Building Smart Learning Analytics System for Smart University

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Abstract. The performed analysis of innovative learning analytics systems clearly shows that in the near future those systems will be actively deployed by academic institutions. The on-going research project described here is focused on in-depth analysis of hierarchical levels of learning analytics and academic analytics, types of data to be collected, main features, and the conceptual design of smart learning analytics for smart university. Our vision is that modern analytics systems should strongly support smart university's "smartness" levels such as adaptivity, sensing, inferring, anticipation, self-learning, and self-organization. This paper presents the up-to-date research outcomes of a research project on the design and development of smart learning analytics systems for smart universities.

Keywords: Smart learning analytics · Smart university · Smart education

1 Introduction

Smart Education (SmE), Smart University (SmU), Smart Learning (SmL), and Smart Classroom (SmC) concepts are rapidly gaining popularity among the world's best universities because modern and sophisticated smart technologies, smart systems, smart devices, as well-data-driven and data-based strategies and solutions, create unique and unprecedented opportunities for academic and training organizations. Using those innovative concepts, universities and colleges may obtain higher standards and innovative approaches to (1) education, learning, and teaching strategies, (2) modeling of students/learners as objects and education/learning as processes, (3) unique and/or high technology-based services to local in-class and remote/online students, (4) set-ups of modern highly technological smart classrooms with easy Web-based audio/video interactions between local/remote students and faculty, and collaboration between in-class and remote students, (5) design and development of Web-based rich multimedia learning content with interactive presentations, video lectures, Web-based interactive quizzes and tests, instant knowledge assessment and automatic posting of attendance, class activities, and learning assessment outcomes on course web sites,

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visualization of data in various forms including student, faculty and department dashboards, and many other advantageous features [1, 2].

Our vision is based on the idea that SmU, SmE, SmC, SmL – as smart systems – should implement and demonstrate significant maturity at various “smartness” levels or smart features, including (1) adaptation, (2) sensing (awareness), (3) inferring (logical reasoning), (4) self-learning, (5) anticipation, and (6) self-organization and re-structuring [3]. This is the reason that we consider emerging learning analytics (LA) as an integral part of SmE, SmL, and SmC concepts.

The Society for Learning Analytics Research defines LA as: “… the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” [4].

“A recent report from the U.S. Department of Education makes the point that on the program and institutional level, learning analytics can play a role that is similar to that of already existing business intelligence departments and applications. Just as business intelligence may utilize demographic, behavioral and other information associated with a particular enterprise and its customers to inform decisions about marketing, service and strategy, learning analytics promises to do something similar in educational terms” [5].

1.1 Learning Analytics’ Goals and Objectives: Literature Review

Various authors of available publications define the goals of LA in different ways. For example, in accordance with Siemens [6], “The broad goal of learning analytics is to apply the outcomes of analyzing data gathered by monitoring and measuring the learning process, as feedback to assist directing that same learning process. …Six objectives are distinguished: predicting learner performance and modeling learners, suggesting relevant learning resources, increasing reflection and awareness, enhancing social learning environments, detecting undesirable learner behaviors, and detecting affects of learners.”

Suchithra et al. [7] believe that “The main purpose of Learning Analytics is to improve the performance of learners. Also, the environment of learning in which the learner undergoes is enhanced which will ultimately result in a quality education. Learning Analytics helps educator/teacher to understand the students. Learning capabilities can be improved for the learners. … The Learning Analytics aims at the curriculum design, predicting the students’ performance, improving the teaching learning environment, decision support system for Higher Education Institutions, personalized approach to individual students, online and other learning modes including mobile, subject wise teaching and learning, subjects which has practical and evaluation process in the education system. … Learning Analytics is about the collection, analysis of data about the learners. It is an emerging field in research which uses data analysis on every tier of educational system”.

Borkar and Rajeswari presented the following approach in [8]: “Learning analytics approaches in general offer different kinds of computational support for tracking learner behavior, managing educational data, visualizing patterns, and providing rapid feedback to both educators and learners”.

Additionally, Tempelaar et al. [9] argue that “The prime data source for most learning analytic applications is data generated by learner activities, such as learner participation in continuous, formative assessments. That information is frequently supplemented by background data retrieved from learning management systems and other concern systems, as for example accounts of prior education”.

1.2 Learning Analytics on University Level: Literature Review

In accordance with Suchithra et al. [10], “Institution can use academic analysis to know the success of the students. It can also be used to get the attention of public. Report of the analysis can be used for the publicity of the institution.”

