anatomy within the practical dissection laboratory in order to expose the students to the structure of the human body, animals and internal organs (Farlex, 2014). In the context of this subject, Ganguly (2010) stated that human anatomy didactic lectures supplemented by practical dissections are designed to facilitate long-lasting understanding of the subject. However, anatomy students have been observed to experience issues in retaining information regarding the subject (Ganguly, 2010; Whelan et al., 2015).

The AR technology has also been advocated by prior studies (Chehimi et al., 2007; Norman et al., 2012) to solve the above mentioned learning problems and to revise the subject matter frequently. Also, Antony et al. (2018), Cole et al. (2017) and Bergman et al. (2013) stressed that in retaining longer information, knowledge repetition should be facilitated, and with mAR technology, the student is enabled to access learning information as frequently as he needs. In this context, time and location facilitation can impact learner's motivation, and optimum facilitation could lead to enhanced students' learning outcomes (Di Serio et al., 2013; Jamali et al., 2015; Markwell, 2003). Added to this, motivation is a source of energy for students to become responsible, be hopeful, and remains interactive in their learning activities (Chiang et al., 2014; Di Serio et al., 2013). Important to realize that, through these experiences the motivation can be improved by observing others to use an efficient learning method, for instance mAR, it is proven can reinforce the student's self-efficacies which resulted to enhance the learning (Hanafi et al., 2017).

Considering the fact that effective learning is attributed to technology use in learning, it is important to investigate the educational effectiveness evaluation. Hence, in this research the effectiveness of learning through the use of mAR is examined. This research also proposes a framework that aims to regulate the tools and evaluate the motivation of students-centered learning through mAR. Prior studies in literature have concentrated on developing virtual contents for AR but largely ignored mAR, particularly with regards to measuring learners' motivation. Despite the extensive use of mAR, research is still needed regarding its use to relay a more robust experience, especially in the context of user evaluations of motivation (Azuma et al., 2011; Di Serio et al., 2013).

The findings are contributed to help educationists and instructors, administrators, and educational planners in understanding the importance of mAR as an educational tool to increase learning outcomes in the context of higher education institutions.

Attention in higher learning overview

In this context, digital technology has contributed a new aspect into teaching the subject of anatomy and it possesses significant value to the students in terms of effectively viewing and retaining information in their memory for the purpose of future learning results (Ganguly, 2010). Because learning activity takes place in the learning environment, it is deemed to be a part of it in the sense of place, time and space (Piccoli et al., 2001). According to Piccoli et al. (2001) the learning environment appears to be the factor that remains the same as opposed to behaviours and efficiency and as such, the subject has to match the learning environment with the help of technology (e.g. web-based technology).

In relation to the human anatomy subject, learning resources and techniques in the classroom contribute to the challenges in memory retention and this requires attention. It is without a doubt that the present learning techniques used to teach science subjects entail the use of computers and traditional methods, the combination of which is used in majority of higher learning institutions.

II. CONCEPTUAL BACKGROUND

Adoptions and calibrations of framework

This section presents a framework that can regulate the tools and measure the motivation of student-centered learning using mAR as illustrated in Figure 1. Previous studies focused on the development of virtual contents for AR, but were deficient in mAR particularly in regard to the measure of the learners' motivation. Although mAR is common, there is still a need for more research on its use to convey a compelling mAR experience specifically in user evaluation of motivation (Azuma et al., 2011). In particular, motivation studies of mAR in education as a learning tool is still lacking (Lee, 2012; Margetis et al., 2012; Rogers, 2012; Tarng et al., 2012; Ternier et al., 2011). Consequently, the theory of dimensions and antecedents of VLE by Piccoli et al. (2001) are adopted in investigating the effectiveness of the learning outcomes in tertiary education. VLE is specifically selected due to its similarity in antecedents required to assess mAR framework presented in this research.

With reference from VLE framework (Piccoli et al., 2001), one attribute which is motivation is selected from the Human Dimension as the platform of the framework.

Based on this conceptual framework, a model is developed to evaluate how mAR enhances the learning outcomes as shown in Figure 1. The suitability of the hypothesised model is assessed using Structural Equation Modelling (SEM). The model expands to Learning Modes/Groups and Student Motivation. The conceptual framework comprises two independent variables which are (i) learning modes (mAR-based and non-CLM-based) and (ii) motivation (the effectiveness of mAR in learning environment is to be investigated). Meanwhile, the learning outcome as dependent variable holds three attributes which are perceived learning effectiveness, satisfaction, and self-efficacy.

We investigated learning activities within environments that improve learning outcomes for the student using mAR.

Several variables such as motivation, learning modes, perceived learning effectiveness, self-efficacy and satisfaction of learning outcomes were measured. The specific focus was the potential use of mAR in university settings. Education was selected as the domain due to the lack of AR medium and the use of mAR for learning activities. The use of mAR and its impact on student learning outcomes was measured.

