Learning Analytics for Smart Learning Environments: A Meta-Analysis of Empirical Research Results from 2009 to 2015

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Abstract

Although several qualitative analyses appeared in the domain of Learning Analytics (LA), a systematic quantitative analysis of the effects of the empirical research findings toward the development of more reliable Smart Learning Environments (SLE) is still missing. This chapter aims at preserving and enhancing the chronicles of recent LA developments as well as covering the

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abovementioned gap. The core question is where these two research areas intersect and how the significant LA research findings could be beneficial for guiding the construction of SLEs. This meta-analysis study synthesizes research on the effectiveness of LA and targets at determining the influence of its dimensions on learning outcomes so far. Sixty-six experimental and quasi-experimental papers published from 2009 through September 2015 in the domain of LA were coded and analyzed. Overall, the weighted random effects mean effect size (g) was 0.433 ($p = 0.001$). The collection was heterogeneous ($Q_t(66) = 78.47$). Here, the results of the statistical and classification processes applied during the meta-analysis process are presented and the most important issues raised are discussed.

Keywords

Learning analytics • Smart-learning environments • Meta-analysis review • Systematic review • Effectiveness • Classification of research papers

Introduction

Mobile learning (m-learning) has been acknowledged for the unique opportunity it offers for authentic learning experiences anytime and anywhere (Tatar, Roschelle, Vahey, & Penuel, 2003). Mobile technologies can facilitate learning "anytime and anyplace," offering a continuous learning experience that is personal, situated, and contextual (Traxler, 2007). The thriving spreading of smart devices combined with the development of novel online technologies (e.g., cloud computing, Internet of things, social networking services) has led m-learning to evolve into "smart learning" and to attract increased attention in a variety of contexts (Kim, Song, & Yoon, 2011). Thus, smart learning, as emerging learning paradigm, enables learning to take place anywhere and anytime.

Smart leaning has been considered and defined as a concept that combines the characteristics and advancements of ubiquitous learning with those of social learning, based on interactive digital content and services, beyond the employment of smart devices alone (Noh, Ju, & Jung, 2011). Therefore, smart learning can be regarded as learning in interactive, intelligent, and tailored environments, supported by advanced digital technologies and services (e.g., context-awareness, augmented reality, cloud computing, social networking service) (Lee, Zo, & Lee, 2014).

The recently formed International Association for Smart Learning Environments (IASLE; see http://www.iasle.net/) encloses and adopts a broader interpretation of what constitutes a Smart Learning Environment (SLE). According to Spector (2014), a SLE is one that primarily is effective, efficient, and scalable; desirably is engaging, flexible, adaptive, and personalized; and potentially is conversational, reflective, and innovative.

Still, researchers indicate that, in order to support students to learn in real-world contexts in smart ways, various factors need to be taken into account when designing and developing learning systems. A comprehensive and accurate description of the context is important when constructing pervasive and ubiquitous computing environments and applying them in educational praxis (Economides, 2009).

Discovery and evaluation of measures of motivation, participation, collaboration, dropout and satisfaction, measures of affect, attention and expectations, measures of attendance and retention (as predictors of learning), attitudes, degree of competence, and educational assessment and performance – which are all prerequisites in SLEs – need to be established through the accuracy of a meta-analysis of published results.

Learning analytics (LA) research results are expected to provide the necessary – missing at the time – insight into these features. That is because the LA research community has shifted from the traditional (and sometimes monotonous) analysis of learners' digital trails or numerical big data (e.g., online material access, digital learners' records, grades, and length of interaction with the learning environment) and is moving toward exploring multiple, complex, and information-rich data sources and sophisticated digital environments that employ mobile and smart devices and are inspired from *real-world contexts*.

By definition, learning analytics is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs" (Long & Siemens, 2011; see https://tekri.athabascau.ca/analytics/). Therefore, like in any other *context-aware system*, LA procedures retrospectively monitor and track the different digital traces related to the context, interpret and map the real current state of these data, organize them, use these data (e.g., decide adaptations, recommend, provide feedback, guide the learner), and predict their future state (Economides, 2009). The target is to inform and empower learners, instructors and organization about performance and goal achievement, evaluate the use and effectiveness of educational resources, and facilitate decision-making accordingly, by providing recommendations for improving them.

Although several literature review articles appeared in the domain of Learning Analytics (Bienkowski, Feng, & Means, 2012; Ferguson, 2012; Papamitsiou & Economides, 2014; Romero & Ventura, 2013) and have presented up-to-date comprehensive qualitative overviews of the current state in this area, a meta-analysis of the empirical research findings toward the development of more reliable SLEs is still missing.

This chapter aims at preserving and enhancing the chronicles of recent learning analytics advances development as well as covering the abovementioned gap and presenting a well-structured quantitative evaluation of the most significant works published in this area. It also aims at drawing wider conclusions from quantitative, experimental research studies and developing a more cumulative knowledge-base.

For the purposes of this study, international databases of authoritative academic resources and publishers were extensively and iteratively searched. This systematic search of the research literature from 2009 through September 2015 identified more than 400 studies on LA and more than 200 studies on SLE. Next, the quality of the collected literature according to rigorous quantitative and qualitative rules was assessed, and the inclusion criteria were explicitly defined. Sixty-six experimental and quasi-experimental empirical papers published during this period in the domain of LA were coded and analyzed.

