Technology-Enhanced Learning Analytics System Design for Engineering Education

Kushal Abhyankar and Subhashini Ganapathy

Abstract—**The field of technologically enhanced learning (TEL) allows for the visualization of different patterns of user behaviors. These trends represent the usages of the technology based educational content. The visualization of this information leads to the formation of a comprehensive analytics system to process the metadata. The efforts to the formation of this learning analytics system were initiated with a comprehensive ethnographic research conducted over the engineering students of Wright State University to understand the pain points in studying engineering subjects. The focus of this research is primarily over the development, testing and evaluation of the educational content over small form factors devices in order to provide an interactive form of learning support to the engineering students. The usage data will be collected from the students with the help of the questionnaire designed to understand the affinity towards the technology. The data will be collected to understand the user attitude, ease of use, behavioral and social effects on the user as well as the user affinity towards the technology. The metadata presentation forms the learning analytics system, which will serve as the performance benchmark for the educators, technology developers, education administrators and stakeholders.**

Index Terms—**Mobile computing, technology enhanced learning, learning analytics, model analysis.**

I. Introduction

In the field of education, the term technology enhanced learning (TEL) is getting special focus due to the utilization and consumption of cutting edge technology to assist learning. Especially in the field of engineering education, the use of TEL proves to be a valuable asset to learn about the concepts, which mostly appear abstract to the students due to the deductive teaching practices [1]-[5]. The informal learning practices employ the latest content delivery systems to deliver the learning experience beyond the regular classroom limits [5]-[8]. Due to industry demands for the well versed engineers, the students should not only be thorough with the knowledge of Science, Technology, Engineering and Mathematics (STEM) subjects, but also should be able to understand and provide to the global demands asked by the organizations. These global demands include showcasing of the excellent communication skills to convey and effectively listen to thoughts, presentation proficiency and user empathy. The engineers should also understand the overall impact of their work and contribution from the economic, environmental and community perspective [9]. It is therefore extremely vital to equip and train the engineering students with the real world problems and initiate the problem based learning environments for them. The students and the educators are both committed to look for the better teaching and learning avenues. The advancement in the content presentation and delivery technology according to the user experience and demands generated the need for the analysis of the usage and the requirements data collected from the users, which plays an important role in the entire content and graphics development process.

The use of technology in the field of education is not unfamiliar. Most of the applications of the technology are silo solutions and the integration of the technology in the field of education lacks a systematic approach [9], [10]. Through this research, we present a systematic approach to leverage the approach of specific problem orientated technology development to a generalized TEL solution delivery system. The systematic approach is described in further section. The process of the development of information from the data gives rise to analytics. In the field of education, because of advanced technology and an overall thought of education process remodeling to answer to the rapidly evolving demand for the knowledge base, analytics play a critical role.

Learning analytics leads this research to the predictive model development with the user intention as output with the quantitative constructs as building blocks of the model. The reliability and the validity of the entire model will be tested with the help of the statistical methods such as Chronbach's alpha test and the partial least squares method.

II. Systematic Education Supportive Technology Development

The proposed process for technology development has been divided into three distinct phases to deliver the most acceptable educational content over the small form factors devices. Fig. 1 represents the phases of the research methodology to provide the mobile technology based scaffolding support.

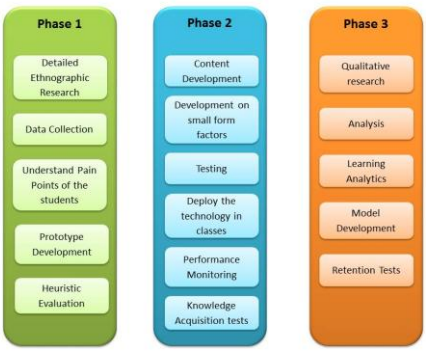

Fig. 1. Research phases.

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The steps involved in the development of the scaffolding content have been categorized as ethnographic research, content development, testing and data collection and formation of learning analytics. These steps are explained as follows:

A. Ethnographic Research

It is one of the most vital steps to understand the target user requirements and expectations from the technological support they would be receiving. When understanding the user expectations for the technological support, the researchers should be able to distinguish between the requirements which are strictly for support purposes and extraordinary expectations which may lead the technological support into overindulging the users up to the level of pampering. The ethnographic research also gives an idea about the points of integration of technology into the educational practices.