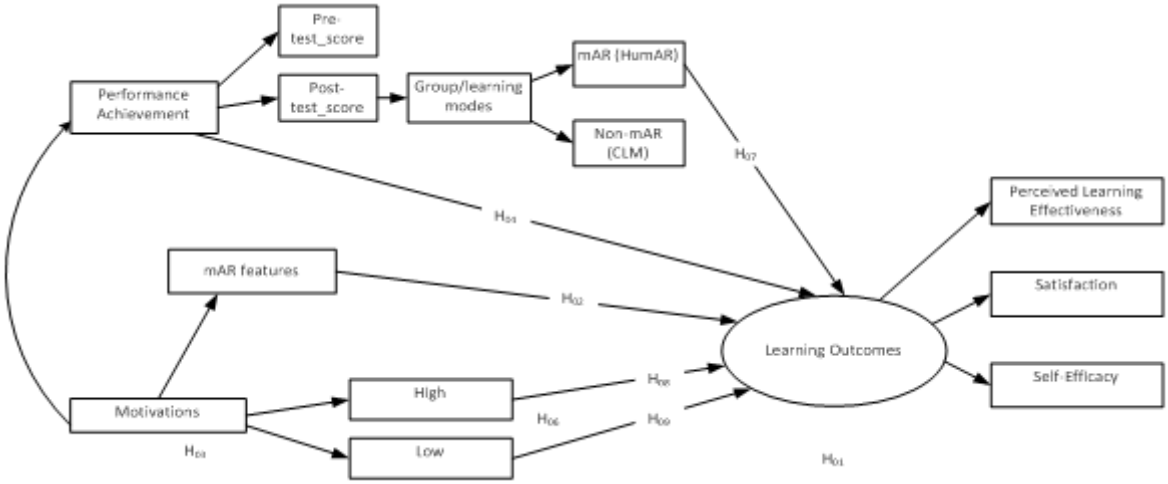

Fig. 1 Research model and hypothesis development

Refer to Figure 1, the conceptual framework comprises two independent variables, namely, learning modes (mAR-based and non-CLM-based); and motivation, to be investigated into the effectiveness of mAR in the learning environment. While, the learning outcomes as dependent variable, which holds three attributes; perceived learning effectiveness, satisfaction and self-efficacy. Accordingly, we analyzed these attributes that might be significant antecedents in the calibration of the mAR learning framework in the developed following null hypotheses:

- H_{01}: The dimensions do not fit for the model framework of mobile-Augmented Reality (mAR) effectiveness.
- H_{02}: mAR-features are not a significant antecedent for the learning outcomes in the model framework of mobile-Augmented Reality (mAR) effectiveness.
- H_{03}: Motivation is not a significant antecedent for the learning outcomes in the model framework of mobile-Augmented Reality (mAR) effectiveness.

Motivation

The study of human motivation includes the concept of perceptions of control, what need to achieve, curiosity, attributions for success or failure and anxiety. A trait will be based on these conditions, with respect to the motivational characteristics, for instance, intrinsically and extrinsically (high and low level) (Keller, 2010). With motivation as part of the crucial component in determining the student's achievement (Abd Wahab, 2007), this research intends to seek the same value apply in mAR learning. The motivation extends to the suitable platform as the learning medium, for the students who are required to complete any task as part of their assignment and revision out of the classroom. Without a proper platform, will result the student's learning into downfall and demotivated (Nincarean et al., 2013; Stanisavljević-Petrović et al., 2015; Hanafi et al., 2017).

Intrinsic

Intrinsically motivated refers to individuals who are moved by their own reasons, none of which is expected to be rewarded despite the job being done (Keller, 2010). Astudy by Tripathi (2015) highlighted the importance of encouraging students to get intrinsically motivated in the classroom. Intrinsic motivation is the fundamental element of knowledge where the students are able to take control and have ownership over their learning. This reflects the fact that students who are driven by their interest are slightly more motivated to get involved and complete any given tasks. Other than that, Handley's (2010) view was discussed in Tripathi (2015) who stated that over time, student engagement and content delivery need to be reconsidered. If these aspects are not being well delivered during learning session, it can cause disruption within the learning environment.

Extrinsic

In contrast, extrinsically motivated means that individuals engage in tasks for rewards that occur after completing them, not for the pleasure that comes along the journey of completing the tasks (Keller, 2010).

The relationship between motivation and task satisfaction has been reported to be effective in improving workers' task satisfaction (Alam et al., 2015). Alam et al. (2015) further argued that there are chances to incite them through management style, business design, and company events. Additionally, other motivational factors include money, conditions of service, communication, and data accessibility. From the results obtained in their study, we will be embarking on the similar psychological needs, together with mAR features in the learning environment. Data accessibility is highlighted in their study and with ubiquitous learning concept; information will be easily accessible and can be viewed regularly. Furthermore, appropriate learning style, syllabus design, and learning activity play an essential role to obtain promising results which help to increase learners' level of self-esteem in a motivated-based learning environment (Alam et al., 2015; Van der Kleij et al., 2015).

The learning modes, which undergo the performance tests, are focusing on the cognitive learning outcomes. Whilst, attributes perceived learning effectiveness, satisfaction and self-efficacy are categorized under affective learning outcomes. MAR is asserted to have positive effects on the learning process and on the learning experiences on the basis of two aspects namely cognitive learning and affective learning outcomes.

Cognitive learning outcomes

The learning process based on the cognitive perspective has been extensively addressed in a current study by Laks (2015). According to him, learning is a process comprising of three phases; 1) experience/information, 2) storage as knowledge or skill and; 3) performance or behavior. It begins with information reception and acquisition experience. The next phase entails information storing as knowledge and transformation of such knowledge in a specific subject matter. In this phase, the retrieval and indexing of stored information are facilitated in the brain and memories are produced as a result. The experience and the processes of memory are interconnected with each other and specifically, the memory gets indexed by the learning process within a robust textual context of the experience. In other words, when new things are learned, they get connected through interactions and inter-linkage with previously experienced interactions. Consequently, performance and behavior are interrelated with both prior processes (Laks, 2015). To investigate the significant difference in the cognitive learning outcomes in the learning modes and motivation, therefore, we developed the following null hypotheses:

- H_{04}:There is no significant difference in the performance achievement in the mAR-mode and non-mAR mode.
- H_{05}: There is no significant difference in the performance achievement for high-motivated learners in mAR mode.
- H_{06}: There is no significant difference in the performance achievement for low-motivated learners in mAR mode.

Affective learning outcomes

Augmented reality technology pulls students' attention into visualizing a layer of information on real objects through handheld devices like tablets and smartphones (Siemens, 2014). Affective learning outcomes in relation to this include the perceptions of students of their satisfaction, attitude, respect and appreciation for their experiences during the learning process (Klopfer et al., 2010). This paper highlights perceived learning effectiveness, satisfaction and self-efficacy as a group in the affective learning outcomes.