This meta-analysis synthesizes research on the effectiveness of LA and targets at determining the influence of LA dimensions on learning outcomes so far. A discussion of the most important issues raised beyond the meta-analysis is also provided.

The chapter is organized as follows: section "The Need for a Meta-Analysis Review" is a brief introduction to the need for a meta-analysis of the published empirical LA research results, as well as the motivation and rationale of this study toward enhancing the development of SLEs. At the end of this section, the research questions of this study are explicitly stated. Section "Methodology" describes the methods followed for producing the meta-analysis and specifies the inclusion criteria for the selected papers. Section "The Sample of the Key LA Studies" summarizes the sample of the sixty-six LA works. Section "Analysis Results" presents the results of the statistical analysis and classification process applied on the selected papers. Section "Findings, Discussion and Conclusions" outlines the major findings of the meta-analysis process, presents the major characteristics of SLE, and discusses on (a) how these findings are associated with SLE, and (b) future implications of current empirical research results and their potential exploitation on developing SLEs and building-rich learning experiences.

The Need for a Meta-Analysis Review

This section presents findings and inspiration from previous learning analytics reviews. In particular, Romero and Ventura (2007) reviewed sixty works, including articles, conference proceedings, and working papers published from 1995 to 2005, showing how data mining was used in traditional classroom and distance education settings, discriminating between web-based courses, learning content management systems (or virtual learning environments), and adaptive and intelligent systems. In a follow-up review, Baker and Yacef (2009) compared the eight most-cited papers in educational data mining and distinguished between popular educational data mining research techniques and algorithms.

Ferguson (2012) examined the technological, educational, and political factors that have driven the development of analytics in educational settings, charted the emergence of learning analytics, and focused on the relationships between learning analytics, educational data mining, and academic analytics. Yet, Romero and Ventura (2013) presented an up-to-date comprehensive overview of the current state in data mining in education, targeting on the objectives, methods, knowledge discovery processes, and tools adopted in educational data mining research. Similarly, Suthers and Verbert (2013) considered the roles of learning analytics, arguing that they should function as a "middle space" between learning and analytics, whereby learning analytics should bring together various stakeholders and perspectives. However, all three reviews did not explore numerical findings or empirical results.

More recently, Papamitsiou and Economides (2014) investigated research trends in 209 mature pieces of research work on learning analytics from 2008 to 2013 taken from online digital libraries. In general, they categorized 40 key studies according to the adopted research strategy (category), research discipline (topic), learning settings, research objectives (goals), data gathering (sources and data-types) and analysis technique (method), and results and evaluated the findings with nonstatistical methods. Results showed the most popular domains in learning analytics studies are (a) pedagogy-oriented issues (e.g., student modeling, prediction of performance, assessment and feedback, reflection and awareness), (b) contextualization of learning (e.g., multimodality, mobility), (c) networked learning (e.g., MOOCs, social learning platforms), and (d) educational resources handling.

Motivation and Rationale of the Research

The abovementioned studies offer syntheses crucial to understanding issues related to learning analytics, but are incomplete; although these studies and initiatives provide important insights into the dynamic, nonlinear developments of the field of research in learning analytics over time, they lack a coherent, consistent, statistically guided decision about the strength of observed effects and the reliability of results across the range of selected studies. For example, they fail to account for the distribution of research purposes and methods of among the various articles, along with the type of learning setting used.

The Research Questions

In the context of this background, this study adopts a meta-analysis and research synthesis method in addressing the following research questions:

1. *Research Question 1 (RQ1): To provide an overview of the status of learning analytics in educational praxis*, including who is using them and why (i.e., distribution of educational contexts), which domain subjects are being taught (i.e., representation of disciplines and courses), which pedagogical approaches are adopted (i.e., distribution of pedagogical objectives and goals), and which data gathering (types of data) and analysis technique (method) are employed.
2. *Research Question 2 (RQ2): To quantify the overall effectiveness of integrating learning analytics for guiding the design and development of effective SLEs*, and explore the extent to which learning analytics results could influence SLE design strategies. Specifically, the present study poses two subquestions: (1) Where LA research results and SLE need intersect? (2) How LA research results could be mapped to the characteristics of SLEs addressed in the respective SLE studies?

Methodology

Traditional methods for literature review – event those that are systematic – focus on a qualitative presentation and interpretation of findings from analyzed studies. Meta-analysis, on the contrary, focuses on the range and strength of the *effects* across studies and is a suitable method for finding relationships across studies that are obscured in other approaches. Therefore, since meta-analysis is considered as an objective and quantitative methodology for synthesizing previous studies and research on a particular topic into an overall finding, it consists a more efficient and effective way to summarize the results of large numbers of studies than subjective judgment. This claim is valid because meta-analysis allows for collecting, coding, comparing, or combining results from different studies and interpreting those using statistical methods similar to those used in primary data analysis. Actually, at the heart of every meta-analysis process lies the statistical combination of results across studies (Lipsey & Wilson, 2001).

As Rosenthal (1984) indicates the unit of analysis in meta-analysis is the impact of variable *x* on variable *y* (*effect size*). The effect size makes meta-analysis possible because it is the *dependent variable* and because it standardizes findings across studies such that they can be directly compared (Lipsey & Wilson, 2001). Thus, any standardized index can be an *effect size* (e.g., standardized mean difference, correlation coefficient, odds ratio) as long as it meets three rigorous rules: (a) is comparable across studies (generally requires standardization), (b) represents the magnitude and direction of the relationship of interest, and (c) is independent of sample size. It should be noted that different meta-analyses may use different effect-size indices (Lipsey & Wilson, 2001).

