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COMMENTARY



Piecing the learning analytics puzzle: a consolidated model of a field of research and practice

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ABSTRACT

The field of learning analytics was founded with the goal to harness vast amounts of data about learning collected by the extensive use of technology. After the early formation, the field has now entered the next phase of maturation with a growing community who has an evident impact on research, practice, policy, and decision-making. Although learning analytics is a bricolage field borrowing from many related other disciplines, there is still no systematised model that shows how these different disciplines are pieced together. Existing models and frameworks of learning analytics are valuable in identifying elements and processes of learning analytics, but they insufficiently elaborate on the links with foundational disciplines. With this in mind, this paper proposes a consolidated model of the field of research and practice that is composed of three mutually connected dimensions – theory, design, and data science. The paper defines why and how each of the three dimensions along with their mutual relations is critical for research and practice of learning analytics. Finally, the paper stresses the importance of multi-perspective approaches to learning analytics based on its three core dimensions for a healthy development of the field and a sustainable impact on research and practice.

KEYWORDS

Learning analytics;
educational research;
learning design; data
science; and interaction
design

Introduction

Learning analytics is a field developed to harness unprecedented amounts of data collected by the extensive use of technology in education. The formation of learning analytics brought together researchers and practitioners from a wide range of fields such as education, psychology, economics, statistics, data mining, and information visualisation. Although individuals from all these domains had previously worked with data in what is now commonly referred to as learning analytics, they did not have a joint forum for exchanging ideas, methods, and results. The announcement of the first International Conference on Learning Analytics (LAK) held in Canada in 2011 can probably be marked as the official point for the field formation (Long, Siemens, Conole, & Gašević, 2011). Since then the field has come a long way which is well demonstrated through a number of achievements. For example, the

proceedings of the LAK conference are among the top eight most cited publications in education technology (Google Scholar, 2016). The Society for Learning Analytics Research (SoLAR)¹, as a leading professional organisation in learning analytics, has developed a strong influence among a wide range of organisations and stakeholders. The field has a specialised journal with a rapidly rising reputation – Journal of Learning Analytics². There is also a healthy growth in the number of doctoral students and quality of their work (Pechenizkiy & Gašević, 2014). Finally, many education institutions, systems, and funding bodies have made significant investments into learning analytics; and a broad network of events and organisations in all parts of the world³.

Learning analytics is an interdisciplinary field of practice and research that takes a holistic approach to employing data to address questions of relevance for learning, teaching, and education (Siemens & Gasevic, 2012). The commonly used definition, adopted by SoLAR, defines 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” (Long et al., 2011). The purpose of analytics – both for understanding and optimisation of learning – implies practical and research components of the field. The holistic nature is recognised through the study of learning context and environments. Finally, the interdisciplinary nature is demonstrated through a broad representation of different fields in learning analytics publications, events, and initiatives (Dawson, Gašević, Siemens, & Joksimovic, 2014).

Although it is widely accepted that learning analytics is a bricolage field borrowing from many related disciplines, there is still no consolidated model that systematises how these different disciplines are pieced together. The paper aims to address this gap in the literature and proposes a consolidated model of learning analytics that recognises its key characteristics – field of research and practice, holistic in nature, and interdisciplinarity. The model synthesises existing results in learning analytics and suggests that learning analytics is composed of three mutually connected dimensions – theory, design, and data science. To illustrate why the consideration of the three dimensions is critical for learning analytics, the paper starts with a critical interrogation of the scope, topics, and challenges of learning analytics. The paper then goes on to review the dimensions of the model and their mutual relationships, and finally, concludes with a discussion of the implications for future research and practice.