Perceived learning effectiveness

Perceived learning effectiveness is defined as the prospective user's computer acceptance behavior. It also provides the probability that using a specific computer application will increase their performance (Davis et al., 1989). To measure this subjective probability, there are four metrics, i.e. perceived usefulness, perception of use, interactive learning and behavioral intention. These metrics understand the extent, importance and implications of formal and informal learning with respect to reinforcement and learning speed, support for higher-order cognitive progresses and fortification of beliefs, as well as perceived in learning environment (Delanghe, 2001; Shawn Green &*Bavelier*, 2003; de Freitas and Levene, 2004; de Freitas, 2004; Klabbers, 2003).

Satisfaction

Satisfaction on the other hand measures the system quality, information quality and user satisfaction's individual or organizational impacts (DeLone et al., 2003). The satisfaction construct has dimensions, which are learner interface and content personalization (intention to use). To analyze an accurate measurement for this conceptual framework, quality of delivery will be taken into consideration in the satisfaction scale. Based on Ocker and Yaverbaum(1999), satisfaction is broken into several dimensions such as "learning, solution quality, solution content, and student perceptions regarding satisfaction with the learning experience". The achievement of these dimensions may increase the quality of learning outcomes.

Self-efficacy

While, self-efficacy symbolises people's opinion on how a learner is capable and competent in organising and executing the required actions (Piccoli et al., 2001). In this paper self-efficacy refers to the learning activities using mAR technology and how students will be able to cooperate and control the self-centred learning environment. Self-efficacy consists of perceived self-efficacy, learning strategies, conceptualization and control. It refers to the mAR learning activities and the ability of students to interact with and control the self-centred learning environment. It is also to investigate the confidence level of the students in learning using mAR. It is one way to determine whether the self-esteem will be built and nurtured through mAR learning. Additional, the use of mAR has the potential to boost learning activities into a motivated learning environment. In pursuance of the research, the following null hypotheses were developed for testing:

- H_{07}: There is no significant difference in the learning outcome between students in mAR mode and those in non-mAR mode.
- H_{08}: There is no significant difference in the learning outcome for low-motivated learners in mAR mode.
- H_{09}: There is no significant difference in the learning outcome for high-motivated learners in mAR mode.

III. MATERIAL AND METHODS

For the purpose of the present research, learning activity is considered as actions and movements of the learner during the learning process that has to be taken into consideration.

Participants

The sample population for this research was higher level Biological Science students, aged between 17 to 28 years old. They were selected based on the current enrolment at public and private universities in the Central Region part of Malaysia. This sampling decision was made based on the aforementioned problem statement. Three universities were selected from the list using the simple random method. The random sampling was implemented because "*sample does not have known probability of being selected as in convenience or voluntary response surveys*" (PennState, 2015).The selected universities were Universiti Putra Malaysia (UPM) in Serdang, Malaysia; UniversitiTeknologi MARA (UiTM) in Shah Alam, Malaysia, and Cyber University College Medical Sciences (CUCMS) in Cyberjaya, Malaysia. The students were in the field of science, studying any biology-related course or unit. For each selected university, two or four classes were determined as suitable for the experimental criteria in terms of their learning materials. For instance, the practical dissection sessions used multimedia computer technology and were equipped with museum laboratories.

Data collection tool

The quasi-experimental study method was employed in this research, allows data collection either from small or large group numbers of tertiary education level students. Data were collected from the survey technique that uses questionnaire as the instrument in pre/post-test sessions.

Human Anatomy in Mobile-Augmented Reality (HumAR) Application

A prototype of mobile-AR for a specific syllabus such as body anatomy topic was built as a module of the experimental application. This prototype application is called Human Anatomy in Mobile-Augmented Reality (HumAR), was utilized as one of the mechanisms to collect data from the mAR group of students (Figure 2). HumAR assists students in completing tasks in pre-test and post-test quiz.

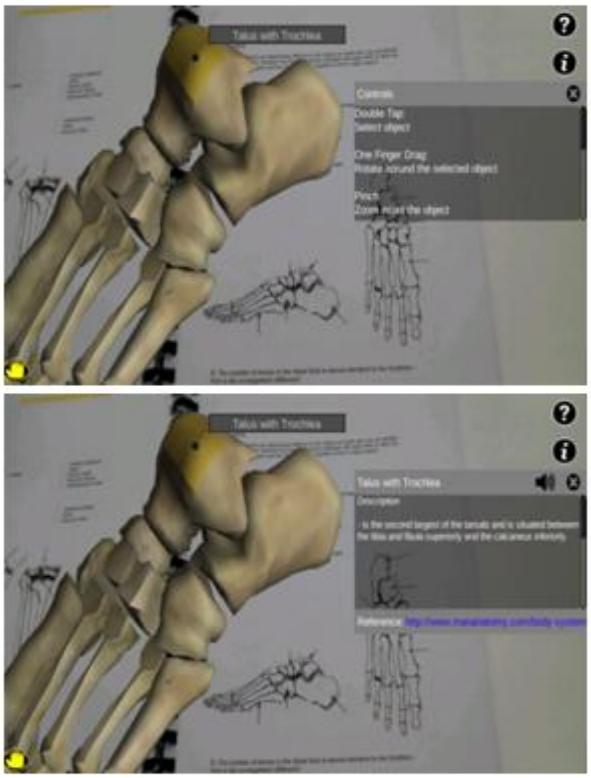

Fig. 2 Prototype HumAR interface

Grouping

The participants were randomly divided into two learning modes. One group was based on mAR-mode (HumAR) and another group was non-mAR mode (CLM). The classes were randomly chosen and all participation in this research was on voluntary basis.