Meta-analysis is a clear 12-step activity: (1) problem specification, (2) search for and identification of studies, (3) creation of the studies database, (4) selection of studies for review according to criteria, (5) review studies, (6) development of coding scheme, (7) abstract/coding studies, (8) selection of suitable effect size statistic, (9) transformation and weight effect sizes, (10) assessment of heterogeneity, (11) assessment of bias, and (12) synthesis and presentation of results.

Data Sources and Search Strategies

After determining the problem, i.e., the need to conduct a meta-analysis of learning analytics research results, the appropriate studies were searched and collected. For that reason, the article pool was determined and accessed and the key search terminology was declared. International databases of authoritative academic resources and publishers, including Scopus, ERIC, Google Scholar, Science Direct, DBLP, and ACM Digital Library, were extensively and iteratively searched. International journals, such as the *Australian Journal of Educational Technology*, *British*

Journal of Educational Technology, *Journal of Computer Assisted Learning*, *Educational Technology and Society*, and *IEEE Transactions on Learning Technologies*, were also manually scanned. The search terms included *learning analytics, learning analytics tools, learning analytics case studies, educational data mining, and knowledge discovery in education*. Furthermore, and since the core objective of this chapter was to investigate how the empirical learning analytics research results could be exploited for guiding the developments of SLEs, the abovementioned literature data sources (plus the *Smart Learning Environments Springer Open Journal*) with key terms related to this research field were also scanned. These included: *smart learning applications, smart learning case studies, smart classrooms applications and smart classroom systems*. The search process spanned from May 2015 to October 2015. The time frame of the search was bound within the last 7 years (2009–2015).

The initial search, and after deleting the duplicate records, yielded 653 abstracts published between 2009 and 2015 that were related to these research areas (416 related to learning analytics and 237 related to smart learning environments). These articles were then imported into a database containing the title, authors, year published, name of journal/conference, abstract, and keywords. In the second stage, a screening for experimental and quasi-experimental research took place within the previously generated database, while articles presenting conceptual analysis or research reviews, case studies and qualitative research, survey research, and pre-experimental studies were all excluded at this stage. Conference papers or book chapters were excluded. In total, 137 studies met the inclusion criteria and were used in the following analyses.

Studies were eligible for inclusion in the meta-analysis if they complied with the following three criteria:

1. *The application of learning analytics technique or method was the key variable of the study.* The experimental group had an intervention based on a learning analytics application and was compared with a control group that used traditional learning/teaching. The study should provide an in-depth illustration of the followed methodology (e.g., clear settings, fully explained experimental procedure)
2. According to Lipsey and Wilson (2001), *sufficient information* (e.g., means, standard deviations, t, F, or chi-square values) *was available to calculate effect sizes*.
3. *Sufficient presentation of the findings* (e.g., analytical discussion of findings and interpretation of results, use of figures and tables when needed) with clear and specific measurable parameter (e.g., retention, dropout, performance, etc.) as the major dependent variable.

Application of these criteria yielded 66 articles that were acceptable for inclusion in the meta-analysis.

Data Coding and Analysis

Next, an article classification according to nine features was executed. These nine features were: (a) year published, (b) adopted research strategy (category), (c) research discipline (topic), (d) learning settings, (e) educational contexts, (f) research objectives (goals), (g) pedagogical approach, (h) data gathering (data sources and types), and (i) analysis technique (method).

- *Category*: experimental, quasi-experimental, empirical studies, or surveys.
- *Topic*: humanities, social sciences, natural sciences, STEM studies, and professional studies.
- *Learning settings*: Virtual Learning Environments (VLEs), Learning Management Systems (LMSs), Cognitive Tutors (CTs), computer-based and web-based environments, mobile settings, educational games, Massive Open Online Courses (MOOCs), and social learning platforms.
- *Educational contexts*: formal learning, nonformal learning, and informal learning
- *Goals*: student/student behavior modeling, prediction of performance, increase of students' and teachers' reflection and awareness, measure students' participation and satisfaction, affect observations, improvement of provided feedback and assessment services, prediction of dropout and retention, recommendations, and user acceptance.
- *Pedagogical approach*: lectures, discovery and exploration, collaborative learning, problem-solving, game-based learning, self-directed study, computer-assisted testing, project-based learning, and mixed methods.
- *Data sources*: log files, questionnaires, interviews, Google analytics, open datasets, virtual machines, communities of practice, social media, learning environments enhanced with analytics, and mobile applications.
- *Data analysis methods*: classification, clustering, regression, text mining, association rule mining, social network analysis, genetic programming, discovery with models, visualization, statistics, and Technology Acceptance Model.

Calculating the Effect Size

The effect size (ES) was used to quantify the effects of learning analytics. ES is defined as the difference between the means of two groups divided by the standard deviation of the control group (Glass, 1976). For studies that reported means and standard deviations for both experimental and control groups, ES was calculated from the measurements provided.

Given the diversity of research quality, interventions, populations, and sample sizes among existing primary research, effect-size estimate precision varied. Thus, a conversion was made from Cohen's d to Hedges' g for all outcomes (Cooper, 1989).