Learning analytics: scope, topics, and challenges

Learning analytics encompasses a wide range of activities that are broadly associated with the four core elements of learning analytics – collection, measurement, analysis, and reporting – identified in the definition of learning analytics (Long et al., 2011). Reimann (2016) notes that, while the use of data in educational research and learning sciences has been present for quite some time, learning analytics differs from the “traditional” data analyses in education as it focuses on the longitudinal collection of a large number of data points from authentic learning environments. Although the field of learning analytics supports the collection of a wide range of

data, a bulk of existing work in learning analytics is dedicated to digital traces collected through the interaction of people with technology, content, and/or other people (Siemens & Gasevic, 2012). An important task of learning analytics is the development of measures that can (1) offer practical insights into learning processes and outcomes, and (2) be theoretically interpreted (Gašević, Dawson, & Siemens, 2015). For analysis, learning analytics adopts a wide range of methods from the fields such as data mining, statistics, social network analysis, process mining, and text analysis. Exchange of analysis methods is also a point of active collaboration between educational data mining and learning analytics (R. Baker & Siemens, 2014; Siemens & Baker, 2012). Finally, reporting in learning analytics aims to provide actionable insight to a broad range of stakeholders by building on principles of information visualisation and human-computer interaction (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013).

Learning analytics covers a number of different topics of research and practical significance for learning, teaching, and education (Dawson et al., 2014; Ferguson, 2012). Without any pretension to provide a systematic and comprehensive overview of the literature, we only highlight some of the themes that attracted much attention in the current literature. Prediction of student retention and learning outcomes are among the most popular topics in learning analytics due to their practical relevance for educational institutions (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). Analysis of twenty-first century skills (Buckingham Shum & Deakin Crick, 2016), self-regulated learning (Roll & Winne, 2015), and social learning (Dowell et al., 2015) are topics gaining much attention in learning analytics. Research on topics such as learning behaviour (Käser, Klingler, & Gross, 2016), strategies (Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015), dispositions (Buckingham Shum & Deakin Crick, 2012), and affective states (D'Mello, 2017) are commonly used to inform designs of learning analytics presentations to stakeholders (Verbert et al., 2013). Privacy protection (Drachslar & Greller, 2016), ethics (Ferguson, Hoel, Scheffel, & Drachslar, 2016), policy (Macfadyen & Dawson, 2012), infrastructure (Aperio Foundation, 2016), and standards (Bakharia, Kitto, Pardo, Gašević, & Dawson, 2016) are also key themes associated with the systemic adoption of learning analytics in educational institutions (Ferguson et al., 2014).

Existing work in learning analytics provides some proposals for models of learning analytics that either identify dimensions of learning analytics or process phases or both of the previous two. A reference model of learning analytics is suggested by Chatti, Dyckhoff, Schroeder, and Thüs (2012) that identifies four key dimensions of learning analytics each one dedicated to the following four questions: what – data, environment, and context; why – objectives; how – methods; and who – stakeholders. Similarly, these four dimensions, with somewhat different names and scope, are also recognised in a generic framework for learning analytics proposed by Greller and Drachslar (2012). The Greller and Drachslar generic framework also includes internal limitations (i.e., competencies and acceptance) and external constraints (i.e., norms and conventions). An interactive process model of learning analytics is suggested by Steiner, Kickmeier-Rust, and Türker (2014) through a synthesis of several other process models and consists of the following phases: data selection, data capturing, data aggregation, data reporting, prediction, acting

upon results, and refinement. Finally, Scheffel, Drachsler, Stoyanov, and Specht (2014) propose a framework that recommends quality indicators for learning analytics organised across dimensions commonly identified in the existing models/frameworks.

Although much growing excitement around learning analytics is evident, there are also several challenges that the field is grappling to address. For example, concerns are often reported in connection with the relevance of the ways how predictive models are constructed to inform teaching practice (Gašević, Dawson, Rogers, & Gasevic, 2016). The accuracy of predictive models, when applied in different contexts, is found to decline (Jayaprakash et al., 2014) or to identify predictors that are not relevant for teaching practice (Gašević et al., 2016). Evaluation of the effectiveness of learning analytics dashboards with learners in practice is rare (Verbert et al., 2013) and even when available, results of some of the existing studies are not positive. For example, adverse effects of learning analytics dashboards on the intrinsic motivation of undergraduate students were also reported (Krumm, Waddington, Teasley, & Lonn, 2014). Difficulties in interpretation of learning analytics dashboards commonly available in learning management systems by learners are documented (Corrin & De Barba, 2014). Some early warning alert systems are shown to promote suboptimal teaching practice (Tanes, Arnold, King, & Remnet, 2011), even when they generate profits in student retention (Arnold & Pistilli, 2012). The methodological validity of some of the studies on the use of learning analytics has been challenged in public debates (Caulfield, 2013) and such challenges are supported by recent results of replications studies (Dawson, Jovanović, Gašević, & Pardo, 2017).