Each cohort in each university had the same experimental HumAR and CLM groupings. It was thought that multiple respondents from three different universities would enhance the validity of the study and minimise common source bias. Procedures of data collection and experimental session were carefully kept the same to avoid any misconception or gap between universities. There was insufficient research on the placebo effect in some of the research theses, especially when dealing with technology interventions in educational settings. Nonetheless, the placebo effect, an issue that was raised in the experimental method in social science, had been taken into account during the design of the experiments. The following steps were taken into consideration to avoid this issue:

- Consultation with academic, technology and course (Human Biology) experts.
- Advice from the experts through discussions regarding the research design.
- Random separation of subjects into treatment and control groups. Bengston&Moga (2007) have similar opinion that supports the random assignment of subjects to ensure the two groups are equivalent to avoid placebo effects.

- In terms of lack of awareness among all participants with the technology intervention objective, questionnaires used were the same for all participants in the class or lab. At this introductory stage, no group was split, and no participant had prior exposure to HumAR. A relevant body of research is concerned with the occurrence of condition learning in the absence of awareness (Williams &Podd, 2004).
- Anonymity of participants in regard to the use of HumAR.

Pre-test

We conducted pre-test and post-test evaluations. The pre and post-tests were carried out to measure changes in knowledge, behaviors and attitudes of the participants in the learning environment, which can address and reduce the issue of low retention of information by using HumAR. The one-hour focus group sessions were one week apart, so the total duration hours of the focus group sessions were a maximum 2 hours. In a fifteen minute pre-test organized in the first week, students were given a question to answer within 15 minutes without access to any information material or reference books. Thereafter, the students continued with their class activity for 25 minutes. Next, they were given the questionnaire related to the current learning method.

Post-test

The post-test was conducted in the following week. A one-week gap between pre-test and post-test was instituted to minimise the chance of sensitivity of the pre-test threat (Christensson, 2010). During this post-test, the participants were split into two groups. The first group was a control group (non-technology). This group was able to use the physical human skeleton as a resource for their learning activity. In this learning activity, the students were taught for 40 minutes and were required to complete the post-test questions and survey questionnaire at the end of the session.

The second group was exposed to mAR-technology in their learning activity. The students were given training in the use of the prototype HumAR application prior to the commencement of the learning activity. Similar procedures were used with the control group. The learning activity lasted 40 minutes, after which, the post-test questions and final survey questionnaires were distributed to students for completion.

Data analysis

This research is divided into two parts of analyses. The first part analyzed the results obtained from the sample's descriptive statistics and the statistical analysis results based on the developed hypotheses. The analyses were taken out through a several statistical techniques such as the descriptive statistical analysis, the independent sample t-test and paired-samples t-test and Analysis of Variance (ANOVA and Multivariate Analysis of Variance (MANOVA).

While the second part enumerates, analysis of the model fit through Structural Equation Modeling (SEM-AMOS) approach. The stages involved; measurement model via exploratory factor analysis (EFA), confirmatory factor analysis (CFA) and discriminant validity. Finally, the model fitness has been analyzed through model indices for structuring model.

IV. RESULTS ON THE EFFECTIVENESS OF LEARNING USING MAR LEARNING MODE

Demographic statistics

The final sample totaled 260 students. The students were equally randomly divided into two groups. One group was based on mAR-mode (HumAR) and another group was non-mAR mode (CLM). An even number of 130 has been divided into both groups. The participants' ages ranged from 18 to 28 years old. The mean age of the participants was 19.65 years old. There were 22.3% (29) male and 77.7% (101) female in CLM group, whilst, 30.8% (40) male and 69.2% (90) female in HumAR. Overall, the sample consisted of 26.5% (69) male and 73.5& (191) female students. Students without experience in human anatomy when they were in secondary school accounted for 51.9% (135 students) of the total respondents, while those who had experience accounted for 48.1% (125 students). The same procedures of data collection or experiment session was organized thoroughly. Therefore, there was no bias or gap between these groups.

The effectiveness of learning using mAR/non-mAR learning mode

Cognitive learning outcomes

To determine whether the groups' namely the mAR mode group where the students were exposed to mobile-AR-based group, and the non-mAR mode group, where the students were exposed to current learning classroom practices, differ in the scale of performance achievement, we employed the independent sample t-test. From the statistics result, the mean and standard deviation of scores for the dependent variables between the participating groups are presented in the Table 1. The mAR mode group obtained performance achievement mean score of (M=22.207, SD=5.226) that was greater compared to the score obtained by the non-mAR mode group (M=17.200, SD=6.992). Significant differences were found between them from the independent t-test based on the significance level of 0.05, the difference being (t=-6.541, df 258, p=.000<.05).

Table. 1 Result of independent t-test on performance achievement in mAR and non-mAR mode

	Group	N	Mean	Std. Deviation	t	df	Sig
Performance Achievement	Non-mAR mode	130	17.200	6.992	-6.541	258	.000
	mAR mode	130	22.207	5.226			

The fundamental assumption of homogeneity of variance (Table 2) that underplays ANOVA in this case was violated and homogeneity of variance was not met showing that the variance of post-test scores of performance achievement between the groups was not the same based on their high

and low motivation. Therefore, an alternative option was implemented, which is the Welch's test (employed in inhomogeneous variance) as recommended by Moder (2002).

Table. 2 Results of Welch Test in the Performance Achievement

	Statistics	df1	df2	Sig
Welch	*10.472*	*1*	*191.430*	*.001*

Table. 3 Results of ANOVA for between-subjects in high and low motivated students

Source	Dependent Variables Post-test	Type III Sum of Squares	df	Mean Square	F	P
Within Group	Perform Achievement	372.802	1	372.802	8.675	.004
Between Group	Perform Achievement	11087.394	258	42.974		
Total	Perform Achievement	11460.196	259			

The results of ANOVA (Table 3) then revealed a significant difference in the post-test scores in terms of performance achievement of high motivated students (M = 21.500, SD = 5.451) and low motivated students (M = 18.905, SD = 6.987), with the Welch test result 10.472, p=.001<.0.05). Moreover, the ANOVA result showed a difference in terms of performance achievement between highly motivated students and low motivated students (F = 8.675, p = .004<.0.05). Highly motivated students obtained higher performance achievement scores compared to low motivated students.

