



Analysis of Effective Learning Outcomes from The Application of Smart Learning

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Abstract—The article delves into the impact and potential of smart learning methods on educational outcomes. This study critically examines the integration of technology and innovative pedagogical approaches in education, highlighting their role in enhancing learning experiences. Through a comprehensive analysis of various smart learning strategies, tools, and platforms, the article explores their influence on cognitive development, engagement, and knowledge retention among learners. Drawing upon empirical data and case studies, the research investigates the effectiveness of smart learning in diverse educational settings. By evaluating learner performance, feedback mechanisms, and adaptability of smart learning, the article contributes to a deeper understanding of its implications for modern education. The findings underscore the importance of effectively designing and implementing smart learning initiatives to foster meaningful and lasting learning outcomes.

Keywords —*smart learning, learning outcomes, effective learning*

I. INTRODUCTION

Smart City is an urban smart city where digital technology is embedded in all services and functions. The Smart City concept is a general label that may imply various nomenclature and contexts. It is still growing and covers several fields, areas and sectors. Several studies tried and are still trying to define a smart city and to determine the main characteristics and aspects for each city to be considered in order to be smart. Frost and Sullivan identify several key aspects that define a Smart City (Figure 1: The Smart City Concept): smart governance and education, smart energy, smart development, smart mobility, smart infrastructure, smart technology, smart healthcare and smart citizens. intelligent[1]. While the Institute of Electrical and Electronics Engineers (IEEE) defines Smart City as a city that brings together technology, government and society to enable the following characteristics: smart city, smart economy, smart mobility, smart environment, smart people, smart living, smart government[2][3].

One of the main aspects for cities to be smart is developing smart education and smart learning environments. Smart Learning Environment (SLE) is an environment that enhances learning technology that integrates the criteria and functions of smart learning systems and context-aware learning everywhere. Meanwhile, Smart Education is an education system that allows students to learn using the latest technology and allows them to study anytime and anywhere through the technology offered in their Smart Learning Environment[4][5]. According to Smart Education has three main dimensions: educational and learning outcomes[6][7], ICT and smart technologies offered and organizational dimensions. In this paper, we emphasize the importance of effective measurement of learning outcomes as a major aspect in the environment smart study. The aim of this paper is to find more effective and appropriate ways to measure and assess learning outcomes. In the following sections, this paper demonstrates the relationship between intelligent learning environments[8], learning outcomes and learning analysis. Then, it indicates the key key features to be included in any learning analysis tool developed for use in assessing and measuring learning outcomes. Finally, this paper highlights some of the challenges one might face developing such an LA tool and suggests future work.