Hedges's g, a standardized mean difference between two groups, as the effect-size index for this meta-analysis, was used in this study. The preference for Hedges's g over other standardized-difference indices, such as Cohen's d and Glass's Δ, is due to the fact that Hedges' s g can be corrected to reduce the bias that may arise when the sample size is small (i.e., $n < 40$; Glass, McGaw, & Smith, 1981).

Assessing Heterogeneity and Evaluating Publication Bias

The classical measure of heterogeneity is Cochran's Q, which is calculated as the weighted sum of squared differences between individual study effects and the pooled effect across studies, with the weights being those used in the pooling method. Q is distributed as a chi-square statistic with k (number of studies) minus 1 degrees of freedom. The collection of sixty-six works appeared to be heterogeneous ($Q_t(66) = 78.47$), which indicates that there are differences among the effect sizes, resulting from factors other than subject-level sampling error, such as the diversity of the pedagogical approaches, diversity of analytical methods, etc.

For the evaluation of the publication bias, a funnel plot with each Hedges' s g plotted against its standard error was first produced. The majority of the studies clustered symmetrically near the mean effect size toward the top of the graph. No study on the left side of the mean was projected as missing. This suggested the absence of publication bias.

The Sample of the Key LA Studies

As stated in the introduction, LA constitute an ecosystem of procedures that successively gather, process, report, and act on machine-readable data on an ongoing basis in order to advance the educational environment and reflect on learning processes. In general, these procedures initially emphasize on measurement and data collection and preparation for processing during the learning activities. Next, they focus on further analysis, reporting of data and interpretation of results, targeting to inform and empower learners, instructors and organization about performance and goal achievement, and facilitate decision-making accordingly (Papamitsiou & Economides, 2014).

The annual conference on Learning Analytics and Knowledge, as well as *the Journal of Learning Analytics* and many other relevant events and accredited journals, attracted the increased interest of learning analytics researchers and provided the research community with interesting results. Learning Analytics seems to provide new opportunities for tracking and analyzing learners' behavioral data and interpreting them in an educationally meaningful way.

From previous reviews of literature, it became apparent that four major axis of the LA empirical research have provided significant findings so far, including (a) pedagogy-oriented issues (e.g., student modeling, prediction of performance, assessment and feedback, reflection and awareness), (b) contextualization of learning (e.g., multimodality, mobility), (c) networked learning (e.g., MOOCs, social learning platforms), and (d) educational resources handling.

Prediction of dropout and retention have been extensively investigated by LA researchers (e.g., Cambruzzi, Rigo, & Barbosa, 2015; Dejaeger, Goethals, Giangreco, Mola, & Baesens, 2012; Lykourentzou, Giannoukos, Nikolopoulos, Mpardis, & Loumos, 2009; Macfadyen & Dawson, 2010). The issue of motivating engagement in learning activities and consequently increasing students' satisfaction and retention was also explored (e.g., Dejaeger et al., 2012; Giesbers, Rienties, Tempelaar, & Gijselaers, 2013; Guo, 2010; Guruler, Istanbullu, & Karahasan, 2010). Another crucial issue in LA research was how to increase the instructors' awareness, identify "disconnected" students, and evaluate visualizations regarding their capabilities on informing students about their progress compared to their peers (e.g., Ali, Hatala, Gašević, & Jovanović, 2012; Ali, Asadi, Gašević, Jovanović, & Hatala, 2013; Lin, Yeh, Hung, & Chang, 2013; Fidalgo-Blanco, Sein-Echaluce, García-Peñalvo, & Conde, 2015; Tempelaar, Rienties & Giesbers, 2014). In the context of social/open learning, the researchers explored the usefulness and motivation capabilities of dashboard-like applications regarding their self-reflection and self-awareness opportunities (e.g., Aramo-Immonen, Jussila, & Huhtamäki, 2015; Epp Demmans & Bull, 2015; Hernández-García, González-González, Jiménez-Zarco & Chaparro-Peláez, 2015; Romero-Zaldivar, Pardo, Burgos, & Kloos, 2012; Romero-Zaldivar, Pardo, Burgos, & Kloos, 2012; Tabuenca, Kalz, Drachsler, & Specht, 2015; Tanes, Arnold, King, & Remnet, 2011; van Leeuwen, Janssen, Erkens, & Brekelmans, 2014; van Leeuwen, Janssen, Erkens, Brekelmans, 2015; Xing, Wadholm, Petakovic & Goggins, 2015).

However, the landscape on LA research is rapidly changing. Lately, the educational research community is moving toward exploring different, multiple, more complex, and more information-rich data sources (e.g., haptic media and tangible computing, mobile platforms, wearable computing, immersive learning environments, shared workspaces, social networking media, MOOCs), in order to identify new suitable measures of learning and success (e.g., affect, attention, attitudes, community structure, degrees of competence, expectations, participation, satisfaction, social dynamics, attendance, and retention) and develop applications that are expected to enable personalized learning on a large scale. For these purposes, researchers are developing environments and applications to facilitate their investigations (i.e., learning environments enhanced with analytics, big data applications, classroom orchestration, open data, and data access for learners) (e.g., Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2015; Aramo-Immonen et al., 2015; Joksimović, Gašević, Loughin, Kovanović, Hatala, 2015; Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015; Moissa, Gasparini, & Kemczinski, 2015; Muñoz-Merino, Ruipérez-Valiente, Alario-Hoyos, Pérez-Sanagustín, & Delgado Kloos, 2015; Rienties & Rivers, 2014; Tempelaar, Rienties, & Giesbers, 2015; van Leeuwen et al., 2014; Veletsianos, Collier, & Schneider, 2015).

