RESULTS

109 studies fulfilled the eligibility criteria. The majority (exactly 83) of the selected studies were published in scientific journals and 26 studies were published in international conferences.

The publication year is restricted between 2011 and 2019 (to exclude outdated research)
The language is English
The reviewed research includes only peer-reviewed papers & articles
Research to which the researchers have full text access; whether via open access or provided by the academic networks of the University of Vigo, Arab Academy for Science, Technology, & Maritime Transport, and the Egyptian Knowledge Bank
Research that applies LA and EDM techniques, either solely or combined with self-report instruments, to measure SRL and its skills

Table 1 Eligibility Criteria

More than half (exactly 59) of the selected studies used data analytics in association with other self-report instruments. The remaining 51 studies utilized data analytics techniques alone.

From Figure 2, it can be noticed that the number of publications studying the utilization of LA and EDM tools in SRL assessment was gradually increasing during the period from 2011 to 2018 t except for a slight decline in 2014 and 2017.We found 8 publications from the 1st of January to the 1st of April 2019.

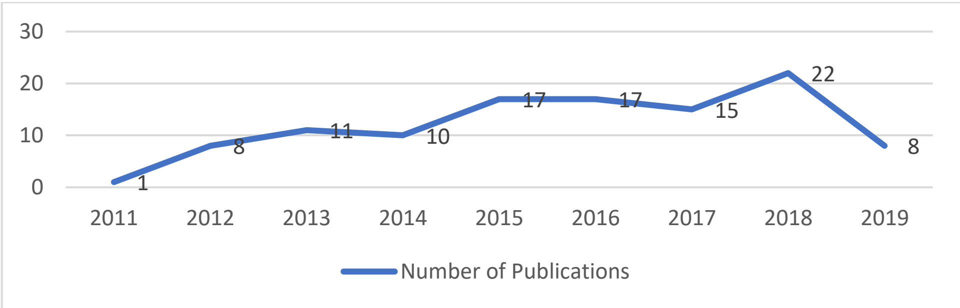

Figure 2 Distribution of the selected studies by the year of publication

The findings indicate the existence of five disciplines where studies assess SRL using data analytics techniques. These disciplines are: undergraduate university education, school education, open online education, post-graduate education, and workplace settings. The majority of studies (61.82%) were devoted towards assessing SRL in undergraduate university education; followed by school education (22.73%), open online education (7.27%), post-graduate education (5.45%), and workplace (2.73%) respectively.

What are the commonly used techniques of data analytics in SRL assessment?

A large proportion of studies depends on the analysis of trace data generated in log files. Log files generated by LMS can recognize the behavioural changes of learners during course progression, their interaction with their peers, and their performance in assessments [You 2016]. Log files can also be generated by the means of video annotation software [Gašević, Mirriahi, & Dawson 2014; Gašević et al. 2017; Pardo et al. 2015] or an induction-mining algorithm [Poitras, Doleck, & Lajoie 2018; Poitras et al. 2017]. Other researchers used multimodal trace data (including physiological data such as heart rate, eye-tracking data, step count, facial expressions, and weather conditions; in addition to learning activities) [Bouchet et al. 2013; Di Mitri et al. 2016; Trevors et al. 2016; Di Mitri et al. 2017; Tempelaar, Rienties, & Nguyen 2018; Taub & Azevedo 2019].

Log file analysis includes investigation of trace data left by learners which can lead to a better understanding and discovery of the learners' behavioural patterns [Li et al. 2018].

Traces obtained from log files enable the provision of consistent information regarding the learners' usage of cognitive tools during the learning process [Malmberg, Järvelä, & Kirschner 2014]. [Siadaty, Gašević, & Hatala 2016] presented a trace-based methodology for SRL measurement.

The next subsections present a brief description regarding the data mining techniques used for SRL assessment. Each technique and the number of studies using it are presented in Table 2.

Cluster Analysis

Clustering is an unsupervised technique; typically used to categorize the learner behavioural profiles into subset clusters [Romero & Ventura 2010; Segedy, Kinnebrew, & Biswas 2015]. In the same paper, one or more clustering method can be used. Overall, clustering is the most popular technique. It has been used in 42 studies. This popularity is because clustering enables the provision of more adaptive scaffolding either through agent-based Intelligent Tutoring Systems or Virtual classrooms [Bouchet et al. 2013].

The most commonly used cluster analysis technique in this systematic review is Agglomerative Hierarchical Clustering (22 studies) followed by K-means clustering (13 studies). Latent Profile Analysis (LPA) was applied in 6 studies. 3 studies applied Expectation-Maximization (EM) clustering algorithm, while clustering using Tamhane's Post Hoc Test and K-medoids clustering were applied in only one study for each.

