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Research Article

Towards Mapping Competencies through Learning Analytics: Real-time Competency Assessment for Career Direction through Interactive Simulation

Puja Khatri[a]* (ORCID: 0000-0002-3154-0865), Khushboo Raina[b] (ORCID: 0000-0003-0390-5545), Caroline Wilson[c] (ORCID: 0000-0002-0213-506) and Michael D. Kickmeier-Rust[c] (ORCID: 0000-0003-0957-0037)

[ab]Guru Gobind Singh Indraprastha University, India; [c]Coventry University, UK; [d]University of Teacher Education St. Gallen, Switzerland

*For correspondence please contact pujakhatri12@gmail.com

Abstract

The selection of career paths and making of academic choices is a difficult and often confusing task for young people. The impact on their lives, however, is enormous as it can determine entire future career possibilities. In India, a general remedy to this stress is that instead of choosing a field of study tailored to individual preferences and strengths, topics are chosen that align with the traditional choices of the students' families or their friends. This can have the effect of entrenching patterns of intergenerational inequity. The aim of this research is to give students greater access to the knowledge capital which will help them make better choices. This is achieved by engaging students in the career planning process, in order to convey information in a likeable and credible way. The COMPCAT (Competency and Career Assessment Tool) game engine combines the use of learning analytics and real time, interactive computer simulations designed to gain insights into the students' engagement in the making of these complex decisions. This paper presents the conceptual architecture of the game and demonstrates its role in enhancing the learning effectiveness of the students.

Keywords: Learning analytics, Digital educational games, Higher education, Career competency assessment, Student engagement

Introduction

Technology is having an increasing and substantial influence in all areas of education (Kovanovic 2017). The growing focus on educational data mining and learning analytics is considered to have high potential for learning efficacy (Adams Becker et al. 2017). In many countries, new technologies have become mainstream educational tools. In India, there is a clear absence of these tools and techniques to assess the learning, skills and performance outcomes of students. At the same time, the country needs a rapid enhancement in the quality and quantity of graduates who are ready to take on graduate-level jobs that match their skills. Such skilled workers are in short supply, and can command a skill premium (Cain et al. 2014). The premium is contributing to widening inequality, in that, while India's economy has been growing impressively, there is a persistent trend since 1990 of only the top 20% of the population gaining from this (Jain-Chandra et al. 2016). It is the highly educated who are benefitting most: Cain et al. (2014) estimate that education level explains more than 40% of increasing inequality, whether in rural or urban areas. Inequality in India is intergenerational, particularly in the case of low-skilled and low-paying occupations, in that the children of fathers who are low skilled and low paid are more likely to end up on the same path (Motiram and Singh, 2012). It follows that if a student's choices are limited by the influence of their parents or friends, this cycle is unlikely to be broken.

India has the largest youth population in the world, with 600 million young people under the age of 25 (Trines 2018). In India, only 6% of the total graduates are employable (Sundar 2018), far fewer than countries having comparable median income. Dropout rates are high. The major reasons for the relative poor participation and success rates in the Indian higher education system are given as; the absence of a personalised approach to education (based on the capabilities of each student), the non-availability of resources, absence of technological infrastructure, absence of skill based learning and absence of real-time modules (Kumar 2016). At the same time some of the problems for students begin with the poor selection choices of subjects to study. Instead of critically engaging with the options, students end up taking courses irrelevant to their ambitions, only to regret it later (Kumar 2011).

There is a need for the students to take decisions for their subjects and career as per their own latent competencies instead of parental pressure and following traditional career paths unthinkingly. One possible solution to poor decision-making could be to have students take part in a learning analytics gaming simulation designed to gauge their core interests.

