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A MULTI-LAYERED TAXONOMY OF LEARNING ANALYTICS APPLICATIONS

Andy Nguyen
University of Auckland, a.nguyen@auckland.ac.nz

Lesley A. Gardner
The University of Auckland, l.gardner@auckland.ac.nz

Don Sheridan
University of Auckland, d.sheridan@auckland.ac.nz

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Completed Research Paper

Andy Nguyen
University of Auckland
12 Grafton Rd, Auckland, New Zealand
a.nguyen@auckland.ac.nz

Lesley Gardner
University of Auckland
12 Grafton Rd, Auckland, New Zealand
l.gardner@auckland.ac.nz

Don Sheridan
University of Auckland
12 Grafton Rd, Auckland, New Zealand
d.sheridan@auckland.ac.nz

Abstract

Digital technologies have become immersed in education systems and the stakeholders have discovered a pervasive need to reform existing learning and teaching practices. Among the emerging educational digital technologies, learning analytics create a disruptive potential as it enables the power of educational decision support, real-time feedback and future prediction. Until today, the field of learning analytics is rapidly evolving, but still immature and especially low on ontological insights. Little guidance is available for educational designers and researchers when it comes to studies applied learning analytics as a method. Hence, this study offers a well-structured multi-layered taxonomy of learning analytics applications for deeper understanding of learning analytics.

Keywords: Learning analytics, Knowledge Management, Taxonomy

Introduction

Given the rapid development of digital technologies, digitalization has not only changed the business models of commercial organizations but the digitalization of education has offered great value-producing opportunities, opportunities for improved decision-making, and hence new practices for learning and teaching. Among the emerging digital technologies in education, learning analytics specifically are gaining interest of researchers and educators. Learning analytics are having an impact on personalized education, objective evaluation, and institutional decision making.

Given the rapid development of digital technologies, digitalization has not only changed the business models of commercial organizations (Markovitch & Willmott, 2014) but the digitalization of education has offered novel value-producing opportunities, opportunities for improved decision-making, and hence new practices for learning and teaching (Kagermann, 2015). Among the emerging digital technologies in education, learning analytics specifically are gaining interest of researchers and educators. Learning analytics are having an impact on personalized education, objective evaluation, and institutional decision making.

The term ‘learning analytics’ is generally credited to George Siemens and is, in essence, an amalgam of many analytic techniques and methods focused on the learning and teaching process (Siemens & Tittenberger, 2009). Given that the term is relatively new, there are few (no) studies from a meta perspective documenting the use of various LA applications and their complimentary interaction with an aim to create better decision-making opportunities in higher education. Sensing an opportunity, in this paper, we address the following research question: How to classify learning analytics applications into a taxonomy according to “what” are their central components and “how” can they may be used?

In order to answer the research question, this study applies the taxonomy development methodology in information systems by Nickerson, Varshney, and Muntermann (2013) to produce a valuable model for the classification of various applications of learning analytics. The resultant taxonomy is believed to contribute functional, descriptive knowledge related to learning analytics. It is intended as an aid in understanding the systemic context of learning analytics and their key elements.

THEORETICAL BACKGROUND

Definition of Taxonomy

Taxonomy refers to a scientific system to classify objects of interest in a domain conceptualized from multi-dimensional characteristics. A taxonomy can be defined as a set of dimensions constructed by mutually exclusive and collectively exhaustive characteristics. In each dimension, each object must have one and only one of the characteristic and no object can have more or less than a single characteristic to comply collectively exhaustive and mutual exclusive restrictions respectively. In addition, the characteristics can be further grouped into categories to form hierarchical dimensions. Prat, Comyn-Wattiau, and Akoka (2015) formulated a taxonomy (T) with categories (Cat) of hierarchical dimensions (D) as following:

$$T = \left\{Dim_i, i = 1 \ldots, n \middle| Dim_i = \left\{Cat_{ij}, j = 1 \ldots, k_i\right\}\right|$$

$$Cat_{i1} = \{Char_{im}, m = 1 \ldots, p_i; p_i \geq 2\} \wedge \forall j \geq 2, Cat_{ij} \subsetneq Cat_{i1}\}$$

During the iterative process of taxonomy development, we have noticed that each learning analytics application is a multifaceted object thus a multi-layered taxonomy with hierarchical dimensions rather than a flat one. Prat et al. (2015) formulation of taxonomy is adopted as the base for the development of a taxonomy for learning analytics application.