Mattingly et al. [11] argue that “Learning analytics in higher education is used to predict student success by examining how and what students learn and how success is supported by academic programs and institutions. … The focus is to explore the measurement, collection, analysis, and reporting of data as predictors of student success and drivers of departmental process and program curriculum”.

Siemens et al. in [12] wrote: “It is envisaged that education systems that do make the transition towards data-informed planning, decision making, and teaching and learning will hold significant competitive and quality advantages over those that do not”.

1.3 Learning Analytics on Course Level: Literature Review

Multiple publications are available regarding the approaches, concepts, and proposed framework for LA at the course level. For example, Dietz-Uhler and Hurn in [13] argue that “Goals that learning analytics address include predicting learner performance, suggesting to learners relevant learning resources, increased reflection and awareness on the part of the learner, detection of undesirable learning behaviors, and detecting affective states of the learner. … Data as login frequency, site engagement, student pace in the course, and assignment grades to predict course outcome. … Performance on course assignments and tests at various times in the course significantly predicted final grades.”

In accordance with Dyckhoff et al. in [14], “Masses of data can be collected from different kinds of student actions, such as solving assignments, taking exams, online social interaction, participating in discussion forums, and extracurricular activities. This data can be used for Learning Analytics to extract valuable information, which might be helpful for teachers to reflect on their instructional design and management of their courses.”

Ruiperez-Valiente et al. in [15] present the following vision of learning analytics: “The Khan Academy…platform provides an advanced learning analytics module with useful visualizations for teachers and students…the Khan Academy platform provides different learning analytic features by default.”

1.4 Levels of Learning Analytics: Literature Review

In general, LA may have several levels or layers of hierarchy and/or maturity. For example, Siemens et al. in [16] introduced a general hierarchical framework for LA levels that include 3 levels for LAs: (1) LA on personal level (analytics on personal performance in relation to learning goals, learning resources, and study habits of other classmates), (2) LA on course level (social networks, conceptual development, discourse analysis, "intelligent curriculum"), and (3) LA on departmental level (predictive modeling, patterns of success/failure). Additionally, for academic analytics they introduced (4) LA on institutional level (learner profiles, performance of academics, knowledge flow, resource allocation), (5) LA on regional level (state/provincial): comparisons between systems, quality and standards, and (6) LA on national/international level.

On the other hand, Lynch et al. in [12] proposed an LA sophistication model that contains the following LA maturity levels: (1) awareness, (2) experimentation, (3) organization, students, faculty, (4) organizational transformation, and (5) sector transformation.

1.5 Smart Learning Analytics: Literature Review

The idea of smart learning analytics (SLA) is in an embryonic state at this moment; a thorough search on the Internet discovers a few relevant publications. For example, Giannakos et al. in [17] defined "Smart Learning Analytics as a subset of learning analytics that focuses on supporting the features and the processes of smart learning". The authors primarily concentrated on "recent foundations and developments [of Smart Learning Analytics] in the area of Video-Based Learning" [16]. On the other hand, Boulanger et al. introduced in [18] "… a framework called SCALE that tracks finer level learning experiences and translates them into opportunities for custom feedback. … Students have been provided with customized feedback to optimize their learning path in programming".

Multiple publications are available on various topics related to LA aspects. Unfortunately, the aforementioned and multiple additional analyzed publications do not provide detailed information about SLA from the smartness levels point of view, i.e. levels of (1) adaptivity, (2) sensing, (3) inferring, (4) anticipation, (5) self-learning, and (6) self-organization [1–3]. Additionally, the analyzed publications are focused on applications of LA to learning process of students and/or life-long learners; however, they do not emphasize the fact that LA should demonstrate "smartness" features (or be smart) and strongly support all designed smartness levels, including the "self-learning" level, i.e. an ability of a smart university "to learn" about itself and, therefore, be able "to self-optimize" its operation and main business functions.

2 Project Goal and Objectives

The overall goal of the on-going research, design, and development project at the InterLabs Research Institute at Bradley University (Peoria, IL, USA) is to use a systematic approach to identify, analyze, test, design, and eventually implement various components of SLA system for an entire SmU. In order to achieve this goal, the project team selected the following objectives:

- analysis of most recent innovative developments in LA and SLA areas;
- analysis of existing LA levels;
- analysis of available software systems that may support learning analytics, and potentially, SLA;
- identification of main features of SLA – types of data to be collected and processed, and main functionality of SLA system

A summary of up-to-date project findings and outcomes is presented below.

