International Journal of Advanced Science and Technology
Vol. 29, No. 6s, (2020), pp. 1558-1571

The Divergence of Learning Analytics Research

Nur Maisarah Shahril Khuzairi[*a], Zaihisma Che Cob[a]
[a]*College of Science Information Technology, Universiti Tenaga Nasional, Malaysia*

Abstract

This study represents a review of Learning Analytics journals with the goal to examine reported research objectives, educational data collected and the intended end-user of the corresponding analysed data proposed by all current studies available in relevant databases. A total of 62 research articles were selected from an initial accumulation of 373 papers for this review. The findings present a clear divergence of Learning Analytics research into distinct subsets and it is revealed that the term "Learning Analytics" is labelled indiscriminately. We then show how a categorization of research subsets will prompt a reduction of term sprawl and also to avert confusion in the current education research environment. With this key points above we offer an approach to classify future Learning Analytics research into three specific subsets (student-centric, teacher-centric and institution-centric) based on identifiable criteria with the goal of fostering new avenues for future ground breaking research works in education.

Keywords: *Learning Analytics, learning and teaching, pedagogy, educational research, data for learning*

1. INTRODUCTION

Learning Analytics in education constitutes an emerging research field, in which learners' data (eg., academic performance, participation, demographics) are collected and analysed to optimize the learning environment (Leeuwen, Janssen, Erkens & Brekelmans, 2014; Viberg, Hatakka, Balter & Mavroudi, 2019, Selwyn, 2019). In Learning Analytics, the interpretation of learners' data helps stakeholders and decision-makers to understand learning patterns to enable them to predict learning outcomes and inform interventions beforehand. Hence, the use of Learning Analytics has gained prominence over the past few years. According to Google Trends, the term 'learning analytics' has been trending worldwide from 2011 to 2019, returning search interest value of 44 in 2011 and currently a total of 99 in 2019, with 100 being the highest value to indicated search interest on Google's search tool. Also Horizon Report for Australia Tertiary Education has indicated a growing focus on measuring learning as one of the top three trends (Johnson, Adams-Becker & Hall, 2015). Another reason that learning analytics has become a major area of study over recent years is due to the evidence-based education system where funding levels have to be justified both academically and financially (Marsh & Farrell, 2014; Dix & Leavesley, 2015). Hence precious educational resources of an institution can be allocated for optimal returns on investment that yields a higher quality education system as a whole.

With the increased amount of interest in Learning Analytics, many studies have been conducted to describe the concepts and processes of analysis and delivery, along with frameworks and implementation strategies for Learning Analytics have been developed to assist the effective take up. But there has been a term sprawl in recent additions of research on Learning Analytics. Some scholars interpret Learning Analytics as the use of large data sets and data mining techniques to provide information for decision makers (Lonn, Aguilar & Teasley, 2015). While other studies draw attention to educators' concern and behaviour in relation to Learning Analytics (Ali, Asadi, Gasevic, Jovanovic & Hatala, 2013; Leeuwen et al., 2014). As such there is no definite demarcation in the terminology of Learning Analytics, it has been use as a one stop label to any study related to education and analytics without the consideration of its original definition and relevance to its primary research.

Learning Analytics was first introduced in the 1st International Conference on Learning Analytics and Knowledge (LAK) (2011), and it is understood as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environment in which it occurs". However, the term has been suffering the symptoms of term sprawl (Siemens & Long, 2011) which has led to confusion between the areas of studies, data utilized and targeted stakeholders encompassed by Learning Analytics. These definitions share an emphasis on converting educational data into useful action to foster learning but when it is scrutinized deeper, there is a divergence in Learning Analytics research where its objectives, data and target audience differ greatly.

Today, the concept of Learning Analytics has been implemented in various situations and education institutions around the world. Some studies indicate that Learning Analytics offers many positive educational results such as improved learning outcomes, while others have highlighted limitations that exists within its scope. For example, the perspective of the end-user of the analytics (eg. educators) is not being taken into consideration for the Learning Analytics design (Leeuwen, 2015); stakeholders are faced with data deluge (Michos & Hernandez-Leo, 2016); and inappropriate visualization tools that do not support easy data interpretation for educators and students (Chou et al., 2017). The literature indicates that even though there have been much effort put to understanding and analysing various aspects of Learning Analytics, but none of these studies have addressed the relationship between educational data and its end-user, or systematically categorized it which can result to an ineffective take up. Hence, this paper aims to fill in the gap by presenting a comprehensive classification of Learning Analytics research by introducing divergence subsets based on its objectives, educational data and end-users involved. The paper also highlights the relationship between the educational data and end-users to create a better understanding for researchers and practitioners on the types of educational data available and its relevance to each end-user.

2. PURPOSE OF THE STUDY

The overarching focus of this study is to deepen the understanding regarding the relationship of educational data collected and the end-user of the analytics proposed in Learning Analytics research which includes students, educators and administrators. But to date, only a few studies have reviewed the literature on this relationship. These few reviews are typically focused on a summary of the research work done by a publication range or by the types of educational data used. For example, these studies were only conducted at higher educational settings (Avella, Kebritchi, Nunn & Kanai, 2016; Ferguson & Clow, 2017; Leitner, Khalil & Ebner, 2017), whereas some focused on general Learning Analytics contexts (Ferguson et al., 2016; Jivet, Scheffel, Specht & Drachsler, 2018; Viberg et al., 2019). Bodily and Verbert (2017) study is limited to Learning Analytics systems that report data directly to students only.

It is not clear these types of educational data are deemed relevant to all end-users or only to a particular user of the analytics. A more concise review will be able to assist researchers to map areas of uncertainty and to depict a bigger picture of the relationship between educational data and its end-user. Therefore, this study initially reviews the educational data and end-users involved in the research studies on Learning Analytics, covering from the year 2011 where Learning Analytics was first introduced to its most current. With that, this will detail the current state of affair with educational data in Learning Analytics classifying it based on its objectives, data and end-user which should provide a useful guidance to researchers for further exploration.