Taxonomy of Learning Analytics Applications

The literature in Information Systems shows extensive use of taxonomy such as a methodology for developing and validating a cybercrime taxonomy (Land et al., 2013), a taxonomy of smart objects (Lopez et al., 2011), and a taxonomy of knowledge management outcomes for SMEs (Khosravi et al., 2014). In this paper, we focus on the development of a taxonomy of learning analytics applications.

As an emerging research discipline, Learning Analytics has been referred to using various terms and definitions in both general use and research. In a broad sense, learning analytics can be interpreted as applications of data analytics in learning and teaching. At LAK11 (2011), the 1st International Conference on Learning Analytics, The Society for Learning Analytics Research, (https://solaresearch.org/) defined Learning Analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". Recently, this definition has been widely adopted in the research community (Siemens, 2013).

Using learning analytics, educators and researchers have been able to predict student success to improve teaching and learning (Dietz-Uhler & Hurn, 2013; Gašević, Dawson, Rogers, & Gasevic, 2016; Siemens & Long, 2011). Learning analytics applications provide up-to-date data about the learning activities, student engagement, the student's profile, and relevant historical data from previous semesters to model the learning process and forecast the student's future performance. Based on the predicted information, the instructor can take necessary interventions and focus more attention on at-risk students. For instance, Siemens and Long (2011) suggest that a model of successful student behaviours can support the faculty to encourage weak students to increase their involvement in the activities critical for academic success. The model includes data about the frequency of accessing and using learning applications such as LMS tools and discussion boards. Using the model of successful student behaviours, the instructors may revise learning activities and remove those not related to final grades, i.e. teaching something that is not assessed.

Likewise, Arnold and Pistilli (2012) proposed an early intervention solution for academic faculty called Course Signals. The system uses educational data to predict student performance and reports the outcomes to the students via a personalized email. The collected data using included not only grades but also past academic history, students' demographics, and learning engagement. The reported information contains a stoplight or traffic signal which is used to show how each student is performing. All students could be informed of their current learning performance and at-risk students would be informed about their need to change to improve their status. This example demonstrates the use of learning analytics from the instructor's perspective as well as at the student level.

Greller and Drachsler (2012) recommend using learning analytics to inform the teaching team about gaps in knowledge presented by the students. Improvements in the curriculum and instructional design and documentation ensures students and teachers can better understand learning needs and performance. At the classroom level, identifying the knowledge gaps, aids the teachers by focusing on missing knowledge parts or a specific, at-risk, group of students. For instance, they can provide students with additional resources and exercises on particular pieces of information to broaden students' understanding of the essential learning content.

Furthermore, learning analytics has enabled learning personalization and adaptive learning systems in higher education (Greller & Drachsler, 2012; Kerr, 2016). Adaptive learning systems, also known as personalized or individualized learning applications, refer to those that can adapt to student interactions with the system based on a relatively insignificant amount of data generated by the students (Kerr, 2016). The learning analytics engine is the central component of an adaptive learning system as it collects and analyses user data on a real-time basis. For example, Hsieh, Wang, Su, and Lee (2012) proposed a fuzzy logic-based personalized learning system for enhancing adaptive English learning. The system recommends articles that are appropriate for a learner's level of English ability and also identifies their need to review words within their working vocabulary. The resultant analyses have confirmed that the proposed personalized learning system improves learning as well as motivates the students to continue.

In summary, the findings of the current literature have found a number of important applications for learning analytics in learning and teaching. However, no attempt has been made to classify these applications in a formal structure to provide an overview of the field. As a result, an important priority should be to categorize the applications of learning analytics to offer useful insights into the nature of learning analytics.