We posit that much of the above issues can be attributed to the shortage of guidelines that are grounded in foundational disciplines of learning analytics and that should inform activities related to different dimensions of research and practice in learning analytics. Existing models and frameworks, discussed above, are valuable contributions that go beyond the definition of learning analytics and offer possible operationalisations of what learning analytics research and practice should involve. However, they insufficiently detail links between the principles established in disciplines on which learning analytics builds as a bricolage field such as educational research, learning sciences, psychology, human-computer interaction, data mining, or research methods. This paper aims to address this gap in the existing literature by proposing a consolidated model of learning analytics.

Consolidated model of learning analytics

We posit that the foundational principles of learning analytics can be grouped around three mutually connected dimensions – theory, design, and data science. We also posit that the most effective results in and with highest validity for research and practice can be achieved only once the principles of all three dimensions are considered. The consolidated model (Figure 1) does not exclude the existing models and frameworks of learning analytics, but rather complements them.

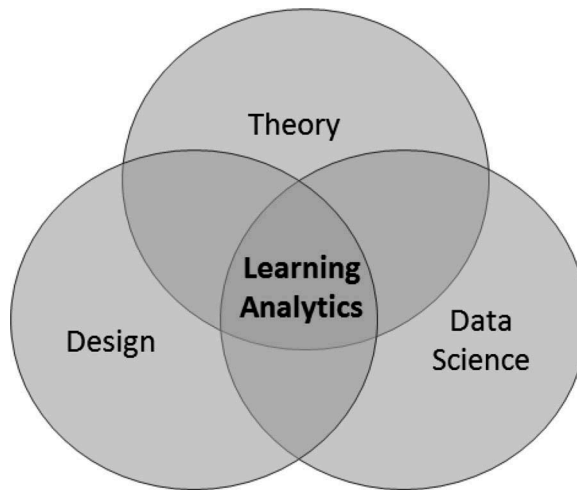


Figure 1. Consolidated model of learning analytics.

Theory

As a field that seeks to contribute to broad educational research and practice, the theory in learning analytics needs to play a pivotal role. Early adoption of data-driven approaches in research and practice of learning, teaching, and education sparked much enthusiasm and shed some light on the power of data science methods (Romero & Ventura, 2010). However, data-driven applications were soon recognised as not sufficiently informative for research and practice of learning analytics (Gašević et al., 2015). Such weaknesses in data-driven approaches led to the emphasis of theory-orientation of learning analytics as one of the fundamental differences with other mainstream data-driven approaches (R. Baker & Siemens, 2014). In his critique of preliminary advocates of data-driven analytics (e.g., Andreson (2008)), Reimann (2016) suggests that such atheoretical approaches to learning analytics are a misconception of what scientific method is and “the logical (and ethical) error of using descriptions of the past as prescriptions for the future” (Reimann, 2016, p. 136).

There is a growing agreement on theory-orientation as critical for research and practice of learning analytics. Theory orientation has been recognised as essential for informing the choice of questions asked and hypotheses tested (Rogers, Gašević, & Dawson, 2016; Wise & Shaffer, 2015). Theory is suggested as a driving aspect for the selection of methods used for study design and data analysis (Reimann, 2016; Rogers et al., 2016). Various scholars also argue that results from the learning analytics research should be interpreted with respect to and inform existing theory (Gašević et al., 2015; Reimann, 2016; Wise & Shaffer, 2015). Finally, producing actionable insights for practitioners (Gašević et al., 2016; Rogers et al., 2016) and designing environments and tools that integrate learning analytics for different stakeholders (Marbouti & Wise, 2016) should be theoretically grounded.

