That Dashboard Looks Nice, But What Does It Mean? Towards Making Meaning Explicit in Learning Analytics Design

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ABSTRACT

As learning analytics (LA) systems become more common, teachers and students are often required to not only make sense of the user interface (UI) elements of a system, but also to make meaning that is pedagogically appropriate to the learning context. However, we suggest that the dominant way of thinking about the relationship between representation and meaning results in an overemphasis on the UI, and that re-thinking this relationship is necessary to create systems that can facilitate deeper meaning making. We propose a conceptual view as a basis for discussion among the LA and HCI communities around a different way of thinking about meaning making, specifically that it should be explicit in the design process, provoking greater consideration of system level elements such as algorithms, data structures and information flow. We illustrate the application of the conceptualisation with two cases of LA design in the areas of Writing Analytics and Multi-modal Dashboards.

CCS CONCEPTS

• **Information systems** → Data analytics; • **Human-centered computing** → Visualization design and evaluation methods

KEYWORDS

Learning analytics, user interface design, information systems, meaning making, embodied cognition

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1 INTRODUCTION

Analysing data collected from the interaction of users with educational technology has attracted much attention as a promising approach for improving our understanding of students and supporting teaching and learning in many and varied ways [5]. This, together with an interest in big data innovations in education, has brought forward the emergence of a new interdisciplinary field called *Learning Analytics* (LA) [19]. Human factors research and development in this field are critical because users (e.g. teachers and students) are often required to make meaning in deeper (pedagogical) ways than surface interpretation of interface elements (e.g. see reviews of cases in [20-22, 26]). Thus, the design of the *user interfaces* (UIs) needs to include consideration of how whole-of-system decisions affect the intended meaning-making for the user.

In a sense, learning environments can be complex [8]. Students bring to their learning a diversity of perspectives. Rarely, if ever, will all students hold the same understanding of the learning task at hand [7]. Yet, despite this diversity, there is an expectation that the students should come to a common understanding that aligns with the learning objectives. The desire is that all students will make meaning according to a desired learning outcome. When using LA tools to support learning, for some theoretical and practical approaches, the expectation is similar to what is expected with other support systems: that all students will come to a common understanding about the analytics presented to them [4]. Much of the burden of achieving this outcome falls to the interface between the system and the student, the UI. A similar situation applies for those LA systems targeted at instructors as support for their teaching.

However, meaning-making is not an automatic process that can be reduced to providing users with information, even assuming that they can all make sense of the UI elements in the same way [2]. The situation where some design elements work well and others do not is a familiar one, and we suggest that for some of these cases users may be attempting to use these elements as part of a meaning-making process that is somewhat different than that which determined the interface design. It is commonly thought that a high quality UI will result in better understanding for the student or the teacher [17]. However, this is not necessarily the case [3]. As a result, good quality UI's can fail to produce improvements in learning, and poor UIs can result in good learning outcomes.

We argue that two errors can be easily made during the design of LA systems: (1) failing to consider the system implications of the complexity and situated nature of the learning, including the psychosocial factors that influence how individual students approach the task; and (2) assuming a direct link between representational aspects of the system and the intended psychosocial meaning. In simple learning tasks, these errors may not result in any adverse effects [2]. However, in situations where '*deep meaning-making*' is required on the part of the student or their teachers, we suggest that these errors can

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have a significant negative impact on the efficacy of the LA system to deliver on learning outcomes. In essence, we suggest that it is possible for a LA system to provide a positive user experience (UX), and yet not deliver in terms of the learning goals. Therefore, designing for UX while necessary, is not sufficient.

The purpose of this paper is to trigger discussion among the LA and HCI communities to consider a different way of thinking about representation and meaning. To that end, we present a perspective based on a three-year learning analytics project [6], originally drawn from the theory of Embodied Cognition [11]. We introduce this perspective as a conceptual view for making meaning explicit in the LA design process and illustrate it with two authentic LA cases, showing how this view may influence design for students and teachers, respectively.

2 A CONCEPTUAL VIEW FOR RE-THINKING LA INTERFACE DESIGN

In recent decades the field of Cognitive Science has gathered an increasing amount of empirical evidence in support of embodied views of cognition [13]. Significantly, these views hold that the relationship between the world and how the user makes sense of that world is an indirect one that has been shaped by the user's bodily interaction with their environment for the whole of their life [10]. In these embodied views, meaning-making is more closely related to the user's cognitive 'image-schemas', 'prototypes', and 'frames' developed over time, than to the particular moment of interaction. We suggest that one of the implications for LA design is that user meaning-making needs to be considered in terms of these cognitive conceptualisations, not just in terms of the user's interaction with an interface. Although some work on general interface design has made the role of meaning central [2, 12], in many cases the relationship between the UI and meaning-making on the part of the user remains implicit rather than explicit.