The primary round of ethnographic studies carried out at Wright State University with engineering students yield some of the most interesting results involving the difficult topics and subjects in engineering domain. The methods and results of these studies are discussed in [11]. The secondary round of ethnographic research was the deep dive anthropological study. This study yielded the shortcomings, expectations and support requirements of the students in the engineering curriculum. The outcomes of this study are as discussed in [12]. This step of the research was designed to observe some of the possible reasons for these roadblocks and how can they be answered individually. This ethnographic research was also designed to understand possible methods and solutions from student perspective. We designed a survey template to distribute and collect the data from the students. Due to the limitation of space, we will not be able to showcase the survey table in this paper. We compiled the lists of the respective subjects offered in the engineering degree program with the help of individual departments. Short informal interviews with the respective professors who taught these subjects were done after compiling the list of the subjects. These interviews yielded the syllabi of these various subjects taught at the College of Engineering and Computer Science, Wright State University. The syllabi yielded a comprehensive list of the sub topics taught under these individual courses. These sub-topics were presented to the students who were going to take this survey. The survey allowed the students to comment in detail about the reasons why the subject is difficult to learn. The survey also presented the students a chance to comment on the possible resources that could be implemented in the education system and made available to the students to learn the subjects better. The students could also comment about the possible improvements in terms of interactions and probable technology use in the education system around the engineering curriculum.

The participating students were the engineering students at Wright State University or alumni who had been in the engineering degree program for more than two years at least 2 years. These surveys are designed to understand ‘why’ the students are disinterested in learning these subjects and how the learning experience can be improved. With this survey template, the students commented generously on the difficult topics they learnt or have been introduced to in their undergraduate engineering education and the specifics of the topics learnt or have been introduced to. The students also commented on the methodology and educational settings with which they were trying to learn the subjects. The students also annotated on what additional scaffolding settings could have been helpful for them to learn those concepts. The survey also accelerated the data collection for the minor pain points to maintain the log which contained the entire set of pain points for the students who were exposed to the current educational systems.

From the results of the ethnographic research phase, it was evident that the students are looking for something much beyond just the classroom teaching and traditional interactions. The subjects that are already difficult are becoming very hard as the advanced applications of these subjects are introduced into the curriculum [12].

B. Content Development, Testing and Data Collection

As described in [12], we are in the process of deploying the designed course content in order to provide a scaffolding support to the students taking the basic statistics course through the School of Engineering and Computer Sciences at Wright State University.

The development of the technology will be platformed over the small form factors devices or the mobile devices. The mobile technology is a non-invasive technology which can provide the technology support to the learners without forcing them lose their orientation of the surroundings. This form of technology is a modern ubiquitous style that is the most accessible, universally available and inexpensive form of technology [13].

For the statistical design of experiment, we are going to identify 72 volunteers for only one semester who would be willing to participate in this experiment. We will be identifying 24 students from the GPA group 2-2.5, 24 from GPA group above 2.5-3, and 24 from GPA group above 3-4.

Before beginning the experiment, we will be identifying 72 students who fit in the GPA groups described above who took the course in the previous semester. We will be classifying them into GPA groups before they took this subject; we will be characterizing their performance in the examinations carried throughout this class. The performance measurement will form our base for the comparison of the performance of the GPA groups with and without the technology scaffolding support.

For this specific experiment, we will be developing the small form factors based content only for a few concepts that are the most difficult for the students to understand. We will be providing this digital content to the student participants taking this class. We will be developing the content for 72 devices as explained in Table I.

TABLE I: THE DISTRIBUTION OF SMALL FORM FACTORS DEVICES OVER THE TESTING GROUP

Type (Size) of the device	Number of Devices
4”	24
7”	24
10”	24

Four of each device will be given to each GPA group.

