The Motivations of Virtual Learning For Artificial Intelligence Learner In Egyptian Higher Education

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Abstract:

Hybrid Learning (HL) is becoming increasingly prominent in Egyptian higher education, but there remains a number of barriers to HL that must be carefully considered in applying, adapting, and accepting this kind of learning method. This paper seeks to analyse the views of learners towards VL according to Self-Determination Theory (SDT), and identifies the motivations for adapting HL in Artificial Intelligence (AI) in an Egyptian higher education establishment. SDT is approached from a different perspective and the relationship between Intrinsic Motivation (IM), Extrinsic Motivation (EM) and Amotivation (AM) is analysed and related to the motivations of the hybrid learning approach. A self-administered questionnaire was used to collect data from 491 undergraduate learners who were geographically widely spread around the Colleges of Artificial Intelligence (CAI) at the Arab Academy for Science, Technology & Maritime Transport (AASTMT) in Egypt: Al-Amien, Matrouh. This present study examines Egyptian undergraduates’

IM, EM, AM, Autonomy, Structure, and Involvement with respect to the adaptation of the BL method. The findings were coded and fed into statistical package for Social Science (SPSS^{24}) and Analysis of Moment structure (AMOS^{24}) for data analysis. Confirmatory Factor Analsysi (CFA) was used to confirm the dimensions under study are verified by SDT, as Structural Equation Modeling (SEM) was applied to find the effect of the SDT on artificial intelligence students' motivation in Egypt. The research contributes to the application of SDT within the field of HL through an analysis of the views of lecturers towards the motivations that virtual learning offers to Artificial Intelligence (AI) educators in Egypt. Finally this study suggests that the CAI at AASTMT should pay more attention to IM, EM and AM in the work environment. The variation in responses from different levels of the learner indicates a need for AASTMT to provide the educators with development opportunities in order to successfully integrate HL into their AI Education programmes.

Keywords: Hybrid Learning, Self-Determination Theory and Artificial Intelligence Education.

دوافع التعلم الافتراضي لمتعلم الذكاء الاصطناعي في التعليم العالي المصري

الملخص:

أصبح التعلم الهجين (HL) بارزًا بشكل متزايد في التعليم العالي المصري، ولكن لا يزال هناك عدد من العوائق التي تحول دون HL والتي يجب مراعاتها بعناية في تطبيق وتكييف وقبول هذا النوع من أساليب التعلم. تسعى هذه الورقة إلى تحليل آراء المتعلمين تجاه VL وفقًا لنظرية تقرير المصير(SDT) ، وتحدد الدوافع لتكييف HL في الذكاء الاصطناعي (AI) في مؤسسة التعليم العالي المصرية. يتم التعامل مع SDT من منظور مختلف ويتم تحليل العلاقة بين الدافع الداخلي (IM) والتحفيز الخارجي (EM) والتحفيز (AM)وترتبط بدوافع نهج التعلم الهجين. تم استخدام استبيان ذاتي الإدارة لجمع البيانات من ٤٩١ طالبًا جامعيًا منتشرين جغرافيًا على نطاق واسع حول كليات الذكاء الاصطناعي (CAI)في الأكاديمية العربية للعلوم والتكنولوجيا والنقل البحري (AASTMT) في مصر: الأمين، مطروح. تبحث هذه الدراسة في الطلاب الجامعيين المصريين IM" و EMو AM و AM و Autonomy و Structure و Involvement فيما يتعلق بتكييف طريقة .BL تم ترميز النتائج وإدخالها في الحزمة الإحصائية للعلوم الاجتماعية (SPSS24)وهيكل تحليل اللحظة (AMOS24) لتحليل البيانات.

تم استخدام العامل التأكيدي Confirmatory Factor Analysis (CFA) لتأكيد أن الأبعاد قيد الدراسة يتم التحقق منها بواسطة SDT، مثل نمذجة المعادلة الهيكلية (SEM) تم تطبيقه للعثور على تأثير SDT على دافع طلاب الذكاء الاصطناعي في مصر. يساهم البحث في تطبيق SDT في مجال VL من خلال تحليل آراء المحاضرين تجاه الدوافع التي يقدمها التعلم الافتراضي للذكاء الاصطناعي أخيرًا، تشير هذه الدراسة إلى أن CAI في AASTMT يجب أن تولي مزيدًا من الاهتمام لـ IM و EM و AM في بيئة العمل. يشير التباين في الاستجابات من مختلف مستويات المتعلم إلى الحاجة إلى AASTMT لتزويد المعلمين بفرص التنمية من أجل دمج HL بنجاح في برامج تعليم الذكاء الاصطناعي الخاصة بهم.

الكلمات المفتاحة : التعلم الهجين ونظرية تقرير المصير وتعليم الذكاء الاصطناعي.

1. INTRODUCTION

Education has become a commodity which individuals seek to invest in for their own personal gain, to ensure fairness of opportunities, and as a way to a better future life (Davies, 1998). Artificial intelligence is one of the most disruptive innovations in education, and the topic has attracted the attention instructors and learners. Artificial Intelligence (AI) is being applied in various fields, including education (González-Calatayud *et al.*, 2021), especially in medical-health case sector. Educators are now faced with a selection of teaching methods to choose from, such as virtual, traditional face-to-face learning or virtual learning (McCutcheon *et al.*, 2015; McCorduck, 2004). The development of Information and Communication Technology (ICT) has been accompanied by a significant increase in the opportunities for Virtual Learning Environments (VLE). In the traditional face-to-face learning setting, learners have become more interested in virtual learning environment, as it provides them with powerful supporting learning media tools.

The evolution of Self-Determination Theory (SDT) proposes that motivation has greatly influenced individual behaviour (Ryan and Deci, 2000a,b). As stated by Kirzner and Miserandino (2023) SDT shows to be an effective approach in supporting human behavioral change.

SDT goes beyond a simple focus on emotional, social, or cognitive factors that influence motivation and instead focuses on an individual's interactions with an environment and the impact of these interactions (Sanguinetti, 2024, p.11).

VLE provides learners with an alternative education that could increase the degree of motivation through the advantages offered in the hybrid learning method. Motivation has been recognised as a critical issue affecting the hybrid-learning environment. A generally accepted definition of virtual learning is as a best mixture of the traditional face-to-face learning with the use of synchronous distance education (real-time interaction) and/or asynchronous distance education (non-real time interaction) methods.

In 2015, Zuoyebang, Chief AI Architect, has quickly become one of the greatest virtual education platforms in China, where learners can take a picture of their homework assignment and receive a step-by-step clarification from a virtual instructor (Tang, 2024). Casas-Roma and Conesa (2021) and Zawacki-Richter et al. (2019) suggested that the combination of AI into hybrid learning in higher education organizations should offer a fair, accessible, and quality teaching for every part of society. Therefore, this research study investigates learners' motivations in participating in hybrid learning and their relationship to the SDT framework of Deci and Ryan (1985). It also will provide new insights into SDT and AI learners' motivations in the use of hybrid learning in Egypt by developing a research models. Research models have been previously been proposed which address how different structures can influence virtual learning outcomes (Chen and Jang, 2010; Johnson et al., 2008). On the other hand, the use of a virtual learning environment (VLE) in Egypt remains rather sporadic and there is a need to overcome the barriers of VLE to be able to adopt hybrid learning.

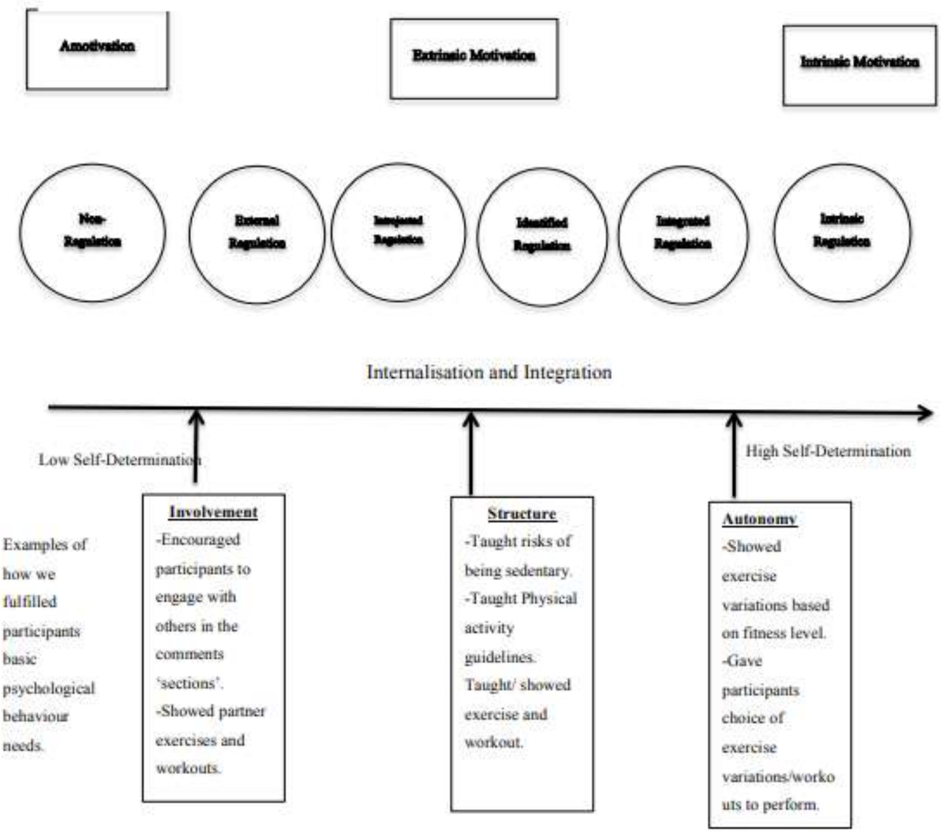
2. LITERATURE REVIEW

2.1 Self-Determination Theory of Human Motivation

Self-Determination Theory is a framework for motivation developed by Edward L. Deci and Richard M. Ryan (1985). Grolnick (2015, p.65) states, "*SDT is a theory of human motivation that addresses individuals' initiation of behaviour"*. SDT is *''one of the most comprehensive and empirically supported theories of motivation available today*" (Pintrich and Schunk, 2002, p.257). This theory is based on organismic models, which assume people are active organisms, motivated to assimilate and integrate knowledge and capacities in both their physical environment as well as social environment (Wehmeyer *et al.*, 2016). As stated by Ryan and Deci (2017) SDT has proven to predict enhanced learning, performance, creativity, optimal development and psychological wellness.