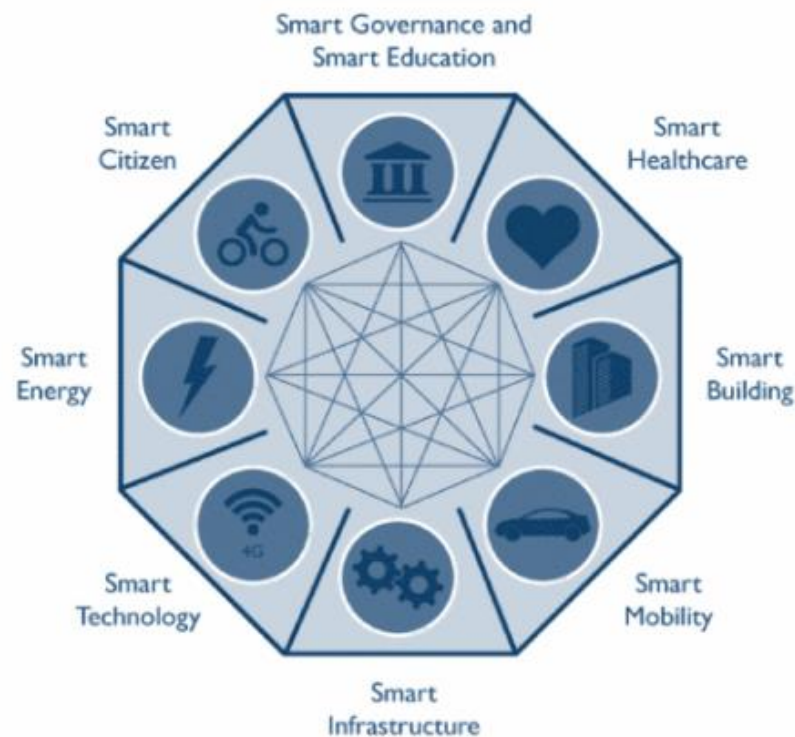


Figure 1 : Smart City Concept

II. THEORETICAL BASIS

Many research efforts have attempted to define an intelligent learning environment (SLE) and to identify the main characteristics that make up such an environment. SLE as an open, intelligent and integrated learning space based on constructivist learning theory, integrated learning theory and modern educational methods consisting of tools, tools, techniques, media, teaching resources, and related teacher and student communities[9]. Koper defines SLE as a physical environment enriched with digital devices, context aware and adaptive, to promote better and faster learning. An intelligent learning environment is also defined as a technology-enabled learning environment that makes adaptations and provides appropriate support (e.g.,

guidance, feedback, instructions or tools) at the right place and at the right time based on individual learner needs, which may be determined through analysis[10].

An smart learning environment not only allows students to access digital resources and interact with learning systems anywhere and anytime, but also actively provides them with the necessary tutoring, instructions, supporting tools or learning suggestions to them in the right places, on the right. time and in the right form. Basically, an intelligent learning system can be thought of as a technology-enhanced learning system capable of advising learners to learn in the real world with access to digital world resources[11].

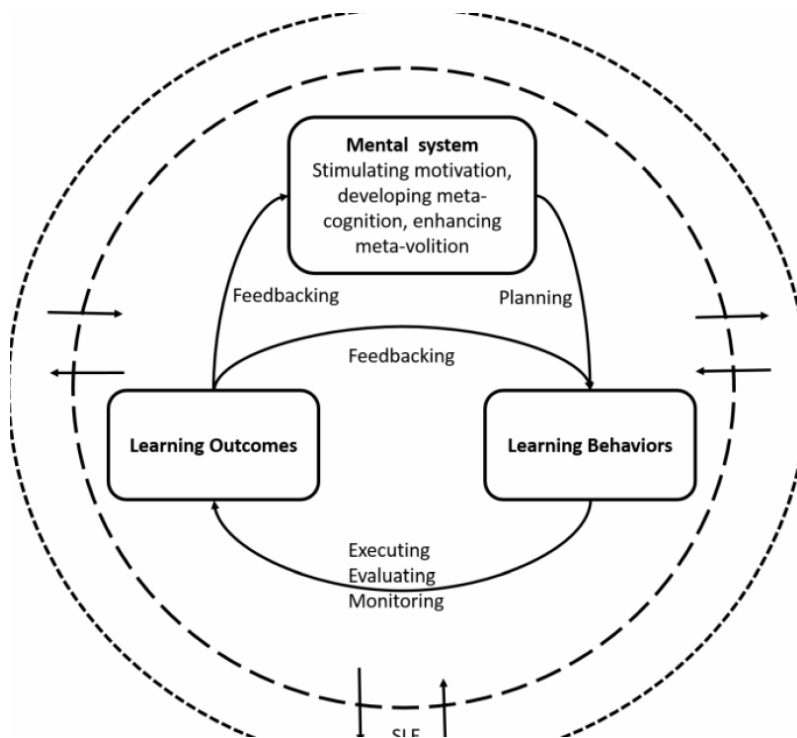


Figure 2 : Smart Learning cycle

An effective intelligent learning cycle consists of three factors: mental system, learning behavior and learning outcomes. (Figure 2: Smart Learning Cycle)[12].

The key components of the mental system are motivation to learn, meta-cognition and meta-will. Effective intelligent learning mental preparation includes arousing students' mental systems, developing meta-cognition and increasing meta-will. The condition for effective intelligent learning is that students have the motivation to accept learning assignments and want to participate in learning activities. Various stakeholders in SLE such as instructors, students and parents have many ways to communicate with each other in order to build a proper understanding of the relationship between learning outcomes and learning behavior.

