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A Conceptual Framework for Online Authentic Learning to Support Knowledge Construction Among Undergraduates

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Abstract--*The paper presents a conceptual framework of students' knowledge construction through online authentic learning environment in learning inferential statistics that enhance students' performance and knowledge retention. The online learning environment is proposed based on situated learning theory and social learning theory as an approach for promoting knowledge construction of the students. An authentic task will serve as the precursor to encourage social interaction among students, teachers and more experienced experts in the process. The social interaction afforded by online learning environment facilitate students' knowledge construction, leading to students' performance and knowledge retention.*

Key words*--Online Authentic Learning; Knowledge Construction; Knowledge Retention; Inferential Statistic*

I. INTRODUCTION

In globalising education, universities are implementing online learning, which has become an indispensable part for delivery of most of the courses in the 21st century. One of the courses that have gained attention in this mode of delivery is Mathematics, particularly Statistics because it is usually the compulsory subject that serve huge number of students and online learning is viewed as cost saving mean of course delivery. Online learning mode is also preferred for this subject because of technical reasons, such as its ability in assisting visualisation and animation of the concepts in statistics. Areas of online course research in statistics education have focused on the creation, technique, and implementation of course material. However, particularly in online learning, students need to feel motivated to participate in discussion to ensure their successful completion in the online course, with mastery of the knowledge for practical use. Although online statistics learning may have been proven effective, it may not be appealing to 21st century learners. Online statistics learning required to turn the corner and be focused on a mode of instruction that is inherently better than what we have today in conventional education.

Problems in statistics delivery

Most of the time when developing content for online learning, educators tended to converting content from conventional courses into an online format without pedagogical change. Higher education today is replicating the instructional design of conventional face-to-face courses in the online medium. For example, according to Lockwood (1) the content for introductory business statistics is dull and too mechanical without direct application to business application. At the same time, the delivery of statistics in online environment should not be

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merely delivery of content using technology or teaching from a distance, but rather the subject matter of the course should be of primary importance for the students (2) and which specific teaching practices are effective in best facilitating student learning (3).

The current curriculum has failed to provide contextual learning for students in learning inferential statistics meaningfully. As (4) put it:

"One old attack, from outsiders who put mathematical logic ahead of meaning-in-context is that statistics is largely just a collection of recipes that can be learned by rote and applied without thought. A newer attack with more substance comes from those who put context first: learning enough mathematics to understand where our methods come from is an obstacle to simply getting the job done" (pg.267).

Upon completion of the statistics course, students are unable to apply the knowledge learned in their research project or in real life dealings, even for students scoring high grade in the course (5). As we advanced into the age of information, we need to train people to be statistically literate at workplace and also in their daily life. The students need to be taught to think about social situations in which data are used and to give students an understanding of and hands on experience with the role of statistics in scientific discovery.

For decades, statistics educators have been acknowledging statistics (statistical inference) as one of the most demanding subject due to its high level of abstraction (6,7), complexity (8), lack of confidence (9) and the persistence misconceptions of students (10,11). Tishkovskaya et al. (12) expressed the concern of the fact that these courses affect life-long perceptions of and attitudes towards the value of statistics for many students, and hence many future employees, employers and citizens.

It has been recognized that the students of the 21st century think and learn differently than those from previous generations (13). This trend suggests the need to revisit and potentially update conventional teaching practices. Any change in teaching techniques should aim at promoting learning and hence should be guided by learning theory. Hence, this paper aimed to propose a conceptual framework for online authentic learning for learning inferential statistics to support knowledge construction among undergraduates.

II. LITERATURE REVIEW

In this section, we provide a review of the learning theories as well as elements that assisted us in developing the conceptual framework for online authentic learning to support knowledge construction among undergraduates in learning inferential statistics that enhance students' performance and knowledge retention.

Situated learning theory

Situated Learning Theory by Lave et al. (14) posits that learning is unintentional and situated within authentic activity, context, and culture. Lave et al. (14) call this a process of "legitimate peripheral participation" as this learning does not usually involve deliberate effort but rather participating and observing practitioners at the periphery or side in a community of practice or collaborative project, which eventually will move from peripheral participation to central participation as learning takes place.

Situated learning requires knowledge to be presented in authentic contexts, the settings and situations that would normally involve that knowledge. Social interaction and collaboration form essential components of situated learning. Learners become involved in a 'community of practice' which embodies certain beliefs and

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behaviors to be acquired. As the beginner or novice moves from the periphery of a community to its center, he or she becomes more active and engaged within the culture and eventually assumes the role of an expert. Situated learning is also related to Vygotsky's (18) notion (to be discussed in the following subsection) of learning through social development.