Modeling learners, enhancing social learning environments, detecting undesirable learner behaviors, and detecting affects of learners are among the core objectives of LA research (Verbert, Manouselis, Drachsler, & Duval, 2012). However, profiling learners without taking into account the emotional aspects that may hinder their progress can only offer an incomplete view of the learning experience. Several studies have indicated that affect and behavioral engagement can lead to differences in learning (e.g., Cheung & Song 2015; Joksimovic, Gasevic, Kovanovic, Adesope, & Hatala, 2014; Moridis & Economides, 2012; Rienties & Rivers, 2014; Tempelaar, Niculescu, Rienties, Giesbers, & Gijselaers, 2012; Terzis, Moridis, & Economides, 2012). D'Mello (2013) defines emotion-aware learning technologies as solutions that are able to sense the learner's emotional state (bored, confused, anxious, or frustrated, etc.) and then provide affective (emotional) feedback. Feidakis, Daradoumis, Caballe, and Conesca (2013) claim that the integration of emotion analysis into advanced learning technologies has potential to offer a more authentic and meaningful learning experience, either individual or social. A vast body of research on student retention indicates that academic performance can be reasonably well predicted by a range of demographic, academic and social integration, and psycho-emotional and social factors (e.g., Credé & Niehorster, 2012; Richardson, 2012). Different emotional data collection methods for supporting emotion-awareness detection and analysis in advanced learning systems have been employed and explored, both on preexisting and on newly generated and gathered, structured (e.g., use of sensors to capture biometric signals from learners, verbal or pictorial scale questionnaire of psychological factors, open-ended questions and interviews), and nonstructured (e.g., text data input from blogs, discussion forums, emails, learning diaries) data (e.g., Moridis & Economides, 2009).

Complementary to that, in the mobile learning context, Leong, Lee, and Mak (2012) explored the impact and usefulness of SMS free-text feedback to teacher regarding the feelings of students, after a lecture. Their goal was to visualize positive and negative aspects of the lecture by taking advantage of the limited SMS length and the use of emoticons in order to provide free-text feedback to teacher. In mobile learning context but from a slightly different viewpoint, Chen and Chen (2009) developed a tool that uses six computational intelligence theories according to the web-based learning portfolios of an individual learner, in order to measure students' satisfaction during mobile formative assessment. In a case study, Fulantelli, Taibi, and Arrigo (2015) demonstrated the application of the task-interaction framework that aims at supporting educational decision-making in mobile learning to learning scenarios based on the use of mobile devices. Finally, Tabuenca et al. (2015) suggested cues on how mobile notifications should be designed and prompted toward self-regulated learning of students in online courses.

Moreover, integrating LA into Serious Games (SG) design is expected to improve the assessment of progress, performance, learning outcomes, game quality, and user acceptance (Bellotti, Kapralos, Lee, Moreno-Ger, & Berta, 2013). In principle, all SG make use of in-game mechanisms for the assessment of player performance and progress, in order to respond appropriately to the player's actions. Indeed, many games monitor the player's progress in the game and assess the level of performance achieved. High performance in a game, however, does not necessarily imply effective learning. Various authors (Westera, Nadolski, & Hummel, 2014) point the fundamental difference between a performance orientation and a learning orientation. In general, learning and particularly higher order learning requires opportunities for reflection, informed repetition, self-evaluation, pauses, and even the preparedness to make mistakes and learn from them.

Approaches like unobtrusive assessment (often labeled as "stealth assessment") does not interrupt the flow in the game (Shute, 2011) and allows for providing feedback to the players during game play and is coherent with implicit learning. LA offer powerful tools for the assessment of game-based learning. The related processes of data gathering and analysis for the evaluation of SGs can be implemented at least in two possible ways: First, in-game analytics refers to collecting information from the individual player during game play in order to check the adequacy of the experience (Serrano-Laguna, Torrente, Moreno-Ger, & Fernández-Manjón, 2012) and to provide adaptive support and personalization of the game/learning experience (Minović, Milovanović, Šošević, & Conde González, 2015; Westera, Nadolski, Hummel, Wopereis, 2008; Westera et al., 2014). Second, an off-line (posterior) analysis gathers data from a population of players/learners for the purpose of quality assurance, evaluation, and improvement of the SG design (Baalsrud Hauge et al., 2015).

Analysis Results

The Comprehensive Meta-Analysis (Borenstein, Hedges, Higgins, & Rothstein, 2006) software for data analysis was used in this study, using independent samples as the unit of analysis and with both fixed-effect and random-effects models (Cooper, 2010). In this study, version 3 of the software was employed.

The overall mean effect size in this meta-analysis was $g = 0.433$, which is statistically significant, $z = 4.65$, $p = 0.001$, and of a medium magnitude (Cohen, 1988), meaning that enhancing learning with learning analytics is significantly more effective than traditional teaching/learning and assessment methods.