3 Smart Learning Analytics: Hierarchical Levels

Our vision of an SLA system is based on the concept that SLA should have a hierarchical layered structure and strongly support all major components of SmU, including

(1) SmU stakeholders, including students, faculty, professional staff, administrators, life-long learners, donors, alumni, etc.;
(2) SmU main smartness features, including adaptation, sensing, inferring, self-learning, anticipation, self-optimization or re-structuring (see Table 1 below);
(3) SmU curricula, i.e. a set of smart programs of study and smart courses at SmU – those that can, for example, change (or optimize) its structure or mode of learning content delivery in accordance with given or identified requirements (due to various types of students or learners);
(4) SmE and SmL at SmU – main processes and business functions at SmU;
(5) Smart Pedagogy (SmP), i.e. a set of modern pedagogical styles (strategies) to be used at SmU;
(6) smart learning environment at SmU, including smart classrooms, smart labs, smart departments and smart offices, etc.;
(7) smart software systems at SmU, i.e. a set of university-wide distinctive smart software systems at SmU – those that go well beyond those used at a traditional university;
(8) smart hardware at SmU, i.e. a set of university-wide smart hardware systems, devices, equipment and smart technologies used at SmU – those that go well beyond those used at a traditional university);
(9) smart technology, i.e. a set of university-wide smart technologies to facilitate main functions and features of SmU and smart campus, for example, Internet-of-Things, cloud computing, iSafety, ambient intelligence, etc.;
(10) SmU resources, including financial, technological, human, and other types of resources.

As a result, we proposed the following hierarchical levels of SLA system:

(1) **Personal level** is the lowest level of the SmU for various types of stakeholders – students, faculty, professional staff, administrators, long-life learners, etc.; for

Table 1. SmU smart features [1]

SmU features	Details
Adaptation	SmU ability to automatically modify its business functions, teaching/learning strategies, administrative, safety, physical, behavioral and other characteristics, etc. to better operate and perform its main business functions (teaching, learning, safety, management, maintenance, control, etc).
Sensing (awareness)	SmU ability to automatically use various sensors and identify, recognize, understand and/or become aware of various events, processes, objects, phenomenon, etc. that may have impact (positive or negative) on SmU's operation, infrastructure, or well-being of its components – students, faculty, staff, resources, properties, etc.
Inferring (logical reasoning)	SmU ability to automatically make logical conclusion(s) on the basis of raw data, processed information, observations, evidence, assumptions, rules, and logic reasoning
Self-learning	SmU ability to automatically obtain, acquire or formulate new or modify existing knowledge, experience, or behavior to improve its operation, business functions, performance, effectiveness, etc. (A note: Self-description, self-discovery and self-optimization features are a part of self-learning)
Anticipation	SmU ability to automatically think or reason to predict what is going to happen, how to address that event, or what to do next
Self-organization and configuration, re-structuring, and recovery	SmU ability automatically to change its internal structure (components), self-regenerate, and self-sustain in purposeful (non-random) manner under appropriate conditions but without an external agent/entity. (A note: Self-protection, self-matchmaking, and self-healing are a part of self-organization)

example, students can get data-driven dashboard on (a) current academic performance in a course, on programs of study, etc., and (b) progress of development of various skills, including analytical, technical, management, and communication skills;

(2) **Course level** for students, learners, faculty, department chair, etc.; for example, faculty can compare academic performance of a selected student with (a) all students in the same class during current semester, (b) with all students in this class during recent semesters – based on these data a faculty can predict student's learning ability, final grade, etc.; additionally, faculty can compare student academic performance in courses that use (a) various modes of learning content delivery (face-to-face, online, blended), (b) various learning strategies (learning-by-doing, games-based learning, flipped classroom, adaptive learning, etc.)

(3) **Concentration/minor program level** (i.e. a level of a group of specialized courses) for students, faculty, administrators; for example, a department chair

can assess academic performance of (a) majors from his/her department, and (b) students from other departments who take a selected concentration, certificate or minor program at his/her department;

(4) **Departmental/program of study/curriculum level** for students, faculty and administrators; for example, chair of department can perform predictive analysis for various students and faculty; identify patterns of success for various types of students and faculty; perform data-driven control of enrollment into departmental programs - certificate, concentration, minor and major programs;

(5) **University level** is the highest level of a SmU for administrators, alumni, donors, etc.; for example, provost's office can monitor (a) student academic performance in various courses and programs, (b) retention rate in a major, department, college, university, etc.