A longitudinal study of SDT by Deci and Ryan (1985) pointed out that there are three Basic Psychological Human Innate Needs (BPHIN): autonomy, structure and involvement. Chen and Jang (2010) and Sanguinetti,(2023) highlighted the classification of the three behaviours of BPHIN: first, autonomy means a sense of control. For instance, autonomy generally can be classified, such as when the instructors are enjoying the sense of freedom, happiness and pleasure in the interaction with their learners within the classroom environment. Second, structure refers to the individual feeling competent toward accomplishment of tasks and activities. Moreover, it states to the sense of developing mastery in accomplishments that are optimally challenging and that further develop one's capacities (Domenico & Ryan, 2017). Thirdly, involvement refers to the individuals who were affiliating with others. Involvement refers to the way instructors were experiencing the connection between the learners and the learning materials. SDT identifies three instructor support dimensions of classroom exercise in both traditional face-to-face and virtual learning environments: autonomy, involvement (relatedness), and structure (competence) (Bedenlier *et al*., 2020; Chiu 2021a,b; Roorda *et al*., 2011; Casale *et al*., 2023). According to educational literature studies, Ballmann and Mueller (2008) and Darner (2009) stated that the three BPHIN allow the participants to maximize academic success, to minimize the number of dropouts and to develop the learner's ability to support self-determination. SDT is a framework of the three BPHIN, and it also underlines the concept of Intrinsic Motivation (IM), Extrinsic Motivation (EM) and Amotivation (AM) (Deci and Ryan, 1985; 2000) as shown in Figure 1.

Figure 1- Self-Determination Theory of Motivation Framework by Deci and Ryan



Source: Deci and Ryan (1985; 2000)

The three types of motivation have traditionally been classified as follows: intrinsic motivation, extrinsic motivation and amotivation. First, IM refers to individual behaviour that is benefiting from the freedom of choice. This indicates that the individual experiences the freedom of happiness when accomplishing tasks and activities. IM is broken into three subtypes: intrinsic motivation to know and learn, intrinsic motivation to achievement and accomplishment, and intrinsic motivation to experience stimulation and engagement. First, intrinsic motivation to know and learn refers to the individual's desire to understand in learning things (Spittle *et al*., 2009; Vallerand *et al*., 1992; Vallerand *et al.*, 1997). It is representative of intrinsic motivation in education educational environment (Barkoukis *et al*., 2008). Second, intrinsic motivation toward achievement and accomplishment is when the individual's behaviour is undertaken to gain senses of achievement, success and capability (Spittle *et al.*, 2009; Vallerand *et al.*, 1992; Vallerand *et al.*, 1997). It focuses on the process rather than the outcome of an activity (Barkoukis et al., 2008). Thirdly, intrinsic motivation to experience stimulation and engagement relates to involvement and may be delineated (Vallerand *et al*., 1992; Vallerand *et al*., 1997). It refers as what an individual will "*experience stimulating sensations*" (Vallerand *et al*., 1992, p.601)

EM is the second type of SDT, and refers to an individual's behaviour that is benefiting from the choice of accepting and gaining tangible compensation. For example, learners are willing to acquire information and knowledge in order to obtain higher or better rewards (Breen and Lindsay, 1999). It is a "type of learning engagement that is not naturally triggered but instead, is sparked by an interpersonal or intrapersonal force" (Mikail et al., 2017, p.213).

EM is broken into four subtypes: integrated, identified, introjected and external regulations. First, the highest self-determination is the integrated regulation, as it takes place when a person engages in an activity because it has been "*fully incorporated into the self*" (Dyrlund and Wininger, 2006, p.136). Second, identified regulation is when an individual is doing something because it is in accordance with one's identity (Gillard *et al.*, 2007). Thirdly, introjected regulation refers to when an individual is doing something to avoid negative feelings or to attain high self-esteem (Vlachopoulos *et al.*, 2013). Fourthly, external regulation depends on external contingencies, for example, to attain a reward or avoid negative feedback (Müller and Palekčić, 2005). In the educational setting, EM refers to individual/learners who are motivated to follow their science courses in order to obtain their driver's license as guaranteed by their parents at the end of their high school studies are supposed to be externally motivated (Guay, 2021).

Finally, AM refers to the behaviour of individuals who are feeling a desire due to a lack of human intention, and/or withdrawals of reaching their outcomes toward certain tasks. SDT brings together many of the concerns of conceptual motivation, and it also serves as a guide for future fields of research (Meyer and Gagné, 2008). Therefore, up to now, it is a rapidly growth theory of motivation in various domains in literature, especially in virtual learning environment. Recent studies offer contradictory findings about the adaptation of the SDT in the educational environment (Ratelle *et al.*, 2007a,b).

2.2 Self-Determination Theory as Framework in the Hybrid Learning Environment

Recent developments in SDT have proven its use in the educational setting. The SDT framework has been applied at schools and universities for measuring the effect of motivation on learners and instructors.

Application of the principles of SDT to education focus on how principals and teachers can facilitate the satisfaction of the basic psychological needs of teachers and learners, respectively so that schools are places in which all parties can develop intrinsic or fully internationalized extrinsic motivation (Ryan and Deci, 2017, p. 380-381).

The development of Information Communication Technology (ICT) along with networked computing has created many innovative educational environmental opportunities (Bachman and Stewart, 2011). The advances in technology usage have supported education in benefiting hybrid learning activities for learners, and they have led to an increase in learners' levels of motivation. The future SDT studies should look more closely at how advanced technologies in virtual learning and remote classrooms motivate learner engagement and learning (Ryan and Deci, 2020). They also stated in their studies that future SDT should focus on the design of learning technology to motivate engagement and learning. Chen and Jang (2010) mentioned that motivation should be taken seriously in the virtual learning environment. Based on Butz *et al.* (2014) technology-enriched educational settings have been variously termed virtual, distributed, remote, blended learning, e-learning, web-enhanced, and internet-based. However, distance learners faced lots of different barriers until the emergence of hybrid learning.

2.2.1 Hybrid Learning Motivations for Learners

In the Higher Education literature, distance education has widespread technology integration, where administrators face technological, organisational, pedagogical, and cultural challenges in helping their institutions adapt to changes (Howell *et al.*, 2004). Hybrid learning encourages both instructors' and learners' motivation for learning and engagement (Ho *et al.*, 2006; Holenko and Hoić-Božić, 2008) and is a mixture of the motivations of e-learning and traditional face-to-face learning.

In the virtual learning environment, graduate learners are significantly more motivated in IM compared to undergraduate learners, as they have more options and therefore are more intrinsically motivated to take virtual learning. Poon (2012; 2013) highlighted that learners have motivations in mixed method learning, including improved learning outcomes, access flexibility, a sense of community, the effective use of resources, and learner satisfaction. However, there are common types of motivation for both graduate and undergraduate learners in adopting the hybrid learning concept.

2.3 Artificial Intelligence (AI) in Education Environment

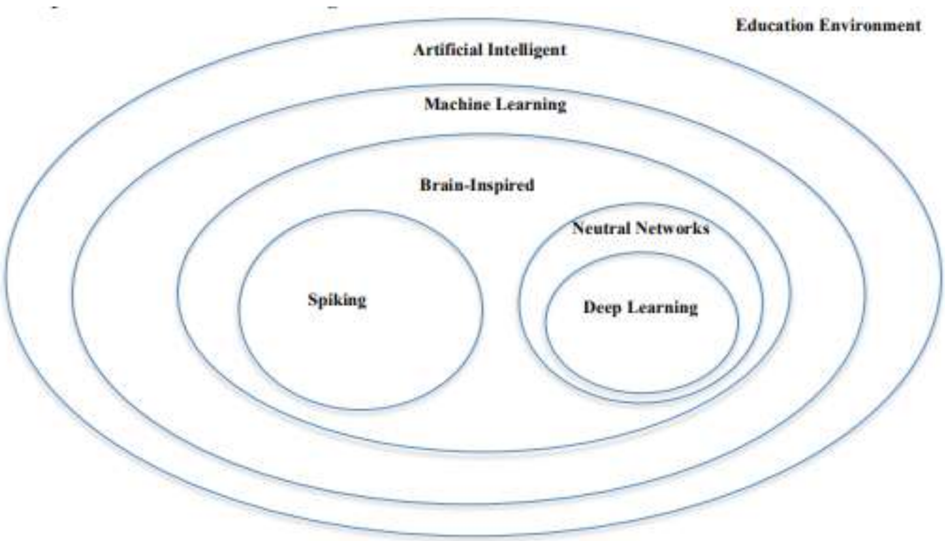
Artificial Intelligence (AI) has emerged as an essential aspect in meeting the demands of industry and government. AI is a key technological advancement that has allowed humans to replace manual work with superior mental capacities and intellectual levels in a variety of sectors (Kumar *et al.*, 2023). Dogan *et al.* (2023) revealed that AI and virtual education have different methods in terms of methodologies and scope, however, several other studies proposed to examine the literature on AI and higher education and it had a noticeable expansion after 2007.