Classification

Classification algorithms are supervised algorithms which predict the membership of individual data instances into groups relying on quantitative information concerning the feature(s) of these instances; according to a training set of formerly labeled items [Phyu 2009; Romero & Ventura 2010]. In the same paper, one or more classification methods can be used. Overall, classification has been used in 19 studies.

Regression analysis algorithms are the most frequently utilized classification algorithms in the selected studies; they were used in 17 studies. Bayesian classifiers were used in 6 studies. Neural networks were exploited in 5 studies. 4 studies utilized Decision tree classification. The same number used support vector machines. A single study exploited k-Nearest Neighbor algorithm.

Temporal Data mining techniques (Sequence mining and Process mining)

EDM techniques that use temporal patterns of SRL examine the connections among recurrent SRL events according to their order and temporality. They include sequence mining and process mining (workflow mining) [Reimann, Markauskaite, & Bannert 2014; Malmberg et al. 2015]. In the same paper, one or more temporal data mining technique can be used. Overall, temporal data mining has been used in 26 studies.

Sequence mining examines event behavioural patterns, involving the occurrence frequency of these patterns [Taub & Azevedo 2019]. Sequence mining methods are implemented either separately, or combined (differential sequence mining methodology) to differentiate between frequent patterns among learners [Kinnebrew, Loretz, & Biswas 2013]. 15 studies have employed sequence mining.

The concept of Process Mining is to create a process model to comprehensively describe and discover the processes in an event log file. Events in the event log can be time-stamped or fully-ordered sequences [Sonnenberg & Bannert 2015; Reimann, Markauskaite, & Bannert 2014]. The exploited process mining methods include fuzzy miner, different versions of ProM software, PM^2 method, bupaR process mining, Markov models, heuristic miner, and conformance checking. 13 studies have employed process mining.

Other Analytics

This review indicates the use of less frequent tools for SRL assessment, include Social network analysis (SNA) [Gewerc, Rodríguez-Groba, & Martínez-Piñeiro 2016], Burst-detection [Piotrkowicz, Dimitrova, & Roberts 2018], Mobile learning analytics [Tabuenca et al. 2015], Anomaly detection data mining technique [Taub et al. 2014], Summarization technique [Taub et al. 2014], and Principle component analysis [Umbleja & Ichino 2016].

Clustering	Number	Classification	Number	Temporal data mining	Number
Agglomerative Hierarchical	22	Regression analysis	17	Sequence Mining	15
K-means	13	Bayesian Classifiers	6	Process Mining	13
Latent Profile Analysis	6	Neural Networks	5		
Expectation-Maximization	3	Decision trees	4		
Tamhane's Post Hoc Test	1	Support Vector Machines	4		
K-medoids	1	K-Nearest Neighbor	1		
Total	42	Total	19	Total	26

Table 2 Distribution of data mining techniques among studies

What are the types of data used to assess SRL?

The data used in different papers can be classified into seven categories. The selected papers utilized one or more of those data types (cf. Figure 3):

1. Log data (used in 77 studies): It emerges as a result of learner's interaction in learning environments and tools such as LMS, Intelligent Tutoring Systems (ITS), nStudy tool, gStudy tool, mobile devices, and video annotation software.
2. Assessment results (used in 27 studies): It includes scores of exams, quizzes, pre-& post-tests, assignments, mind maps, as well as Workplace-Based Assessment (WBA).
3. Multimodal data (used in 9 studies): It includes physiological data such as heart rate, eye-tracking data, step count, facial expressions, and weather conditions; in addition to learning activities.

4. Demographic data (used in 9 studies): It includes data such as gender, age, class level, faculty, & study mode [Broadbent & Fuller-Tyszkiewicz 2018].
5. Chat and forum conversations (used in 5 studies): It involves online discussions among learners [Järvelä, Malmberg, & Koivuniemi 2016; Wise & Hsiao 2018].
6. Self-reported data from learners via instruments including various types of questionnaires, interviews, surveys, SRL quizzes, TAP, and Motivated Strategies for Learning Questionnaire (MSLQ) and its subsets (used in 59 studies).
7. Video recordings (used in 5 studies).

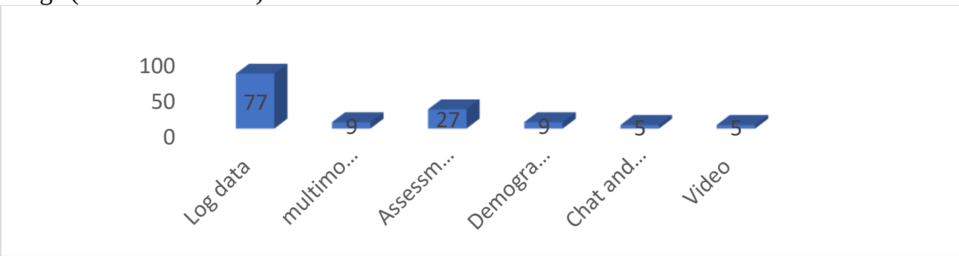

Figure 3 Distribution of studies according to used data

What are the frequently measured SRL behaviours/ features/ components?