4 Smart Learning Analytics: Types of Data to Be Collected/Processed

An SLA system should collect numerous pieces of data in order to support the idea of the *Data* $\mapsto$ *Information* $\mapsto$ *Knowledge* $\mapsto$ *Smartness* continuum at a SmU. Several examples of types of data to be collected by SLA system are presented in Table 2.

Table 2. Types of data to be collected by SLA system at SmU (examples)

SLA level	Types of data to be collected	Types of data to be collected (cont.)
University level	• Campus-related data • College or school-related data • Department-related data • Programs of study-related data (major, minor, concentration, certificate, etc.) • Student enrollment-related data • Student data (name, gender, DOB, DOA, credits obtains, course taken, grades, attendance, etc.) • Total numbers of students (full-time, part-time, undergraduate, graduate, etc.)	• Retention rate (%) • Graduation on time rate % • Faculty-related data (name, start date, level of education, promotion/tenure dates and decisions, etc.) • Student demographics data • Professional staff data • Demographic characteristics etc.
Program of study (curriculum) level	• Numbers of various students in a program (majors, non-majors, etc.) • Student data • Courses in a program • Retention/successful completion rates	• Faculty data • Post-graduation data (in program's area) etc.

(*continued*)

Table 2. (*continued*)

SLA level	Types of data to be collected	Types of data to be collected (cont.)
Course	• Number of students who regularly engage in course • Student goals • Course learning goals, objectives and expected outcomes • Course pre-requites • Course software and hardware systems, smart classroom and technology needed • Number of lecture views, logins to course web site, course LMS, PowerPoint slides, tutorials, assignments, discussion forums, etc.	• Student individual grades/scores on various course assignments • Class average grades/scores on various course assignments • Mean and standard deviation of scores • Attendance • Student behavior in a class • Student feedback etc.

5 Smart Learning Analytics: User Requirements

The introduced concept of SLA hierarchical levels and types of to-be-collected data enabled us to create a comprehensive list of user requirements to SLA system functionality. Table 3 below contains examples of such requirements from students, faculty, and department chair for one hierarchical level – LA on course level.

Table 3. SLA course level: SmU user requirements (examples)

Users type	Desired functions in SLA system (examples)
Faculty	• Keep track of student attendance and activities in the class • Keep track on student grades/scores for various course assignments • Collect data on of all standard calculations for grades for each course assignment (mean, standard deviation, etc.) • Compare scores and grades, student attendance, etc., of current students vs students in previous semesters of the same class and/or the same class with different faculty • Predict student academic performance, specific score, final grade, etc. • Model student success in a course, and his/her analytical, technical, management and communications skills
Depart-ment chair	• Keep track of course instructor accomplishments versus other faculty at the department, or at the same course (but other sections) • Compare student academic performance in a given course vs. student performance in the same course but in other sections, in previous semester, etc. • Access data of course academic performance of any student

(*continued*)

Table 3. (*continued*)

Users type	Desired functions in SLA system (examples)
Students	• Keep track of grades on tests, quizzes, labs, etc. • Keep track of what assignments are due when, when exams are, etc. • Keep all information about one specific class in the same place • Keep track of individual grades compared to other students in the class (anonymous comparative analysis) • Calculate what grade must be gotten on different assignments/tests/labs in order to maintain or get a grade of A, B, C, etc. • Calculate GPA depending on what grade is gotten in the class • Input experience level in information covered in the class to output expected grade • Give projected grade in class based on the grades in the grade book at any given time • Request help from professor/TA/etc. if not doing well in a course

6 Analytics Systems Analyzed

Multiple software systems used in the LA area were reviewed or analyzed with the purpose of identifying those suitable for SLA; the obtained outcomes are presented in Table 4.