Therefore, the entire group will get all the different sizes of form factors. As the performance measurement, we will be monitoring the examination performance for all the students assisted with the scaffolding. With standard ANOVA, we will be able to see if there is a significant difference between the average performance of the students who studied without the technology assistance and the students who studied with the technology assistance.

All of the participating students will be asked to fill out questionnaires, which will be distributed over the course of two-three weeks. These questionnaires will probe the students to answer about the individual sub attributes and the primary attributes. These answers will directly be quantified because of 7 scale likert style question designing. Therefore, the raw data collected will directly be the available quantified data ready to be arranged and visualized.

C. Learning Analytics

As the students are exposed to the scaffolding technology, to understand and gauge the effectiveness of the technology introduction, the students will be given the follow up questionnaire which will probe them for the inputs over the individual attributes. These attributes form the base of the raw data that will be used for visualization and for further processing. The questionnaires will be distributed during and after the completion of the experiment. The raw data will then be used for the formation of the visualization system for the student performance monitoring and technology development expectations. Table II explains the process of the arrangement of the specific questionnaires to gather the data from the students in the form of specific attributes. The formation and organization of these attributes assist in capturing the metadata from the raw format of the collected data.

TABLE II: THE DISTRIBUTION OF THE COMPONENTS OF THE METADATA VISUALIZATION SYSTEM-LEARNING ANALYTICS

Name of the primary attribute	Constructing root attributes (if any)		
Performance Expectancy	Perceived Usefulness		
	Extrinsic Motivation		
	Job Fit		
	Relative Advantage		
	Outcome Expectations		
Effort Expectancy	Perceived Ease of Use		
	Complexity		
	Ease of Use		
Social Influence	Subjective Norm		
	Social Factors		
	Image		
	Perceived Behavioral Control		
	Facilitating Conditions		
	Compatibility		
Facilitating Conditions	Perceived Behavioral Control		
	Facilitating Conditions		
	Compatibility		
Self-Perception	Attitude Towards Technology	Attitude Towards Behavior	Behavioral Beliefs
			Outcome Evaluations
		Intrinsic Motivation	
		Affect Towards Use	
		Affect	
	Self-Efficacy		
	Attainment Value		
	Perceived Enjoyment		
	Self-Management of Learning		
Mobility			
User Experience	Usability		
	Desirability		
	Accessibility		
	Credibility		
	Findability		
	Usefulness		
	Valuability		