AI has the potential to address several of the major challenges in education today, such as medical and health care sector. AI helps in innovate teaching, learning practices as well as enhance learning performance. It refers not only to face-to-face education format and smart digital learning environments, but it denotes to source of smart mechanic, personalized and automatic learning processes. AI enables innovative forms of education interaction between instructors and students. The term AI is defined as:

"an artifact able to acquire information on the surrounding environment and make sense of it, in order to act rationally and autonomously even in uncertain situations" (Cugurullo, 2020, p.3).

Machine Learning, adaptive learning, ontologies, semantic technologies, natural language processing, deep learning and AI are often used interchangeably in the literature. As shown in Figure 2, the relationship between deep learning, machine learning, and artificial intelligent in education setting (Sze *et al.*, 2017).

Figure 2- Deep Learning in The Concept of Artificial Intelligent Broad and Narrow Perspective in Education Setting



Source: Sze et al. (2017, p.2296)

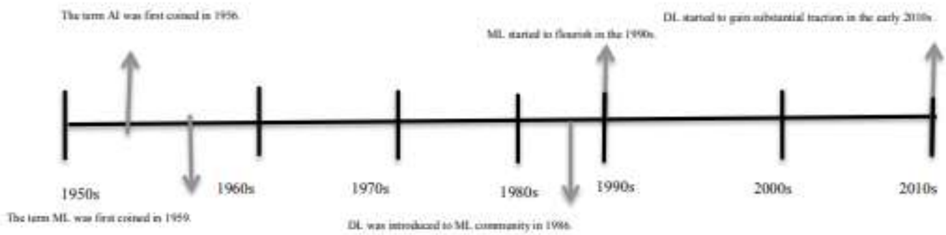
In 2021, Korteling and his colleagues stated in their study that the AI as always linked to human intelligence is a mistake, in which the similarity between human and artificial intelligence is really remarkable. Furthermost, AI functions process data and run self-learning techniques behind the scenes (Sapci and Sapci, 2020). AI as an artifact able to obtain information and knowledge on the surrounding environment and make sense of it, in order to act rationally and autonomously even in uncertain circumstances (Cugurullo, 2020).

Previous research has heightened interest in AI and the use of AI in different sectors is currently an area of dynamic study of interest (Cugurullo, 2020; Sapci and Sapci, 2020; Korteling *et al.,* 2021; Guan *et al.*, 2020). The literature research field of Artificial Intelligence (AI) began to perform as an academic discipline since 1956 (Russell and Peter, 2021; McCorduck, 2004). Papert and his colleagues (1971) stated that teaching for AI can be traced to the 1970s when LOGO programming and Turtle robot was introduced to young students.

Guan et al. (2020) pointed out that the concept of AI began to gain popularity in the 2000 to 2019, and this was due to the need for advanced technologies in education evolve over time in the industry and government fields. This is due to the paradigm shifts and emergent technological trends that are gaining prominence in the field of educational setting. However, In the 1930s, Alan Turing developed the first Turing machines for intelligent mathematical calculations that can be undertaken automatically, paving a way for the start of the AI technology

(Ali et al., 2023, p.2). However, Chen and his colleagues (2020) shows in their study of AI in educational environment the major evolutionary process of AI, from initial AI, to ML, and to the recent Deep Learning (DL), as seen in Figure 3

Figure 3-The Major Evolutionary Process of AI, ML, and DL



Note 1: Developed based on the introduction of AI
Source: Chen et al. (2020,p.5)

The literature highlighted that AI came from multiple disciplines, such as science and technology. Aiken and Epstein, (2020) stated that AI is a discipline of science and technology that allows intelligent computers and computer programs to undertake actions traditionally requiring human intelligence. Guan *et al.* (2020) and Chen *et al.* (2020) classified AI in education by different researchers as shown in Table 1.

Table 1- The Definition of AI In The Education Environment

Researchers	Year	Definition
Ross	1987	AI techniques can permit the intelligent tutoring systems itself to solve the problems which it sets for the user, in a human-like and appropriate way, and then reason about the solution process and make comments on it.
Hwang	2003	Summarized AI in education context as intelligent tutoring system that helps to organize system knowledge and operational information to enhance operator performance and automatically determining exercise progression and remediation during a training session according to past student performance.
Johnson *et al.*	2009	The authors summarized AI as artificially intelligent tutors that construct responses in real-time using its own ability to understand the problem and assess student analyses.
Nabiyev	2010	AI as the ability of a computer-controlled device to perform tasks in a human-like manner
Roll & Wylie	2016	A systematic overview of 47 articles from 1994, 2004, and 2014 in the Journal of AIED
Popenici and Kerr	2017	AI is defined as computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and use of data for complex processing tasks.
Tuomi	2018	AI being capable of learning how to think like a human.
Florea and Radu	2019	Position paper, discussing issues relating to the relationship between AI and distance education
Zovko & Gudlin	2019	Position paper, discussing issues concerning consequences brought by AI disruptive technology to students, faculty, and society.
Hinojo-Lucena *et al.*	2019	Bibliometric analysis of 132 scientific articles on AI in higher education indexed in Web of Science and Scopus databases during 2007–2017
Ocana-Fernandez *et al.*	2019	Position paper, discussing issues relating to the relationship between AI and its implementations in higher education.
Chatterjee & Bhattacharjee	2020	AI is defined as computing systems capable of engaging in human-like processes such as adapting, learning, synthesizing, correcting and using of various data required for processing complex tasks.
Garg	2020	Position paper, providing guidance for medical educators to be properly prepared for AI.

Source: Guan et al. (2020, p. 136), and Chen et al., (2020, p.3)

In the educational setting, AI became popular within academia worldwide, as it established formal degrees in AI at programmes in different educational levels, such as graduate and undergraduate levels (Tuomi, 2018; Roll and Wylie, 2016; Ocana-Fernandez *et al.*, 2019; Garg, 2023). The new generation of academic instructors are more welling and even most familiar with the use of technology in working environment, especially those who use computers during their teaching and researching (Alshboul et al., 2018). Guilherme (2019) identified that AI has been introduced to the physical and online classroom environment, and it is not a new concept for instructors and learners, as it worked on the linkage through the business executives' perspective. Dogan *et al.* (2023) and Florea and Radu (2019) examined on their studies that AI from the perspectives of virtual distance education and AI technologies help in motivated learners and instructors by the increasing use of technology in the education setting. AI has to be considered to create the workforce needed to face this new advanced technological transformation (Florea and Radu, 2019). Until now, there is a need for more development in the content of AI to meet the demands of industry and government. AI draws from multiple disciplines and an increasing number of teaching methods that demonstrate the complexity associated with it (Ng *et al.*, 2023).

In the 4th Industrial Revolution, AI is currently taking place around the world, and it is changing the lives of many individuals in both developing and developed countries (Khalifa *et al.*, 2021). In the literature studies, Arabic countries have started researching and utilizing AI within their educational systems, such as Saudi Arabia, UAE, Libya, Oman, Lebanon, Palestine, and Egypt (Haneya *et al.*, 2021). By the end of 2017, in the United Arab Emirates, artificial intelligence is at the heart of the government's strategic initiatives plan (Khalifa *et al.,* 2021). In Egypt, the Egyptian government focus on the importance of AI and the use of its applications in various fields in order to accomplish the state's goals in building digital Egypt (Gomaa and Emam, 2023; Touni and Magdy, 2020; Abass et al., 2023).

In 2019, the Ministry of Communication and Information Technology in Egypt created the National Council for Artificial Intelligence (NCAI), partnering with governmental organizations, academics, and AI businesses to form Egypt's national AI strategy with the aim to utilize AI to accelerate the process of achieving Egypt's developmental goals, and especially the United Nations' Sustainable Development Goals (Sharawy, 2023, p.30).

As a developing country, Egypt has begun considering the integration of AI in various domains (Ali, 2023). By the mid 2020, numerous developments materialised through publications related to AI in different domains in Egypt, such as "tourism and hospitality management" (Touni and Magdy, 2020, Abass *et al.*, 2023), and education (Zawacki-Richter *et al.*, 2019; Pedró, 2020; Dhawan and Batra, 2021; Ragheb *et al.*, 2022; Sharawy, 2023; Alzahrani, 2022).

According to ranking of Egyptian Government in the index issued readiness by the "Oxford Insight" Foundation and the International Development Research Center by 55 ranks, making Egypt 56th in the world among 172 countries (Touni and Magdy, 2020). Egyptian government in order to successfully implement AI technologies in their system, the focus must not only be on the infrastructure, the government, or the policies, but on the society as well (Ali, 2023). Yasmeen and her colleagues (2015) stated that private universities are more likely to implement Information Technology in education sectors comparing to public universities. They pointed out that private universities are better in the availability of technological facilities and equipment. Moreover, Egypt is attempting to focus on its young generation is through university programs that include technical and non-technical majors in AI (Ali, 2023). As mentioned by Loveluck (2012) Egypt is facing several challenges in public higher education relating to limited resources, infrastructure, and access to quality education. Alaa El-Din (2022) stated there are only five public and private higher education institutions who are offering a degree of AI and its applications: American University in Cairo, German University in Cairo, Cairo University, Ain Shams University, and the Arab Academy for Science and Technology. However, nowadays, there are about 40 public and private universities, which offer accredited post-graduate and undergraduate programs for AI in Egypt.