In this paper, we use the word '*meaning*' not in the surface sense of 'interpreting', but in a '*deeper*' sense of 'a thorough understanding'. We acknowledge that all UX experience involves some level of interpretation and sense-making, but we argue that not all UIs make clear the requirement for a user to gain a full and rich understanding of that which the system is presenting to them. This has been acknowledged as a still unresolved issue in the space of interaction design, particularly for those interactions that users must have with data representations (see [25] p. 473).

It is common for the designer of a system to be pre-occupied with its usability, and for UI design to be the focal point of this objective. It is not surprising then, that most of the goals and metrics of user experience are measured at an interaction level (e.g. [1]). Some of these measures include, for example, learnability, long-term performance, error-rate, satisfaction, attractiveness or retainability [9]. However, some other *'deeper'* aspects may equally affect the user experience that go beyond the interaction aspect of the UI [15]. In some applications, the usability of the application is tied significantly to the meaning that the user makes of the information that the application provides. Much work has been done in the area of information visualisation to develop insight-based methodologies and enhance the users' visualisation literacies [14, 18, 24, 27]. Although this bulk of work has been critical for developing better visualisation designs, we suggest that it is not just how the information is presented that influences meaning, the very nature of the information (e.g. structure, temporality, and relatedness) can play a critical role in how the user makes meaning. However, these attributes are rarely governed by the interface, but rather are determined by lower level system design decisions (e.g. database schema, event processing code). We provide examples of this later in our illustrative cases. For us, an underlying motivation for considering additional aspects of the system is made evident when meaning-making is foregrounded. In the following section, we present a conceptual model that encapsulates this objective of make meaning explicit.

2.1 The Conceptual View

In this section we present a conceptual view of LA design that is based on a three-year project on reflective writing analytics [6]. We suggest that there are significant gains to be made in designing human-computer systems by re-thinking the relationship between the knowledge in human and computer worlds, and through an explicit separation of representation and meaning, as held by the theory of Embodied Cognition [11]. The conceptual view depicted in Figure 1 presents the interaction between human and computational knowledge as two epistemic domains; that is two areas of knowledge and the accompanying resources for establishing and using that knowledge.

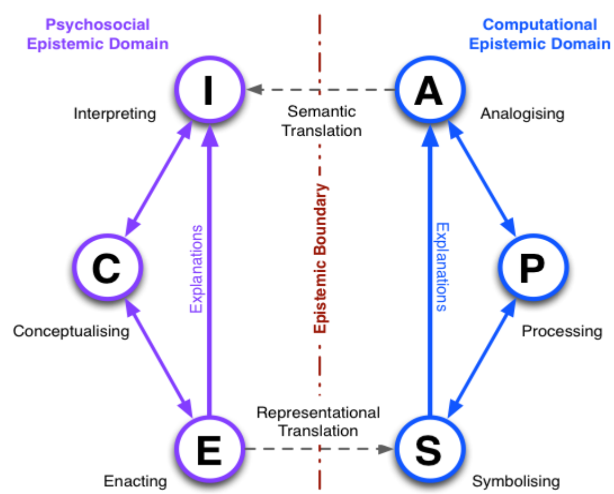

Figure 1. A conceptual view of LA Design that distinguishes between representational interaction and meaning-making derived from [6].

This view conceptualises human-computer interaction, not as a physical sensory process via interface usage, but as information that is processed both in a psychosocial domain (human) and a computational domain (computer). It also differentiates between how the domains interact at a data representation level (representational translation) and a meaning making level (semantic translation). This distinction conceptualises the idea that meaning within the interaction needs to be understood and addressed differently than data representation. The figure depicts 3 psychosocial nodes (I, C and E) and 3 computational (A, P and S) nodes. However, it is not the nodes themselves, but rather the edges or interrelationships between them (which we call *aspects*) that are important. The following paragraphs define the 8 aspects.

2.1.1 Psychosocial Aspects.

Interpreting-Conceptualising (*I-C)* involves the user's construction of meaning through interpreting situations in relation to self, and conceptualising that meaning.

Conceptualising-Enacting (C-E) involves the user expressing meaning in a way that instantiates it beyond their own mind. It involves action or expression which may result in the creation of an artefact or digital trace (e.g. writing, activity record).