As seen from Table 1 and Fig. 1, most of the studies (>58 %) are published in two acknowledged peer-reviewed journals, the *Computers and Education* and *Computers in Human Behavior*, followed by *Educational Technology and Society*

Table 1 Distribution of published works per journal

Journal	#Of studies	Percentage (%)
Computers and Education	23	34.85
Educational Technology and Society	4	6.06
Computers in Human Behavior	16	24.24
Expert Systems with Applications	3	4.55
International Journal of Serious Games	2	3.03
The Internet and Higher Education	4	6.06
Journal of Universal Computer Science	2	3.03
Procedia Computer Science	3	4.55
Other	9	13.64

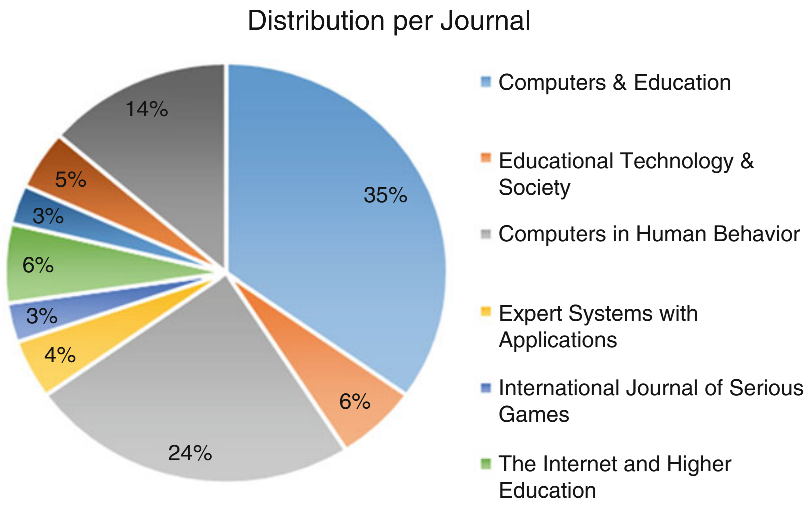

Fig. 1 Distribution of LA works per scientific journal

Table 2 Distribution of published works per journal

Year	#Of studies	Percentage (%)
2009	6	9.09
2010	4	6.06
2011	5	7.58
2012	12	18.18
2013	8	12.12
2014	6	9.09
2015	25	37.88

(6.06 %) and *The Internet and Higher Education* (6.06 %), which are also of high impact to the research community. This indicates that the published works receive high acceptance and recognizability and are treated as significant contributions to the educational community.

Table 2 presents the distribution of published results under meta-analysis per year. Most studies were published in 2015 (37.88 %) followed by those published in 2012 (18.18 %). This trend is also depicted in Fig. 2, expressing explicitly the increased interest of exploring the potential of learning analytics in educational praxis.

Table 3 shows the distribution of selected articles according to the adopted research strategy. In agreement to the inclusion/exclusion criteria, all of the studies should present numerical results and align to an experimental research category. Thus, 36.36 % of the studies were experimental studies, while 24.24 % and 22.73 % were case studies or empirical studies, respectively. In this meta-analysis review, one longitudinal study (1.52 %) was included.

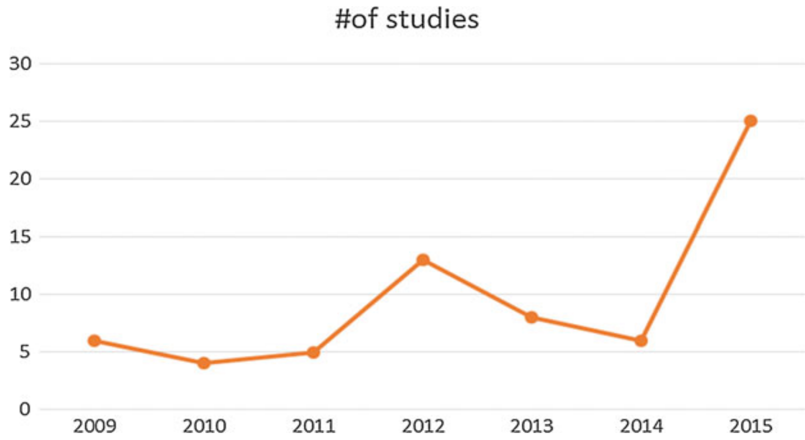

Fig. 2 Increase in number of published works per year

Table 3 Distribution of published works per research strategy

Category	# Of studies	Percentage (%)
Experimental	24	36.36
Quasi-experimental	5	7.58
Empirical	15	22.73
Case study	16	24.24
Survey	5	7.58
Longitudinal	1	1.52

Table 4 Distribution of published works per learning setting

Learning setting	# Of studies	Percentage (%)
VLEs/LMSs	12	18.18
MOOC/social learning/CSCL	10	15.15
Web-based education	15	22.73
Computer-based education	16	24.24
Game-based	4	6.06
Mobile	4	6.06
Other	5	7.58

Table 4 presents the distribution of published articles in accordance to the very important learning setting adopted during experimentation. As shown in this table, most of the works follow a web-based educational schema (22.73 %), while virtual learning environments and learning management systems are also very popular among LA researchers (18.18 %). Social learning, including collaborative setup and the large-scaled Massive Open Online Courses (MOOCs), is also common learning environment for LA research (15.15 %). The interesting results, however, are those referring to experimentation within newly introduced learning settings in the learning analytics domain, such as mobile learning, game-based learning (6.06 % in both cases).