To achieve the purpose, we identified all relevant articles that are related to Learning Analytics published in Social Sciences Citation Indexed (SSCI) journals from 2011 to 2019. The following research questions (RQ) guided the research design and data collection:
RQ 1: What are the objectives of the studies and the end-users of the analytics efforts?
RQ 2: What types of educational data were collected in Learning Analytics research?
RQ 3: What is the relationship between educational data collected and the end-user of the analytics effort?

ISSN: 2005-4238 IJAST

3. METHODS
3.1 Manuscript selection

As it is impossible to include all related studies (Heitink, Van der Kleij, Veldkamp, Schildkamp & Kippers, 2016), henceforth a set of criteria is defined in the selection process. For this study, scientific articles on Learning Analytics which were published in prestigious scientific journals relevant to the field and relevant research work directly cited in the initial identified publications and the use of databases in which studies are indexed such as Education Resources Information Centre (ERIC), IEEE Explore, Science Direct, SpringerLink and SSCI.

The search strategy used is the advanced search function and keywords namely "Learning Analytics" and "Analytics". Additionally, the use of Boolean operators (OR, AND) among the keywords was also performed in order to extend the search results. While conducting the search, the timeframe was specified from the year (2011 – 2019) as Learning Analytics is a young field and the adoption and emergence of journal articles has only increased since 2012. The document type "article" and the language "English" were selected as the search parameters.

A three-step article search process was adopted in this study presented in a flow chart in Figure 1. Firstly, the articles meeting the predefined criteria as mentioned above were selected. These articles were downloaded as abstract to a computer and each article was examined to check whether it was relevant to the study. Along with that, inclusion and exclusion criteria was included where articles that cover Learning Analytics as a primary component instead of merely mentioning the term. Lastly, duplicate articles and articles that do not meet the selection criteria were removed from the pool. The search process led to 62 articles.

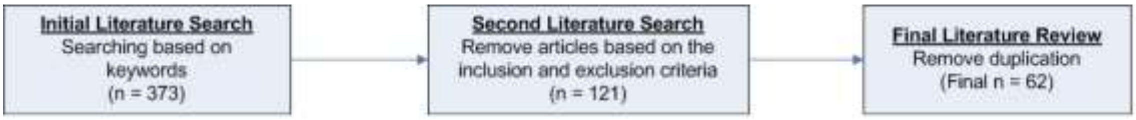

Fig. 1 Procedure of Article Selection

3.2 Data Coding and Analysis

To ensure an effective analysis of the articles, the qualitative data analysis software program ATLAS.ti 8 was used to manage, facilitate the task of coding and analysis of the data by a single researcher. The qualitative data was analysed using qualitative content analysis method that enables systematic categorization of the content (Berelson, 1952).

The two RQs (RQ1 and RQ2) were leading during the coding of the data. To code the objectives, educational data and end-users of the Learning Analytics, all of the methods, findings and results sections were read and during the reading process, attention was given to determinant words that indicate the objectives, educational data used and end-users involved in the studies. Likewise, the discussion and conclusion sections from the articles were read in order to code the relationship between educational data and end-users (RQ3).

Finally, the codes were then grouped into related categories based on the similarities that they share. Findings and results are presented in the next section of this article. To ensure a concise review, examples of publications were selected and presented in tables to highlight the key points. Even though the analysis included 62 articles but not all of the publications are cited or discussed in detail.

4. RESULTS AND DISCUSSION
4.1 General distribution of the studies

The distribution information of studies over time is shown in Figure 2 and briefly discussed as below.

The analysis shows that, since the first introduction of Learning Analytics in 2011 has led to an incremental rise of research efforts in learning technologies as it offers new opportunities for stakeholders to understand and improve the learning environment. This new data and insights may be used to influence both teaching and learning practices (Viberg et al., 2019).

As such one possible explanation for the increase of popularity is the fact that Internet technologies are made to be more accessible to the masses, making learning data easily available via online learning environments.

As shown in Figure 2, the escalation of studies related to Learning Analytics is obvious from 2014 onwards and with a consistent effort between 2014 to 2019. Hence, it is likely that the interest in Learning Analytics will continue to consistently grow after 2019.

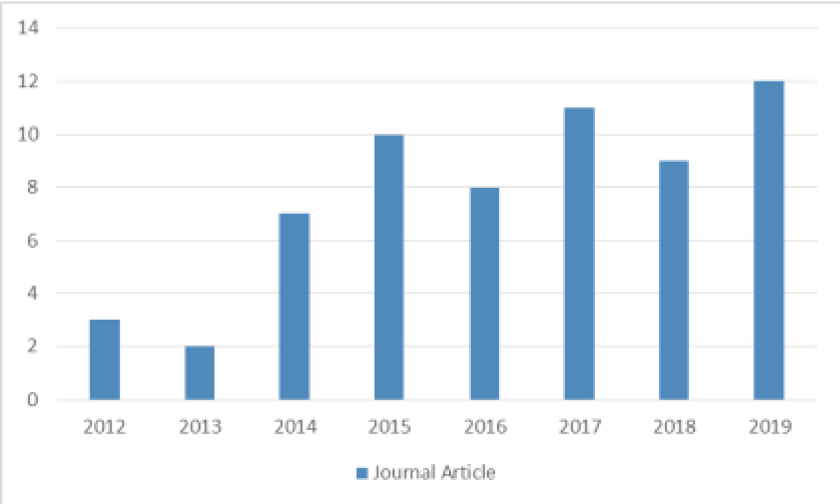

Fig. 2 Article distribution based on the year of publication

4.2 RQ 1: What are the objectives of the studies and the end-users of the analytics efforts?

As a result of the open coding, three categories were created for the objectives based on the end-users of the analytics effort (student-centric, educator-centric, and institution-centric). Then the categories created are subdivided into detailed sub-categories according to the nature of its objectives. While some studies reported to address more than one single objective therefore it was coded with more than one sub-category. The findings for each category is depicted in Table 1.