Research Method

This research seeks to develop a taxonomy with comprehensive dimensions that can be considered as an artifact in the design science research paradigm (Hevner, March, Park, & Ram, 2004). Design science research originated within the field of engineering (Vaishnavi & Kuechler, 2004) and was introduced to IS research community in the 1990 (Nunamaker Jr, Chen, & Purdin, 1990). The methodology involves diagnosing observed practical problems to establish research questions, solving the problems, developing artefacts to demonstrate the comprehensive solution, and evaluating the presented result. The designed artefacts are inserted into a body of knowledge to offer additional understandings of the application or relevant area. In this paper, we describe a process to design a taxonomy of LA applications to inform and organize emerging applications of learning analytics.

In doing so, we adopted Nickerson et al. (2013) seven-step, iterative method to build a taxonomy. This method considers previous approaches from different domains and extends the classification techniques in social sciences, used by Bailey (1994), to specify a formal development of a taxonomy in the field of Information Systems. In brief, the proposed process starts with the determination of meta-characteristics and ending conditions, then proceeds through several iterations of building and revising objects, their characteristics and dimensions, to render an anticipated taxonomy. The iterative process only ends once the required ending conditions are fulfilled.

At first, the meta-characteristic is the central aspect to regulate the selection of the distinguishing characteristics in a taxonomy. The meta-characteristic reflects and focuses on the purpose of the taxonomy development. Following this step is the determination (definition) of the objective and subjective ending conditions for the iterations of taxonomy construction. Each iteration can follow either conceptual-to-empirical or empirical-to conceptual approaches.

Conceptual-to-empirical refers to the approach that conceptualizes the taxonomy's dimensions at first then identifies characteristics for each dimension. Once the dimensions and characteristics are determined, the real-life objects will be mapped into appropriate group to form or revise the taxonomy.

On the other hand, the empirical-to-conceptual starts from the identification of real-life objects then determines sharing characteristics among each group of objects. Aa a final step, the characteristics are classified into groups to create or revise the taxonomy. The approach selection depends on the availability of data and the researcher's relevant knowledge. As noted the iterative process only ends once both objective and subjective ending conditions are satisfied.

In this paper, our first iteration follows empirical-to-conceptual approach to examine LA applications from the existing literature and determine initial dimensions and characteristics of taxonomy. We collected the literature from several journals and conference proceedings related to information systems in education, educational technology, and particularly learning analytics. Our strategy for literature search follows the process of formulating the search terms proposed by Wen et al. (2012).

The evaluation of the initial taxonomy leads to the second iteration which adapted conceptual-to-empirical method. The second iteration revises initial results to propose a comprehensive taxonomy of learning analytics applications. The third iteration uses empirical-to-conceptual scheme to evaluate the ending conditions of the revised taxonomy.

TAXONOMY DEVELOPMENT

Meta-Characteristics and Ending Conditions

The meta-characteristics should reflect the goal of the taxonomy thus this research defines the meta-characteristics based on the formulated research questions. Hence the meta-characteristics are: "What" are high-level components of learning analytics applications and "how" they are applied in educational environment.

The iterative development process of a taxonomy ends once both objective and subjecting ending conditions have been fulfilled. We adopted Nickerson et al. (2013) ending conditions and outlined ending conditions applied in the development of the taxonomy as showed in Table 1.