3. METHOD

3.1 Participants

The survey was then administered to a total of 491 undergraduate AI learners at College of Artificial Intelligent (CAI) branch of Arab Academy for Science, Technology and Maritime Transport (AASTMT) and in differing year groups. Among the respondents who participated in this survey, 99% (n=488) of them were Egyptian and 1% (n=3) were Non-Egyptian (Palestine), as shown in Table 2. It can also be found that around 82% (n=403) of the sample are males, while only around 18%(n=88) are female. Moreover, it can be noticed that they majority of the sample size 77%(n=377) are between 18 and 22, while 1%(n=3) are between 23-25 years old.

Table 2- Basic Demographics of Respondents

Characteristics		Frequency	Percentage	Total
Gender	Male	403	82%	491
	Female	88	18%	
Age	Under 18	110	22%	491
	18-22	377	77%	
	23-25	3	1%	
	Above-26	1	0%	
Nationality	Egyptian	488	99%	491
	Non-Egyptian	3	1%	

3.2 Data Collection

This research study conducted self-administered questionnaires distributed in a classroom environment. Respondents were from one branch in the College of Artificial

Intelligent, AASTMT located in Egypt: Al-Amein, Matrouh. The anonymous questionnaires were conducted in English as all learners were registered on AI undergraduate programmes. The data collection collected in Spring Semester was between February to July 2023.

3.3 Measures

A questionnaire survey was used as a quantitative research method. A questionnaire survey targeted a sample of Egyptian AI of the English Undergraduate Programme for learners in the College of Artificial Intelligent (CAI), AASTMT in Egypt. It measures the degree of motivation among Egyptian learners with regard to AI education. A frequency distribution of responses is the most common form of data description for a limited number of values or categories (Alreck and Settle, 2004). This case study examines Egyptian undergraduates' IM, EM, AM, Autonomy, Structure and Involvement with respect to the acceptance of the HL concept. Data was coded and fed into Statistical Package for the Social Sciences (SPSS[22]) and Analysis of Moment Structure (AMOS[24]) for data analysis. Confirmatory Factor Analysis (CFA) was used to confirm the dimensions under study are verified by SDT. In addition, Structural Equation Modeling (SEM) was applied to find the effect of the SDT on AI learners' motivation. The questionnaire focused on six dimensions expressing learners' levels of motivation toward adaptation and acceptance of Hybrid Learning such as IM, EM, AM, Autonomy, Structure and Involvement.

3.4 Data Analyses

Hybrid learning helps to enhance learners' perceptions of the educational setting. This section presents an empirical study for the current research through displaying statistical analysis and the findings of the studied sample of learners in the CAI at AASTMT.

Standard and sophisticated statistical analysis, including AMOS-SEM, recommend a sample size of 200 as fair and 300 as good (Tabachnick and Fidell, 1989, 1996, 2001). Using the convenient sampling design, 505 students were initially chosen to respond to the questionnaire. However, only 491 respondents were able to finish the questionnaire. The qualified responses were used to select the 491 respondents for sampling. The descriptive analysis of this section only presents the learners' responses for each sub-dimension, therefore, the mean and standard deviation, are shown in Table 3.

The mean value of "*Intrinsic Motivation to Know and Learn*" is found to be 4.035 with a standard deviation of 1.1163. In addition, the mean value of "*Intrinsic Motivation Toward Accomplishment*" is found to be 3.937 with a standard deviation of 1.046. Moreover, the mean value of "*Intrinsic Motivation to Experience Stimulation"* is found to be 4.044 with a standard deviation of 0.986.

The mean value of "*Extrinsic Motivation/ Integrated Regulation*" is found to be 4.0325 with a standard deviation of 0.984. The mean value of "*Extrinsic Motivation/Identified Regulation*" is found to be 4.3084 with a standard deviation of 1.0433. Additionally, the mean value of "*Extrinsic Motivation/ Introjected Regulation (Self regulation)*" is found to be 4.018 with a standard deviation of 0.998. The mean value of "*Extrinsic Motivation/ External Regulation*" is found to be 4.1721 with a standard deviation of 0.925.

The mean value of "*Amotivation/Lack of Social Presence*" is found to be 3.881 with a standard deviation of 1.209. The mean value of "*Amotivation/ Lack of Overall Learning Arrangement*" is found to be 3.922 with a standard deviation of 1.234. In addition, the mean value of "*Amotivation/ Lack of Learning Knowledge and Experience*" is found to be 3.721 with a standard deviation of 1.255. The mean value of "*Amotivation/ Lack of Learning Mood*" is found to be 3.334 with a standard deviation of 1.241.

Finally, the mean value of "*BPHIN /Autonomy*" is found to be 4.224 with a standard deviation of 0.93451. The mean value of "*BPHIN/ Structure"* is found to be 4.1364 with a standard deviation of 0.98818. Finally, the mean value of "*BPHIN/ Involvement*" is found to be 3.721 with a standard deviation of 1.255.

Table 3- Reliability, Validity Indicator of Sub/Variables Under study

Sub/Variables	No. of Items	Cronbach's Alpha (α)	Construct Validity Indicator	SD	M	Result
Intrinsic Motivation to Know and Learn	4	0.919	0.959	1.11629	4.0346	***Agree***
Intrinsic Motivation Toward Achievement and Accomplishment	4	0.928	0.963	1.04573	3.9367	***Agree***
Intrinsic Motivation to Experience Stimulation and Engagement	4	0.954	0.977	0.98548	4.0438	***Agree***
Integrated Regulation	4	0.950	0.978	0.98390	4.0325	***Agree***
Identified Regulation	4	0.932	0.965	1.04329	4.3084	***Extremely Agree***
Introjected Regulation (Self regulation)	4	0.944	0.972	0.99821	4.0179	***Agree***
External Regulation	4	0.947	0.970	0.92460	4.1721	***Agree***
Lack of Social Presence	4	0.957	0.978	1.20861	3.8815	***Agree***
Lack of Overall Learning Arrangement	4	0.963	0.981	1.23385	3.9221	***Agree***
Lack of Learning Knowledge and Experience	4	0.955	0.978	1.25457	3.7208	***Agree***
Lack of Learning Mood	4	0.938	0.969	1.24097	3.3344	***Neutral***
Autonomy	4	0.918	0.958	0.93451	4.2240	***Extremely Agree***
Structure	4	0.900	0.949	0.98818	4.1364	***Agree***
Involvement	4	0.907	0.952	1.06730	4.0747	***Agree***

Note: %= Percentage; SD= Standard Deviation; M=Mean

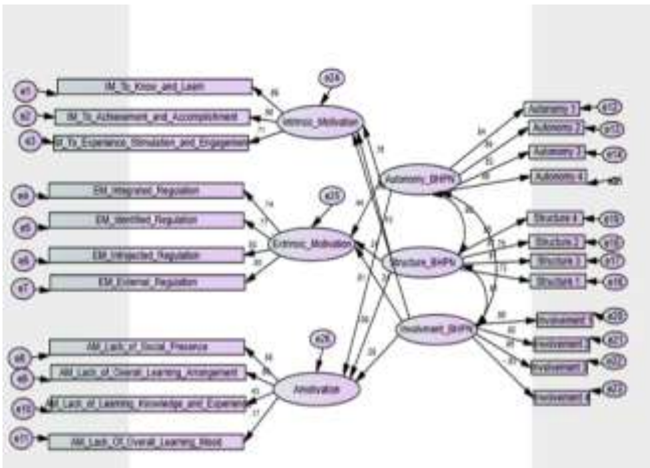
This above Table also shows that respondents considered the majority of sub/dimensions under each function to be either "*Extremely Agree*" or "*Agree*" while there are no responses for either "*Extremely Disagree*" or "*Disagree*". It could be seen that the learners placed an emphasis on "*EM/Identified Regulation*" (4.3084), and "*BPHIN/Autonomy*" (4.2240). "*AM/Lack of Learning Mood*" received a "*Neutral*" response, which was surprising considering that such skills are necessary for the use of HL, but is probably related to the learners' perceived structure in this area. The remainder of the sub-variables were considered important in accepting and applying HL.

All items having an alpha coefficient greater than 0.7 are considered as reliable items (Hair *et al.*, 2010). The loadings of items for each of the variables under study exceed 0.60, as shown in above Table 3. It can be noticed that Cronbach's Alpha for all items under study is greater than 0.7. In this study, Cronbach Alphas for all the sub-variables ranged from 0.963 (*Amotivation/ Lack of Overall Learning Arrangement*) to 0.900 (*BPHIN / Structure*). Also, the study indicates adequate construct Validity for the variables under study. For example, the highest construct validity measure is "*Amotivation/Lack of Overall Learning Arrangement*", which is 0.981, and the lowest construct validity measures are "*BPHIN / Structure*", which is 0.949.

4. RESULT

The researcher applied a SEM using AMOS[24] to build a research model, as shown in Figure 5. It presents the relationship between the dimensions under study, which are "*IM*", "*EM*", "*AM*", "*Autonomy*", "*Structure*", and "*Involvement*". The purpose of the SEM is to conduct various possibility analyses for the selected covariance curve in the hypothesised model in order to identify the optimal goodness of fit with the highest *p*-value with the connected combination of covariance curves among the six variables (Chen, 2005). The hypothesis path results of the proposed modified model are reported in this section to test hypotheses. Homes-Smith (2001) pointed out that SEM produces regression weights, variances, covariances, and correlations in its iterative procedures, which converge on a set of parameter estimates. The critical values of the standardised and unstandardised regression weights were examined for significance of the path between variables shown in the nine research hypotheses (see Table 8). The unstandardised regression weights estimates path for H_1, H_2, H_3, H5, H_8, and H_9 are 0.694, 0.359, 0.611, 0.202, 0.183, and 0.147, respectively. All of the hypothesis estimates were significant except three H_4 (0.101), H_6 (0.033) and H_7 (0.071). In addition, the probabilities of getting critical ratios are 0.217, 0.741 and 0.087.