Table 1. Objectives based on End-User

Objectives Based on End-User	Objectives Sub-categories	f	%	Example
Student-Centric (n = 15)	Learning Analytics Personalization	8	53.33	Wang and Lin (2019)
	Learning Progress & Outcomes	4	26.67	Fidalgo-Blanco, Sein-Echaluce, Gracia-Penalvo and Conde (2015)
	Engagement (Time Spent)	2	13.33	Zhang, Meng, Pablos and Sun (2017)
	Self-Regulated Learning	2	13.33	Martin, Nacu and Pinkard (2016)
	Student Reflection	1	6.67	Chou et al. (2017)
Teacher-Centric (n = 18)	Educational Intervention	12	66.67	Tempelaar, Rienties, Mittelmeier and Nguyen (2018)
	Teacher's Adoption of LA	4	22.22	Martinez-Maldonado, Shum, Schneider, Charleer, Klerkx and Duval (2017)

	Teacher Behaviours	3	16.67	Leeuwen, Jassen, Erkens and Brekelmans (2015)
	Ethical & Data Privacy	2	11.11	Rodriguez-Triana, Martinez-Mones and Villagra-Sobrino, (2016)
	Personalization	2	11.11	Kelly, Thompson and Yeoman (2015)
Institution-Centric (n = 19)	Learning Behaviour	8	42.11	Motz, Carvalho, Leeuw and Goldstone (2018)
	Learning Analytics Adoption	6	31.58	Ferguson et al. (2014)
	Performance Prediction	6	31.58	Casey (2017)
	Overall Performance	5	26.32	Tempelaar, Rienties and Giesbers (2015)
	Ethical & Data Privacy	5	26.32	Elouaziz (2014)
	Student Retention	1	5.26	Buerck and Mudigonda (2014)
Others (eg. Researchers)		10	16.13	Nistor and Hernandez-Garciac (2018)

Student-centric

As the title suggests, the objective focuses on students specifically grouped under this category. Shown in the table above this includes learning analytics personalization, learning progress and outcome, engagement (time spent), self-regulated learning and student reflection.

More than half of the studies 53% reported on personalization which is customizing the learning analytics dashboard as to the students' preferences, making it as user-friendly as possible. Schumacher and Ifenthaler (2018) conducted an interview with university students to study their expectation towards features of learning analytics systems and the findings revealed that students are willing to use learning analytics provided it delivers features supporting them in planning and organization of their learning process, also providing self-assessments and delivering adaptive recommendations. Other studies such as Howell, Roberts and Mancini (2018) also supported the findings in terms of the students' likelihood to ignore or not use learning analytics alerts when there are continuous alerts which are identical in nature. Therefore, it is important to focus on personalization of the learning analytics dashboards based on the students' needs in order to promote long term usage.

The review also indicates that learning progress and outcomes (27%) and engagement in terms of time spent (13%) are meaningful sub-objectives which is an important element in the education context. Learners displayed an interest in knowing and understanding their learning progress and outcomes. Aside from that, a study on empowering students with added value of the customised student-centred analytical dashboard, which showed that having the opportunity to access and learn about their own online activities engagement data had facilitated prompt discussion of their results with their peers and reported to achieve higher final marks in assessments (Aljohani et al., 2018). Bodily and Verbert (2017) also suggested that when students have control over their learning it intrinsically encourages them to succeed.

With the introduction of learning analytics dashboards in Learning Management System (LMS), it encourages the opportunity for self-regulated learning (13%). This study drew attention to the use of student profiles, actual behaviours and learning outcomes in providing support for students with different self-regulated learning profiles (Kim, Yoon, Jo & Branch, 2018).

Finally, student reflection (7%) was reported by Chou et al. (2017) where they applied visualized learning analytics as the open student model approach to visualize learning outcomes for student reflection and the findings showed a positive response from students with majority of them reporting that their learning progress has helped them in reflecting on their competencies. More research effort is needed not only in learning analytics personalization and learning progress but also in terms of student reflection in order to promote a long-lasting learning experiences.

Teacher-centric

Teacher-centric objectives encompass studies that address educators which includes educational intervention, teacher adoption of Learning Analytics, teacher behaviours, ethical and data privacy and also personalization.

As reported by the findings, the most prominent objective of learning analytics studies is educational intervention (67%). With a diverse amount of data collected from learning analytics, teaching intervention can be tailored to meet a specific student's needs instead of the traditional one-fit-all approach in teaching. It is known that teaching approaches are important in creating an effective learning environment for students to maximize its benefits. For example a study found that an educator's course preparation and guidance is positively affecting on students' completion of learning tasks and their engagement overall (Ma, Han, Yang & Cheng, 2015). Furthermore, recent studies also supported these findings that the core standpoint of educational analytics should move beyond merely tracking and reporting students' activity but also supports teachers with insights on how to systematically intervene their teaching practice in order to create actionable learning analytics for educational intervention (Sergis et al., 2017; Tempelaar, Rienties & Nguyen, 2017). This may explain why educational intervention is a favourable objective compared to other titles as it provides guidelines and explanations of how educational intervention may be carried out in the classroom.

However in order to successfully implement Learning Analytics in classrooms, the teacher's adoption (22%) and behaviours (17%) have to be taken into consideration. According to the author, research efforts highlighting on educators and learning analytics are scarce especially on the development of learning analytics tools (Ali et al., 2013). The study also suggested that educators who are engaged in online teaching courses are more likely to adopt the tool and perceive utilities of the tool faster than those who are not. The utilities that would affect teachers' adoption includes features such as providing feedback about individual lessons, identifying the domain topics that students are having difficulties with and hints or suggestions on how to improve the courses instead of merely pointing out the problems. Hence having Learning Analytics tools to lower information load among teachers will promote its adoption (Leeuwen, 2015). Learning Analytics can be potentially effective for teachers because it could provide additional evidence to enhance their diagnosis of a situation. In a subsequent study also argued that supporting tools such as Learning Analytics increases teachers' confidence to act, they were better able to identify problems and provide specific explanations of their actions (Leeuwen et al., 2015).