Table 5 Distribution of published works per research objectives

Research objectives (goals)[a]	# Of studies	Percentage (%)
Student/student behavior modeling	18	27.27
Prediction of performance	24	36.36
Increase (self-) reflection and (self-) awareness	8	12.12
Prediction of dropout and retention	12	18.18
Improve assessment and feedback services	15	22.73
Participation and satisfaction	9	13.64
User acceptance	4	6.06
Affect observations	5	7.58
Recommendation of resources	4	6.06

[a]It should be noted that most of the studies had more than one research objectives; thus, the aggregated number of studies surpasses the total number of studies imported for meta-analysis

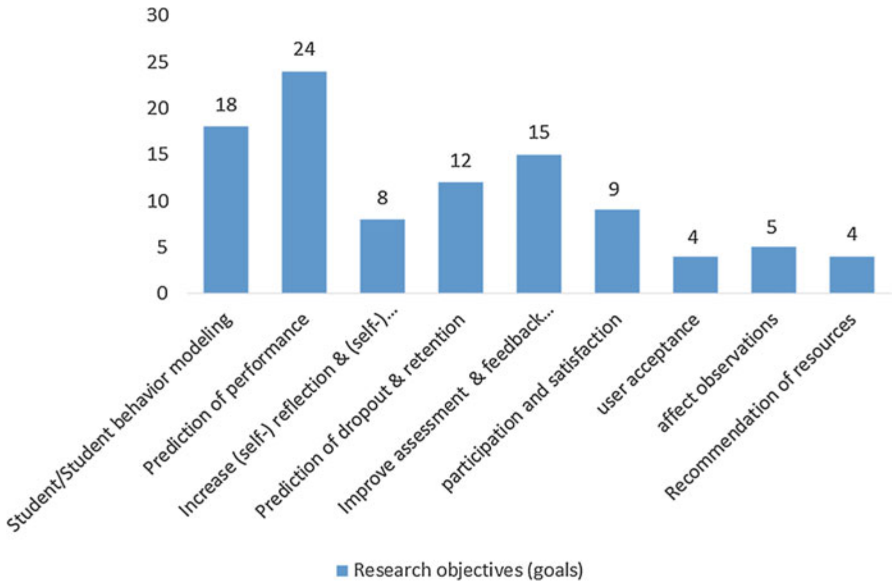

Fig. 3 Distribution of published works per research objectives

Moreover, Table 5 and Fig. 3 present the distribution of published articles per research objectives. As shown in this table, several studies focus on pedagogically meaningful analysis on collected students' data in order to shed light to the whole picture from students/students' behavior modeling (27.27 %) to self-regulated learning (12.12 %), prediction of performance (36.36 %), participation and satisfaction (13.64 %), and prediction of dropout and retention (18.18 %).

Finally, Table 6 presents the distribution of published works per data analysis method, highlighting the use of classification (30.30 %) and statistical methods for data manipulation (22.73 %). Other familiar methods include clustering (18.18 %)

Table 6 Distribution of published works per data analysis method

Data analysis method[a]	# Of studies	Percentage (%)
Classification	20	30.30
Clustering	12	18.18
Regression	7	10.61
Text mining	12	18.18
Association rule mining	8	12.12
Social network analysis	5	7.58
Discovery with models	3	4.55
Visualization	7	10.61
Statistics	15	22.73

[a]It should be noted that most of the studies had more than one methods of data analysis; thus, the aggregated number of studies surpasses the total number of studies imported for meta-analysis

and text mining (18.18 %), with the following Association rule mining (12.12 %), regression and visualization (10.61 %).

Findings, Discussion, and Conclusions

Learning analytics are distinguished by their concern for providing value to learners, whether in formal, informal, or blended settings. Moreover, the meta-analysis showed that the researchers pointed out that LA helps teachers identify which activities lead to effective student interactions.

Research Question 1(RQ1): Overview of the Status of Learning Analytics in Educational Praxis

Following a quantified methodology and approach, the previous meta-analysis revealed the "peak" learning technologies that sufficiently support the learning processes, i.e., information-rich data sources – like haptic media and tangible computing, mobile platforms and wearable computing, augmented reality, educational games computer vision, and speech recognition – that allow for identification of new, suitable measures of learning and success (e.g., affect, attention, attitudes, community structure, degrees of competence, expectations, participation, satisfaction, social dynamics, attendance, and retention).

Every "click" within a digital learning environment may be valuable actual information that can be tracked and analyzed. Every simple or more complex action within such environments can be isolated, identified, and classified through computational methods into meaningful patterns. LA researchers set the educational context within limits in which previously it was almost impossible to infer behavior patterns, due to their high levels of granularity. In such advanced learning contexts, from traditional classroom to real-life situations, and from mobile settings to large-scaled, massive online courses, LA research community determines simple and/or sophisticated factors as predictors of performance and explores their predictive value and capabilities by tracking actual data and changes on behavioral data. The goal is to identify the most significant factors in order to develop better systems. These systems will allow students to monitor their own progress and will help them evaluate and adjust their learning strategies to improve their performance in terms of learning outcomes.

In general, learning, and particularly higher order learning, requires opportunities for reflection, informed repetition, self-evaluation, pauses, and even the preparedness to make mistakes and learn from them. These attributes are also investigated from the LA research community, and good practices are suggested in published empirical studies. These studies should constitute a paradigm shift from traditional methods and methodologies to the new smart technologies that should facilitate self-regulated learning.