The present study attempts to analyse this issue. We propose an innovative approach to convey the necessary information and attitudes for an appropriate selection of career opportunities. This approach, termed COMPCAT (Competency and Career Assessment Tool) is based on the strength of game-based learning in combination with learning analytics. The fundamental idea is to use an appealing game plot to engage the users, and to use learning analytics as a means to analyse activities and subject preference in order to support adequate and individualised career counseling. This study is the first one to attempt such assessment of intrinsic interests of students enrolled in higher education institutions in India. It will be beneficial to regulatory bodies, authorities, academics, students, parents and researchers. It also has value to countries beyond India which are also still at the development stage in the use of learning analytics in a career counselling environment. A study by Cuff (2017) on UK students found they tended to choose their subjects on the basis of the difficulty level of the subject, advice received from their parents and friends along with how much they enjoyed it. As a consequence, one in three graduates in the UK has a mismatched set of skills to their jobs once they leave university (Steed 2018). In another study conducted on the students at a university in the USA, students were found to make subject choices on the basis of advice from coaches or teachers or under a sense of family obligation (Fizer 2013). The fundamental issue of ignoring intrinsic interest and opting for subjects on other criteria is thus global in nature.

Literature review

Fredericks, Blumenfeld, and Paris (2004) define student engagement as a multidimensional construct made up of behavioral, emotional and cognitive elements. An engaged student puts impetus into learning (Burrows, 2010). Engagement needs to be active to be effective (Appleton et al. 2006) and learning analytics is a means to support this active learning. Siemens et al. (2011, p. 4), define learning analytics as, ‘the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the environments in which it occurs’. According to Adams Becker et al. (2017), learning analytics provides a framework to make requisite improvements in learning performance on the basis of the learning history of students. The research pertaining to learning analytics is in a very nascent stage in India, but its potential impact on educational practices is huge (Ellis 2013). The concept has gained popularity in commercial, academic and political domains. According to Piety, Hickey, and Bishop (2014), learning analytics has been described as a part of the field of educational data science which is rapidly emerging and comprises business intelligence (which is creating its space in higher education), educational data mining, web analytics and machine learning.

Serious games

Over the past decade, game-based learning has entered all educational areas (Dörner et al. 2016) and meta-reviews have revealed their beneficial effects (e.g. Wouters and van Oostendorp 2017). A particular strength of serious games is that they motivate and engage students actively. Student engagement is signified by the involvement and effort of students and a change in observable behavior (Yin and Wang 2016). Indicators of student engagement are academic achievements, belongingness towards the institution, course clarity, attendance, grades, value for learning and assignment completion (Burrows 2010). Fredericks, Blumenfeld, and Paris (2004) identify three dimensions of student engagement: cognitive, emotional/affective and behavioral. Game plots can transport these dimensions into concrete instruction/learning scenarios. These game plots can be personalised to enhance the relevance of the content. There are a variety of techniques which can be used to achieve this, such as cognitive feedback, motivational feedback, meta-cognitive feedback, progression hints and knowledge-based hints (Peirce, Conlan, and Wade 2008). Simulations make use of the applications of interactive dynamic media in order to support users at every step while making choices (Holzinger, Kickmeier-Rust, and Albert 2008). The mode of the representation of these simulations is very important as it has significant impact on the learning process and performance of the user.

COMPCAT (Competency and Career Assessment Tool)

From an educational perspective, computer games offer a promising approach to make learning more engaging, satisfying, and probably more effective. COMPCAT established a novel approach to engage students and, at the same time, accompany career planning activities with learning analytics features.

The conceptual design of COMPCAT has made use of the methodology adopted in the EC-project ELEKTRA (Enhanced Learning Experience and Knowledge Transfer) as elucidated by Linek et al. (2009). The same authors suggested that the methodology used can be taken as a base for other game-based learning modules as well as serious games. Their suggested methodology develops a framework for establishing the structure, establishing interdisciplinary cooperation, and supporting various interrelated subsystems and growth cycles which facilitate the improvements and development of educational games design continuously. The methodology of the ELEKTRA project involves macroadaptivity, microadaptivity, metacognition and motivation. Macroadaptivity refers to the instructional design and managing the available learning situations; microadaptivity refers to the awareness about the skills of the learner and a set of pedagogical rules; metacognition refers to one’s knowledge about one's own intellect or cognition; and motivation pertains to various approaches meant for learning and enjoyment.