With students' data made available via Learning Analytics, there are some studies concerning ethical and data privacy (11%). These issues in utilizing this data emerged not only on the institutional level but also the small-scale classroom level (Rodriguez-Triana et al., 2016).

Apart from that some studies also addressed personalization of learning analytics tools specifically for teachers (11%) because how information is visually presented may help to deal with the abundance of data, creating a sense-making environment for teachers (Charleer, Klerkx & Duval, 2014).

Institution-centric & Others (eg. Researchers)

Though students and teachers are the two primary components in the educational environment, the review imposes a number of institution-centric studies as well. This is because Learning Analytics data enables institutions to justify any change of their educational direction and policy both academically and financially. Hence institution-centric objectives focus mainly on learning behaviour, Learning Analytics adoption, performance prediction, overall academic performance, ethical and data privacy and student retention.

The most commonly reported objective is students' learning behaviour (42%) which includes students' effort and engagement in a subject matter, preferred learning styles, learning strategies and characteristic of students. If a student's learning behaviour and pattern can be identified such as how they organize and manage their learning process, this may enable for better informed decisions in education and modifications where necessary (Aljohani et al., 2018). This subsequent study also stated that students' learning behaviour is associated with their course performance (Jovanovic, Gasevic, Dawson, Pardo & Mirriahi, 2017). Those who were more active in regulating their learning had a higher course performance as compared to those who were not. Moreover their learning behaviour allows institutions to understand the causal relationship between an intervention and its learning outcomes, as well as aid decisions on resource allocation.

Another prominent institution-centric objective is Learning Analytics adoption (32%). It has always been a challenge to introduce changes especially at an institutional level as it involves multiple entities. Institutions need to understand the benefits and drawbacks related to adoption, as there is often a confusion between Learning Analytics used to support students, educators or institutions. Hence a study has introduced RAPID Outcome Mapping Approach (ROMA) framework that offers a step-by-step method for Learning Analytics adoption at scale from planning to evaluation in order to encourage confidence among institutions (Ferguson et al., 2014).

With the emergence of easily accessible learning data, predicting students' performance (32%) and also overall academic performance (26%) has become a leading interest of institutions as a means to identify those at-risk of attrition or academic failure early on (Dawson, Gasevic, Siemens & Joksimovic, 2014). Now administrators can intervene in situations before a student reaches a level of performance that they cannot recover from and consequently dropping out. However, the result from this study revealed that there is no single predictors of academic success even within the same discipline (Gasevic, Dawson, Rogers & Gasevic, 2016). According to another study, in order to systematically predict students' performance in tertiary education, psychometric factors of ability, personality, motivation and learning strategies is important in modelling of students' academic performance too (Gray, McGuinness, Owende & Carthy, 2014). Moreover an emphasis on the measure and algorithm selection and construction are paramount to an effective student performance prediction model (Wanli, Rui, Eva & Sean, 2015).

Similarly teacher-centric and institution-centric studies have the concern of ethical use of data and privacy (26%). Khalil and Ebner (2016) argued that tracking interactions of students in Learning Analytics research could unveil critical issues regarding privacy. With this in mind, the authors present a de-identification method that combine anonymization strategies and learning analytics techniques to keep the process of learning analytics in progress while reducing the risk of disclosing the students' identities.

Lastly, student retention (5%) is not commonly reported in this review as its characteristics identify more closely to big data hence many of such studies are addressed under the category of Education Data Mining (EDM). Future investigation on student retention could focus more on EDM.

4.3 RQ 2: What types of educational data are collected in Learning Analytics research?

Table 2. Educational Data collected in Learning Analytics

Categories	Educational Data	f	%	Example
Demographics	Nationality	9	14.52	Tempelaar et al. (2017)
	Gender	9	14.52	Tempelaar et al. (2015)
	Age	7	11.29	Gasevic et al. (2016)
	Language	2	3.23	Gasevic et al. (2016)
Performance-based	Engagement	30	48.39	Kim et al. (2018)
	Current Academic Performance	16	25.81	Schumacher and Ifenthaler (2018)
	Used Resources	16	25.81	Bodily and Verbert (2017)

	Past Academic Performance	15	24.19	Knight, Brozina and Novoselich (2016)
	Task Completed	11	17.74	Ma et al. (2015)
	Quantity of Students	5	8.06	Chou et al. (2017)
	Learning Strategies	2	3.23	Schumacher and Ifenthaler (2018)
Behavioural-Attitude	Motivation	8	12.9	Tan, Koh, Jonathan and Yang (2017)
	Self-Perception	5	8.06	Tempelaar et al. (2017)
	Behaviours	4	6.45	Gray et al. (2014)
	Learning Style	3	4.84	Tempelaar et al. (2015)
	Effort	3	4.84	Chou et al. (2017)
	Student Characteristic	2	3.23	Casey (2017)
Others	Eg. video event distribution, repetition of video intervals, the total number of attempts in solving the exercises, the number of hints called for by students and the number of students entering the course.	20	32.26	Ruiperez-Valiente, Munoz-Merino, Gascon-Pinedo and Kloos (2015)

A multitude of educational data are recorded in Learning Analytics which can be divided into primary categories such as demographics, performance-based, behavioural-attitude and others (as shown in Table 2).

In demographics, the educational data found are nationality (15%), gender (15%), age (11%) and language (3%). Demographic data is commonly used by institutions to study its significance with the prediction of academic success related to courses (Naderi, Abdullah, Aizan, Sharir & Kumar, 2009; Arnold & Pistilli, 2012; Gasevic et al., 2016). In addition to this, demographic data provides a more detail insight on emotional gender roles and also the differences in cultural traits in influencing student behaviours (Tempelaar et al., 2018). This type of data has proven essential to supporting educators and institutions in their course planning and teaching approach.