Figure 4- The CFA of Initial Research Model For Learners After SEM Test



The initial model fit indicators of research model were CMIN/df=2.20247, ρ-Value<0.001, GFI=0.912, CFI= 0.951, IFI=0.951, TLI=0.946, RFI=0.924 and RMSEA=0.060, as shown in Table 4. However, the results indicated that one reflective sub-variable had very poor reliability, where the factor loading was less than 0.50 (see Figure 4 before deleting). Consequently, this initial model was improved.

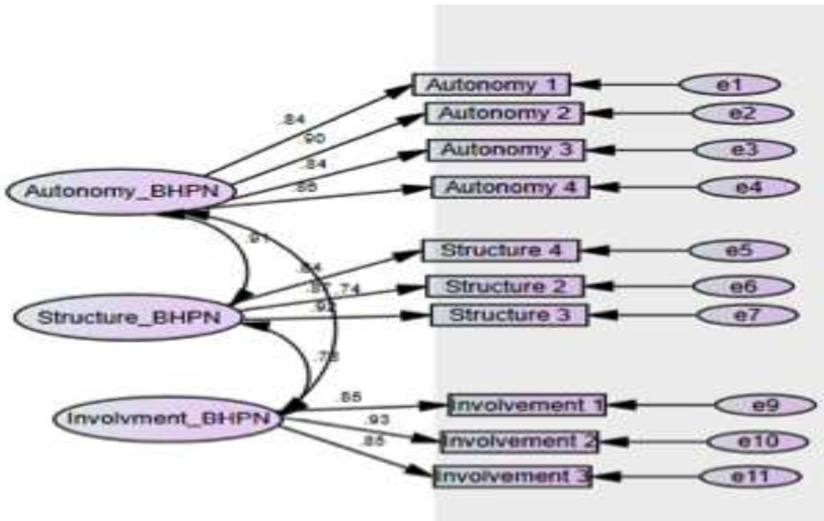
Table 4- Some Fit Measures of the Initial Structured Model

Statistical Test	Initial Model	Threshold (General Rule for Acceptable Fit If Data Are Continuous)
Absolute Goodness of fit Index		
Chi-Square/df (CMIN/DF)	2.202	≤ 3 Good; ≤5 Sometimes Permissible
CMIN	486.554	
DF	221	
P-Value for the Model	0.000	$\geq \mathbf{0.05}$
GFI	0.912	$\geq \mathbf{0.95}$Generally Recommended
AGFI	0.888	≥Performance Has been Good in Stimulation studies
PGFI	0.720	The Closer to 1 the better, though it is typically Lower than other indices and sensitive to model size.
RMR	0.037	
RMSEA	0.060	<0.05-0.08 with confidence interval
Incremental Goodness of Fit Index (Baseline Comparisons)		
NFI	0.934	≥ 0.95 For Acceptance
RFI	0.924	≥ 0.95 For Acceptance
IFI	0.951	≥ 0.95 For Acceptance
TLI	0.946	≥ 0.95 Can Be 0>TLI> 1 For Acceptance
CFI	0.951	≥ 0.95 For Acceptance
Parsimony Goodness of Fit Index (Parsimony-Adjusted Measure		
PCFI	0.822	Sensitive To Model Size
PNFI	0.805	Very Sensitive To Model Size
PRATIO	0.862	The close to 0 the better

Note: GFI=Goodness of FIT Index; AGFI=Adjusted Goodness of Fit Index; RMR=Root Mean Squared Residual; RMSEA=Root Mean Square Error of Approximation; IFI= Incremental Fit Index; TLI=Trucker-Lewis Index; and CFI= Comparative Fit Index.

The results indicated that two latent sub-variables have very poor reliability, where the factor loading was less than 0.50. (see Appendix 1, Figure 1). Therefore, It deleted the sub-dimensions from latent variable such as, "*Structure_1*", from the dimension "*Structure*", to improve model fit. Finally, "*Involvement_4*" from the dimension "*Involvement*" to be able to improve model fit, as shown in Figure 5. Appendix 1, Figure 2 shows the final latent variables of the research model before improvement. Finally, the latent variables model was developed by deleting some sub-dimensions (error terms) as shown in Appendix 1, Figure 2.

Figure 5- The CFA of Final Latent Variables of the Research Model For Learners After SEM Test



The findings also of the final measurement of initial variables indicated that the chi-square divided by degree of freedom was significant at 3.028, as shown in Table 5. Therefore, this reduces the CMIN/df value from 5.824 to 3.028 along with improving other fit indices in the final overall measurement model. This table also shows some fit measures of the initial and final latent variables results of the SEM assessment, as it showed acceptable fits of Goodness of Fit Index (GFI)=0.942; Comparative Fit Index (CFI)=0.973; Incremental Fit Index (IFI)= 0.973; Tucker-Lewis Index (TLI)=0.961; Root Mean Square of Approximation (RMSEA)=0.089 and Root Mean Square Residual (RMR)=0.032.

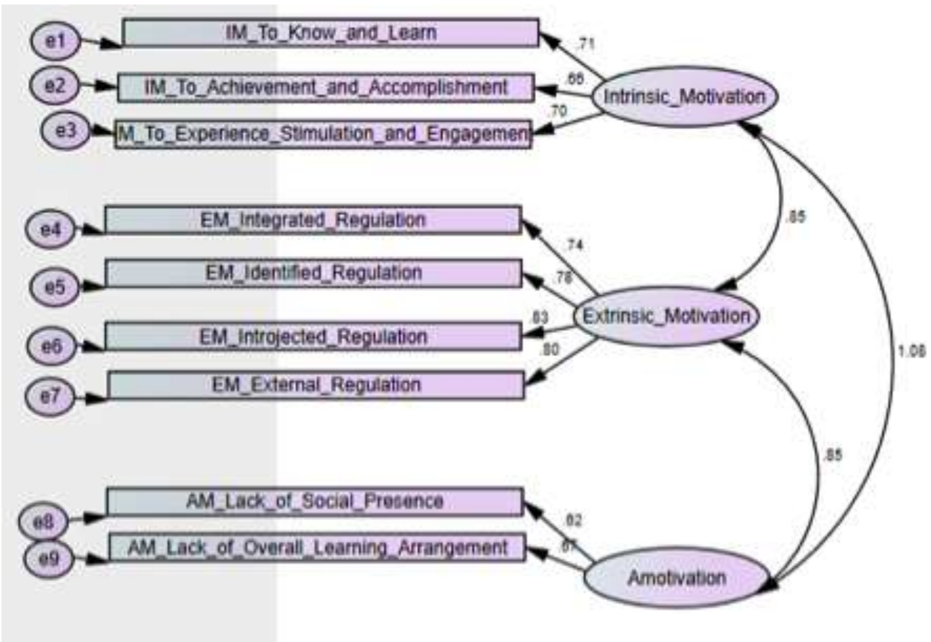
Table 5- Some Fit Measures of the Initial and Final Latent Variables of Structured Model

Statistical Test	**Initial Model**	**Model Results**	**Threshold (General Rule for Acceptable Fit If Data Are Continuous)**
Absolute Goodness of fit Index			
Chi-Square/df (CMIN/DF)	5.824	3.028	≤ 3 Good; ≤5 Sometimes Permissible
CMIN	186.375	81.759	
DF	32	27	
P-Value for the Model	0.000	0.000	$\geq \mathbf{0.05}$
GFI	0.931	0.942	$\geq \mathbf{0.95}$Generally Recommended
AGFI	0.895	0.900	≥Performance Has been Good in Stimulation studies
PGFI	0.609	0.548	The Closer to 1 the better, though it is typically Lower than other indices and sensitive to model size.
RMR	0.033	0.032	
PNFI	0.742	0.688	The Close To 1 The Better, Though It Is Typically Lower Than Other Indices And Sensitive To Model Size
PCFI	0.748	0.692	
RMSEA	0.083	0.089	<0.05-0.08 with confidence interval
Incremental Goodness of Fit Index (Baseline Comparisons)			
NFI	0.962	0.967	≥ 0.95 For Acceptance
RFI	0.949	0.954	≥ 0.95 For Acceptance
IFI	0.968	0.973	≥ 0.95 For Acceptance
TLI	0.958	0.961	≥ 0.95 Can Be 0>TLI> 1 For Acceptance
CFI	0.968	0.973	≥ 0.95 For Acceptance
Parsimony Goodness of Fit Index (Parsimony-Adjusted Measure			
PCFI	0.748	0.692	Sensitive To Model Size
PNFI	0.742	0.688	Very Sensitive To Model Size
PRATIO	0.733	0.711	The close to 0 the better

Note: GFI=Goodness of FIT Index; AGFI=Adjusted Goodness of Fit Index; RMR=Root Mean Squared Residual; RMSEA=Root Mean Square Error of Approximation; IFI= Incremental Fit Index; TLI=Trucker-Lewis Index; and CFI= Comparative Fit Index.

Concerning the reflective variables, the results also indicated that one reflective sub-variable had very poor reliability, where the factor loading was less than 0.50, as shown in Appendix 1, Figure 3. Therefore, It deleted the sub-dimensions from reflective model such as" *AM/Lack of Learning Knowledge and Experience*" and "*AM/Lack of Overall Learning Mood"* from the dimension "*Amotivation*" to be able to improve the model fit, as shown in Figure 6.