Learning behavior is a two-way interaction between students and the learning environment, the purpose of this behavior is to cause desired changes in what students know and what they can do. This learning behavior in SLE can be summarized as the behavior of information retrieval, information processing, information release and interpersonal communication[5].

Learning Outcomes are formal statements of what students are expected to learn in a course. Expected learning outcomes statements refer to specific knowledge, practical skills, areas of professional development, attitudes, higher order thinking skills, etc. The faculty members expect students to develop, learn or master during the course. Learning outcomes should be

SMART: Specific and simple - Measurable - Achievable and achievable - Realistic and relevant - Time-bound and on target. These learning outcomes must result from different interactions in SLE[8].

III. TECHNOLOGY ANALYSIS IN A SMART LEARNING ENVIRONMENT

Smart learning environment is able to record every detail of student learning behavior. It also provides a good opportunity for various stakeholders such as instructors, students, educational institutions and researchers to obtain valuable and important information through this behavioral analysis. SLE involves context awareness. Where the context can include the user's initial knowledge, learning style, learning speed, current activities, goals (results), available study time, location and interests [8]. All of the information gathered about student learning behavior and its interactions with different contexts needs to be analyzed to be useful. The need for extraction and analysis for derived data is attracting the attention of the technological and intelligent society. Hence, various analytical technologies are starting to join the learning process as they involve the techniques and tools used to produce and communicate 'actionable intelligence' from big data sets leading to data driven decision making[13]. Analysis technology can incorporate students' personal aspirations in assessing the value of specified learning opportunities[14].

Learning analytics supports students' intelligent learning environment. Because it helps in monitoring student behavior in a timely manner and utilizes network information for more effective and intelligent discussion and interaction activities. In 2006 Retalis considered learning analysis and interaction analysis as a promising way to better understand learner behavior. Learner behavior provided in different learning management systems are some of the smart tools that provide instant feedback on learning behavior and help learners identify value. their studies. They also help identify gaps between knowledge, skills, and projected learning outcomes by measuring student progress in related tasks and activities. Learner behavior can track and record the learning process and learning outcomes and provide users with appropriate learning content to fill those gaps taking into account the user's context. Explore the analytical tools provided on the LMS platform and specifically in Moodle's focus on assessing student performance and academic progress such as student participation, activity completion, course overview, progress bar, and engagement analysis. Defining course outcomes in LMS such as Moodle is available but with many limitations regarding the analytics, tools and techniques needed to assess these learning outcomes and to measure student achievement[15].

There is a need for analytical tools that can measure student performance in different LMS activities and relate this to the appropriate learning outcomes, in other words to measure the effect on student learning outcomes. These tools will assist in evaluating the level of achievement of learning outcomes which will assist in making decisions about what will happen next. In order to develop effective analytical tools that facilitate measuring learning outcomes, predicting performance and assessing decision making, this paper proposes several key features to be considered in the design and implementation stages.

IV. FEATURES OF MEASUREMENT OF LEARNING OUTCOMES

The main feature we propose aims to help develop learning analysis tools capable of predicting student success of course outcomes using different LMS activities and functioning as an early warning system.

A. Mapping LMS Activities Against Different Learning Outcomes

Every LMS like Moodle captures and stores vast amounts of sophisticated user activity and interaction data. Different types of data can be considered as student activities and can be involved in measuring course outcomes. These types of activities can be generated by the LMS itself as a result of user interaction such as the types of resources accessed, login frequency, open and completed assessments and other site engagements or can be generated by an instructor and stored in the LMS such as quizzes, assessments and assignments. High-impact learning activities were significantly related to all measures of learning outcomes. It is very important to identify these activities and map them to related learning outcomes in a way that helps in dynamically determining the level of attainment of learning outcomes. The level of achievement of learning outcomes will depend on the completion of related activities over a certain period of time. For example, if a learner completes a certain number of related activities within a certain duration then he or she has mastered the related learning outcomes.