Table 1: Ending Conditions for the Development of the Taxonomy

<table>
<tr><td rowspan="6">Objective Ending Conditions</td><td rowspan="2">The definition of a taxonomy satisfied.</td><td colspan="2">Each dimension consists of mutually exclusive characteristics</td></tr>
<tr><td colspan="2">Each dimension consists of collectively exhaustive characteristics</td></tr>
<tr><td>Generalizability achieved.</td><td colspan="2">All objects of interest or a representative sample of them have been investigated.</td></tr>
<tr><td rowspan="3">Comprehensive sets of dimensions and characteristics obtained.</td><td colspan="2">Each characteristic of each dimension must include at least one classified object.</td></tr>
<tr><td colspan="2">No changes (new, update, merge, split, or delete) of dimensions or characteristics in the last iteration.</td></tr>
<tr><td colspan="2">Every dimension is unique and within each dimension, every characteristic is unique.</td></tr>
<tr><td rowspan="5">Subjective Ending Conditions</td><td rowspan="3">Appropriate number of dimensions and characteristics used to classify all objects of interests.</td><td>Concise</td><td>Limited number of dimensions and characteristics used</td></tr>
<tr><td>Robust</td><td>Adequate number of dimensions and characteristics to differentiate among objects</td></tr>
<tr><td>Comprehensive</td><td>All essential dimensions and characteristics to classify all objects of interest.</td></tr>
<tr><td rowspan="2">Ease of Use</td><td>Extendible</td><td>Uncomplicated insertion of new dimensions and new characteristics or additional characteristics of an existing dimension.</td></tr>
<tr><td>Explanatory</td><td>All dimensions and characteristics can offer useful explanation about every object.</td></tr>
</table>

Initial Taxonomy - The First Iteration

In the initial iteration, we adopted empirical-to-conceptual approach as several LA applications were identified from the literature. Table 2 shows a list of applications gathered from existing literature and a brief description for each one.

Table 2: A Summary of Learning Analytics Applications

Application	Research Paper(s)	Description
Visualize Learning Activities	Fortenbacher et al. (2013); Leony et al. (2012); Ruipérez-Valiente, Muñoz-Merino, Leony, and Kloos (2015); Verbert, Duval, Klerkx, Govaerts, and Santos (2013);	Learning analytics trace all learning activities performed by users on the Learning Management System (LMS) to produce visual reports on the learning process. The reports can support both students and teachers to boost learning motivation, adjust practices and leverage learning efficiency (Shum, Gasevic, & Ferguson, 2012).
Access Learning Behavior	Blikstein (2011); Ramesh, Goldwasser, Huang, Daumé III, and Getoor (2014)	Learning analytics can be used to collect user-generated data from learning activities and offer trends of learning engagement. Analyzing those trends can discover learning behavior of the students and identify their learning styles.
Predict Student's Performance	Arnold and Pistilli (2012); Pistilli, Arnold, and Bethune (2012); Wolff, Zdrahal, Nikolov, and Pantucek (2013)	There have been several attempts using learning analytics to predict student's success and identify at-risk students. Based on existing data about learning engagement and performance, learning analytics apply statistical models and machine learning techniques to predict later learning performance. By doing so, likely at-risk students can be spotted out for early intervention.
Individualize learning	Hsieh et al. (2012); Kerr (2016); Tseng, Chu, Hwang, and Tsai (2008)	Adaptive or individualized learning systems apply learning analytics to consume a relatively small user-generated data to adjust its content for each learner. Furthermore, user profiles and other sets of data can be collected and analyzed to offer greater personalized learning experiences.
Evaluate Social Learning	De Liddo, Shum, Quinto, Bachler, and Cannavacciuolo (2011); Ferguson and Shum (2011)	Not limited to the assessment of formal learning on the LMS, learning analytics can be applied to investigate learner's activities on social networks to evaluate the benefits of social learning.
Improve Learning Materials and Tools	Macfadyen and Dawson (2012); Persico and Pozzi (2015)	Learning analytics can track student's usage of learning materials and tools to identify potential issues on those. LA can also offer objective evaluation of learning materials and tools.

From the identified learning analytics applications, the following dimensions and corresponding characteristics have been recognized:

Time-based Feedback: Learning analytics can offer meaningful information regarding either the past trends, current events or foreseen occurrences. The past trends provide insights into previous learning processes or behaviors by discovering common patterns and anomalies among the historical datasets (Blikstein, 2011; Ramesh et al., 2014). In other cases, learning analytics can response to the user based upon user interactions with the system on the real-time basis (Hsieh et al., 2012; Kerr, 2016; Tseng et al., 2008). In addition, learning analytics can apply predictive techniques to offer information about the upcoming events or states (Dietz-Uhler & Hurn, 2013; Wolff et al., 2013; Xing, Guo, Petakovic, & Goggins, 2015). Therefore, time-based dimension consists of three characteristics, namely real time feedback, retrospective feedback and prospective feedback.