Performance-based data in Learning Analytics studies recorded data mainly on engagement (48%), current academic performance (26%), used resources (26%), prior academic performance (24%), task completed (18%), quantity of students (8%) and learning strategies (3%). A considerable amount of studies measured the performance-based data based on students' engagement in terms of time spent engaging with a Learning Analytics dashboard such as submissions or posts on discussion boards and viewing activities (Fidalgo-Blanco et al., 2015; Ma et al., 2015; Howell, Roberts & Mancini, 2018). One possible reason for this is the consistent emphasis of active student engagement to assist academic performance and achievement of learning outcomes (Jovanovic et al., 2017). On this point, a study by Chou et al. (2017) also found that current and prior academic performance aids to estimate the competency level of a student by helping them in reflecting and goals setting. Since the Learning Analytics tools are able to capture a large variety of data in real time, other inputs such as used resources, task completed and learning strategies were also recorded and put into consideration to measure one's academic performance.

Behavioural-Attitude data is difficult to be measured and collected systematically because it is a state of mind but that said researchers are encouraged to move beyond simple engagement metrics to measuring disposition data. As dispositional learning analytics may have the potential to provide an actionable bridge between learning analytics and educational interventions such as counselling activities (Tempelaar et al., 2017). With that in mind, the behavioural-attitude data recorded in this study includes motivation (13%), self-perceptions (8%), learning behaviour (6%), learning styles (5%), effort (5%) and student characteristic (3%). A subsequent study demonstrated that the potential of such data to be used in combination with learning data extracted from Learning Analytics dashboard, to provide a better signalling of underperforming students and intervention handles in both the short and long term (Tempelaar et al., 2018). Additionally, this study also highlighted prior academic performance is a good predictor for future academic performance but behavioural-attitude data such as self-perception also contributes a significant factor in prediction (Gray et al., 2014). The opportunity to capture this types of data can be useful for educators to create a more engaging and motivating learning environment, hence better overall academic success.

Educational data which is marginally reported or obscure have been placed under others (32%). This includes data such as video event distribution (Ruiperez-Valiente et al., 2015), social interaction (Bodily & Verbert, 2017), the number of students entering the course (Ma et al., 2015), usage of different critical lenses and talk types (Tan et al., 2017), instructors feedback (Dringus, 2012) and more. It is not clear whether this types of data contributes to Learning Analytics in a meaningful way, therefore further research is needed to resolve this question.

4.4 RQ 3: What is the relationship between educational data collected and the end-user of the analytics effort?

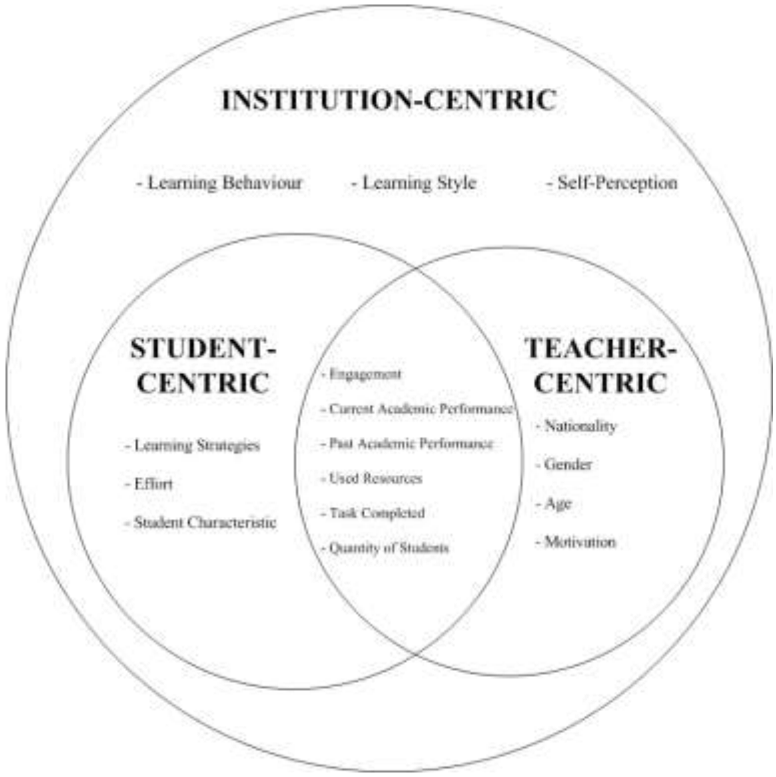

Fig. 3 Subset classification of Learning Analytics based on end-users.

Learning Analytics can be designed to address different end-users with a variety of educational data available. The use of appropriate educational data in relation to the objectives and the end-users will yield targeted and effective result. But currently there is often confusion as to the data used for Learning Analytics to support students and educators, as well as those used by institutions for comparisons (Ferguson et al., 2014). Therefore the figure above represents the relationship between educational data and end-users as a guidance for educators, institutions and future researchers.

It is evident that each end-user will acquire interest in different sets of educational data. For example, demographics data on age, gender and nationality are irrelevant to the student-centric studies as such data will not help a student in gaining better understanding of their learning progress, whereas demographics data is important to institutions and teacher-centric studies as it enables them to understand the students background in order to design a more comprehensive teaching approach and course planning. Consequently to identify the relationship between educational data and its end-user we analysed the objectives of the studies based on their end-user and corresponding educational data used in the study.

In Figure 3 the intersection between educational data shows that students and educators (i.e. student-centric and teacher-centric) share an interest in a set of common educational data. Mainly in the form of performance-based data such as current and prior academic performance, engagement and used resources. There are several reasons for this preference. Schumacher and Ifenthaler (2018) stated that to meet students' expectations towards Learning Analytics and their willingness to use it for learning, it must be able to support them in analysing their current academic performance, so they can revise or extend beyond the provided learning content. In other studies (Chou et al., 2017; Knight et al., 2016), when students have access to their performance charts and tables, it assists them in understanding the correspondence between their courses and performance also enhancing their ability to self-regulate their learning process. These data is also useful for educators to identify students at-risk to perform early interventions (Dawson et al., 2014; Ma et al., 2015; Casey, 2017) and for institutions to predict academic performance and improve curriculum design (Gray et al., 2014; Mendez, Ochoa, Chiluiza & Wever, 2014).