Studies that investigated situated learning environment (7,15–17) found this learning approach can enhance the learning of statistics, provided much attention is paid to the organisation of the learning environment in terms of contextualised activities, group common interest, diversity of participants involved and the of the system to encourage participation. Verhoeven (17) in her effort to encourage students to see the value of statistics for society and for their future careers, used community based group projects as a learning approach for introductory statistics courses and discovered that the grades of students who participated in group projects is significantly higher compared to students who did not take part in any student projects in their course. In subsequent evaluative study on statistics projects from students' perspective, Verhoeven (7) classified the first year students experience gain as providing added values, learning experience and group dynamics.

Vygotsky's social development theory

Vygotsky's (18) Social Development Theory suggest that individual maximum potential is met through social interaction. There are 3 major concepts covered by Vygotsky's Social Development Theory. Firstly, is the role of social interaction. Vygotsky (18) highlighted that socialisation affects the learning process in an individual. He believes that intellectual development occurs first between people in a social context before it is internalised within the individual when he mentioned:

"Every function in the child's cultural development appears twice: first, on the social level, and later, on the individual level; first, between people (interpsychological) and then inside the child (intrapsychological). This applies equally to voluntary attention, to logical memory, and to the formation of concepts. All the higher functions originate as actual relationships between individuals" (p57).

Secondly, is the concept of more knowledgeable others (MKO). The MKO refers to someone or something who has a better understanding or a higher ability level about a particular task, process, or concept than the person who is attempting to learn. Although self-initiated learning and discovery is effective, learning becomes more productive and contributory to cognitive development when acquired from an MKO.

The third is the concept of Zone of Proximal Development (ZPD). As described by Vygotsky (18), "ZPD is the distance between the actual development level as determined by independent problem solving and the level of potential development as determined through problem solving under guidance, or in collaboration with more capable peers" (pg. 38). When a student is in the ZPD for a particular task, difficult skills for the students can still be achieved with guidance and encouragement from an MKO.

Authentic learning

Authentic learning can be viewed as a by-product of situated learning (19). It is an instructional approach which view learning process as a function of the activity, context, and culture in which it occurs. This means that students learn content through activities rather than acquiring information organised by instructors. These activities consist of real-life task that provides opportunity for complex collaborative effort.

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In the framework of authentic learning by Herrington et al. (20), usable knowledge is best gained in the learning settings that feature the following characteristics; provide authentic contexts that reflect the way the knowledge will be used in real life, provide authentic tasks, provide access to expert performances and the modelling of processes, provide multiple roles and perspectives, support collaborative construction of knowledge, promote reflection to enable abstractions to be formed, promote articulation to enable tacit knowledge to be made explicit, provide coaching and scaffolding by the teacher at critical times, and provide for authentic assessment of learning within task.

In the aim to provide learning in context, the lessons for authentic learning should be planned in such a way that it is situated in real world setting. However, in the planning of authentic learning, the persistent question that comes into picture is: how real does it need to be? Herrington et al. (21) argue that realism in authentic learning can be a real learning context or a realistic simulation, provided it create cognitive realism:

“However, the contexts and tasks do not need to be real (at least in the sense proposed by Savery and Duffy, 1996), nor need they comprise complicated plots and well-defined characters, and anticipate selected outcomes (in the way proposed by Macedonia & Rosenbloom, 2001). They do not need to have a verisimilitude approaching virtual reality. Instead they should aim to provide “cognitive realism” rather than reality itself” (pg 90).

The emerging technologies such as Web 2.0 foster online authentic learning environment. New social media and technologies encourage shared knowledge and the development of participatory culture. This naturally leads to participatory online learning, such as online authentic learning, taking the advantage of these emerging technologies as cognitive tools.

One of the major challenges in statistics education is the high level of complexity and the distance between in-class examples and ‘real world’ experience. Statistics would become more accessible if students could learn how to put research results to use, i.e. context-specific situations.