COMPCAT provides a platform where learning and entertainment go hand in hand. The basic idea behind this version of the game at this stage is to make students pursuing higher educational courses at MBA-level aware about the subjects that they are going to study in subsequent semesters and to gauge their interest in a particular subject. The game represents a planet wherein the students would be taken on a space trip and allowed to spend their vacation with a few friendly aliens. Each alien introduces the student to an area of management and its relevance and contribution to sustain life on that planet. The major subjects of management, along with their related streams, are introduced to the students: marketing, human resource management, finance, international business, and information technology. The student is initially allowed to stay with all possible selected aliens and then can in the second phase makes a choice to stay with their preferred aliens (signifying an area of interest) (Figure 1).

Insert Figure 1: Screenshot of the original game, about here

The entire scenario is based on a previously developed game named 'Feon's Quest' (Kickmeier-Rust 2012). This game has been developed in the context of the European 80Days project and demonstrates adaptive game balancing features on micro as well macro levels (Kickmeier-Rust 2018). Assessments can be made on the basis of: (i) the frequency of visit to a preferred alien, (ii) time spent with that alien, and (iii) the ability to handle and help that alien. The interaction with the friendly alien companion is designed to provide concrete information about career opportunities and to help students identify their personal preferences and options.

Technically, the game is based on the unity game engine and applies a modular conceptual architecture. The approach allows games deployment for the most common technical platforms. To provide the necessary learning analytics features, the game is connected to the open Lea's Box platform (http://eightydays.cognitive-science.eu). This platform allows connecting data sources (e.g. the game) to an open analytics engine (Kickmeier-Rust and Albert 2017), which in turn can inform the game through a web service connection about concrete adaptations and recommendations to the students. The online platform allows students, as well as teachers/consultants, to access statistics and analyses of a particular student and their interaction with the game.

Focus Group

Before the research was conducted, three subject experts and three students from an MBA management programme were invited to discuss the detailed design of COMPCAT in a focus group. The focus group lasted 2 hours and was moderated by the first author of this paper. A detailed simulation scenario with the module specifications along with some intermediate snapshots of the game was shown to the group to assess their reactions about the tool. Reactions of the focus group members informed the study team's thinking about the capacity of the tool to increase participant understanding of the concepts of management and the capacity of the tool to serve as a significant catalyst in improvising the decision making of the students.

Research objectives

The aim of the study is to analyse the effect of the learning analytical tool on the learning effectiveness of the students. It is then to suggest recommendations about the impact of the learning analytical tool on the enhancement of the learning effectiveness of the students. The study was conducted in the year 2017–2018.

The hypotheses are that for the students taking part:

- H1: There exists a positive relationship between the student engagement and learning effectiveness of the students.
- H2: There exists a positive relationship between the learning analytical tool and learning effectiveness of the students.
- $H_0$3: The learning analytical tool does not mediate the relationship between student engagement and learning effectiveness.

Methodology

A cross-sectional survey-based design was adopted to conduct the study. The sample for the study was drawn from a list of institutions held by AICTE (All India Council for Technical Education). Out of the list of 237 institutes, only institutes which offered management courses at the post-graduate level were considered. Of these institutes, five were selected to be considered for the study using the fish bowl simple random sampling technique (performed in front of members of the focus group which had informed the study).

The questionnaire had four sections. The first carried questions about the demographic profiles of the respondents. The remaining three carried questions regarding perceptions about the level of student engagement (SE), level of learning effectiveness (LE) and the learning analytical tool (LAT). Based on the comments of the focus group experts and extensive literature review, it was hypothesised that the impact of SE on LE would be mediated by LAT. A mediator is a variable which occupies a position between the independent variable and the dependent variable, and mediation analysis enables investigation of the relative relationship (Hoyle and Robinson 2004).

Construct Measurements

All items are measured at 7-point Likert scale where '1' represents Strongly Disagree and '7' represents Strongly Agree. Scores greater than the average indicate higher level of agreement with the items.

Student Engagement (SE): The standardized questionnaire devised by Fredericks et al. (2004) was taken to measure this. The indicators for SE in the model are: Cognitive Engagement (CE), Emotional Engagement (EE) and Behavioral Engagement (BE) and the items include 'paying attention in class', 'following instructions at the institution', 'completion of assignments' etc.