Affective learning outcomes

Based on Table 4, the mAR mode group obtained learning outcomes mean score of (M=4.081, SD=.443) that was greater compared to the score obtained by the non-mAR mode group (M=3.653, SD=.440). Significant differences were found between them from the independent t-test based on the significance level of 0.05, the difference being (*t*=-7.819, df 258, *p*=.000<.05).

Table. 4 Independent Sample t-test Results for Group Differences on Learning Outcomes

	Group	N	Mean	Std. Deviation	t	df	Sig
Learning Outcomes	Non-mARmode	130	3.653	.440	-7.819	258	.000
	mARmode	130	4.081	.443			

ANOVA was conducted with learning outcomes as the dependent variable. The fundamental assumption of homogeneity of variance assumption that underlies ANOVA was not met. Stated clearly, the variance of post-test scores of learning outcomes for the two groups with high and low motivation differed. Therefore, Welsch's test is the other option for such situation (Moder, 2010). The results showed significant differences in the post-test scores for highly motivated students (M = 4.214, SD = .310) and low motivated students (M = 3.941, SD = .518) in terms of learning outcomes with a Welch test (Table 5) value of (13.153, p=.000<.0.05). Later, the ANOVA test results (Table 6) showed significant differences when it comes to learning outcomes between highly motivated and low motivated students (F = 13.346, p = .000<.0.05) indicating that highly motivated students scored greater post-test scores compared to low motivated counterparts in learning outcomes.

Table. 5 Results of Welch Test for the Learning Outcomes

	Statistics	df1	df2	Sig
Welch	*13.153*	*1*	*102.539*	*.000*

Table. 6 Results of ANOVA for between-subjects in high and low motivated students

Source: Post-test	Dependant Variables	Type III Sum of Squares	df	Mean Square	F	P
Within Group	Learning Outcomes	2.418	1	2.418	13.346	.000
Between Group	Learning Outcomes	23.195	128	.181		
Total			129			

P<.05

V. RESULTS ON THE THEORETICAL MODEL OF HOW MAR ENHANCES THE AFFECTIVE LEARNING

Measurement of model through Exploratory Factor Analysis (EFA)

Data analysis was conducted with the help of component analysis with Varimax rotation. Prior authors like (Tabachnick et al., 2001), Steven (2002), Hair et al. (1998), and Nunnally (1978) had established criteria for the determination of factor structures. The first criterion is to include the components having Cronbach's alpha value of 0.70, Kaiser-Meyer-Olkin (KMO) value of 0.50, and Bartlett's test of sphericity of (<.05), and screen test.

Five separate exploratory analyses were carried out through Varimax rotation to measure the study constructs i.e. motivation, perceived learning, self-efficacy, satisfaction, and mAR-features. Steven (2002) presented a cut-off for statistical significance of factor loading upon which the sample size is based on. Furthermore, Steven (2002) argued that factor loading ranging from 0.29-0.38 is acceptable for 200-300 participants as samples. Nevertheless, for a parsimonious outcome to a cross-loading of 0.30 for more than a single factor, only the higher amount for every variable would be employed to determine the set of variables comprising a specific factor. Five constructs in the calibration model have been tested. The summary of measurement scales is shown in Table 7.

Table. 7 Summary of item measurement scale for variables

Variable	KMO	DF	Sig.	Alpha
Self-efficacy	.916	28	.000	.918
mAR-features	.876	10	.000	.891
Satisfaction	.884	55	.000	.885
Motivation	.871	55	.000	.854
Perceived learning effectiveness	.805	136	.000	.736

Confirmatory Factory Analysis (CFA)

Confirmatory factor analysis (CFA) was used to confirm if the number of factors and the indicators on them (loading of factors) adhere to the expectations based on pre-established theory (Garson, 1998). Hence, in this study, we conducted validity tests to determine the level to which the measurement tool measures what it is expected to measure.

Therefore, confirmatory factor analysis was performed to test the overall measures' acceptability through RMSEA, CFI, TLI and ratio χ^2 = chi. The acceptable range from these indices, the ratio should not be more than 5, the TLI should be higher than 0.80 and the CFI should also be higher than 0.80 (Kelloway, 1998; Kline, 1998; Hair et al., 1998; Hwang, 2007). According to Table 8, all variable indices fall within the ample range stated above.

Discriminant Validity

Table 9 presents the correlations between the model's variables. All the constructs appeared to have satisfactory discriminant validity as estimated by the correlations that were not significantly high. In this regard, correlations of around 0.90 should not be ignored as it is a great cause for concern (Pallant, 2005). If the researcher encounters such a case, he should consider dropping one of the strongly correlated variable pair or combining them into one measure (Pallant, 2005). In this research, the entire variables had low to moderate relation with other variables, supporting the fact that the relations of all values failed to achieve the recommended value as presented in the table.

In addition to the above, past studies (Ruehlman et al., 2005) stated that model fit can be enhanced through co-variation between the indicators. Also, the integration of covariance between two items would enhance the model fit (Byrne, 2010) and thus, by using the covariate between each two items, the results showed good data fit.

Moreover, the following values were found; CFI of 0.966, TLI of 0.960, RMSEA of 0.050, a ratio of 1.635 (less than 5), indicating that the entire values based on the criteria established, provided a sound data-model fit. It was also evidenced that discriminant validity is met and we decided to accept the identified construct and the model to have achieved discriminant validity.