Figure 6- The CFA of Final Reflective Variables of the Research Model For Learners After SEM Test



The findings of the final measurement of reflective variables indicated that the chi-square divided by degree of freedom was significant at 1.587, as shown in Table 6. Therefore, this reduces the CMIN/df value from 2.058 to 1.587 along with improving other fit indices in the final overall measurement model. This table also shows overall SEM assessment showed acceptable fits of Goodness of Fit Index (GFI)=0.964; Comparative Fit Index (CFI)=0.971; Incremental Fit Index (IFI)= 0.971; Tucker-Lewis Index (TLI)= 0.956; Root Mean Square of Approximation (RMSEA)= 0.027 and Root Mean Square Residual (RMR)=0.031.

Table 6- Some Fit Measures of The Initial and Final Reflective Variables Results

Statistical Test	Initial Model	Model Results	Threshold (General Rule for Acceptable Fit If Data Are Continuous)
Absolute Goodness of fit Index			
Chi-Square/df (CMIN/DF)	2.058	1.587	≤ 3 Good; ≤5 Sometimes Permissible
CMIN	382.745	77.745	
DF	186	49	
P-Value for the Model	0.000	0.000	≥ **0.05**
GFI	0.956	0.964	≥ **0.95**Generally Recommended
AGFI	0.941	0.933	≥Performance Has been Good in Stimulation studies
PGFI	0.599	0.514	The Closer to 1 the better, though it is typically Lower than other indices and sensitive to model size.
RMR	0.034	0.031	
RMSEA	0.058	0.027	<0.05-0.08 with confidence interval
Incremental Goodness of Fit Index (Baseline Comparisons)			
NFI	0.954	0.962	≥ 0.95 For Acceptance
RFI	0.939	0.943	≥ 0.95 For Acceptance
IFI	0.969	0.971	≥ 0.95 For Acceptance
TLI	0.958	0.956	≥ 0.95 Can Be 0>TLI> 1 For Acceptance
CFI	0.969	0.971	≥ 0.95 For Acceptance
Parsimony Goodness of Fit Index (Parsimony-Adjusted Measure			
PCFI	0.722	0.647	Sensitive To Model Size
PNFI	0.0712	0.641	Very Sensitive To Model Size
PRATIO	0.745	0.667	The close to 0 the better

Note: GFI=Goodness of FIT Index; AGFI=Adjusted Goodness of Fit Index; RMR=Root Mean Squared Residual; RMSEA=Root Mean Square Error of Approximation; IFI= Incremental Fit Index; TLI=Trucker-Lewis Index; and CFI= Comparative Fit Index.

The findings of the final measurement of model testing indicated that the chi-square divided by degree of freedom was significant at 1.652, as shown in Table 7. Therefore, this reduces the CMIN/df value from 2.202 to 1.652 along with improving other fit indices in the final overall measurement model. it also shows the overall SEM assessment showed acceptable fits of Goodness of Fit Index (GFI)=0.952; Comparative Fit Index (CFI)=0.961; Incremental Fit Index (IFI)=0.961; Tucker-Lewis Index (TLI)=0.953; Root Mean Square of Approximation (RMSEA)=0.064 and Root Mean Square Residual (RMR)=0.034.

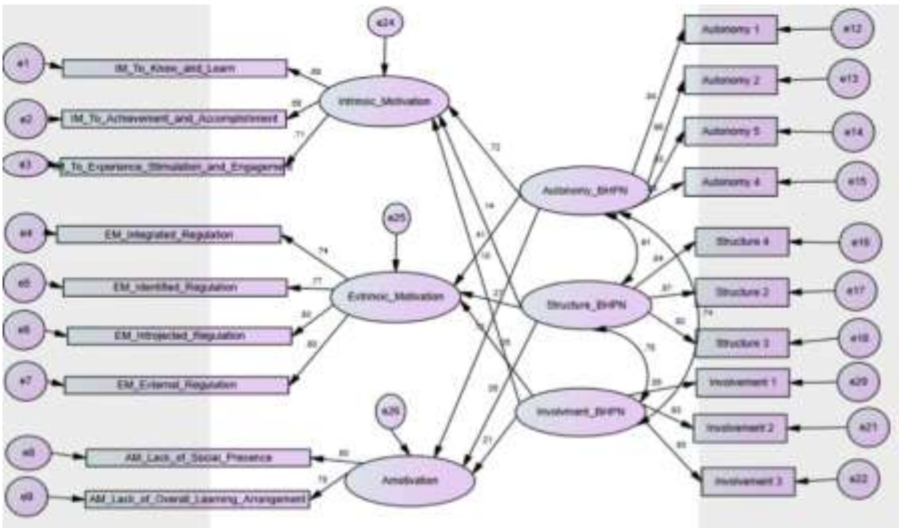
Table 7- Some Fit Measures of the Overall Structured Model

Statistical Test	**Initial Model**	**Result Model**	**Threshold (General Rule for Acceptable Fit If Data Are Continuous)**
Absolute Goodness of fit Index			
Chi-Square/df (CMIN/DF)	2.202	1.652	≤ 3 Good; ≤5 Sometimes Permissible
CMIN	486.554	313.961	
DF	221	190	
P-Value for the Model	0.001	0.001	$\geq \mathbf{0.05}$
GFI	0.912	0.952	$\geq \mathbf{0.95}$Generally Recommended
AGFI	0.888	0.898	≥Performance Has been Good in Stimulation studies
PGFI	0.720	0.681	The Closer to 1 the better, though it is typically Lower than other indices and sensitive to model size.
RMR	0.037	0.034	
RMSEA	0.060	0.064	<0.05-0.08 with confidence interval
Incremental Goodness of Fit Index (Baseline Comparisons)			
NFI	0.934	0.947	≥ 0.95 For Acceptance
RFI	0.924	0.935	≥ 0.95 For Acceptance
IFI	0.951	0.961	≥ 0.95 For Acceptance
TLI	0.946	0.953	≥ 0.95 Can Be 0>TLI> 1 For Acceptance
CFI	0.951	0.961	≥ 0.95 For Acceptance
Parsimony Goodness of Fit Index (Parsimony-Adjusted Measure			
PCFI	0.822	0.787	Sensitive To Model Size
PNFI	0.805	0.775	Very Sensitive To Model Size
PRATIO	0.862	0.819	The close to 0 the better

Note: GFI=Goodness of FIT Index; AGFI=Adjusted Goodness of Fit Index; RMR=Root Mean Squared Residual; RMSEA=Root Mean Square Error of Approximation; IFI= Incremental Fit Index; TLI=Trucker-Lewis Index; and CFI= Comparative Fit Index.

As explained by these indicators, the model exhibits satisfactory parameters, thereby providing a good basis for testing the hypothesised paths. Standardised Loadings were all significant and greater than 0.54. This is in line with Comery and Lee (1992) with all factors' loadings being good variations. It was found that the values of the below mentioned indicators are acceptable, which means that all the divisions' estimated dimensions fit. Based on the acceptance results of CMIN/df (1.652) and GFI (0.952), the SEM model of the study implies a goodness of fit of the hypothesised model. Figure 7 shows the results of the standardised estimate for final research model used in this study. Appendix 1, Figure 5 displays the results of the unstandardised estimate for final model goodness of fit, which has shown an overall improvement, as well as other statistics.

Figure 7- The Final Research Model For Learners After SEM Test



The researcher applied a SEM using AMOS[24] to build a research model, as shown in Figure 5. It presents the relationship between the dimensions under study, which are "*IM*", "*EM*", "*AM*", "*Autonomy*", "*Structure*", and "*Involvement*". The purpose of the SEM is to conduct various possibility analyses for the selected covariance curve in the hypothesised model in order to identify the optimal goodness of fit with the highest *p*-value with the connected combination of covariance curves among the six variables (Chen, 2005). The hypothesis path results of the proposed modified model are reported in this section to test hypotheses. Homes-Smith (2001) pointed out that SEM produces regression weights, variances, covariances, and correlations in its iterative procedures, which converge on a set of parameter estimates. The critical values of the standardised and unstandardised regression weights were examined for significance of the path between variables shown in the nine research hypotheses (see Table 8). The unstandardised regression weights estimates path for H_1, H_2, H_3, H_7, H_8, and H_9 are 0.694, 0.541, 0.745, 0.184, 0.296, and 0.515, respectively. All of the hypothesis estimates were significant except three H_4 (-0.065), H_5 (-0.024) and H_6 (-0.638). In addition, the probabilities of getting critical ratios are 0.725, 0.896 and 0.087, which is below 1.96.

Table 8- The Study Structural Model Fits

Hypotheses	Path		S. Est.	Uns-Est.	S.E.	C.R	*P*	Result
H1: There is an Effect of perceived Autonomy on Intrinsic Motivation	Intrinsic Motivation ←	Autonomy	0.717	0.624	.094	6.655	.001	Accepted
H2: There is an Effect of Perceived Autonomy on Extrinsic Motivation	Extrinsic Motivation ←	Autonomy	0.408	0.359	.078	4.580	.001	Accepted
H3: There is an Effect of Perceived Autonomy on Amotivation	Amotivation ←	Autonomy	0.718	0.611	.112	5.441	0.001	Accepted
H4: There is an Effect of Perceived structure on Intrinsic Motivation	Intrinsic Motivation ←	Structure	0.138	0.101	.082	1.234	0.217	Rejected
H5: There is an Effect of Perceived Structure on Extrinsic Motivation	Extrinsic Motivation ←	Structure	0.273	0.202	.071	2.827	0.005	Accepted
H6: There is an Effect of Perceived Structure on Amotivation	Amotivation ←	Structure	0.046	0.033	.099	.331	0.741	Rejected
H7: There is an Effect of Perceived Involvement on Intrinsic Motivation	Intrinsic Motivation ←	Involvement	0.097	0.071	.041	1.753	0.080	Rejected
H8: There is an Effect of Perceived Involvement on Extrinsic Motivation	Extrinsic Motivation ←	Involvement	0.247	0.183	.036	5.056	0.001	Accepted
H9: There is an Effect of Perceived Involvement on Amotivation	Amotivation ←	Involvement	0.205	0.147	.050	2.971	0.003	Accepted

Note: X2/df=1.652;P Value<.001;GFI=0.952;CFI=0.961;IFI=0.961;TLI=.953;RMSEA=0.064; and RMR=0.034. All Hypotheses significant level P<0.01, except H4, H6 and H7. S.E=Standard Error; C.R=Critical Ratio; p=p-Value; S.Est.=Standardised Estimate; Uns-Est.=Understandised Estimate.