TimeBased_Feedback={Realtime_Feedback (RT); Retrospective_Feedback (RF); Prospective_Feedback (PF)}

Primary Data Source: Learning analytics applications can collect multiple data sets from various sources such as learning management systems (LMS) (Arnold & Pistilli, 2012; Duval, 2011), social network platforms (Cho, Gay, Davidson, & Ingraffea, 2007; Siemens & d Baker, 2012) and enrolment systems. In this case, each LA application tends to adapt several sets of data mainly gathered from the main source. Some caution is essential to identify the primary data source of LA applications to better understand "how" to design, develop and implement the applications in an effective manner. The primary data source is formulated as a dimension consisting of following characteristics: Learning Management System (LMS), Social Network (SN), and Others (ODS).

Data_Source={Learning_Management_System (LMS); Social_Network (SN); Others (ODS)}

Data State:In the current context, collected data appear in various forms and sizes but they can be broadly classified into three categories namely dynamic data, static data and semi-dynamic data. Dynamic data is being frequently updated at very short intervals, usually measured in seconds. One typical example of dynamic data is the tracking logs that record all interactions between the system and users. On the other hand, static data, such as exam scores, rarely change over time. Semi-dynamic data

Data_State={Dynamic (D); Static (S); SemiDynamic (SD)}

Unit of Analysis: Learning analytics applications focus on different learning objects to offer object-oriented information. For example, some applications may look at student performance by analyzing the student's assignment grades and exam scores (Tair & El-Halees, 2012) while another investigates events related to learning activities (Ramesh et al., 2014). The units of analysis are identified as student performance (marks), learning activities (events) and course curriculum (objectives). The course curriculum can be drilled down to learning materials and contents.

Unit_of_Analysis={Student_Performance (SPer); Learning_Activities (LAct); Course_Curriculum (CCur)}

Primary Users: Primary users are those who directly use and get benefits from the application. Primary users may be teachers (T), learners (L), or researchers (R). This dimension relates to the aggregated and strategic level of the learning analytics. Learners often receive individual analysis whereas teachers and researchers demand aggregated reports for groups of students. A learning analytics application may target different user groups at the same time thus we consider all possible combination to keep the characteristics mutually exclusive.

Primary_User={Teacher(T), Learner(L), Teacher&Learner(TL), Researcher(R), Researcher&Teacher(RT), Researcher&Learner(RL), Researcher&Teacher&Learner(RTL)}

Communication: We noted that information can be either unidirectional or bidirectional. In other words, information may either flow only from learning analytics system to users or both from the application to users and from users to the application. We formulated the information flows as a dimension called communication consisting of interactive (INT) and informative (INF) characteristics.

Communication={Interactive(INT), Informative(INF)}

Initial Taxonomy of Learning Analytics Applications

During the identification of above dimensions, the characteristics of each dimension have been systematically checked to comply with the requirement that all characteristics within each dimension Combining above dimensions, an initial taxonomy of learning analytics applications is constructed as following:

T_LA0={TimeBased_Feedback(RT,RF,PF), Data_State(D,S,SD), Data_Source(LMS,SN,ODS),

Unit_of_Analysis(Sper,LAct,CCur), Primary_User(T,L,TL), Communication(INT,INF)}

Table 3 shows the initial taxonomy of learning analytics applications constructed from the above formulation. As new dimensions and characteristics have been created in this iteration, the development of the taxonomy continues.

Table 3: Initial Taxonomy of Learning Analytics Applications

Initial Taxonomy of **LA Applications**	**Time-based Feedback**			**Data Source**			**Data State**		**Unit of Analysis**				**Communication**		**Primary Users**
Learning Analytics Application	RT	RF	PF	LMS	SN	ODS	D	S	SD	SPer	LAct	CCur	INT	INF	
Visualize Learning Activities		X		X			X				X			X	LT
Access Learning Behavior		X		X					X		X			X	LTR
Predict Student's Performance			X			X			X	X				X	T
Individualize learning	X			X			X				X		X		L
Evaluate Social Learning		X			X			X			X			X	TR
Improve Learning Materials and Tools		X		X			X					X		X	T

A Multi-Layered Taxonomy of Learning Analytics Applications

We revised the dimensions of the initial taxonomy and characteristics of each dimension based on the literature on learning analytics. As new dimensions conceived from the literature, we adopted conceptual-to-empirical approach for the second iteration. A layer structure is applied to arrange the categories of dimensions to improve explanatory and extendible. At first, critical dimensional layers are identified from the existing research then a taxonomy is constructed and evaluated.