Potential to analyse and identify patterns in large data sets is often associated with learning analytics. While highly promising to include large population numbers with

unprecedented numbers of data points, this also results in a high statistical power where many associations, even those with very small effect sizes (Cohen, 1992), can be detected as significant (Wise & Shaffer, 2015). The role of theory in such cases is to identify which of these associations are meaningful and include them into analytical models as hypotheses to be tested. Theory also allows for validating whether associations between some learning-related constructs extracted from digital traces and learning outcomes should be even considered valid. In some cases, there is no theoretically justified relation between a digital trace, which represents a record of an event about the use of a learning tool, and a learning outcome. Rather, the tool use is provided in the environment to trigger a learning process, which can then facilitate reaching particular outcomes (Reimann, 2016). In such cases, if data about learning processes is not collected, we might not be able to understand whether certain learning processes are activated, and if so, under what conditions and what learning outcomes are associated with different conditions. Likewise, data about context are rarely used in learning analytics, even though context critically shapes learning according to contemporary theories (Winne, 2006). Such imperfect practices have direct implications for the current endeavours in learning analytics to collect data about activation of learning processes; the collection of data about learning processes is frequently not the case. Data about learning processes can be gathered through the use of established self-report instruments (Lust, Elen, & Clarebout, 2013), theory-based instrumentation of learning environments (Siadat, Gašević, & Hatala, 2016; Zhou & Winne, 2012), discourse (Kovanović et al., 2016), psychophysiological measures (Azevedo, 2015), and different qualitative methods.

Adoption of theory can help explain the reasons for inconsistencies in the results across several studies and clarify psychological, sociological, contextual, cultural, instructional, and other mechanisms that affected the results. For example, building on Winne and Hadwin's (1998) model of self-regulated learning, Gašević and colleagues (2016, 2015, 2017) showed that accounting for external (e.g., instructional design) and internal (e.g., motivation and prior knowledge) conditions is essential for interpretation of the results of analytics in order to inform both research and practice. Failing to account for contextual conditions (in a broad sense) could lead towards misinterpretation of findings and limit replication of existing research in different settings (Gašević et al., 2016). Similarly, Joksimović and colleagues (2016) identified a problem of inconsistent results in the association of learning performance with centrality measures in social networks, even though this association can theoretically be justified. Joksimović et al. (2016) theorised and empirically showed that only if the ties in networks are weak, the relationship can be established, and also theoretically justified (Granovetter, 1982).

Sources of theory in learning analytics are not limited only to psychology, but they also include disciplines such as sociology, organisation science, information science, and semiotics. Although both design and data science have their own theoretical foundations, theories that are essential for learning analytics are about human learning, teaching, and education. Connections of theory with design and data science methods are further discussed in the remaining two sections.

Design

As a field of research and practice, learning analytics is intrinsically linked with different forms of design. Design in analytics concerns three main dimensions – interaction and visualisation design, learning design, and study design. Interaction and visualization design is related to providing users with opportunities to gain insights into learning in both research and practice contexts. Study design is related to conducting research studies and evaluations in practice based on rigorous principles. Learning design is related to (theory informed) practice that aims to promote effective learning experience.

Interaction and visualisation design

Much work on learning analytics is related to the development of interactive visualisations that can inform the decision-making of stakeholders. The literature often refers to the designs of different interactive visualisations with the intent to support self-regulation and awareness (Verbert et al., 2013). However, the learning analytics literature offers limited reasoning on how specifically an interactive visualisation will support self-regulation by building on theories and research of self-regulated learning. There is also little empirical evidence in learning analytics that proves a positive impact of such visualisations on self-regulation and more specifically that pins down to any specific process of self-regulated learning that is triggered by such visualisations.

Much of the existing limitations of the design of interactive visualisations are due to the widespread assumption that just an act of visually presenting something will promote desirable learning and that the use of visualisation will ease the interpretation of analytical results. We suggest that the decision of learning analytics needs to build on the existing principles and theories established in technology acceptance, interaction design, and learning science. The theory of cognitive fit does not give benefit of one information presentation over another one in general, but rather suggests that the presentation should be the one that offers the best cognitive fit for a given task (Vessey, 1991). The theory of technology-task fit (Goodhue & Thompson, 1995) suggests that the usefulness of a technology should not be sacrificed solely for the purpose of making the technology easier to use. Users can tolerate a lesser ease of use, if the technology is highly useful, which applies in particular to the technology that supports a complex task as is commonly the case in learning. For example, while easy to understand, the metaphor of traffic lights in Course Signals provided insufficient information to teaching staff to promote the provision of feedback based on established principles in educational literature (Gašević et al., 2015; Tanes et al., 2011).