Educational data such as learning strategies, effort and student characteristic are categorized as student-centric. In several studies, students have reported that they wanted to know time management and scheduling of their studies as well as peers with high-achieving results. This is because it may offer self-monitoring of their learning strategies and provide meaningful information to them in terms of self-evaluation (Knight et al., 2016; Schumacher & Ifenthaler, 2018). This further emphasizes the need to design Learning Analytics features with the idea of supporting students in learning instead of merely recording and analysing the students' data.

Also educational data such as nationality, gender, age and motivation is categorized under teacher-centric because it aids teachers to prepare for learning contents. For example, given a strong focus on statistics in the Dutch high school system would indicate a more advanced mathematics track among Dutch students as compared to other students (Tempelaar et al., 2018). Therefore the data not only provides a guidance for teachers to prepare the learning contents but also to understand the degree to which an approach is more motivating for students.

Finally Figure 3 shows all educational data whether it is demographic, performance-based or behavioural-attitude data is encompassed under institutions-centric. As for an institution to study student behaviour and patterns as a whole, it requires to gather a large and diverse amount of educational data for effective usage and implementation. There are studies reported that although not all educational data is used independently, but by combining different sets of educational data it provides a perspective on the differences that relate to educational interventions and issues on resources allocation for institutions (Ruiperez-Valiente et al., 2015; Tempelaar et al., 2018).

5. CONCLUSION

A review of the Learning Analytics based on its objectives, educational data and end-users is presented. The findings of this research indicates that Learning Analytics is growing in popularity due to its potential to enhance learning and teaching through justifiable sets of data collected from learners. However our examination of extant studies through 2018 also indicates that there has been a term sprawl in the usage of Learning Analytics, where the term has become a one stop label for any study related to education and analytics without consideration of its definition and relevance to the primary research.

This review identifies three main end-users based on research objectives: student-centric, teacher-centric and institution-centric. The classification of the end-user offers a new insights into the relationship between the objectives of a study in relation to its end-user and the educational data that is relevant, creating a guideline for future researchers to conduct more user-centric Learning Analytics research. First, performance-based educational data is a common interest for student, teacher and institution-centric research as these data provides evidence to better academic performance. Secondly, demographics data such as nationality, age, gender and language, tend to be associated with teacher and institution-centric studies.

The direction of Learning Analytics research may improve and become clear with a well-defined relationship between the end-users and educational data offered in this study. Additional research is needed to examine further on the detailed relationship of disposition, behavioural data and its association with the key definition of student-centric, teacher-centric or institution-centric studies in Learning Analytic.

REFERENCES

[1] Ahmi, A., & Mohd Nasir, M. H. (2019). Examining the Trend of the Research on eXtensible Business Reporting Language (XBRL): A Bibliometric Review, International Journal of Innovation, Creativity and Change, 5(2), 1145-1167

[2] Ali, L., Asadi, M., Gasevic, D., Jovanovic, J., & Hatala, M. (2013). Factors influencing beliefs for adoption of a learning analytics tools: An empirical study. *Computers & Education*, *62*, 130-148. https://doi.org/10.1016/j.compedu.2012.10.023.

[3] Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2018). An integrated framework for course adapted student learning analytics dashboard. *Computers in Human Behavior*, *92*, 679-690. https://doi.org/10.1016/j.chb.2018.03.035.

[4] Arnold, K. E., & Pistilli, M. D. (2012, April 29 - May 2). *Course signals at Purdue: using learning analytics to increase student success*. Paper presented at the LAK'17 Proceedings of the 2nd International Learning Analytics & Knowledge Conference, New York, USA. Retrieved from https://doi.org/10.1145/2330601.2330666.

[5] Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning*, *20*(2), 13-29. https://eric.ed.gov/?id=EJ1105911.

[6] Berelson, B. (1952). *Content analysis in communications research*. New York, USA: Free Press.

[7] Bodily, R., & Verbert K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies*, *10*(4), 405-418. https://doi.org/10.1109/TLT.2017.2740172.

[8] Buerck, J. P., & Mudigonda, S. P. (2014). A resource-constrained approach to implementing analytics in an institution of higher education: An experience report. *Journal of Learning Analytics*, *1*(1), 129-139. https://doi.org/10.18608/jla.2014.11.7.

[9] Casey, K. (2017). Using keystroke analytics to improve pass-fail classifiers. *Journal of Learning Analytics*, *4*(2), 189-211. https://doi.org/10.18608/jla.2017.42.14.

[10] Charleer, S., Klerkx, J., & Duval, E. (2014). Learning dashboards. *Journal of Learning Analytics*, *1*(3), 199-202. https://doi.org/10.18608/jla.2014.13.22.

[11] Chou, C. H., Tseng, S. F., Chih, W. C., Chen, Z. H., Chao, P. Y., Lai, K. R. et al. (2017). Open student models of core competencies at the curriculum level: Using learning analytics for student reflection. *IEEE Transactions on Emerging Topics in Computing*, *5*(1), 32-44. https://doi.org/10.1109/TETC.2015.2501805.

[12] Dawson, S., Gasevic, D., Siemens, G., & Joksimovic, S. (2014, March 24-28). *Current state and future trends: A citation network analysis of the learning analytics field.* Paper presented at LAK'14 Proceedings of the Fourth International Conference on Learning Analytics and Knowledge, ACM International Conference Proceeding Series, Indianapolis, Indiana, USA. Retrieved from https://doi.org/10.1145/2567574.2567585.

[13] Dix, A.,, & Leavesley, J. (2015). Learning analytics for the academic: An action perspective. *Journal of Universal Computer Science*, *21*(1), 48-65. http://dx.doi.org/10.3217/jucs-021-01-0048.