It was found that there is a direct, positive and significant impact of “*Autonomy*” on “*IM*” with a standardised estimate of 0.717. It also was found that there is a significant effect of “*Autonomy*” on “*EM*” with a standardised estimate of 0.408. In addition, it was found that there is a significant effect of “*Autonomy*” on “*AM*” with a standardised estimate of 0.718. The data results mentioned that the effect was found to be for “*Autonomy*” on all types of motivation. Examining the effect of “*Structure*” on each of “*IM,* ”“*EM*” and “*AM*” shows that “*Structure*” has an insignificant effect on *“IM”and “AM”* with standardised estimate of 0.138 and 0.046. Regarding “*Involvement*”, it was found that there is a significant positive effect on “*EM*”, “*AM*” with standardised estimate of 0.247 and

0.247 respectively at (99%) of significant level. It also shows that "*Involvement*" has an insignificant effect on "*IM*" with standardised estimate of 0.097.

Figure 7 shows the standardised path coefficients for the research model for learners. Consistent with H_1, H_2, and H_3, perceived "*Autonomy*" support has a positive effect on "*IM*", "*EM*" and "*AM*" (β=0.717, ρ<0.001; β=0.408, ρ<0.001; and β=0.718 ρ<0.001, respectively). There are standardised path coefficients for "*IM*" on "*Intrinsic Motivation To Know and Learn*", "*Intrinsic Motivation to Achievement ad Accomplishment*" and Intrinsic Motivation to Experience Stimulation and Engagement (γ=0.69 ρ<0.001; γ=0.68, ρ<0.001; γ=0.71, ρ <0.001, respectively). Furthermore, there is a standardised estimate path coefficient for "*EM*" on "*Integrated*", "*Identified*", "*Introjected*" and "*External*" *Regulations* (γ=0.74, ρ <0.001; γ=0.77, ρ <0.001; γ=0.83, ρ <0.001; and γ=0.80, ρ <0.001, respectively). Finally, there are the standardised estimates path coefficients for "*AM*" on "*Lack of Social Presence*", "*Lack of Overall Learning Arrangement", "Lack of Learning Knowledge and Experience"* and "*Lack of Overall Learning Mood*" (γ=0.58, ρ<0.001; γ=0.68, ρ<0.001; γ=0.43, ρ<0.001; and γ=0.17, ρ<0.001, respectively). Therefore, H_4, H_6 and H_7 predicted that the standardised path coefficients from perceived "*Structure*" have no significant effect on *"IM", "AM"* (β =0.10, ρ <0.217 and β =0.033, ρ <0.741, respectively).

Therefore, as estimated, hypothesis H_4–H_6 were supported. In addition, H_7 predicted that perceived "*Involvement*" has no significant effect on *"IM"* (β=0.071, ρ<0.080, respectively).

5. DISCUSSION

The present study investigated a model of motivational processes grounded in self-determination theory (Deci and Ryan, 1985, 1991, 2002; Ryan and Deci, 2000a,b, 2000, 2020). It examined a model that encompassed the following theory-based hypotheses as shown in Tables 8 and 9.

Table 9-The Result Study of Research Hypotheses

The Study hypotheses
H1: There is a Significant Effect of perceived Autonomy on Intrinsic Motivation
H2: There is a Significant Effect of Perceived Autonomy on Extrinsic Motivation
H3: There is a Significant Effect of Perceived Autonomy on Amotivation
H4: There is no Significant Effect of Perceived structure on Intrinsic Motivation
H5: There is a Significant Effect of Perceived Structure on Extrinsic Motivation
H6: There is no Significant Effect of Perceived Structure on Amotivation
H7: There is no Significant Effect of Perceived Involvement on Intrinsic Motivation
H8: There is a Significant Effect of Perceived Involvement on Extrinsic Motivation
H9: There is a Significant Effect of Perceived Involvement on Amotivation

Specifically, it explored the role of perceived "*Autonomy*", "*Structure*" and "*Involvement*" in explaining the influence of "*IM*", "*EM*" and "*AM*" in exploring the motivations of hybrid learning in the learning setting. "*BPHIN*" affects the three types of motivation. The need for "*Autonomy*" was operationalised using the motivations of Hybrid Learning in relation with "*IM*", "*EM*" and "*AM*". It appears that participants are more willing to continue using hybrid learning when they feel autonomy, because these basic needs have influence on their "*IM*" and "*EM*" as well as "*AM*", which in turn affects their intention to explore using the hybrid Learning method. However, perceived *"Structure*" has been shown to positively affect "*EM*" only. Although some cultural relativists have maintained, for example, that the need for perceived "*Autonomy*" is important only in cultures that value individualism and are essentially irrelevant in cultures that value collectivism, this turns out not to be the case (Deci and Ryan, 2008). For instance, studies have looked at the "*Autonomy*" of Chinese learners at an age typical to most undergraduate and graduate learners to investigate the western versus eastern perspective on "*Autonomy*" (Zhou, Ma, & Deci, 2009). Feelings of "*Autonomy*", like *"Structure"* and "*Involvement*", are essential for optimal functioning in a broad range of highly varied cultures (Deci and Ryan, 2008), especially in Extrinsically motivation. In this study, Egyptian learners proven that learners desired to get external motivated. Extrinsically motivated refers to tangible reward such as higher grades in order to accept Hybrid Learning environment. Tangible reward also refers to extra bonus and flexibility in attendance online. However, "*Involvement*" shows a no significant on "*IM*". This finding suggests that the effects of BPHIN on self-determination vary from youth to adults (Ahmadi *et al.*, 2012). In this research study, nine hypothesis were tested.

It consisted of SEM analysis of data that was collected among learners from CAI. It tested H_1, H_2, H_3, H_4, H_5, H_6, H_7, H_8 and H_9 based on the path coefficient estimates derived from the SEM analysis (see Figure 7 and Table 8 and 9). In addition, Egyptian learners who are feeling "*Autonomy*" in the virtual environment, that they are intrinsically and extrinsically motivated by the opportunities of hybrid learning.

The results obtained suggest that at least four sub-variables should not be included in this research model in order to improve of this model fit, ("*AM/Lack of Learning Knowledge and Experience*", *"AM/Lack of overall Learning Mood"*; *"Structure/ Structure_1";* and *"Involvement/ Involevemet_4")*. It was found that three out of nine of the hypotheses have an effect on this research model. Learners perceived "*Structure*" has no effect on the two types of the motivation (IM and AM), while "*Involvement*" has no effect on one type of motivation (IM). For example, Egyptian learners' opinion indicated that they do not need separable outcomes to engagement into hybrid learning, as it will not increase or even decrease their level of acceptance of hybrid learning programme.

In summary, some of the results from the learners contradicted previous studies. For example, in the present study, learners who have autonomous motivation toward the Hybrid Learning concept do not have "structure" motivation except externally motivated, in contrast with Deci and Ryan, where individuals feeling autonomy toward the learning environment must be intrinsically and extrinsically motivated; the same holds true with perceived "*Structure*". Moreover, Egyptian learners have proven that EM entails a high level of autonomy, structure and involvement. However, there are some barriers of Hybrid learning which Egyptian learners find manageable and can be overcome.

6. CONCLUSION

This study focused on an important area in the field of hybrid learning through the application of SDT and understanding the motivations of Egyptian learners in using VLE in higher education. It develops a basic conceptual model for learners, and an SDT framework for conceptual insight to answer the basic research question and achieve the research objectives. Therefore, up to now, it is a rapidly growth AI in various domains in literature, especially in Tourism and Hospitality management. A framework was created and implemented to Artificial Intelligence educators in higher education at AASTMT, Egypt. Artificial Intelligence (AI) is being applied in various fields, including education (González-Calatayud *et al.*, 2021). Artificial intelligence is one of the most disruptive innovations in education, and the topic has attracted the attention instructors and learners. Moreover, this research examined how SDT contributed to learners' and instructors' motivations in adapting virtual learning in a developing country in higher education. The investigation of learners' sub-factors of "*IM*", "*EM*" and "*AM*" may lead to the acceptance of hybrid learning and previous studies have not investigated this area to date. It also proved that learners to be able to accept and implement Hybrid learning they must be externally motivated. Consequently, there has to be a sustained effort to conduct future research examining the framework of SDT of virtual learning's motivations related to learners in all fields in higher education.

7. SUGGESTIONS FOR FUTURE RESEARCH

This study contemplated a developing country as these have been overlooked in the extant academic research. It provides some insights and directions for self-determination theory on the motivation of hybrid learning (HL) for future research. This current work used self-determination theory for the benefits of better contextualisation in identifying the best motivations of HL. Future research might consider collecting data from more than one source, as the study process developed was applied to only one case study organisation in an Egyptian academic institution. It is suggested to conduct further quantitative and qualitative research on large-scale cross-institutional and cross-country studies to provide empirical findings to affirm the proposed HL model. For example, a comparative study between two or more countries could show interesting results. Further research could extend the current research framework, as it is necessary to adopt this research model in public schools and universities.