Research Question 2(RQ2): Quantification of the Overall Effectiveness of Integrating Learning Analytics for Guiding the Design and Development of Effective SLEs, and Exploration of the Extent to Which Learning Analytics Results Could Influence SLE Design Strategies

A learning environment may be considered smart when it "makes use of adaptive technologies or when it is designed to include innovative features and capabilities that improve understanding and performance" (Spector, 2014, p. 2). Hwang (2014) acknowledged that the rapid advancement of digital technologies (e.g., augmented reality, computer vision, speech recognition, mobile, and wearable technologies) and analytics technologies (e.g., learning analytics and social-awareness technologies) could provide various possibilities of implementing smart learning environments based on different educational purposes and from different perspectives of pedagogical theories. *It has been recognized that it is an important and challenging issue to propose implementation frameworks of smart learning environments with emerging technologies similar to learning analytics*.

1. Where LA research results and SLE need intersect?

Hwang (2014) suggested that a SLE should *"not only enable learners to access digital resources and interact with learning systems in any place and at any time, but also should actively provide the necessary learning guidance, hints, supportive tools or learning suggestions to them in the right place, at the right time and in the right form.*" And this is exactly the power of LA research results: the meta-analysis highlighted the significant contribution of LA empirical research toward developing and employing tailored feedback mechanisms that are capable of advising learners to learn in the real-world with access to the digital world resources.

Due to learning analytics, every type of interaction can be coded into behavioral schemes and decoded into interpretable guidance for decision-making. This is the point where learning science, psychology, pedagogy, and computer science intersect. The issue of understanding the deeper learning processes by deconstructing them into more simple, distinct mechanisms remains in the middle of this cross-path.

2. How LA research results could be mapped to the characteristics of SLEs addressed in the respective SLE studies?

A smart learning environment should support planning and innovative alternatives (for learner, instructor or both), even more when outcomes are desirable. According to IASLE, it might include features to promote engagement, effectiveness, and efficiency. Such features are inspired from human interpretation of "smart" characteristics and might include support for (a) ***collaboration*** (smart people often seek the advice and guidance of others), (b) ***struggling learners*** (smart teachers identify and help struggling students), (c) ***motivation*** (smart teachers take the time and make efforts to gain attention, show relevance, and provide feedback to develop confidence and satisfaction). In addition, a learning environment that automatically makes ***appropriate adjustments*** to what a learner knows, has mastered, and wants to learn next can be considered smart, just as a person who makes appropriate adjustments to activities and processes given the constraints of a situation or context.

Furthermore, according to Koper (2014), a SLE is a ***context-aware and adaptive*** to the individual learner's behavior learning environment in which the digital devices are integrated to the physical environment of the learner in order to enhance activity tracking, progress monitoring, and learner engagement and to provide additional functionalities, information, and awareness.

The focus of the current meta-analysis is to quantify the significance of LA technology and its added value and to classify and report on these findings. The goal was to examine the appropriateness of LA technologies for guiding the development and construction of smart learning environments. Hwang (2014) identified as central research issues of smart learning –among others – the need for definition of learning and assessment strategies for smart learning, the learning performance, and perception evaluation, as well as the learning behavior and learning pattern analysis. The results presented in the previous section have shown that LA technologies may address satisfactorily these issues. From the meta-analysis, it also became apparent that LA research provided significant results that seem to influence the way people learn and shed light into the conceptual basis of this rapidly growing domain. Under this lens, the results from the conducted meta-analysis highlight the main areas and key objectives of LA empirical studies that could be employed and, as such, strategically guide the development of SLEs.

That is because LA research results come from any educational context – formal and informal learning, workplace, k-12, and tertiary education, including online, distance, blended, mobile, or traditional modes of learning. In all of these settings, various measures of learning, change, and success (e.g., accreditation, affect, emotions, attendance and retention, attention, attitudes, collaboration and cooperation, degree of competence, educational performance, expectations, learner behavior modeling, learning dispositions, metacognition, misconceptions, motivation, off-task behavior, organizational dynamics, participation, satisfaction, social dynamics) have been proposed and evaluated for their suitability, appropriateness, and scalability.

These are only some of the possible directions that could be taken under consideration when targeting the construction of sophisticated learning environments augmented with a "dose" of intelligence or smartness: learning environments enhanced with analytics, big data applications, classroom orchestration, open data, and data access for learners. As an example, Scott's and Benlamri's (2010) work on incorporating technology into the classroom in a way that is both seamless and comprehensive provides a nice contextual paradigm of a useful, practical, and realistic way to incorporate ubiquitous technology into traditional, nontechnical, and social learning situations.

Therefore, this meta-analysis highlighted the methods and approaches that could constitute a guidance map for designing effective smart learning environments, since they can provide accurate and statistically significant critical insights into (a) the individual and collective learning process (i.e., collaboration), (b) the process of identification and scaffolding of struggling students, (c) the motivational effects of different parameters to achievement behaviors, (d) increasing (self and contextual) awareness, and (e) understanding the factors that make adaptation effective for learners. These are all key attributes of SLEs and should be carefully treated during the design and development stages. Thus, LA could be regarded as a generic framework to consult when constructing SLEs.

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