Table 4. Existing analytics systems reviewed or analyzed (non-comprehensive list)

#	Name of analyzed system	System's developer	Technical platform	Ref. #
Commercial systems				
1	Google analytics	Google	Windows/Mac	[19]
2	Clicky	Clicky	Windows/Mac/Linux	[19]
3	Panoramaed		Windows/Mac	[19]
4	Moz Keyword Explorer	MOZ	Windows/Mac	[19]
5	SolutionPath		Windows/Mac	[19]
6	Chartbeat	Chartbeat	Windows/Mac	[19]
7	EdSurge		Windows/Mac	[19]
8	Adobe analytics	Adobe	Windows/Mac	[19]
9	Church analytics		Windows/Mac	[19]
10	Woopra	iFusion Labs LLC	Windows/Mac	[19]
Open source (free) systems				
1	Piwik	Piwik Pro	Windows/Mac/Linux	[19]
2	Open web analytics	OWA	Windows/Mac/Linux	[19]

(*continued*)

Table 4. (*continued*)

#	Name of analyzed system	System's developer	Technical platform	Ref. #
3	Klass data	Klass	Windows/Mac	[19]
4	Cyfe	Cyfe	Windows/Mac	[19]
5	eAnalytics		Windows/Mac	[19]
6	Countly	Countly	Windows/Mac	[19]
7	Unicon		Windows/Mac	[19]
8	Open dashboard		Windows/Mac	[19]
9	OpenReports		Windows/Mac/Linux	[19]
10	Site Meter	Site Meter	Windows/Mac	[19]
11	Ipoll	Griffith University	Mac, Windows, Linux	[7]
12	Moodog	University of California	Mac, Windows, Linux	[7]
13	Equella	University of Wollongong	Mac, Windows, Linux	[7]
14	E2coach	University of Michigan	Mac, Windows, Linux	[7]
15	Signals	Purdue University	Mac, Windows, Linux	[7]
Systems developed by authors of analyzed papers				
1	SPAM system		Windows	[20]
2	STEP UP!		Mobile App	[21]
3	SRES		Windows/Mac	[22]
4	HOU2LEARN		Windows/Mac	[23]
5	ALAS-KA	Ruiperez-Valiente, Munoz-Merino, Kloos	Web-based	[15]
6	LATUX (Learning Awareness Tools – User eXperience)	Martinex-Maldonado, Pardo, Mirriahi, Yacef, Ky, Clayphan		[24]
7	Course signals	Arnold, Pistilli	Windows, Linux	[25]

7 SLA System's Prototype Developed

We developed a prototype of the SLA system for a smart university – the InterLabs SLA system. This system should eventually include the functionality of SLA for SmU as described in Tables 2 and 3. Graphic user interfaces of developed prototype of the InterLabs SLA system for various users are presented in Fig. 1 (student view), Fig. 2 (faculty/instructor view), and Fig. 3 (department chair or administrator view).

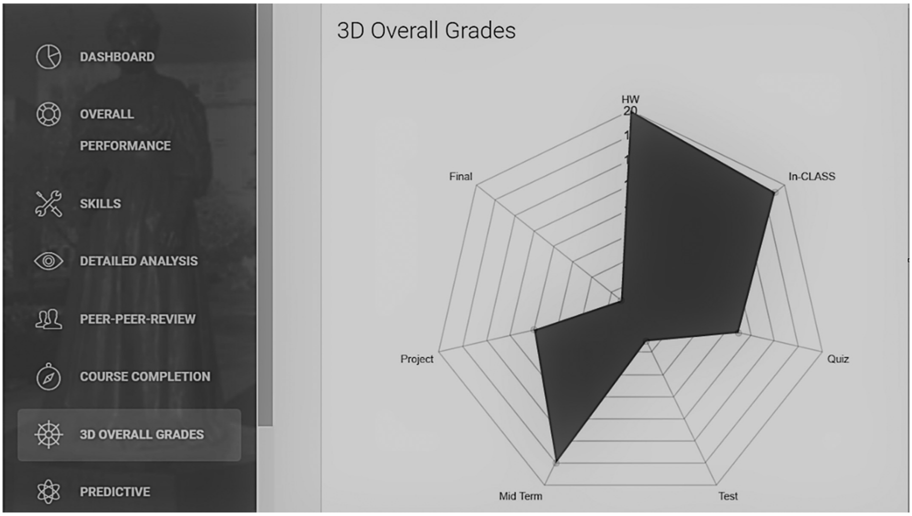

Fig. 1. A prototype of the InterLabs smart learning analytics system: student view