B. Course Map Design

In order to increase the intelligence level of analytical tools to be able to make decisions and recommendations on the assessment of learning outcomes, an effective infrastructure must be built by means of analyzing the roots of each activity and the sequence of different learning outcomes in the course. That is why, dynamic course maps have to be developed effectively that pull out many types of information about the subject and present it all in a single document or “master” interactive map.

The course map is a representation of how the instructor intends to approach and assess each student learning outcome identified using the LMS activity. These are the learning outcomes in chronological order that must be followed during the semester. This helps to align the course elements which are topics, course content, learning outcomes, learning activities and assessments and week of semester together. Interactive course mapping should not only show the learning outcomes ordered by the associated LMS activities but should also place those activities on the learning outcomes achievement scale. In other words, if students complete the activity with a certain value, it means that part of the scale is reached or covered. Weights should be assigned to each mapped activity to make it easier to analyze it later.

C. Qualitative Analysis

Most LMS-related analytics provide traces of student activity on the system and this data is then used to assist the management and effectiveness of institutional teaching and learning. Dawson added that this data analysis can be used to enhance students' learning experiences [12]. That means the analysis tool must not only apply quantitative analysis, but also qualitative, or at least a qualitative interpretation of the findings. Qualitative analysis and interpretation should include assessing the value of students' use of the environment. For example, it not only quantifies who uses the environment for what, but also assesses what might be good and what might be bad experiences, and offers suggestions for moving on a continuum from one to another.

D. Benchmark Identification

There is a need to identify benchmarks for learning outcomes to identify gaps, build business cases, and take action. The importance of benchmarking is to increase the effectiveness of the educational process. Norris, Baer and Offerman emphasize the need for benchmarking both within, and across institutions, with particular emphasis on developing the practices that make

them effective: “most important results analysis, action analytics” can only take place in companies and environments that really truly committed to measuring and improving key aspects of productivity, innovation, and performance [13].

E. Transparency

"Openness" and "learning analysis" are two growing trends in educational technology. Learning Analytics provides empirical evidence of what changes are needed while openness provides permission to make changes, adaptations and enhancements to learning resources. The openness of processes, algorithms and technologies allows researchers to develop their own tools and methods to integrate with any platform. The learning analytics platform should be an open architecture with standards for adding new plugins. Open learning analytics ensures continuous quality improvement. Most LMS-related learning analyzes are researcher- and tutor-oriented. The main goals of the LA technique are adaptation, monitoring, and prediction. Hence, there is a need for Open Learning Analytics which represents the intersection between learning analytics and open learning technologies such as using open standards, APIs and open source software.

V. FUTURE CHALLENGES AND WORK

One of the possible challenges associated with key features is ensuring that the course plans are well designed and that the alignment between the espoused learning outcomes and the different LMS activities is an appropriate match. Confirm that various LMS activities are reliable, adequate and sufficient to measure the adopted outcomes accurately and precisely. Another challenge can be raised when we are dealing with a large amount of data identifying the exact required data to be analyzed. The data extracted from the LMS system is inherently unintelligent. Count counts, access patterns, number of resources accessed and types of resources accessed don't really describe anything by themselves. Intelligence here comes in the interpretation of data with effective analytical skills.

One of the most promising future work can be done by focusing on the effectiveness of combining quantitative and qualitative analytical methods to achieve the breadth and depth of data analysis and interpretation. Quantitative analysis focuses on the basic level of assessment and reporting on learner activity while qualitative tools and approaches show how in-depth examination of content can reveal the types of contributions made, as well as the knowledge, information, tools and experiences that promote learning in the educational process.

VI. CONCLUSION

Learner behavior has potential in the context of assessing learning outcomes which is one of the main dimensions of intelligent goal-oriented education. In this paper we recommend several key features to consider in designing effective learning analysis tools used to measure and assess subject learning outcomes and predict student success. These key features enhance the development of a learning analysis tool that can be customized based on course requirements, activities and requirements, adaptable in any LMS platform and effective in making decisions and recommendations based on quantitative and qualitative analyses.

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