Critical Dimensional Layers

From the literature review, critical dimensions of learning analytics proposed by Greller and Drachsler (2012) best fit with the purpose of this taxonomy development. However, we reasoned that internal limitations and external constraints depend on each unique case; thus, there are instances when these dimensions are not applicable for a generalized taxonomy of learning analytics applications. As a result, they are excluded from the taxonomy construction to ensure the proposed taxonomy has generalizability. The remaining components are conceptualized as the layers of the taxonomy, consisting of Data Layer (...); Stakeholder Layer (...); Objective Layer (...); and Instrument Layer (...).

1.1.1.1 Objective Layer

As Unit of Analysis (...) dimension indicates the targeted objects and indirectly relates to the main objectives of the application, we merged this dimension into the main purpose (Learner-Centric, Event-Centric, Content-Centric). Learner-centric learning analytics focus on the learner as the central unit of analysis whereas event-centric applications principally investigate the user interactions on learning systems. In contrast, content-centric aims for the evaluation of the curriculum, course content and materials.

Main_Purpose={LearnerCentric(LC); EventCentric (EC); ContentCentric(CC)}

To increase the meaning and compatibility, Time-based Feedback (RT, RF, PF) dimension was enhanced to include Feedback Type (Adaptive, Reflective, Predictive) in the Objective Layer. Larusson and White (2014) noted that reflection, prediction and adaptive learning are the core practical implications of learning analytics. Respectively, real-time feedback is classified as adaptive with the intent of chaning the learner's behavior, retrospective feedback (RF) aims to propose self-reflections on learning and teaching, and prospective feedback provides prediction for key performance indicators, i.e. a student's grade based upon activities to date

Feedback_Type={Adaptive(AF); Reflective(RF); Predictive(PF)}

1.1.1.2 Data Layer

Data can be obtained from different educational information systems such as the Learning Management System (LMS). Stakeholders' activities in the educational ecosystem continuously generate many datasets. Apart from static information stored in the databases, the advances in technology allows for the real-time capture of dynamic data. Thus, in the previous iteration. one key characteristic was identified as the 'data state' either static, dynamic or semi-dynamic. The initial iteration also recognized the 'data source'. These characteristics are now categorized in the data layer. It follows that security and privacy concerns restrict access to educational data hence it can be also classified as protected and open data (Greller & Drachsler, 2012). Whatever the classification, the right to use educational data remains a controversial topic and subject top much in debate (Pardo & Siemens, 2014; Slade & Prinsloo, 2013).

1.1.1.3 Stakeholder Layer

Stakeholders may be students, teachers, administrators, departments of education or researchers. Greller and Drachsler (2012) proposed that stakeholders can be either data subjects who produce educational data, often by interacting with the information systems; or data clients who are the beneficiaries of the process by obtaining and controlling the outcome. For example, while a learner accesses learning materials on the Learning Management System (LMS), the system can capture their interaction data such as time spent and navigation path to provide reports to the teacher for better understanding of the learners' engagement. In this case, the learner is a data subject that generates data for the LA process whereas the teacher is a data client and is authorised to obtain the LA results. In some cases, a stakeholder can be both a data subject and a data client at the same time; for example, when they peruse their own data to check their achievements. A self-report may guide a student through a process of self-evaluation and lead to insights about their learning process, revision and review strategies, point to practice sets, other learning materials designed for different learning styles, etc.