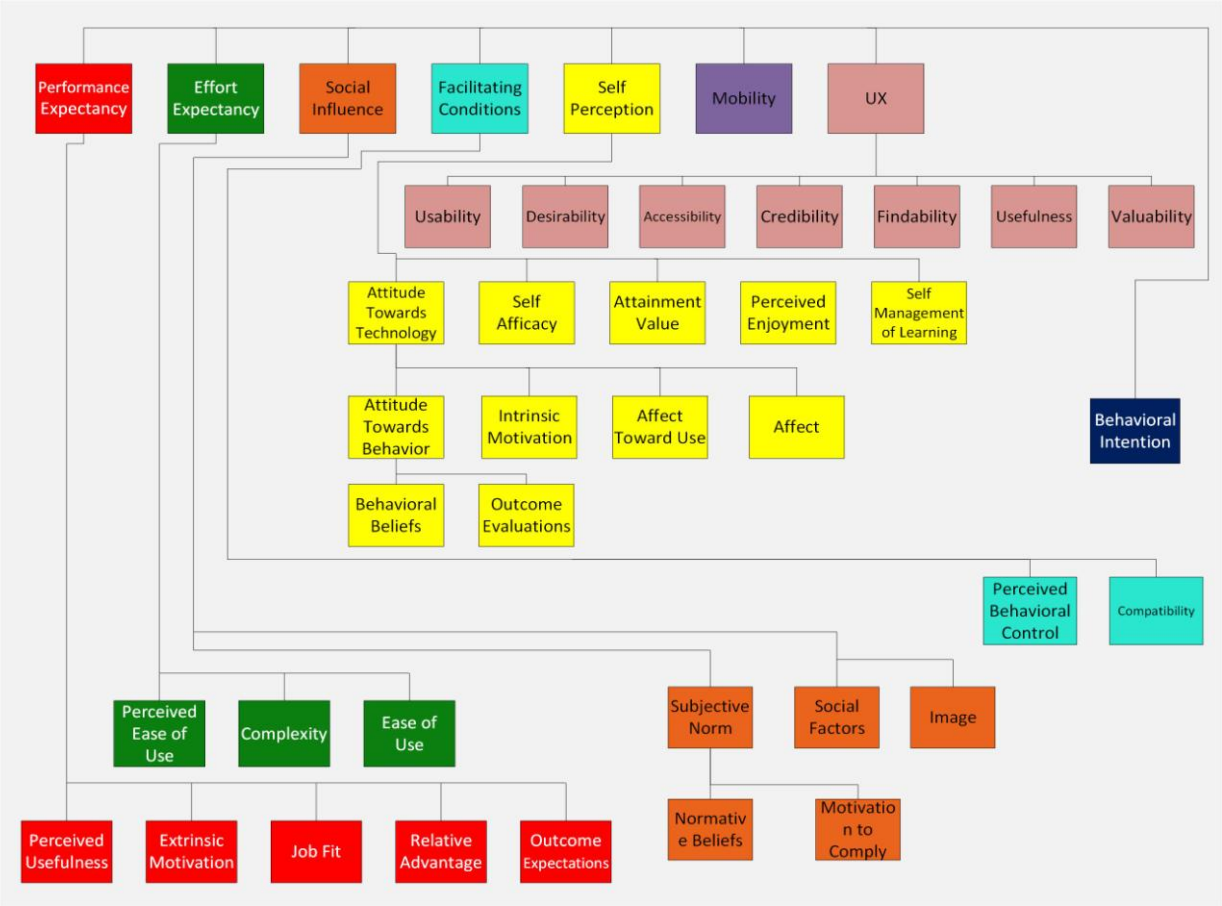

Fig. 2. User centered technology acceptance model diagram.

Learning analytics can be looked at as the information production from the data collected at the course level or at the departmental level. From the course level perspective, the objects of the analysis are social networks, conceptual development, discourse analysis and intelligent curriculum [14]. The departmental level analysis focuses on the predictive modeling, patterns of success/failure. The predictive modeling can be looked at as a powerful component of the process of learning analytics. Many of the highlighted presentations in the Conference of the Learning Analytics and Knowledge have talked about the modular development of the Learning analytics system. In the keynote speech by Börner in the Second Learning Analytics and Knowledge Conference 2012 Vancouver, hosted by University of British Columbia, she mentioned the importance of visual analytics to assist the decision makers in the field of education [15]. Siemens talked about the future use of learning analytics to map and produce the predictive and adaptive learning content as well as a tool to visualizing the learning practices [14]. Vatrapu et al. have developed the modular predictive analysis about the students' perseverance monitoring the students' learning activities [16]. The work by Brooks et al. is concentrated on viewing and understanding the patterns of viewing the lecture and the course content for the students [17]. This work has helped to understand the researchers and the technology developers how the students utilize the available content. The work by De Liddo *et al.* represents five types/dimensions/indicators of the social learning [18]. Lockyer and Dawson presented the relationship between the learning designs and the analytics. With the designed educational content, the performance of the students can be mapped which can be represented to the educators or the automated systems to modify and represent the content to offer a customizable and personalized educational experience [19]. Graf *et al*. developed analytics tool to provide the teachers and course designers with more meaningful information about student's behavior and their use of learning resources within an online course. This work primarily uses the log of data associated with the students' behaviors and actions that is stored comprehensively by the educational institutions [20]. The work from Sharkey outlines the efforts from the University of Phoenix to understand the student background and their progression through the courses to determine the level of their perseverance [21]. This is one of the most successful forms of metadata supported system which uses the information visualization base to leverage the assessment of the raw data collected. The techniques of visualization of the raw data yield a commanding tool for the metadata visualization. Duval presented with a system to map the student requirements to shape the curriculum and the teaching directions. This data visualization system provides a dashboard for the students and teachers to track the progress and therefore, help them to focus on the respective requirements [22]. Clow and Makriyannis analyzed the activity on iSpot, a website to learn about the wildlife through social interaction. This research presents the visualization capability to the learners to track their own learning and compare with others in an informal learning context [23]. Niemann provided the sematic linkage from the metadata to the learning content production system. This research focusses on identifying and addressing the learning objectives of the students [24]. Ferguson and Shum developed the algorithms to identify and explore from the synchronous text chats the data sharing patterns through identification of keywords, phrases to form meaningful dialog [25].