We posit that interaction design in general and design of interactive visualisations in particular in learning analytics needs to be (1) grounded in learning theory, and (2) tailored specifically to promote and evaluate the activation of a particular (set of) learning mechanism(s). Just building on the established principles and mantras for information visualisations and interaction design is criticised as insufficient to create a body of research knowledge and guide evaluations even in the field of information visualisation (Liu, Nersessian, & Stasko, 2008). Wise and her colleagues (2014) and Marbouti and Wise (2016) give a good example of how the design of interactive visualisation can be effectively conducted in learning analytics. Wise et al. build on the existing literature in computer supported collaborative learning that identifies a bias

in which learners read only most recent posts, instead of reading entire threads. This bias constraints the level and quality of knowledge construction, as students do not take advantage of the richness and diversity of complete discussions. Wise and her colleagues proposed two approaches to interactive visualisations (embedded and extracted) (Wise et al., 2014). The empirical validation of this method looked at specific knowledge construction processes activated as a consequence of the use of the interactive visualisations (Marbouti & Wise, 2016).

Learning design

Learning analytics need to (1) account for the effects of learning design in order to achieve theoretically valid results, (2) select relevant data and appropriate analysis methods, and (3) give actionable insights that can inform practice. As already discussed, if the moderating effect of learning design is not considered, predictive models of academic performance cannot reveal factors of significance for teaching practice (Gašević et al., 2016). In such cases, the choices of variables that are used should be driven by the decisions made in learning designs (Lockyer, Heathcote, & Dawson, 2013), including tasks given to learners, tools offered, and collaborations with other people envisioned (Goodyear, 2015). An aggregated analysis of data collated across different courses needs to account for the effects of variance across various groups, where variance is induced by differences in learning designs. In such cases, the nested nature of data should be reflected in the choice of methods that are used for analysis.

Learning analytics need to be integrated into learning designs. Rather than introducing learning analytics just because they are available in the learning environment, a learning design should carefully consider the purpose of the inclusion of learning analytics and their role in connection with specific objectives and tasks in the learning design (Lockyer et al., 2013). Wise (2014) offers a theoretically-grounded and practice-oriented integration of learning analytics with learning design that can serve as an excellent source for the future work. Wise proposes a model that aims to (1) promote the development of learners' agency through personal goal setting and reflection empowered by analytics, (2) offer scaffolding for agency development through reference frames delivered by learning analytics, and (3) foster a dialogue between learners and teaching staff, similar to the notion of visible learning proposed by Hattie (2012), where learning analytics serves as a conversation opener.

Study design

Although high numbers of data points are collected longitudinally in authentic learning settings, learning analytics cannot be removed from the careful consideration of study design. As in conventional educational research, study design is tightly associated with theoretical framing, data collection, analysis, methods, and interpretation. Omissions in the interpretation of the results such as causal vs. correlational can easily be made without consideration of the study design. A study design needs to be outlined even when historical data, routinely collected through operation of learning technology, are analysed. A study design consideration should understand the nature of data collection, possible ways how the data can be analysed, and the types of questions to be answered. Evaluations that test effects of learning analytics-based interventions need to have a

strong emphasis on study design in order to avoid partial interpretations (Caulfield, 2013) and promote replication (Dawson et al., 2017).

Design-based research is suggested to have a “natural” fit with learning analytics, as both are used to inform practice and advance theory (Reimann, 2016). Design-based research is an iterative research method in which each iteration aims to address practical issues that arose in the previous iteration through the use of technological and pedagogical interventions, which are in turn grounded in theory (Anderson & Shattuck, 2012). Therefore, each intervention can be seen as a validation of a theory, while the practical solutions are improved iteratively by typically following quasi-experimental study designs. Context in design-based research (and hence, learning analytics) is considered an intrinsic part of interventions. Therefore, contextual data need to be accounted for in learning analytics “as [they are] providing the resources through which theoretically expected learning processes become realized in a specific learning situation” (Reimann, 2016, p. 137).