Analysis of the structural model

After the measurement models were assessed, the next step involved was the evaluation of the structural model. The hypothesised model was evaluated on the basis of two conditions, i.e. overall goodness-of-fit as well as the feasibility and significance of the estimated model coefficients. A model is acceptable if it meets the acceptable fit, contains valid paths, and explains a moderate-high proportion of the dependent variables' variance. Table 10 displays the standardised loading, C.R., and the goodness-of-fit of the hypothesised model. The table presents the standardised loading for every path of the dependent variable that is included in the model. The entire estimates fell within an acceptable range, with a correlation coefficient that is less than one, no negative covariance, and in the directions that are expected. On the basis of the level of 0.05, all C.R. obtained values that were lower than 1.96, except for one value, indicating the significance of the estimated coefficients.

The goodness-of-fit measure initially showed a poor fit model and thus, two indicators as suggested by Ruehlman, Kanoly, Newton & Aiken (2005) were employed to enhance model fit. As mentioned, this was supported by Byrne (2010), stating that the covariance between two items would enhance model fit and thus, by utilising the covariate between each item as presented in the model. In this case, the outcome reflected a good data fit. The goodness-of-fit measure showed an acceptable model fit. The model fit is indicated by the following, chi-square goodness-of-fit of 67.494, normed chi-square of 1.976, TLI of 0.954, and RMSEA of 0.061. Thus, the goodness- of-fit measures showed good model fit to the data (see figure 3). Moreover, the mAR features significantly antecedes learning outcomes (beta = .14, p<.05) but not motivation (beta = .65, p>.05). According to the results, motivation did not signify an antecedent variable to the learning outcomes (beta =.10, p>.05).

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Table. 8 Summary of overall measurement model fit for all constructs

Variable	RMSEA	CFI	TLI	RATIO χ^2 = chi	Composite reliability	Variance extracted
Self-efficacy	.067	.982	.973	2.161	.75	.86
mAR-features	.076	.989	.979	2.502	.79	.80
Satisfaction	.068	.972	.964	2.213	.89	.74
Motivation	.080	.961	.950	2.651	.80	.68
Perceived learning effectiveness	.052	.966	.959	1.710	.79	.76

Table. 9 Results of Implied Correlation between the Variables in the Model

	1	2	3	4	5
Self-efficacy	1.000				
mAR-features	.177	1.000			
Satisfaction	.108	.151	1.000		
Motivation	.450	.118	.264	1.000	
Perceived learning effectiveness	.754	.198	.130	.534	1.000

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table. 10 Standardized Loading, C.R. and goodness-of-fit Measure for the Hypothesized Model

Hypothesis	From	Path to	Standardized Loading	C.R.	Sig.
H_{01}	mAR Feature	Learning Outcomes	.14*	2.019	Yes
H_{02}	mAR-Feature	Motivation	.65	1.367	No
H_{03}	Motivation	Learning Outcomes	.10	1.672	No
Goodness of fit Measures					
Chi-Square ($\chi 2$)	67.694				
Normed Chi-square	1.976				
CFI	.971				
TLI	.954				
RMSEA	.061				

VI. DISCUSSIONS

This paper's main objective is to determine specific ways where the mobile-augmented reality (mAR) is able to influence learning outcomes. The study examined the effectiveness of learning through the use of mAR and its development process. Finally, it proposes a theoretical model to analyse the way mAR improves learning and performance outcomes.

A comparison was made of the impact of the two learning modes, mobile-Augmented Reality-Based Learning Environment/mAR mode and the current learning method/conventional classroom learning method/non-mAR mode, upon learning outcomes with reference to learning effectiveness, self-efficacy, satisfaction, and performance achievement. Furthermore, the potential impact between the learning modes, the mAR features, as well as the level of learner motivation was investigated through a theoretical model framework, specifically developed using the required dimensions and antecedents of mAR effectiveness.

Learning through computer-based technology, particularly when it comes to science subjects has been evidenced to be effective.

Nevertheless, the majority of researchers evidenced the ease of use of multimedia instead of focusing on its effectiveness in information retention, as required by the students. Many prior studies included psychological student learning styles and learning process in learning with both the VR and AR technology but failed to address the mAR. As such, the studies' findings require replication in the mAR environment.

The effects of mAR learning mode

The results showed that the average of pre-tests is similar, indicating that initial knowledge of the subject matter was consistent and participants has similar abilities prior to one of the groups being exposed to the subject unit. The percentage difference was shown to be positive for both groups in the post-test phase. Moreover, that difference was statistically significant. Upon comparison the result of the mAR group's learning achievement was significantly higher, with a doubling in increment from the CLM or non-mAR group.

This result is in alignment with findings by Chiang et al. (2014) who reported that mAR exposure results in learning benefits in areas of attention, confidence, and other relevant dimensions.

We concluded that mAR was among the best learning methods in solving problems that occur within and outside the classroom environment, particularly when it comes to memorisation. mAR learning mode also effectively influenced students' memory. Students showed higher scores in comparison to their CLM/non-mAR counterparts; a common phenomenon explained and proven through the cognitive load theory (Sweller, 2001). In regards to this, cognitive load according to Young et al. (2014), is the human memory that includes the subsystem of sensory, working memory as well as long-term memory.

A significant relationship was found between learning modes and the student groups (mAR group and non-mAR group). The first question of the study reads, "Are there any significant differences in the learning mode on learning outcomes (perceived learning effectiveness, self-efficacy and satisfaction)?" For a collective outcome, the predictors were combined into a single one and it is used as a proxy for learning outcomes. Based on the results of the analysis, learning modes positively influenced learning outcomes, indicating important divergences in learning model on learning effects – thus, the hypothesis null proposed is not supported. Specifically, every construct was identified and analysed on its own to determine the construct that had the highest contribution. Both perceived learning effectiveness and self-efficacy was found to have the highest significant difference while satisfaction was demonstrated negative result for both learning groups.