D. Model Development

The availability of the raw data gives a scope for building of the intention-predicting model. The model development begins with the idea of arrangement of the data into specific sets and understanding how much each set of the data points affects the decision of the user to accept the technology. The model constructs will be arranged as per the visualization system arrangement shown in Fig. 2 [26]-[32]. The objective of this division process is to understand the total effect of the each subset on the user's behavioral intention to use the technology. The subsets are the constructs of the model called as the User Centered Technology Acceptance model. The division and individual testing process will also highlight the success of future implementation of such technology platform. Our research is also focused on determining the pillars of the model. The pillar research will be steered to understand the strong modules which constitute the model and therefore understand the anchor points. These fortius modules are called as constructs which are the measures of individual elements that influence the behavioral intention of the users and the decision process towards the acceptance and future success of the technology integration. The arrangement of the model and constructs is as shown in Fig. 2.

III. Future Efforts

The direction of our future efforts is the development of a comprehensive visualization system to monitor the responses from the users of the developed technology. As the users are exposed to the developed technology based content and their performance is monitored in the class, the students will be given the users will be provided with the questionnaires to comment on the technology and their attitude towards the technology with respect to the attributes. The visualization will be presented to the education administrators, curriculum designers and content developers as a spider web diagram with each arm representing the average output of each of the primary attribute. By clicking on the individual arm, the user will be able to monitor the outputs of the sub-attributes constituting the data. Therefore, the user research data related to the acceptance of the technology can be visualized comprehensively with the help of graphics and charts. This is one of the most effective ways to visualize the raw data in the form of useful information. This enables an extremely effective metadata visualization system which can be thought as an assisting system for the technology and content developers, administrators, teachers, designers, and stakeholders.

One of the direct derivatives of the learning analytics and the base data is the development of a user intention predictive model which will be able to predict the intention of the user to adopt the technology which will be introduced for scaffolding. The model utilizes the user generated data inputs as individual constructs of the model. These constructs are same as attributes described above and collectively, each construct loads the output user intention with individual weights. The reliability of the predictive user intention is measured with the help of the tests called Chronbach's alpha test and Partial Least Squares method of reliability.

The goal of this research is to provide the engineering students with assisting learning content over the latest available technology of small form factors devices. The content development process leads the development of the process of the standardization of the content presentation. This standardization will be achieved through the taxonomy of design guidelines for the presentation for the interactive assisting content on small form factors devices. The immediate outcome of this research project will therefore address a multitude of the issues with respect to the formation of the standardized methodology for the content development, testing, integration and amendment over a wide range of engineering majors.

IV. Key Contributions

The key contribution of this research is that it allows for development of a framework for educational technology development, testing and systematic integration in education mainstream. The taxonomy of design guidelines developed, as an extension of this research, will be useful for practitioners to easily develop technologies that have high user experience. The user-centered technology acceptance model can help understand the reliability and validity of the collected data.

V. Conclusion

One of the most important and vital contributions from this research will be the development of the taxonomy of design guidelines. With this research, we are introducing a systematic methodology of the development of the framework for the effective integration of the technology into engineering education. This framework development will address the pain points of the students keeping them in primary focus along with the development of the technology. With the development of the learning analytics system, we will be giving a systematic scope for the stakeholders to understand the effectiveness of the technology and the content design for future applications. The user centered technology acceptance model will make sure of the reliability and the validity of the collected data. The model development and analysis will also allow the stakeholders to understand the impact of all the technology and user dependent behavioral constructs on the user intention for the acceptance of the technology.

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