Data science

Methods and techniques of data science are an essential part of learning analytics. They enable the main four phases mentioned in the definition of learning analytics including collection, measurement, analysis, and reporting. Activities related to data collection and measurement in learning analytics require methods that can identify indicators and measures of learning processes, learning outcomes, and learning activities. Traditionally, educational research has used methods for the development of self-reported instruments which theory-driven and for which psychometric criteria of validity are checked such as internal consistency, test-retest reliability, construct validity, and predictive validity. Most of these validity criteria are typically tested with statistical analysis methods such as factor analysis, structural equation modeling, and regression analysis.

Design has started playing a significant role in the development of indicators and measures in learning analytics. Feature engineering is one of the key sub-areas of data science that is of high relevance for the development of indicators and measures in learning analytics. Feature engineering in learning analytics is iterative in nature and requires rapid experimentation, theory-orientation, and creative thinking. According to Baker (2014), feature engineering involves a design process for establishing indicators of learning processes, outcomes, or activities from a wide range of data such as click streams, transcripts of online discussions, or eye gazing. For example, in research, Kovanović et al. (2016), following a design-based approach, showed that measures of text coherence and words associated with specific psychological processes can be useful for the automated detection of knowledge construction mechanisms in asynchronous online discussions. In practice, Civitas Learning (2016) report that derived indicators (e. g., those comparing students’ activities to the rest of the class) are found to offer much better actionable insight for education institutions than those based on raw trace (e.g., the number of attempts to complete a quiz or posts to online discussions).

A wide range of data science methods is used for data analysis in learning analytics. A comprehensive classification of data science methods based on the types of questions they can address is provided by Steiner et al. (2014) and includes: prediction models – for example, classification, regression, and latent knowledge estimation; structure discovery – clustering, factor analysis, outlier detection, domain structure discovery, and social network

analysis; relationship mining – association rule mining, correlational mining, sequential pattern mining, causal data mining; and other approaches – process mining, discourse analysis, and multimodal approaches. A comprehensive overview of the tools commonly used in educational data mining, a sister field from which learning analytics draws methods, is provided by Slater, Joksimović, Kovanović, Baker, and Gašević ([in press](#)).

Although the use of data science methods is assumed in learning analytics, some issues in their application need to be highlighted especially in connection with the two other dimensions of the model – theory and design. As already established, learning analytics is theory-oriented, and thus, the models that are used for analysis need to support theoretical foundations used in different cases. Theory-orientation typically refers to the choice of methods and the interpretation of the results. In the previously mentioned study, Joksimović et al. (2016) showed that standard methods of descriptive social network analysis (SNA) (Wasserman, 1994) are not sufficient to test certain network characteristics such as the propensity of strong ties, reciprocity, and homophilic relationships, which require more advanced statistical SNA methods such as exponential random graph models (Lusher, Koskinen, & Robins, 2012). This finding has direct implications for practice, as the nature of network formation suggests whether centrality in social networks is a predictive indicator of academic performance or not.

Data science methods should recognise that the notion of complex systems is gaining much attention in theoretical underpinnings of learning (Jacobson, Kapur, and Riemman, 2016) and education (Macfadyen, Dawson, Pardo, & Gasevic, 2014). As noted by Reimann (2016), general regression models are insufficient to address the structure and nature of complex systems. For example, referring back to Wise's (2014) proposal for theory grounded integration of learning design and learning analytics, the role of learning analytics in both analysis methods and study design need to be recognised. This is particularly significant given that learning analytics, embedded into learning designs, seek to establish feedback loops between students and teaching staff that did not exist otherwise. Therefore, the application of approaches such as system dynamics as used for understanding of complex non-linear systems is an important direction that has been underexplored in learning analytics.

Data science needs to provide methods that account for multiple dimensions of relevance for the study of learning rather than just using counts of clickstreams. Gašević and colleagues (2015) suggest that Winne's (1997) COPES model (conditions, operations, productions, evaluation, and standards) can serve as an excellent theoretical foundation for the adoption, refinement, and development of data science methods in learning analytics. Data science methods can also be used for a number of other topics in learning analytics. For example, to analyse psychophysiological measures of learning, a combination of digital signal processing and machine learning methods is necessary to obtain insights that can inform theory and practice (Pijera-Díaz, Drachler, Järvelä, & Kirschner, 2016). Text analysis methods are particularly useful to analyse discourse in connection with cognitive, metacognitive, affective, and motivational aspects of learning (Azevedo, 2015), and thus, for the study of conditions, operations, and products of the COPES model. Finally, to examine learning as a process of temporal and developmental nature, methods developed in the process and sequence mining areas can be particularly useful (Molenaar, 2014).