Enacting-Interpreting (E-I) articulates psychosocial knowledge through explanations. It makes explicit that explanation requires a relationship between the enacted expression and the user's interpretation of that expression.

2.1.2 Computational Aspects

Symbolising-Processing (*S-P)* is the computational construction of representations of the user action or expression, and could be the encoding of an artefact. It makes explicit that computational representation is more than mapping user output to computer input, but that algorithms are involved.

Processing-Analogising (*P-A)* involves the expression of the computation in a form suitable for human interpretation. It requires both the anticipation of the user, as well as appropriate computational processing.

Symbolising-Analogising (*S-A)* articulates computational knowledge through explanations. It makes explicit that computational explanation is an interrelationship between the original symbolisation of the user action or artefact, and the analogising of the computational output. Thus, it is understood in terms of both the input from the user and how the user will make sense of the output.

2.1.3 Translational Aspects

Enacting-Symbolising (*E-S)* facilitates the transfer of psychosocial representations to computational representations. This aspect involves the translation of, for example, word symbols into computational numbers, and in doing so aims to take psychosocial characteristics and view them computationally. This aspect provides `Representational Translation' between the epistemic domains.

Analogising-Interpreting (A-I) facilitates the semantic transfer from the computational to the psychosocial. It is concerned with meaning-making through the psychosocial interpretation of the computational analytics. This aspect provides `Semantic Translation' between the epistemic domains.

There are two core features in this conceptualisation: (1) The separation between psychosocial and computational epistemic domains, denoted by the epistemic boundary; and (2) the separation between representational transfer and semantic transfer, denoted by the lack of a direct connection.

3 THE ILLUSTRATIVE CASES

In the following sections, we present two different learning analytics cases that highlight the value of this conceptualisation to LA design for targeting students and teachers respectively.

3.1 Reflective Writing Analytics

Reflective writing is a modern learning experience that requires students to write about a particular situation, identifying personal changes to improve the way they face future challenges [6]. Reflective Writing Analytics (RWA) systems provide computational intervention in the reflective writing process, analysing a student's writing and providing feedback, to enable improvement in both writing and the reflective process.

An early version of a RWA web application (called AWA) [23] performed only sentence level analytics, and provided feedback to students via highlighting and tagging of sentences (see Figure 2 for an example). However, this type of analytics did not allow for the deeper understanding of reflective writing that was required by the learning objectives. Making the need for this level of meaning explicit resulted in a significant change in direction for the application design and involved changes in the whole application architecture to accommodate more than sentence level analytics. Our conceptual view of LA design (figure 1) highlights why this should have been part of the original design process.

For the student users of AWA, their writing can be seen as an artefact of the *Conceptualising-Enacting* aspect of the view. However, making sense of the world around them precedes the act of writing, and requires *Interpreting-Conceptualising* in the construction of meaning. The combination of these two aspects provides a basis for their explanations of what they are reflecting on (*Enacting-Interpreting).* For the student, the meaning in the reflective writing process involves much more than the representation of their sentences, it involves the interaction between all three aspects - it cannot be reduced solely to the writing artefact. In turn, the analytics system needs to consider more than just the representation of words, and their classifications.

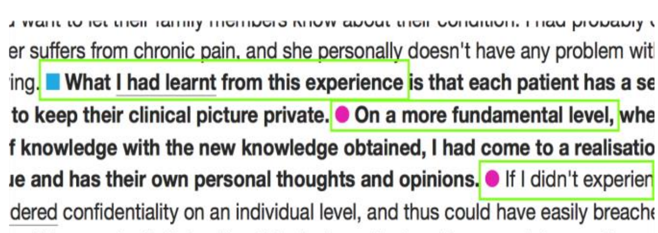

Figure 2. Sentence level feedback to student writers via AWA web application.

Although the computer works with the writing artefact through *Symbolising-Processing*, this provides only a representational translation from the user to the computer (*Enacting-Symbolising*). Such a representation is insufficient for the construction of meaning from the user side as it does not account for the role of *Interpreting-Conceptualising* in the reflective writing process. Mirroring this representation back to the user by highlighting words may provide stimulus for some meaning making, but at this level it is not encouraging the pedagogical meaning making that is required from the reflective writing learning task. The *Symbolising-Analogising* aspect highlights the need for representation to be transformed to accommodate the Semantic Translation back to the user. For the design of AWA, this involved accepting that representation of sentence level analysis was insufficient to provide the required depth of meaning-making, and that the system needed to be architected in a way that accommodated other more complex data structures.