There are few studies (22,23) done on the benefits of authentic learning for statistics students at tertiary level and resulted in positive result. In the exploration to expose undergraduates to authentic data analysis in statistics research, Nolan et al. (23) described the Explorations in Statistics Research workshop is a one-week National Science Foundation of USA-funded summer program that introduces undergraduate students to current research problems in applied statistics. Students of the program acknowledge that the material used is very different from what they are exposed to in traditional coursework and they left the program with a much better understanding of the role of statistics in scientific discovery. (22) on the other hand proposed a framework for infusing authentic data experiences within statistics courses to develop the skills needed for statistics majors define by the 2014 ASA Curriculum Guidelines for Undergraduate Programs in Statistical Science (American Statistical Association 2014).

Knowledge Construction via Computer Mediated Communication

Knowledge construction is a cognitive process whereby learners build understanding of concepts, phenomena, and situations when solving problems (24). Based on the constructivism view, learning occurs when the students construct knowledge from their own understanding and experiences. Knowledge construction is an effortful and situated process, which can be individual or social (25). The process is “situated” because they are

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enabled by social interactions within the particular group that is working together and by the particular technologies used (26,27).

Although knowledge construction is a cognitive process, knowledge is developed through social interaction among learners and between experts and learners. This social knowledge construction is advancing in line with the proliferation of internet, which mediated the process. The technology includes asynchronous and synchronous communication, such as discussion forums or bulletin boards in the learning management system or social software. The process of social knowledge construction is educationally meaningful, not only in the classroom context but also in the web-based learning context (28). Hence, it is a viable choice to research into online learning to foster knowledge construction, particularly in learning inferential statistics.

In recent years, Computer-Mediated Communication (CMC) have become a trend of educational research, as educators and psychologists investigate the learning environments that encourage students to develop basic skills within authentic contexts and that also promote meaningful and collaborative learning (29–31). The study of social knowledge construction in computer based learning environments has been the object of detailed investigation. Heo et al. (29) conducted an exploratory study on the patterns of asynchronous online interaction and knowledge co-construction in project-based learning for undergraduates. They found that the team with the most frequent online interaction benefit positively in their learning performance when students are engaged in higher levels of cognitive processes rather than just information sharing and accepting new ideas with little discussion. Lin et al. (28) analysed the social knowledge construction of high school learners during a collaborative problem solving learning activity. The study done in a synchronous discussion forum of a learning management system indicated that social interaction, regardless of relevancy to the discussion task, is significantly correlated with academic-related discussion content. It was also found that the success of the team project is subjected to the ability of students reaching the higher cognitive level of social knowledge construction.

Knowledge construction is often associated with deep learning, but involving different levels that leads to that. Various scheme of level of knowledge construction (32–35) were developed by researchers. The Interaction Analysis Model developed by Gunawardena et al. (32) is one of the most frequently used instrument and the extent of its use makes it one of the most coherent and empirically validated instruments in the research field (36). According to Gunawardena et al. (32), knowledge construction process involves five phases, namely (i) sharing/comparing information (Phase I), (ii) discovery of dissonance (Phase II), (iii) negotiation of meaning (Phase III), (iv) testing and modification (Phase IV) and (v) application of newly constructed knowledge (Phase V).

Past studies done on knowledge construction level in CMC reveals students construct knowledge at low level (37–39). However, for students meaningful learning and to enable them to be a critical thinker, construction of knowledge at higher level is important (39). As quality of the online interaction supersedes the quantity of the interaction, Heo et al. (29) suggested that the complexity of the project topics given to the students be ill-structured contexts to create more possibility to experience proficient interaction with their peers and deep learning in online learning settings. At the same time learner need to be given learning support in the form of appropriate feedback from the facilitators to keep them on the right track and not wasting too much time figuring out the project scope. Study by Shukor et al. (39) found that triggering argumentation is very important. This finding indicated that educators could assist discussions to promote argumentation such as by asking ques-

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tions or to provoke opinions during the discussions. The process is assisted by authentic problem solving task given to the students to trigger problem solving discussion. This is concurred by (40) which found from their literature review that complex thinking and higher phases of knowledge construction are achievable in different types of communication tools, if activities are designed accordingly.

Students performance

Many students of social sciences have difficulties understanding and applying statistical concepts and procedures (41,42). Some of the reasons identified for this phenomenon is the lack of motivation and statistics anxiety. Consequently, many university students performed poorly in statistics courses. This has led to statistics educators researching into various teaching and learning strategies in the effort to improve students' performance in statistics, particularly inferential statistics. These includes the integration of ICT in teaching statistics such as online learning and diversion from the lecture-based norm teaching such as project-based learning.