However, it is noticeable that data flows in an education system are highly interactive and intertwined thus it is necessary to consider the bi-directional flows of data for the self-evaluation of analytics. As a

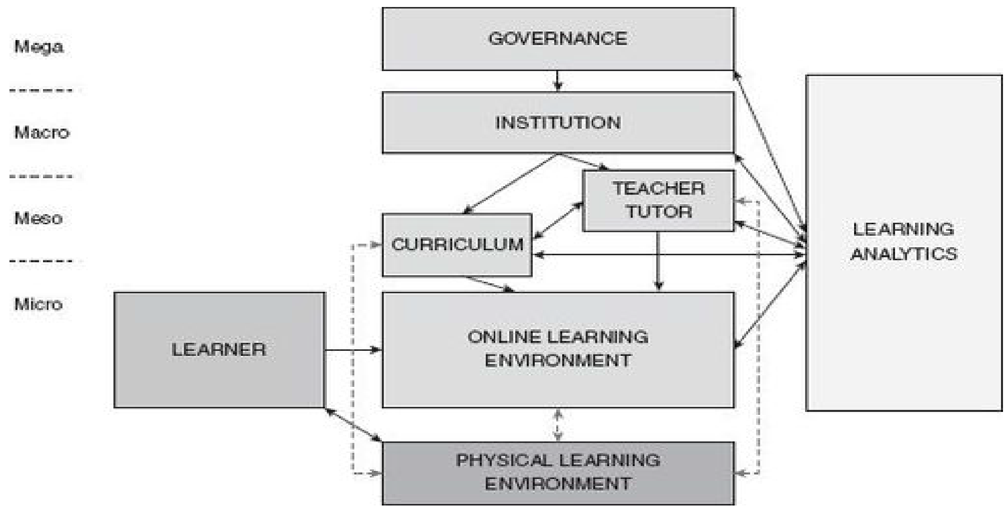

Figure 1: Learning analytics associated with stakeholder levels (Ifenthaler, 2015)

result, the distinction between data subjects and data clients are not vital in designing data analytics applications. Instead, it highlights the importance of determining the stakeholders involved, their objectives, and relevant data flow between them.

As mentioned in the previous iteration, determination of the primary user may support understanding and developing an effective learning analytics application. After revising the initial taxonomy, we identified additional stakeholders such as school administrators and educational decision makers. Combinations of different stakeholder groups imply mutual exclusive restriction, yet are likely to violate the subjective conditions of being Concise and Extendible. We noted that the interactions between stakeholders are also significantly important to learning analytics. As a consequence, we adopted a model of LA associated with addressing stakeholder levels proposed by (Ifenthaler & Widanapathirana, 2014) (Figure 1). Stakeholder levels stated in the framework are namely micro, meso, macro and mega. The model illustrates data flow between educational stakeholders and the position of LA in the learning context. Although it is not apparent in the model (Figure 1), researchers are incorporated at the mega level because they are principle motivating forces for many learning analytics applications and their work relates to generalization of educational knowledge. In other words, agents of knowledge discovery without direct relationships with the stakeholders will be categorized in the mega level.

Stakeholder_Level={Micro; Meso; Macro; Mega}

1.1.1.4 Instrument layer

Instruments are techniques or theories used in learning analytics applications to achieve anticipated objectives. This layer is a critical bridge between other layers of the taxonomy and dependencies existing between the selection of appropriate instruments. For instance, the availability of relevant data also plays an important role in the selection of analytic methods and the process of data analysis. A learning analytics application may also combine multiple instruments to obtain the best possible results. Given that learning analytics are an emerging field it's accepted that related theories and techniques frequently change over time. Therefore, regarding the dimensions on this layer, we focus on the "how" part rather than the question of "what" is the instrument used. As a result, instrument dimensions are conceptualized as Expertise Requirement and Operating Complexity. The expertise requirement indicates the level of knowledge and skills needed to use or develop the particular learning analytics application whereas operating complexity determines the expected time and efforts for operating the application and achieving results. These dimensions are formulated as following:

Expertise_Requirement={Novice(N); Intermediate(I); Advanced(A); Expert(E)}

and Operating_Complexity={Low;Medium;High}

The Multi-Layered Taxonomy

Integrating all the above dimensions and characteristics, this paper proposes a multi-layered taxonomy of learning analytics applications as:

T_{LA} ={Data{Data_State(D;S;SD); Data_Source(LMS;SN;ODS); Data_Access(Open;Restricted)};
Stakeholder(Micro;Meso;Macro;Mega);
Objective{Main_Purpose(LC;EC;CC);Feedback_Type(AF;RF;PF)};
Instrument{Expertise_Requirement(N,I,A,E);Operating_Complexity(Low,Medium,High)}}

Each dimension in this taxonomy is accessed to be mutually exclusive and collectively exhaustive to satisfy the definition of a taxonomy. A representative sample of objects of interest have been investigated to achieve generalizability of the taxonomy. Moreover, this taxonomy consists of seven main dimensions which falls in an appropriate range of seven plus or minus two for a concise and robust taxonomy (Miller, 1956; Nickerson et al., 2013). Nevertheless, the third iteration was conducted to verify the comprehensiveness of the proposed taxonomy as new dimensions and characteristics are constructed in the second iteration. The third iteration also acts as an evaluation of the taxonomy thus it follows empirical-to-conceptual approach which attempts to discover any additional dimensions or characteristics from newly-discovered objects and to map them into the taxonomy.

Evaluation of the Proposed Taxonomy

For the empirical-to-conceptual evaluation, additional learning applications identified from the literature are Assessment of Personal Learning Environments (Fournier, Kop, & Sitlia, 2011), Sophisticated Evaluation of Gamification (Serrano-Laguna, Torrente, Moreno-Ger, & Fernández-Manjón, 2014), Support Educational Decision Making (Fulantelli, Taibi, & Arrigo, 2015) and Examining Virtual Worlds (Fernández-Gallego, Lama, Vidal, & Mucientes, 2013).

All newly-discovered applications of learning analytics are mapped into the proposed taxonomy of learning analytics applications and the results are demonstrated in Table 4.

Table 4: Multi-layered Taxonomy of Learning Analytics Applications

	Objective Layer		Data Layer		Stakeholder Layer	Instrument Layer	
	Main Purpose	Feedback Type	Data State	Data Source	Stakeholder Level	Expertise Requirement	Operating Complexity
Visualize Learning Activities	EC	RF	D	LMS	Meso	Novice	Low
Access Learning Behaviour	EC	RF	SD	LMS	Meso	Intermediate	Low
Predict Student's Performance	LC	PF	SD	ODS	Macro	Expert	High
Individualize learning	CC	AF	D	LMS	Micro	Expert	High
Evaluate Social Learning	LC	RF	S	SN	Macro	Intermediate	Medium
Improve Learning Materials and Tools	CC	RF	D	LMS	Meso	Advanced	Medium
Assessment of Personal Learning Environments	LC	RF	S	SN	Mega	Advanced	Medium
Support Educational Decision Making	LC	PF	SD	ODS	Mega	Advanced	High
Sophisticated Evaluation of Gamification	EC	RF	S	ODS	Meso	Advanced	High

Conclusions and Contributions

As an emerging interdisciplinary field, the term 'learning analytics' is still evolving an concept and subject to ongoing discussions by researchers and practitioners from multiple disciplines. It has been studied from different perspectives including informatics, engineering, and educational perspectives. In this paper, we proposed a multi-layered taxonomy of learning analytics applications. The layers that construct the dimensions of our taxonomy draw from the central components of learning analytics, allowing the applications to be accessed regarding involved elements and strategic capabilities. The iterative development of the taxonomy adopted both empirical-to-conceptual and conceptual-to-empirical approaches to refine meaningful dimensions and characteristics for a comprehensive taxonomy. Empirical data about the objects of interest was collected from the existing literature on learning analytics development and implementation. The conceptualization of layers and dimensions was conducted based on published conceptual frameworks of learning analytics. The results provide an overview of cutting-edge learning analytics applications. The proposed taxonomy also acts as guidelines for designers and academic institutions interested in the applications of learning analytics. Furthermore, our work aims to provide readers and fellow researchers useful insights into the nature of learning analytics.

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