Learning Analytical Tool (LAT): A self-constructed questionnaire was taken for the study. The dimensions of LAT in the model are: Customized Learning Environment (CLE), Step-Wise Approach (SWA) and Student Involvement (SI) and the items comprise 'customization according to learning behavior', 'conducive game environment', 'goal oriented', 'step by step approach' etc.

Learning Effectiveness (LE): A self-constructed questionnaire was taken for the study. The dimensions of LE in the model are: Student Learning Ability (SLA) and Student Inquisitiveness (SIQ). The items corresponding to these indicators are 'able to reciprocate what is being taught', 'appreciated for being a learner', 'knowledge retention', 'proactive towards academic assignments' etc.

Participants

Students of 2-year MBA management courses studying in their first year of the programme were administered the questionnaires. First year students were selected (aged between 21-24 years) so as to help them take a calculated decision towards elective selection that is scheduled to happen during the second year in their course. The measured change sought was to understand the impact of Learning Analytical Tool in enhancing the learning effectiveness and the level of engagement. In total, 250 questionnaires were distributed and 161 completed questionnaires were taken for analysis. Out of 161 respondents 54% were males and 45.9% were females, 88% belonged to 20-22 years of age category and 11.8% were from 22-24 years of age category.

Factor Analysis

While all three question sets were heavily informed by literature review, only student engagement was identified to have a readily suitable standardized questionnaire. The questions to frame the remaining two constructs (LE and LAT) were validated by applying both Exploratory Factor Analysis and Confirmatory Factor Analysis techniques (see Khatri and Raina, forthcoming). All analysis was conducted using PLS SEM 3.0 SmartPLS.

Results

Reliability and Validity of the Model

Reliability (Table 1) is considered satisfactory when Cronbach α and composite reliability are greater than 0.7 (Bagozzi and Yi 1988; Hair et al. 2010). Heterotrait-monotrait (HTMT) ratio (Table 2) is a robust technique to assess discriminant validity of latent variables (Henseler, Ringle, and Sarstedt 2015) and is an estimate of what the true correlation (disattenuated correlation) between two constructs would be, if they were perfectly measured (i.e. if they were perfectly reliable). A disattenuated correlation between two constructs close to one indicates a lack of discriminant validity. Ullman and Bentler (2013) suggest that all parameters (dimensions and constructs) are used. Figure 2 contains a visual representation of the discriminant validity of the latent variables.

Insert Table 1: Reliability of the Constructs about here

Insert Table 2: Discriminant Validity- Heterotrait-monotrait ratio (HTMT) about here

Structural Model

About here: Figure 2. Structural Model

In SmartPLS, the relationships between constructs can be determined by examining their path coefficients and related t-statistics via the bootstrapping procedure (Wong 2016).The strength of connection (path coefficient) indicates the response of the dependent variable to a unit change in an explanatory variable; under the condition that all other variables in the model are held constant (Bollen 1989). In a structural equation model, the path coefficients are similar to correlation or regression coefficients (McIntosh and Gonzalez-Lima 1994). An interpretation of the results of a path model involves testing the significance of all relationships in the structural model by assessing t-statistics (calculated by dividing the original sample from its corresponding standard deviation value), p-values and bootstrap confidence intervals. In the present work, 5% ($p < 0.05$) has been chosen as the level of significance for analysis of results. Using a two-tailed t-test, this 5% significance level requires the t-statistic to be larger than 1.96 (Wong 2016). Table 3 shows the t-statistics and p-values across each relationship and indicates the acceptance or rejection of the null hypothesis.

The relationship between student engagement (SE) and learning effectiveness (LE) was significant ($p = 0.002$), with a t-statistic of 3.149 (greater than 1.96) and β (original sample) equal to 0.263. This indicates the acceptance of alternate hypothesis that SE is positively related to LE. Therefore, H1 was accepted. Similarly, the relationship between learning analytical tool (LAT) and LE is found to be significant ($p < 0.001$) with a t-statistic of six greater than 1.96) and β original sample) equal to 0.505. This indicates the acceptance of alternate hypothesis that LAT is positively related to LE. Hence, H2 is accepted.