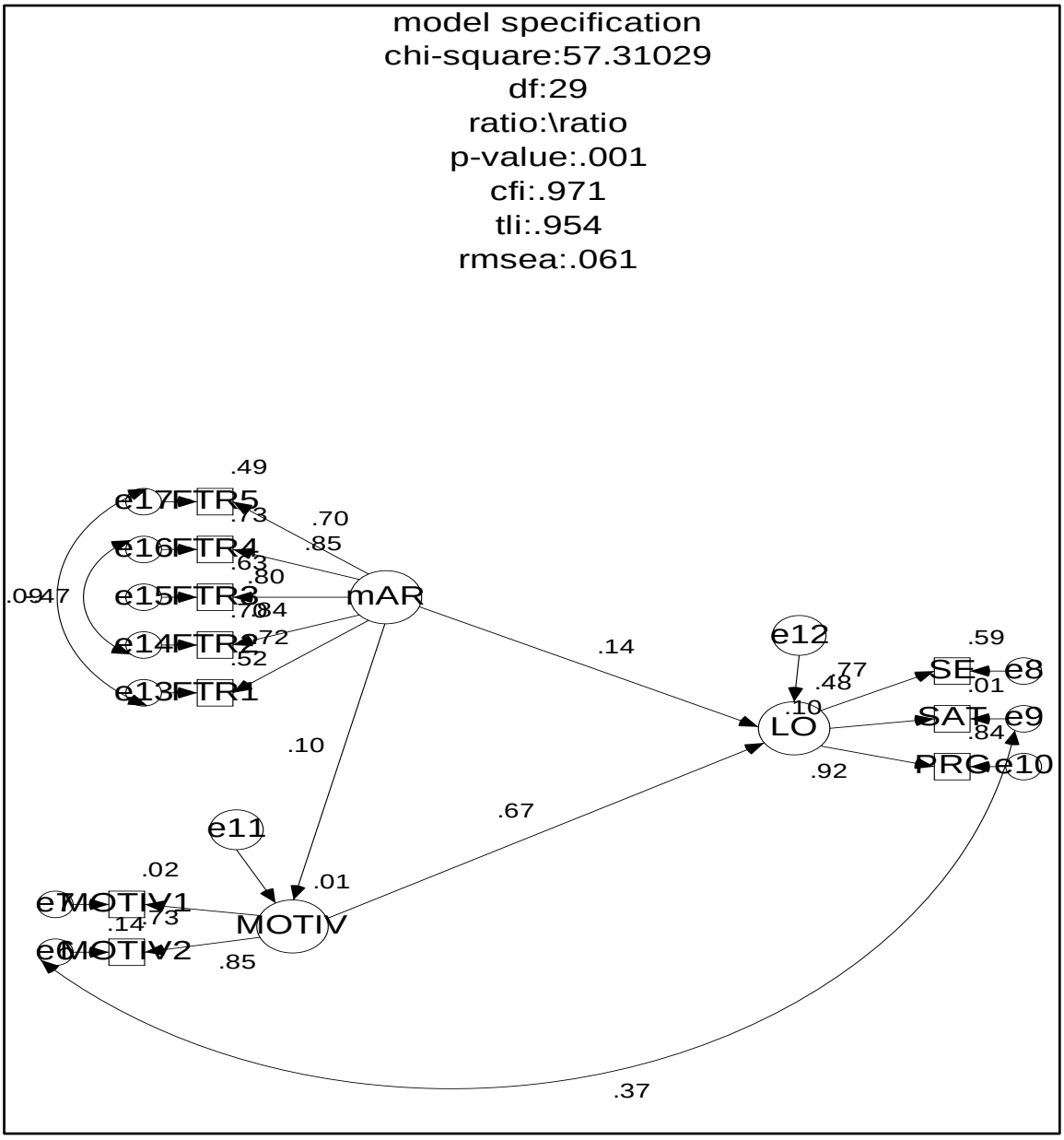

Fig. 3 Standardized loading path for structural models

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The effects of mAR learner's motivation

In this section, the differences in motivation level and its impact on performance achievement and learning outcomes are discussed. The level of motivation is categorised into low and high motivation. Motivation is described as the movement and desire to do something where an individual who is not inspired to act is therefore called unmotivated, while one who is motivated or activated towards the action is deemed to be motivated (Ryan et al., 2000). The primary difference was found to be in the form of intrinsic motivation. This motivation is considered to be doing something that is inherently interesting and enjoyable, whereas extrinsic motivation is about doing something which results to a discernible physical result.

Judging from the experimental results of cognitive learning outcome, a significant difference exists in the motivation level between the two groups. The results specifically showed evidence of high and low levels of motivation, with the former returning a mean of over 19.00 and the latter lower than 19.00. Higher motivation level in students was taken to indicate a greater impact on learning via the use of mAR, where high-motivated students outperformed their lower motivated counterparts. In addition, we demonstrated that students using the augmented reality-based mobile learning approach displayed a greater motivation level in terms of attention, confidence, and relevance dimensions in contrast to those who were exposed to current based learning methods. Specifically, learning through mAR facilitates the focus of students in examining the human anatomy characteristics as neither frequent reference to the supplementary materials nor waiting for turns were required from the lab instructors to provide an explanation of the subject matter. In other words, learning with the help of HumAR highlights the detailed descriptions of bone or joint placements.

The students also revealed that with mobile AR, they could access their learning materials in a timely manner, notwithstanding their real-world locations and as such, they proactively understand the learning content that was displayed by the learning system and their real-world learning objects in the environment. The facility allowed students to learn with ease and therefore lead to increase in the motivation level for learning. In this regard, the importance of diversity in the materials utilised in class was among the factors that motivated the students (Rocío et al., 2015). Rocío et al. (2015) showed that students were encouraged to improve learning opportunities through the use of new technology devices in the classroom environment – sleek, portable, interactive, and informative in comparison to the methods offered by the traditional learning practices.