8. ETHICAL CONSIDERATION

Nowadays, educational scientists are guided by ethical criteria. In conducting quantitative studies, researchers must be taken into their account ethical and legal considerations rules, such as minimizing bias, guaranteeing transparency and safeguarding confidentiality. Hesse-Biber and Leavy (2011, p.59) proposed that *a consideration of ethics needs to be a critical part of the substructure of the research process from the inception of your problem to the interpretation and publishing of the research findings.* Ethical and legal issues are a very important aspect of social science research (Cohen et *al.*, 2000). This present research study considered the use of ethical considerations. There are a number of various issues that need to be considered. For example, there is a need for conducting research studies in education, business, economics and the social sciences. Therefore, it is critical to adapt the ethical consideration to ensure that the research study is legally proven. This research was conducted in Arab Academy for Science, Technology and Maritime Transport (AASTMT) ethical guidelines. It was guided by the ethical principles on research with human participants set out by AASTMT. It is difficult to ensure that the safeguards regarding confidentiality can be guaranteed when secondary analysts examine the results from a questionnaire survey (Alderaon, 1998). Therefore, participants in the research were informed that all the information provided was securely stored, with no access given to anyone other than the researcher for a period of two years. Furthermore, the respondents knew that their responses were confidential, however, the researcher would use them in this study.

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10. APPENDIX 1

Figure-1: The CFA for Initial Latent Variables (Exogenous Factors/ Independent Variables)

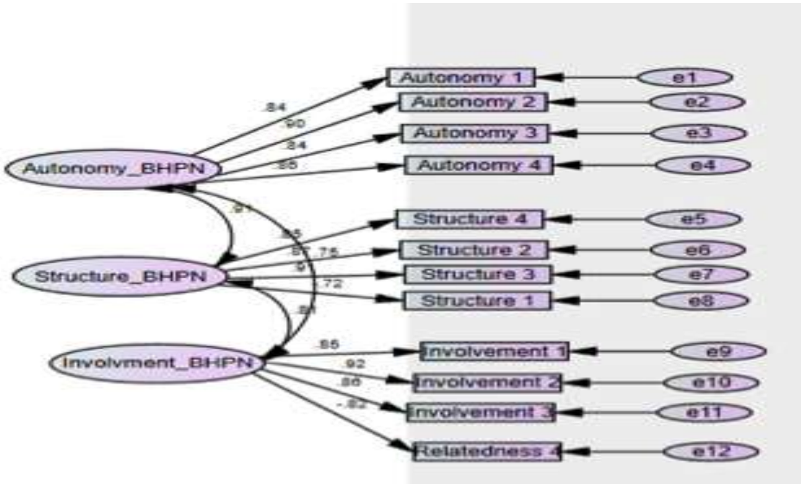

Figure-2: The CFA for Final Latent Variables (Exogenous Factors/ Independent Variables)

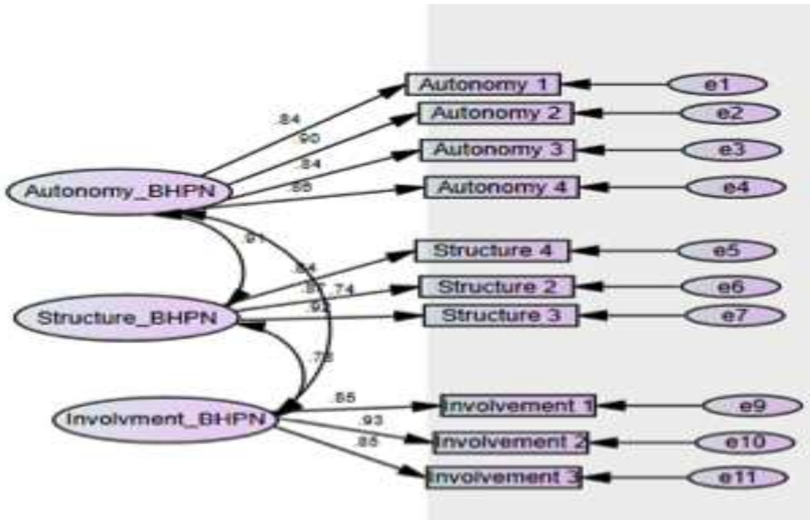

Figure -3: The CFA for Initial Reflective Variables (Endogenous Factors/ Dependent Variables)

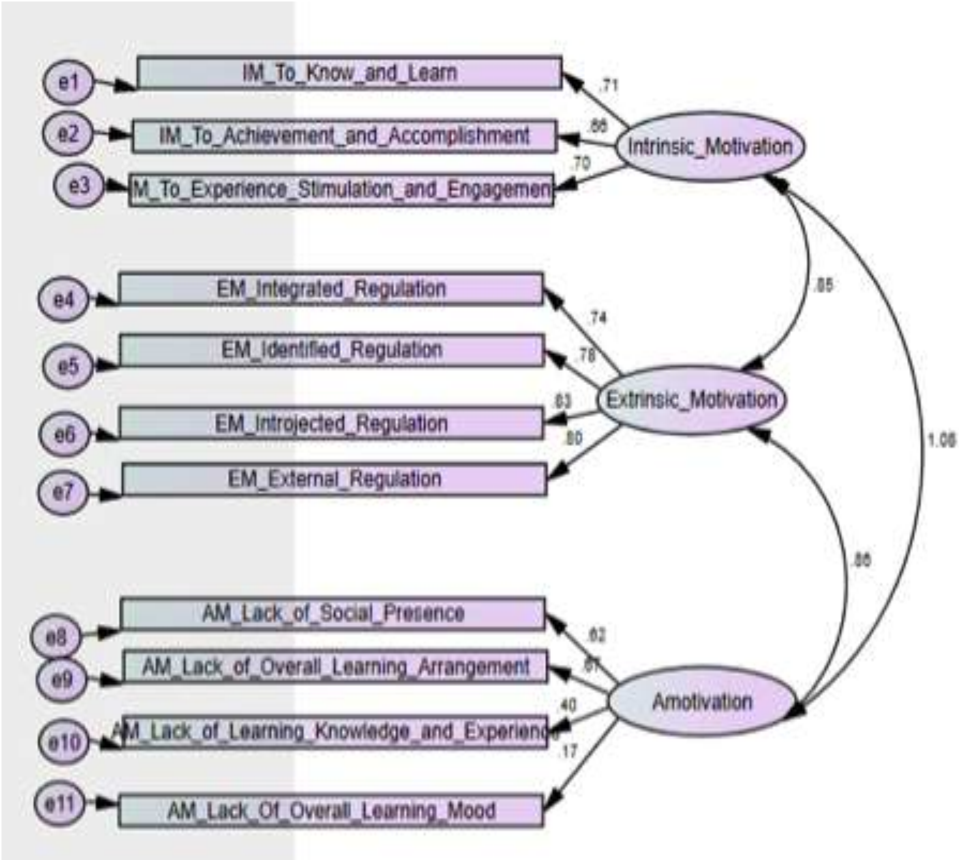

Figure -4: The CFA for Final Reflective Variables (Endogenous Factors/ Dependent Variables)

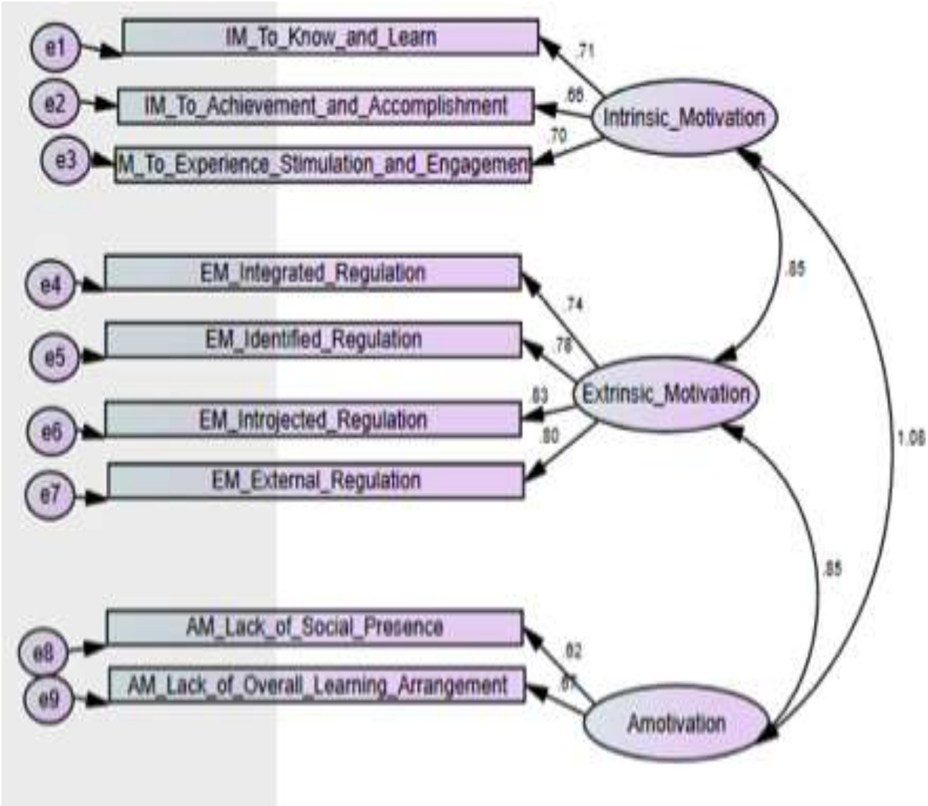

Figure-5- The Final Research Model For Learners After SEM Test (the Un-standardised estimate)