Insert Table 3: Significance of the Path Coefficients about here

Before testing $H_0 3$, the model containing all three constructs needs to be evaluated. The R^2 value is the most common measure for doing this. The value of R^2 (Table 4) lies between 0 to1 and a higher value represents greater predictive accuracy (Hair et al. 2011). F square effect size was analyzed as it is the change in the R^2 value on the omission of a particular independent variable from the model (Table 5).

Table 4: R square of the Structural Model about here

Table 5: F square effect size about here

In addition to evaluating the magnitude of R^2 Stone-Geisser's Q^2 value should be examined (Geisser, 1974; Stone, 1974). Q^2 in Table 6 represents the predictive relevance of the model. The model has predictive relevance for a dependent variable if the Q^2 value for this dependent variable is greater than zero.

Table 6: Q- square Construct Cross- validated Redundancy about here

Mediation Analysis

Having evaluated the model as a whole, mediation analysis was conducted. Hayes' (2009) method was implemented based on the argument that two direct relationships can't result in an indirect relationship. The process entails the estimation of the total and direct effect of predictor on criterion, as well as the indirect effect of the independent variable on the dependent variable through mediator.

Direct Effect

First, the unmediated path between SE and LE was analysed (Figure 3) and it was observed that SE to LE had a significant β of 0.638 and produced an $R2$ of 0.408 for LE (Table 7).

Table 7: Direct Effect of SE on LE about here

Figure 3. Direct effect of SE on LE about here

Indirect Effects

When the mediation relationship with LAT was added, the new paths were significant (SE to LAT had a β of 0.743 and LAT to LE had a β of 0.505). Importantly, the direct path between SE and LE was still significant with a β of 0.263 (Tables 8–10 and Figure 4). These results validated our model by providing strong evidence that LAT acts as a partial mediator and that predicting only a direct relationship between SE and LE is suboptimal. Therefore, $H_0 3$ was rejected.

About here:

Table 8: Indirect Effect Student Engagement*Learning Effectiveness

Table 9: Significance of the Indirect Effect

Table 10: Direct and Indirect Effects with significance

Figure 4. Mediation Model corresponding to the Model 4 given by Hayes (2009)

Discussion and conclusion

Indian graduates have low employability rates and one of the key reasons for this is career choices which are mismatched to their competences. The intrinsic competency and interests of the students are neglected in favour of careers that align with the choices of the students’ families or friends. This can have the effect of entrenching intergenerational inequality. There is urgent need of a tool which can provide a pedagogical approach to enhance the knowledge capital of students, in order to support choices more aligned to competencies. Digital educational games combine learning and enjoyment to offer a potential solution. The COMPCAT game engine, aligned with the use of learning analytics, is able to map the competency of the students to the career matching their personal profiles.

The findings of the study suggest that learning analytics is a potentially powerful tool for enhancing the learning effectiveness of the students in the context discussed in this paper. A partial mediation effect of the learning analytical tool was observed between the relationship of student engagement and learning effectiveness. Thus, the learning analytic tool enhances learning effectiveness. COMPCAT will serve as a catalyst in enhancing the knowledge capital of the students so that they can choose their next subjects in alignment with their intrinsic interests. The applications of the module can be replicated for second year students wherein their intrinsic interests can be mapped to facilitate their decision making to choose an appropriate career. The potential for the tool is that the career decision making of students generally, could become much better once they are aware of their intrinsic competence.

The dimensions to measure learning analytical tool and learning effectiveness are another significant contribution of the study. The comprehensive list of factors enhances the understanding of the concepts and enables future researchers to explore other avenues using these indicators.

The present study is highly pertinent for higher education institutions in India and can be extended to school students also. It also offers insights for countries globally. Although the use of gaming and learning analytics may be more developed in higher education settings beyond India, it is still the case that students globally have a mismatched set of skills to their jobs once they leave university. A tool to address the fundamental issue of sub-optimal subject choices has the potential to boost social mobility by helping guide students towards careers which match their intrinsic competence, and which are successful and rewarding.