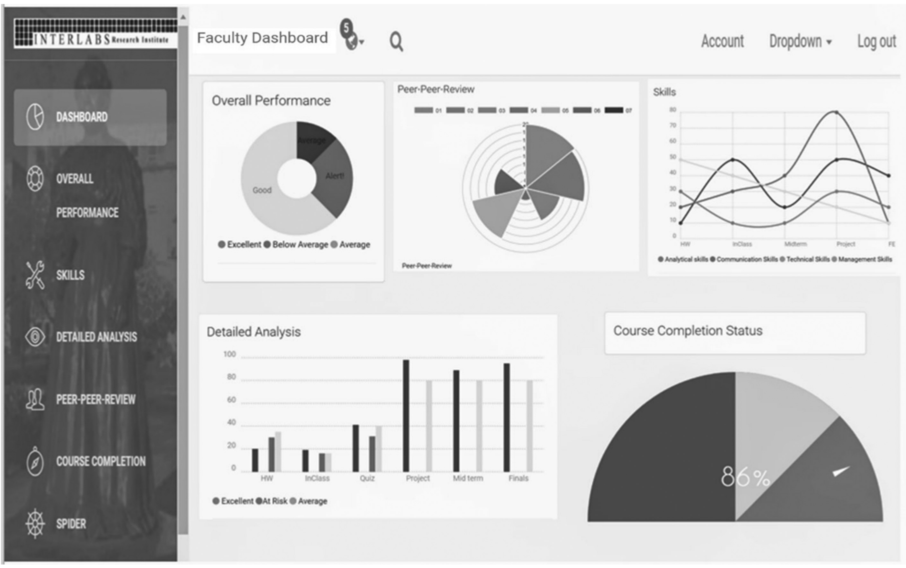

Fig. 2. A prototype of the InterLabs smart learning analytics system: faculty view

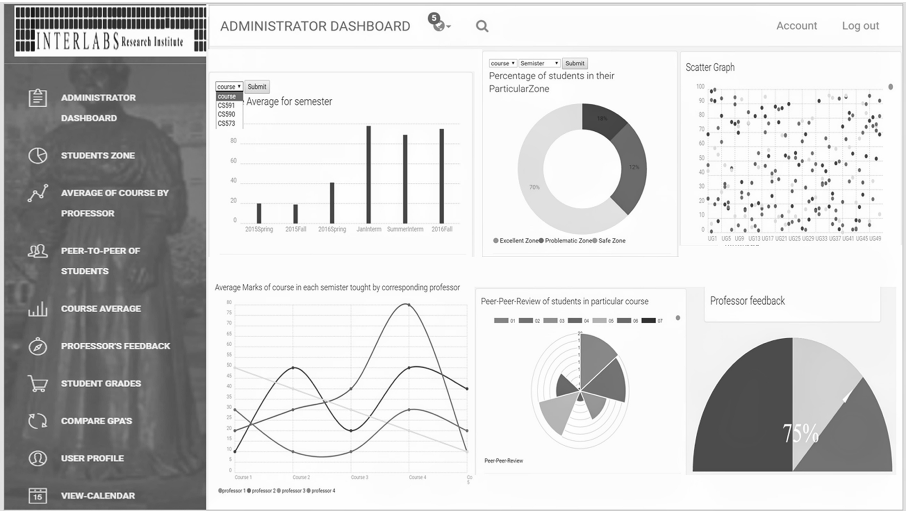

Fig. 3. A prototype of the InterLabs smart learning analytics system: administrator view

8 Conclusions. Next Steps

Conclusions. The performed research and analysis, as well as the obtained findings and outcomes, enabled us to make the following conclusions:

(1) Leading academic institutions all over the world are investigating ways to transform a traditional university into a smart university and benefit from the advantages of smart university, smart classrooms, and smart pedagogy. SLA systems will play a crucial role in SmU success.

(2) It is necessary to identify the main components of SLA systems, including hierarchical levels of SLA system, architectural model of SLA system with main SLA components and relations between them, types of data (data objects) to be collected and processed at SLA systems (Table 2), a set of SmU user requirements to SLA systems on each hierarchical level (Table 3), inputs to and outputs from SLA system, interfaces and protocols to be used, and constraints/limits of SLA system at SmU.

(3) We analyzed 30 + current systems relevant to various aspects of SLA; unfortunately, we could not identify any mature system among the existing ones – a system that will address the SLA features and functionality as required by SmU (Table 3). As a result, we designed and developed a prototype of SLA system - InterLabs SLA.

Next Steps. Based on the obtained research findings and outcomes, the next steps of this research project are to (a) use the Agile Software Engineering process model, (b) create a set of prototypes of SLA system for various types of users, and (c) involve various SmU users into the SLA design and development to ensure quality of final software system.

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