Studies indicated that online learning of statistics can enhance students' performance (43–46). These include the use of online learning that made up of web-based learning, multimedia learning and simulation-based learning. The features in online learning that assist students learning are the timely feedback and social interaction for cooperative learning afforded by this technology (45–47). Dynamic visualization through animation and simulation also allows students to grasp concepts in inferential statistics without the need for mathematical manipulations (43). However, the fact that students have the flexibility to go online at their own time, self-regulation differences among the students such as procrastination becomes an important moderator of successful implementation of online learning for facilitating students' performance (45).

On the other hand, the paradigm shift from the conventional lecture-based teaching into students' centered experiential learning has been gaining attention in improving students' performance in statistics. Collaborative learning (48), cooperative learning (46), situated learning (7) and project-based learning (49) are among the teaching strategies identified for developing students' statistical skills in statistics. These teaching strategies have been integrated into online learning environment to achieve two-fold benefits; teaching strategies that foster students active learning and learning environment that encourages social interaction. As most of these students' centered learning strategies are usually implemented in groups, Krause et al. (46) suggested formation of small and heterogenous group. Small group can focus on elaboration of the material rather than at extensive discussion of multiple perspectives while heterogenous group allows high-performing students learn by externalising and elaborating their own knowledge and low-performing students benefit from peer explanations and assistance.

Knowledge retention

Knowledge retention is part of the acquisition-retention-transfer cognitive (memory) processes involved in learning. Before knowledge is retained, it need to be first acquired. The knowledge acquired is then hold in the memory (retain) for certain period of time, and then transfer of the knowledge occur when it is used to facilitate new knowledge.

There are several models on how the memory system works during learning. In levels-of-processing model (50), the duration a memory will be remembered is determined by the depth of mental processing. Deeper

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processing level leads to better retention than shallow processing. This implies that meaningful learning rather than rote learning promotes retention.

In parallel distributed processing model (51), the memory processing occurs in parallel manner as well as in sequential manner. Information not only being processed in a series of steps but several different processes can be running at the same time. This allows learners to retrieve several inputs at a time, permitting faster reaction and decision.

The information-processing model is the most comprehensive and influential memory model in the recent decades (52). The initial model by (53) proposes three stages of memory system: sensory memory, short-term (working) memory and long-term memory. In the first stage, information enters the memory system through sensory system. Due to the limited capacity of the second stage system (short-term memory), only one part of the information will be selected to be moved to the short-term memory, where information is held for brief duration while being used, via selective attention process. The selection is not arbitrary and the learner will select the information that is most relevant to their sense. Short-term memory is also a working memory because it is where the memory system is actively organizing the information into an information model that make sense out of the pieces of information. When the information is repeatedly used, this important information is gradually transferred from short-term memory into long-term memory, to be retained as knowledge for long period of time. Long-term memory has unlimited capacity. To actively process the long-term memory, however, knowledge must be brought back to the working memory, integrating with new information model.

In order to facilitate knowledge retention, students must be engaged in the learning process (54). This call for a shift from instructivist to constructivist approach to teach the students. Constructivist learning theory emphasises the role of the learner in constructing his own view or model of the material. This theory explains that learning moves from experience to knowledge and not the other way around. It is guided by four principles - learners construct their own meaning; new learning builds on prior knowledge; learning is enhanced by social interaction; and learning develops through authentic tasks (55). For this, instead of emphasising the use of formulae, the development of computational skills and rote memorisation of procedural rules, introductory statistics teaching and learning today need to focus on conceptual understanding, statistical thinking, analysing real data, active learning in classroom, and aligning assessment with students' retention of statistical knowledge. Some of ways suggested by (56) to engage the students includes offering meaningful datasets and allow the students to ask their own questions; simulate workplace environment in classroom; focus on statistical solutions rather than statistical problems; and encourage the students to explain a statistical idea in your own words. Doing and discussing statistics on a daily basis helps students make the language their own, rather than falling back on your notes or their textbook.

Empirical studies (57,58) showed that active learning methods (group projects, cooperative learning-based methods and problem solving activities), tended to improve student retention above 5 months post-course at least for average or below average student compared to the class using traditional lecture-based teaching undergraduate Statistics courses. Although both Kvam (57) and Lovett et al. (58) could not establish statistical significance due to small sample sizes and this aspect need to be of consideration to ensure statistical significance and practical significance are reflecting each other.