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Tables and figures follow:

Figures

Figure 1: Screenshot of the game

Note – although colour figures presented, they are to be reproduced black and white

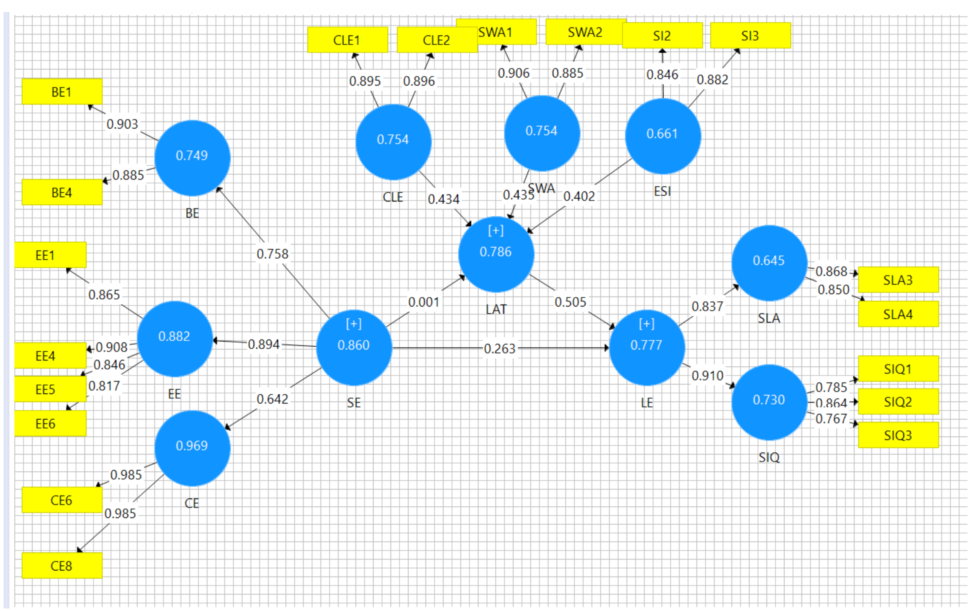

Figure 2. Structural Model

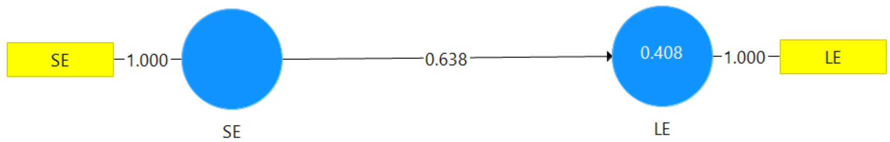

Figure 3. Direct effect of SE on LE

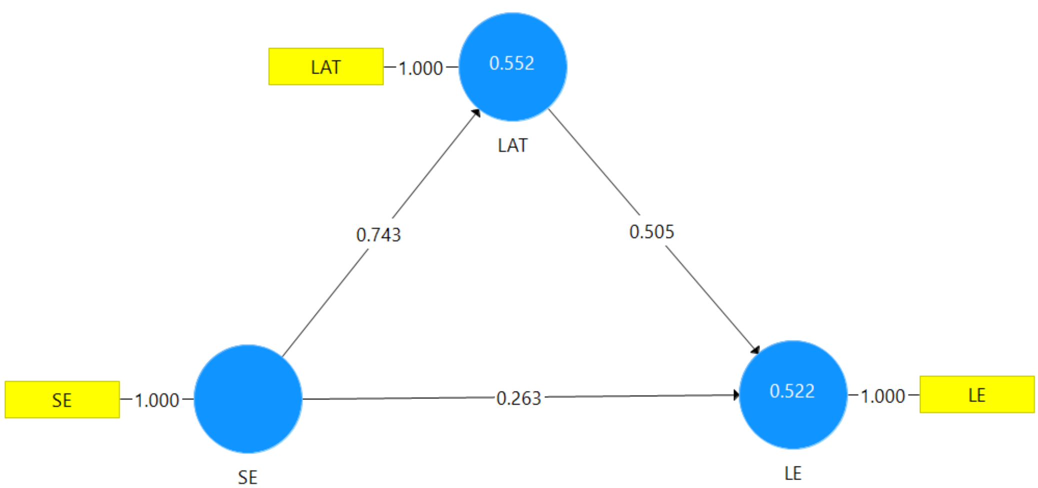

Figure 4. Mediation Model corresponding to the Model 4 given by Hayes (2009)