Discussion and future consideration

The main contribution of the consolidated model proposed in this paper lies in the guidance about key dimensions that need to be taken into consideration in research and practice of learning analytics. Consideration of only one or even two dimensions of the consolidated model is insufficient to unlock the full potential and assure the validity of learning analytics research and practice. The inclusion of only theory and design is not part of learning analytics as it does not make use of any data. The intersection of theory and data science is relevant, but the lack of design deliberation cannot provide sufficient practical or research validity. Finally, the intersection of design and data science is also not enough without the well-established theoretical foundations of learning and teaching.

Although all three dimensions – theory, design, and data science – should be part of learning analytics research and practice, not all of their sub-dimensions are necessary in every situation. For instance, we do not have to always include all sub-dimensions of design. If the focus of learning analytics research and practice is on the “understanding” part of the learning analytics definition (Long et al., 2011), it is not necessary to ponder on interaction and/or visualisation design; unless, the understanding part seeks to understand effects of a visualisation on learning, teaching, or education. In other cases, if a research study, which collates digital traces and data science methods for analysis, is conducted in a controlled setting in which students did not use a specific learning design and/or visualisation, it is not necessary to reflect on learning design and/or interaction design. A special case is design-based research in which learning design, as pedagogical interventions and context, is always an essential component of study design. However, the study design is a required sub-dimension of learning analytics research as well as any practical application that aims to have a robust evaluation.

While in actual implementations the theory dimension is less emphasized, it is still recommended to ground practice in strong (theoretical) principles of learning, teaching, and education. This relates to data science and all three sub-dimensions of the design. Learning designs should be based on established and emerging learning theories and constructs such as cognitive load (Sweller, 1994) or desirable difficulties (Bjork & Bjork, 2011). Interaction design should be more than just attractive visualisations and incorporate elements of theory pertinent to the purpose a visualisation aims to achieve such as support for self-regulated learning or computer supported collaborative learning (Marbouti & Wise, 2016; Wise, 2014). The study design should always be guided by the theoretical considerations as otherwise, the validity of findings for both research and practice could be severely compromised.

The use of different data science methods and systems is an essential dimension of any research and practice in learning analytics. The choice of methods and systems is driven by theory and design in both research and practice of learning analytics. Results produced by the use of data science methods and systems should, in turn, inform theory and design.

The consolidated model of learning analytics, proposed in this paper complements existing models and frameworks of learning analytics (Chatti et al., 2012; Greller & Drachsler, 2012; Steiner et al., 2014) as well as other critical considerations in learning analytics such as privacy, ethics, policy, literacy, and standards (Bakharia et al., 2016; Ferguson et al., 2014; Tsai & Gašević, *in press*; Wasson & Hansen, 2016). The model recommends how theory, design, and data science (1) mutually interact and (2) inform

components of the other models. For example, the what, why, how, and who questions of the Chatti et al. (2012) model, which are present in some forms available in the Greller and Drachsler model (2012), need to be informed by theory, design, and data science. Finally, we posit that the three dimensions – theory, design, and data science – are enabled by and can further inform considerations related to privacy, ethics, policy, literacy, and standards.

The consolidated model of learning analytics suggested in this paper should further inform the research and practice of learning analytics. We expect that the dimensions provided in the model can assist researchers in their deliberations of what elements their studies should include, from the early phases of conceptualisation to the final stages of empirical validation and interpretation of the results. The model is also relevant to practitioners in informing their decisions regarding the choices of learning analytics tools, their integration in existing practice, and evaluation of learning analytics applications. The proposed model can assist in the development of the field of learning analytics by offering foundational dimensions around which existing and future contributions from research and practice will be systematised and critically interrogated.

Notes

1. <http://solaresearch.org>.
2. <http://learning-analytics.info>.
3. <http://lasi.solaresearch.org>.

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