Furthermore, Ryan et al. (2000) detailed motivation level (high or low) to be either extrinsic and intrinsic motivation. Intrinsic motivation is a significant phenomenon for educators where learning and achievement can be motivated or undermined by practices employed by parents and teachers (Ryan et al., 1991). Intrinsic motivation leads to both optimum learning and creativity. More importantly, this type of motivation has the opposite connotation to that of extrinsic motivation. Extrinsic motivation details the factors and forces that motivate or hinder learning. Nevertheless, what is equally relevant is that the emphasis of current reviews is extrinsic motivation although past studies recorded it in a more negative form (Hassanzadeh et al., 2014; Lemos, 2014; Zhang et al., 2015).

While, based on the affective learning outcome's results, mAR is effective in motivating the affective behavior of the students, their motivation level and their perception of their learning experience. In other words, the greater the learning effectiveness perception in the mAR learning mode, the more mAR is considered as an educational tool that improves learning, makes it interesting and motivating. Mobile AR technology assists students in understanding the fundamental concepts of the learning material, identifying the core learning issue, as well as making conclusions and generalizations. In addition, according to the findings, positive behaviors of learners can considerably influence their level of motivation and their behavioral intention towards learning. It can therefore be concluded that learning through mAR develops the students' confidence levels and they learn easily. According to the survey results items of "*I intend to use mAR to assist my learning*" and "*I intend to use mAR content to assist my learning*" obtained a standard deviation higher than 0.8 indicating that perceived ease of use and perception of use are significant predictors of learner's behavioral intention towards mAR use while learning. This finding is aligned with those reported by prior studies that attempted to compare motivation in the learning outcomes between a traditional learning environment and learning via mAR technology (Albrecht et al., 2013; Chiang et al., 2014; Juanes et al., 2014).

Using the mAR method of learning and the prototype HumAR to assist learning, the students provided positive responses to items including "*I think HUMAR is very useful for students nowadays, who use technology, so I suggest to expose students to this application as it is useful and through it memorization is easier*", "*Overall this is a good effort given by authority to enhance/improve the students' understanding, hopefully, it can be expanded to other subjects such as biochemical, microbiology, parasitology, reproduction and genetics*", "*HUMAR is highly recommended to all anatomy students as it can help them in understanding anatomy faster and easier*", and "*I really enjoy using this application*". These feedbacks were revealed between learner's motivation level and self-efficacy, where self-efficacy is considered to be the perceived capability of the individual to perform the required tasks and to realize goals (Bandura, 1997). In the experimental session, the students were given tasks, where each of them was requested to match and provide a description of the non-articulated lower limb parts. Lower limb parts comprise of pelvis, femur, tibia, fibula, tarsus, metatarsals, and phalanges. The result shows the task was successfully completed and immaculate. Therefore, it is a positive influence on the students' capability of completing tasks, and the increase in their motivation level. In addition, the students found the learning activities under mAR-based learning as meaningful and the learning experience through AR technology as interesting. These promising learning perceptions are crucial for a positive learning outcome.

Theoretical causal path

The null hypothesis posited that mAR-features do not significantly fit to the learning outcomes in the model framework of mAR effectiveness but results showed that the hypothesis is rejected. On the basis of the results, mAR features directly and significantly antecede the learning outcomes, a finding that was reported by researcher and justified on the premise that mobile learning with technology can improve learning outcomes. In a recent study, Baran (2014) highlighted the strike down of learning with mobile technologies from prior authors and attributed them to the challenges that teachers face when adopting mobile technologies, the pressure to provide teachers with technology, and the needs of a technology education program (Sansone, 2014; Shuck et al., 2013; and Newhouse et al., 2006). Up until this point in the discussion, the result of this study showed that mAR features significantly influenced learning outcomes, where the results showed it to be an antecedent factor in the interaction latent relationship. The positive relationship is supported with perceived learning effectiveness, self-efficacy and satisfaction. The result can be attributed to the perceived enjoyment (Lee et al., 2015) experienced in the mAR-based learning environment. Furthermore, the responses gathered from the questionnaire survey revealed that the students appeared to enjoy the mAR-based learning's ability to provide 3D realistic images, image smoothness, 360° view, the manipulation of the object and the improvement of real time understanding. In turn, the motivation level and enhanced learning experience affect the students' ability to realize their learning aims in their subjects and this could result in a robust self-centered learning premise. Jamali et al. (2015a) also showed that the majority of the students in their study unanimously agreed that the above feature is required to help their learning surroundings and that the angle view change option motivates them and incites their interest to learn.

On the other hand, motivation was found not as an antecedent for learning outcomes, although there is a direct effect of motivation on affective learning outcomes. Motivation is not the most significant predictor of affective learning outcomes, although the mAR mode was reported to have higher motivation level. It can therefore be concluded that motivation is an independent aspect of affecting learning outcomes as revealed by Briggs (1984) but rejected by Martin and Briggs (1986) and Tennyson (1992).

VII. CONCLUSIONS

In conclusion, the findings confirmed that AR technology via mobile could be leveraged and used as an optimum learning tool exemplifying the use of technology in an educational context. Based on the result, it is proven that mAR is an aided technology that assists in students' learning of the anatomy subject. With regards to the model outcome via the analysis of goodness-of-fit, all the results confirm appropriate and good fit. The results also showed a positive causal path from the mAR features determinant. In a sense of information retention and enhanced learning outcomes. The mAR is significant in the educational environment as it facilitates the understanding of students by supporting abstract ideas during the courses, and enabling the students to learn in a limited time period. Therefore, the present research findings contribute to the literature and dedicated to the issue of the effectiveness of mAR application in the context of the learning environment.

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