Tables

Table 1: Reliability of the Constructs

Construct	Cronbach α	Composite Reliability	Type of Construct	AVE (Average Variance Extracted)
Student Engagement	0.86	0.892	Reflective-reflective	0.510
Learning Analytical Tool	0.786	0.849	Reflective-formative	Content validity was established and VIF values were less than 5
Learning Effectiveness	0.777	0.849	Reflective-reflective	0.529

Table 2: Discriminant Validity- Heterotrait-monotrait ratio (HTMT)

Constructs	Dimensions & Constructs	Behavioral Engagement	Cognitive Engagement	Customised Learning	Emotional Engagement	Student Involvement	Learning Analytical Tool	Learning Effectiveness	Student Engagement	Student Inquisitive-ness	Student Learning Ability	Step Wise Approach
SE	**Behavioral Engagement**											
SE	**Cognitive Engagement**	0.393										
LAT	**Customised Learning Environment**	0.715	0.370									
SE	**Emotional Engagement**	0.648	0.371	0.714								
LAT	**Student Involvement**	0.614	0.493	0.644	0.661							
LAT	**Learning Analytical Tool**	0.806	0.531	1.023	0.767	1.100						
LE	**Learning Effectiveness**	0.751	0.560	0.641	0.581	0.689	0.890					
SE	**Student Engagement**	0.932	0.722	0.782	1.020	0.765	0.901	0.781				
LE	**Student Inquisitiveness**	0.607	0.566	0.485	0.531	0.519	0.773	1.217	0.711			
LE	**Student Learning Ability**	0.835	0.453	0.761	0.553	0.822	0.908	1.166	0.749	0.773		
LAT	**Step Wise Approach**	0.646	0.445	0.521	0.512	0.602	1.007	0.851	0.666	0.883	0.653	

Table 3: Significance of the Path Coefficients

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P**
Learning Analytical Tool-> Learning Effectiveness	0.505	0.498	0.084	6	0.000
Student Engagement -> Learning Analytical Tool	0.743	0.739	0.041	18.123	0.000
Student Engagement -> Learning Effectiveness	0.263	0.271	0.084	3.149	0.002

Table 4: R square of the Structural Model

R^2	**0.52**

Table 5: F square effect size

	Learning Analytical Tool	**Learning Effectiveness**	**Student Engagement**
Learning Analytical Tool		0.239	
Learning Effectiveness			
Student Engagement	1.23	0.065	

Table 6: Q- square Construct Cross- validated Redundancy

	SSO	**SSE**	**Q^2 (=1-SSE/SSO)**
Learning Analytical Tool	161	75.095	0.534
Learning Effectiveness	161	79.92	0.504
Student Engagement	161	161	

Table 7: Direct Effect of SE on LE

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
Student Engagement -> Learning Effectiveness	0.638	0.641	0.051	12.581	0.000

Table 8: Indirect Effect Student Engagement*Learning Effectiveness

	Learning Analytical Tool	***Learning Effectiveness***	***Student Engagement***
Learning Analytical Tool			
Learning Effectiveness			

Student Engagement		0.375	

Table 9: Significance of the Indirect Effect

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
Student Engagement -> Learning Effectiveness	**0.375**	0.374	0.069	5.44	0.000

Table 10: Direct and Indirect Effects with significance

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
Learning Analytical Tool -> Learning Effectiveness	0.505	0.504	0.09	5.591	0.000
Student Engagement -> Learning Analytical Tool	0.743	0.743	0.041	18.152	0.000
Student Engagement -> Learning Effectiveness	0.263	0.267	0.089	2.96	0.003