In this review, we utilized most of the SRL categories as classified by [Garcia, R., Falkner, K., & Vivian, R. 2018] (in addition to the category of learning strategies). The selected studies measure at least one of those categories (cf. Figure 4):

1. Goal-setting, planning, and time management (measured in 57 studies): The learner sets precise goals for him/herself [Zimmerman 2002].
2. Keeping, reviewing records, and monitoring (measured in 36 studies): It refers to the learners' monitoring of their progression toward achieving goals [Zimmerman 2002].
3. Emotion regulation (measured in 21 studies).
4. Learning strategies (measured in 19 studies): It includes behaviours such as reading, repeating, elaboration, judgment of relevance, taking notes, summarizing, coordinating different information sources, activating prior knowledge, peer-learning, processing, questioning, and problem-solving.
5. Self-evaluation (measured in 18 studies): It refers to *"comparisons of self-observed performances against some standard, such as one's prior performance, another person's performance, or an absolute standard of performance"* [Zimmerman 2002].
6. Seeking information and social help (measured in 16 studies): It pertains learners searching for assistance and information from others [Zimmerman 2002].
7. Organizing & transforming (measured in 6 studies).
8. Environmental structuring (measured in 4 studies): It involves the learners' usage of e-learning platforms to alter the digital area for achieving their learning objectives [Garcia, R., Falkner, K., & Vivian, R. 2018].
9. Rehearsing & memorizing (measured in 4 studies).

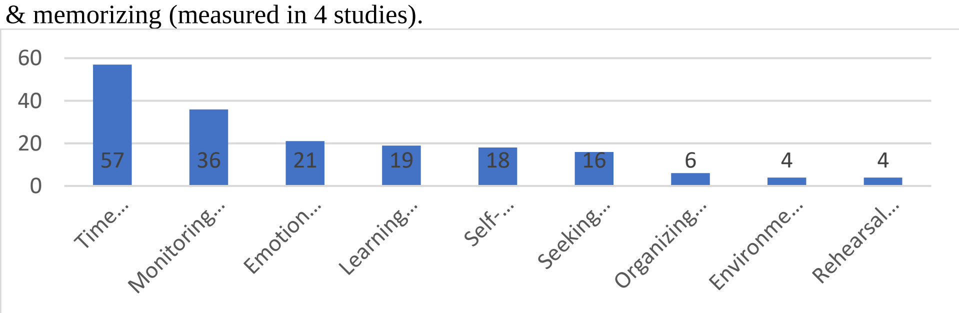

Figure 4 Distribution of studies according to measured SRL

STUDY LIMITATIONS

This study has some limitations. Only research published in English was selected. Furthermore; we found a lot of studies that utilized statistical methods. It was hard to distinguish between studies using statistical methods to provide an analysis of SRL and those that just provide a statistical measure. This study is exploratory and quantitative. It didn't focus on the quality of measurement provided by every studied assessment tool. Finally, the main focus of this review was on the LA & EDM tools used for SRL assessment. This review didn't analyze in depth neither the nature of SRL processes and components being assessed, nor the detailed structure of the data utilized for SRL assessment via LA and EDM tools.

CONCLUSION

This review tries to close a literature gap by providing an overview of the research in the LA and EDM domains for the measurement of SRL; either solely, or in association with self-report instruments. It reveals the allocation of data analytics tools applied, determine the most frequently used ones, and their application disciplines. The review also classifies the data used for SRL measurement, determines the behaviours/features/components measured in each study, identifies the frequently used LA and EDM tools, and finds the applicable disciplines where LA and EDM tools are commonly employed to assess SRL. The main conclusion of this review is that there is a real interest in this field and a great variety of tools and approaches to be followed. Also, it is quite clear that there is no specific solution.

The attained results reveal that the introduction of LA and EDM instruments has not removed the use of self-report instruments. About 54% of the selected studies exploited a combination of self-reported instruments and LA. These findings are compatible with [Panadero, Klug, & Järvelä 2016] and [Pardo, Han, & Ellis 2017] who mentioned that self-reported measures are used in association with other measures to obtain data triangulation and acquire a more complete understanding.

As observed, time management is the most frequently measured SRL behaviour. This result is compatible with the findings of [Tabuenca et al. 2015] who found that mobile devices can be used to track the devoted learning time in mobile learning; and subsequently; improve time management skills of students and support their SRL during online courses.

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