When considering an explicit need for deeper pedagogical meaning making, the requirement for major changes in system design was exposed, resulting in design considerations for much more than just the UI such as algorithm selection, information structure, temporality, and the system architecture necessary for accommodating these considerations.

3.2 Multi-modal Learning Dashboard

The second case that illustrates our approach is a Learning Dashboard designed to be used by teachers in their classrooms [16]. This shows multi-modal information of students' small group collaboration. The representational translation *(Enacting-Symbolising)* was performed when the students interacted with a multi-touch interactive tabletop to build a joint artefact. The computer *Symbolised* and *Processed* the physical interactions between students and the tabletop, their conversations captured using mic-arrays, and changes in the learning artefact. The resulting distilled information was presented in a dashboard (*Processing-Analogising aspect* in our view) which expressed the computation of students' data in a form (apparently) suitable for the teacher's interpretation.

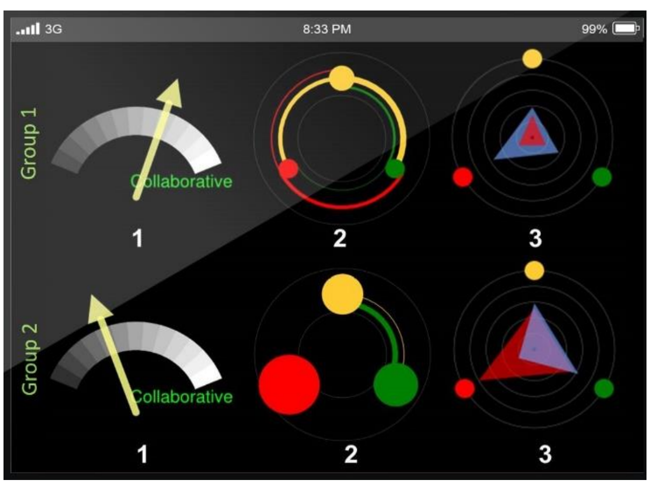

Figure 3. A multi-modal learning analytics dashboard.

This first visualisation shows the *'level of collaboration'* detected by the system (Figure 3 type 1 - left) using a Best-First tree algorithm that classifies each block of half a minute of activity according to a number of features (e.g. speech and touch data activity). The visualisation shows the aggregation of these labelled episodes (e.g. the arrow bends to the right if there are more collaborative episodes). The second visualisation (Figure 3 type 2 - centre) displays the aggregated number of interactions by each learner with other student's objects at the interactive surface, counting the amount of activity (the size of the circles) and the actions on other's objects (the width of the lines that link the circles). The third visualisation (Figure 3 type 3 - right) shows the number of touches (red triangle) and amount of speech (blue triangle) by each learner (represented each by a coloured circle).

When asked, a number of teachers liked the semantic translation (*Analogising-Interpreting)* offered by the mixed radar of participation and the chart of interactions with other's objects graphs. These provided them with enough information to identify possible students' problems. However, most teachers indicated that the first graph, was useful only to confirm their observations using the first two charts. Indeed, most teachers indicated that, although the visualisation was very easy to understand and gave a quick sense of the level of collaboration of the groups, they were not able to fully trust it. Some argued that if they knew more about how the algorithm worked and what data was used, then the visualisation could be very helpful. Full results of this evaluation can be found in [16].

This illustrative example shows how the meaning aspects of the UI can be crucial for determining the overall teacher's experience and the usefulness of the interface. In fact, the second and third visualisations are graphically more complex than the first one. However, the computational features that were not facing the teacher played a significant role in the meaning-making aspect of the dashboard UI design. Thus, this suggests the need for designers to highlight the deep meaning making aspects that need to be considered in the UI design.

4 CONCLUSIONS

The conceptual view presented above, and the illustrative examples show the need to re-think the relationship between meaning, representation and underlying elements for LA design. Our view suggests that explicitly separating meaning from representation encourages a design approach that focuses on the whole system.

We showed the value of applying this view to two educational cases where meaning-making is crucial to the design. In both scenarios, meaning making does not arrive automatically through the users' interaction with the interfaces, but requires a deeper understanding of the computational epistemic domain. In order to achieve the learning or pedagogical objectives in both cases, consideration needed to be given to more than the interface. It also needed to be directed towards the underlying models, algorithms and processes that can influence meaning-making.

Our hope is that this conceptualisation will encourage conversations in the LA and HCI communities about how our thinking influences our design decisions.

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