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Framework for online authentic learning for inferential statistics

Theoretical framework

Based on the theories reviewed, all the important elements for the online authentic learning environment for inferential statistics are put together in a theoretical framework to see their interrelatedness, as depicted in Figure 1.

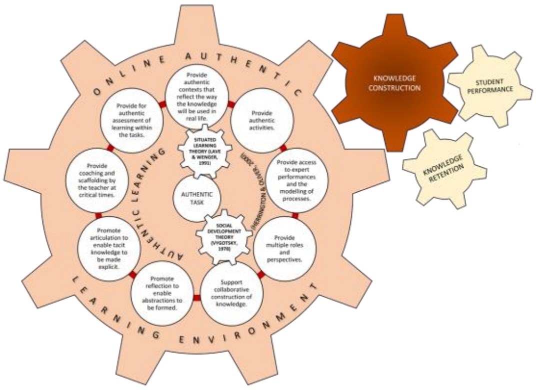

Fig. 1: Theoretical Framework

The situated learning theory form the foundation of authentic learning. In situated leaning, learning is viewed to be affected by situation, i.e learning and context are integrated. According to Lave and Wenger's (14) Theory of Situated Learning, learning is unintentional and situated within authentic activity, context, and culture. With literatures base on this subject, Herrington et al. (59) came out with an authentic learning model with nine critical characteristics of authentic learning. To cater for the needs of the 21st century learner's skills to be technology savvy, this authentic learning model (59) can be implemented in online setting to create the online authentic learning environment.

The authentic task will be taken as the initiating point in this study to establish the critical characteristics of the authentic learning. This authentic task will be in the form of problems for the students to work on in small groups.

Content form the major portion of any course delivery. The material that made up the content will conform to the theory of situated learning, where lessons are presented in real world context. Online technologies will be used to assist in creating realism of the content.

An important feature made possible by Web 2.0 is the social interaction among learners and between learners and facilitators. This feature needs to be incorporated in the online authentic learning environment as according to Vygotsky's (18) Social Development Theory, social interaction plays a central role in cognitive development. At the same time, Lave & Wenger's (14) Theory of Situated Learning also view learning as participation rather than an acquisition.

The online authentic learning environment set up for learning inferential statistics is hypothesised to encourage students' knowledge construction, and hence assists in students' performance and knowledge retention.

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Conceptual framework

From the theoretical framework, we propose the conceptual framework for online authentic learning to support knowledge construction among undergraduates, as illustrated in Figure 2.

The most important element in any learning design is the learning task or activities. A well-crafted task will enable and facilitate the application of the features in the online authentic learning to achieve the intended outcomes (21). Authentic task in the form of problem will serve as the learning task in the online authentic learning environment for inferential statistics. This task will provide activities in the real-life setting. The underlying Theory of Situated Learning by Lave et al. (14) form the basis for the creation of this task.

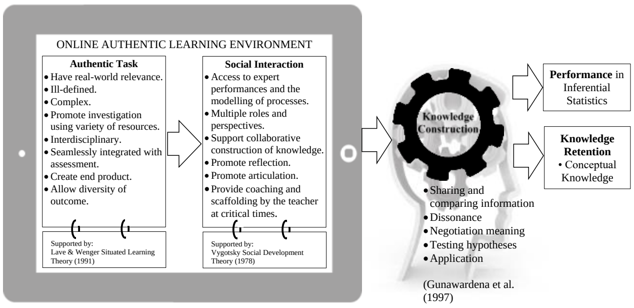

Fig. 2: Conceptual framework

In solving the authentic task in a small group, this will encourage active discussions and form social interactions among the students and between the students and facilitator. Online learning permits social interactions via asynchronous and synchronous communication facilities or discussion forums.

During the social negotiation processes in solving a given task, students build meaning through interactions with peers. The idea of Vygotsky (18) about the importance of social interaction in the learning process provided a guide in this study to look into how online learning environment assists students to construct knowledge socially in learning inferential statistics. The active knowledge construction is hypothesised to lead to students' better performance and retention in online learning as compared to conventional setting.

III. CONCLUSION

Undergraduate courses such as statistics, particularly inferential statistics, require highly contextual content and material to enable students to apply the knowledge learned in real life dealings upon the completion of the course. In addition to that, students' ability to construct knowledge on their own is crucial to ensure they can perform and retain of the knowledge for future use. The online authentic learning environment for inferential statistics that built upon situated learning theory, social development theory and authentic learning is proposed to help in students' knowledge construction that enhance students' performance and retention.

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