[14] Dringus, L. P. (2012). Learning analytics considered harmful. *Journal of Asynchronous Learning Networks, 16*(3), 87-100. https://eric.ed.gov/?id=EJ982677.

[15] Elouaziz, N. (2014). Critical factors in data governance for learning analytics. *Journal of Learning Analytics*, *1*(3), 211-222. https://doi.org/10.18608/jla.2014.13.25.

[16] Ferguson, R., Macfadyen, L. P., Clow, D., Tynan, B., Alexander, S., & Dawson, S. (2014). Setting learning analytics in context: Overcoming the barriers to large-scale adoption. *Journal of Learning Analytics*, *1*(3), 120-144. https://doi.org/10.18608/jla.2014.13.7.

[17] Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., … Ullmann, T. (2016). Research evidence on the use of learning analytics: Implications for education policy. In R. Vourikari & J. Castano-Munoz (Eds.), *A European framework for action on learning analytics* (pp. 1-152). Luxembourg: Joint Research Centre Science for Policy Report.

[18] Ferguson, R., & Clow, G. (2017, March 13-17). *Where is the evidence? A call to action for learning analytics*. Paper presented at LAK'17 Proceedings of the Seventh International Learning Analytics & Knowledge Conference, Vancouver, British Columbia, Canada. Retrieved from https://doi.org/10.1145/3027385.3027396.

[19] Fidalgo-Blanco, A., Sein-Echaluce, M. L., Garcia-Penalvo, F. J., & Conde, M. A. (2015). Using learning analytics to improve teamwork assessment. *Computers in Human Behavior*, *47*, 149-156. https://doi.org/10.1016/j.chb.2014.11.050.

[20] Gasevic, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *Internet and Higher Education*, *28*, 68-88. https://doi.org/10.1016/j.iheduc.2015.10.002.

[21] Gray, G., McGuinness, C., Owende, P., & Carthy, A. (2014). A review of psychometric data analysis and applications in modelling of academic achievement in tertiary education. *Journal of Learning Analytics*, *1*(1), 75-106. https://doi.org/10.18608/jla.2014.11.5.

[22] Heitink, M. C., Van der Kleij, F. M., Veldkamp, B. P., Schildkamp, K., & Kippers, W. B. (2016). A systematic review of prerequisites for implementing assessment for learning in classroom practice. *Educational Research Review*, *17*, 50-62. https://doi.org/10.1016/j.edurev.2015.12.002.

[23] Howell, J. A., Roberts, L. D., & Mancini, V. O. (2018). Learning analytics messages: Impact of grade, sender, comparative information and message style on student affect and academic resilience. *Computers in Human Behavior*, *89*, 8-15. https://doi.org/10.1016/j.chb.2018.07.021.

[24] Hussain, A., Mkpojiogu, E. O. C., Musa, J., Mortada, S., & Yue, W. S. (2018). Mobile experience evaluation of an e-reader app. Journal of Telecommunication, Electronic and Computer Engineering, 10(1–10), 11–15.

[25] Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018, March 7-9). *License to evaluate: Preparing learning analytics dashboards for educational practice*. Paper presented at LAK'18 Proceedings of the 8th International Conference on Learning Analytics and Knowledge, Sydney, New South Wales, Australia. Retrieved from https://doi.org/10.1145/3170358.3170421.

[26] Johnson, L., Adams-Becker, S., & Hall, C. (2015). *NMC technology outlook for Australian tertiary education: A horison project regional report*. Austin, Texas: The New Media Consortium.

[27] Jovanovic, J., Gasevic, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *Internet and Higher Education*, *33*, 74-85. https://psycnet.apa.org/doi/10.1016/j.iheduc.2017.02.001.

[28] Kelly, N., Thompson, K., & Yeoman, P. (2015). Theory-led design of instruments and representations in learning analytics: Developing a novel tool for orchestration of online collaborative learning. *Journal of Learning Analytics*, *2*(2), 14-43. https://doi.org/10.18608/jla.2015.22.3.

[29] Khalil, M., & Ebner, M. (2016). De-identification in learning analytics. *Journal of Learning Analytics*, *3*(1), 129-138. https://doi.org/10.18608/jla.2016.31.8.

[30] Kim, D., Yoon, M., Jo, I. H., & Branch, R. M. (2018). Learning analytics to support self-regulated learning in asynchronous online courses: A case study at a women's university in South Korea. *Computers & Education*, *127*, 233-251. https://doi.org/10.1016/j.compedu.2018.08.023.

[31] Knight, D. B., Brozina, C., & Novoselich, B. (2016). An investigation of first-year engineering student and instructor perspectives of learning analytics approaches. *Journal of Learning Analytics*, *3*(3), 215-238. https://doi.org/10.18608/jla.2016.33.11.

[32] Leeuwen, A. v., Janssen, J., Erkens, G., & Brekelmans, M. (2014). Supporting teachers in guiding collaborating students: Effect of learning analytics in CSCL. *Computers & Education*, *79*, 28-39. https://doi.org/10.1016/j.compedu.2014.07.007.

[33] Leeuwen, A. v. (2015). Learning analytics to support teachers during synchronous CSCL: Balancing between overview and overload. *Journal of Learning Analytics*, *2*(2), 138-162. https://doi.org/10.18608/jla.2015.22.11.

[34] Leeuwen, A. v., Janssen, J., Erkens, G., & Brekelmans, M. (2015). Teacher regulation of cognitive activities during student collaboration: Effect of learning analytics. *Computers & Education*, *90*, 80-94. https://doi.org/10.1016/j.compedu.2015.09.006.

[35] Leitner, P., Khalil, M., & Ebner, M. (2017). Learning analytics in higher education – A literature review. In A. Pena-Ayala (Ed.), *Learning analytics: Fundamentals, applications, and trends* (pp. 1-23). Springer, Cham.

[36] Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior*, *47*, 90-97. https://doi.org/10.1016/j.chb.2014.07.013.

[37] Ma, J., Han, X., Yang, J., & Cheng, J. (2015). Examining the necessary condition for engagement in an online learning environment based on learning analytics approach: The role of the instructor. *Internet and Higher Education, 24*, 26-34. https://doi.org/10.1016/j.iheduc.2014.09.005.

[38] Marsh, J. A., & Farrell, C. C. (2014). Supporting teachers with data-driven decision making: A framework for understanding capacity-building. *Education Management Administration and Leadership*, 1-12. https://doi.org/10.1177%2F1741143214537229.

[39] Martin, C. K., Nacu, D, & Pinkard, N. (2016). An approach to using log data to understand and support 21st century learning activity in k-12 blended learning environment. *Journal of Learning Analytics*, *3*(2), 37-87. https://doi.org/10.18608/jla.2016.32.4.

[40] Martinez-Maldonado, R., Shum, S. B., Schneider, B., Charleer, S., Klerkx, J., & Duval, E. (2017). Learning analytics for natural user interfaces. *Journal of Learning Analytics, 4*(1), 24-57. https://doi.org/10.18608/jla.2017.41.4.

[41] Mendez, G., Ochoa, X., Chiluiza, K., & Wever, B. d. (2014). Curricular design analysis: A data-driven perspective. *Journal of Learning Analytics*, *1*(3), 84-119. https://doi.org/10.18608/jla.2014.13.6.

[42] Michos, K., & Hernandez-Leo, D. (2016). *Towards understanding the potential of teaching analytics within educational communities.* Paper presented at CEUR Proceedings of the 4th International Workshop on Teaching Analytics, Lyon, France. Retrieved from https://repositori.upf.edu/bitstream/handle/10230/32137/michos_IWTA2016_towa.pdf.

[43] Motz, B. A. Carvalho, P. F. Leeuw, J. R. d., & Goldstone, R. L. (2018). Embedding experiments: Staking causal inference in authentic educational contexts. *Journal of Learning Analytics*, *5*(2), 47-59. https://doi.org/10.18608/jla.2018.52.4.

[44] Naderi, H., Abdullah, R. Aizan, H. T., Sharir, J., & Kumar, V. (2009). Creativity, age and gender as predictors of academic achievement among undergraduate students. *Journal of American Science*, *5*(5), 101-112.

[45] Nistor, N., & Hernandez-Garciac, A. (2018). What types of data are used in learning analytics? An overview of six cases. *Computers in Human Behavior*, *89*, 335-338. https://doi.org/10.1016/j.chb.2018.07.038.

[46] Rodriguez-Triana, M. J., Martinez-Mones, A., & Villagra-Sobrino, S. (2016). Learning analytics in small-scale teacher-led innovations: Ethical and data privacy issues. *Journal of Learning Analytics*, *3*(1), 43-65. https://doi.org/10.18608/jla.2016.31.4.

[47] Ruiperez-Valiente, J. A., Munoz-Merino, P. J., Gascon-Pinedo, J. A., & Kloos, C. D. (2015). Scaling to massiveness with ANALYSE: A learning analytics tool for open edX. *Journal of Latex Class Files*, *14*(8), 1-6. https://doi.org/10.1109/THMS.2016.2630420.

[48] Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior*, *78*, 397-407. https://doi.org/10.1016/j.chb.2017.06.030.

[49] Selwyn, N. (2019). What's the Problem with Learning Analytics?. Journal of Learning Analytics, 6(3), 11-19. http://dx.doi.org/10.18608/jla.2019.63.3

[50] Sergis, S., Sampson, D. G., Rodriguez-Triana, M., Gillet, D., Pelliccione, L., & Jong, T. d. (2017). Using educational data from teaching and learning to inform teachers' reflective educational design in inquiry-based STEM education. *Computers in Human Behavior*, *92*, 1-15. https://doi.org/10.1016/j.chb.2017.12.014.

[51] Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, *46*(5), 31-40.

[52] Tan, J. P. L., Koh, E., Jonathan, C., & Yang, S. (2017). Learner dashboards a double-edged sword? Students' sense-making of a collaborative critical reading and learning analytics environment for fostering 21st century literacies. *Journal of Learning Analytics*, *4*(1), 117-140. https://doi.org/10.18608/jla.2017.41.7.

[53] Tempelaar, D. T., Rienties, B., & Giesbers (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157-167. https://doi.org/10.1016/j.chb.2014.05.038.

[54] Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2017). Towards actionable learning analytics using dispositions. *IEEE Transactions on Learning Technologies*, *10*(1), 6-16. https://doi.org/10.1109/TLT.2017.2662679.

[55] Tempelaar, D., Rienties, B., Mittelmeier, J., & Nguyen, Q. (2018). Student profiling in a dispositional learning analytics application using formative assessment. *Computers in Human Behavior*, *78*, 408-420. https://doi.org/10.1016/j.chb.2017.08.010.

[56] Viberg, O., Hatakka, M., Balter, O., & Mavroudi, A. (2019). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98-110. https://doi.org/10.1016/j.chb.2018.07.027.

[57] Wang, H. F., & Lin, C. H. (2019). An investigation into visual complexity and aesthetic preference to facilitate the creation of more appropriate learning analytics systems for children. *Computers in Human Behavior*, *92*, 706-715. https://doi.org/10.1016/j.chb.2018.05.032.

[58] Wanli, X., Rui, G., Eva, P., & Sean, G. (2015). Participation-based student final performance prediction model through interpretable Genetic Programming: Integrating learning analytics, educational data mining and theory. *Computers in Human Behavior*, *47*, 168-181. https://doi.org/10.1016/j.chb.2014.09.034.

[59] Zhang, X., Meng, Y., Pablos, P. O. d., & Sun, Y. (2017). Learning analytics in collaborative learning supported by Slack: From the perspective of engagement. Computers in Human Behavior, 92, 625-633. https://doi.org/10.1016/j.chb.2017.08.012.