Towards a Teaching Analytics Tool for Supporting Reflective Educational (re) Design in Inquiry-Based STEM Education

Conference Paper · July 2016

DOI: 10.1109/ICALT.2016.134

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Towards a Teaching Analytics Tool for supporting reflective educational (re)design in Inquiry-based STEM Education

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Abstract—**Providing appropriate tool-supported guidance to students is an essential aspect of technology-supported inquiry-based STEM education, in order to facilitate them in engaging in diverse inquiry tasks. However, analyzing educational designs and evaluating the level of tool-supported guidance provided towards reflective remedying actions is not a trivial task, especially for novice STEM teachers. In this context, the paper presents the design and preliminary evaluation of an inquiry-based STEM Teaching Analytics Tool. This tool aims to visually analyze and evaluate existing educational designs in terms of the level of technology-supported guidance they offer and support teachers' reflective (re)design. The preliminary evaluation results attest to the high levels of accuracy of the proposed Teaching Analytics Tool and provide evidence of its capacity to inform future Teaching and Learning Analytics tools for facilitating STEM teachers to engage in data-driven reflective (re)design of their practice.**

***Keywords-** Teaching Analytics; Inquiry-based STEM Education; Guidance; Scaffolds*

I. Introduction

STEM education posits the key standpoint that student-centered approaches, such as the inquiry-based approach, should be employed in order to cultivate students' inquiry skills through active experimentation [1]. In order to enhance the effectiveness of such approaches in terms of student performance, emerging technologies such as online labs have been increasingly utilized towards providing 'hands-on' learning experiences to students [2] as well as guidance in engaging in the diverse inquiry tasks of an inquiry cycle (as defined in [3]).

Online labs (namely virtual and remote labs – [4]) are commonly at the core of an inquiry cycle and allow students to conduct scientific experiments using virtual or physical equipment. However, the inquiry cycle also includes other tasks such as the formulation of research hypotheses, the planning of the experimentation process as well as analysis of the collected experimentation data. In order to perform these tasks, students are usually in need of ***guidance*** [5]. However, a common issue that can hinder the effectiveness of delivering online lab-supported inquiry-based STEM educational designs (IED) is that the utilized online labs might not provide adequate guidance to facilitate students perform all the required tasks [6]. In this case, appropriate technology-enhanced guidance from external tools (referred to as *guidance tools*) is needed to complement these design shortcomings [7].

Therefore, analyzing existing IED, evaluating the level of tool-supported guidance provided and performing reflective remedying actions is a significant task, albeit not a trivial one especially when done manually by novice STEM teachers (e.g., [8]). More specifically, these processes could be enhanced by methods and tools that (a) analyze IED in terms of tool-supported guidance so as to *identify* possible existing shortcomings and (b) collect educational data from students during the delivery of the educational design in order to generate insights for *evidence-based reflective (re)design*. There is a lack of such *Teaching and Learning Analytics* tools to facilitate teachers to *analyze* and *reflect* on their teaching practice in terms of guidance provision and effectiveness using insights from students' educational data. This is a highly emerging research challenge not only in STEM education, but in technology-enhanced teaching and learning in general [9], [10].

In this context, this paper (as part of an on-going agenda to tackle the aforementioned issue) addresses the first aspect of this under-researched problem, namely the design and preliminary evaluation of an inquiry-based *Teaching Analytics Tool* (TAt). The proposed TAt aims to enable teachers to visually analyze and evaluate their IED, at the design level, in terms of the level of technology-enhanced guidance they offer. To the best of our knowledge, this is the first attempt to design such an IED TAt.

The remainder of the paper is structured as follows. Section II presents the background of our work. Section III presents the proposed TAt in terms of underlying mechanism as well as proof-of-concept exemplary visualization dashboard outputs. Section IV describes the preliminary evaluation methodology adopted and reports on the results. Finally, Section V discusses the conclusions and outlines future work in the emerging agenda of Teaching and Learning Analytics.

II. Background

A. Concept of Guidance in Inquiry-based STEM Education

Guidance refers to the support provided to students to assist them in effectively engaging in the inquiry tasks of the Inquiry cycle. The concept of guidance has been classified in a set of ***Types***, as follows [11]:

- **Process constraints.** This guidance type mainly relates to the provision of constraints in terms of the options (e.g., variables) that students should consider in the inquiry task.
- **Performance dashboards**. This guidance type is mainly related to tools that provide information on the student's results and progress.
- **Prompts**. This guidance type is related to the provision of (usually) text-based hints to the student on what to do in an inquiry task.
- **Heuristics**. Similar to prompts, heuristics are (usually) text-based hints that present instructions to be followed.
- **Direct presentation of information**. This guidance type mainly relates to the provision of required 'background' information towards engaging/reflecting on a task.
- **Scaffolds**. This guidance type mainly relates to tools that support the student to actually execute tasks, such as hypothesis formulation tools and data analysis tools.

Research has shown that the provision of guidance is essential for the delivery of effective online lab-supported IED [7]. For example, [12] showed that (technology-enhanced) guidance helped students in effectively planning and performing the experimentation process, collecting and processing data, as well as communicating results. Moreover, guidance has been shown to enhance student reasoning on their performance [13], formulation of hypotheses [14] and analyzing experimentation data [15].

Thus, it is evident that the provision of guidance can be exploited in online lab-supported IED to facilitate students in engaging in diverse inquiry tasks. The latter can be grouped in a set of seven overarching categories, as described in [3]: (a) Stimulate curiosity through provision of information, (b) Formulate hypotheses / questions, (c) Plan the experimentation process, (d) Perform the experimentation process (e.g., conduct experiments or construct models), (e) Collect and analyze experimentation data, (f) Draw conclusions and reflect on the experiment results and (g) Communicate results. Therefore, the previously mentioned Guidance Types can support different inquiry tasks (e.g., a *scaffolding* tool for *formulating hypotheses*) creating ***Guidance Instances***.

As aforementioned, a commonly cited issue in the literature, is that online labs (which are at the core of the IED) usually afford only a sub-set of the guidance instances required for the inquiry tasks of an inquiry cycle [6]. Therefore, in these cases, external ICT tools (i.e., ***guidance tools***) are commonly utilized to appropriately *complement* these design shortcomings. Commonly, STEM teachers are expected to manually perform this non-trivial process of analyzing IED towards evaluating the level of tool-supported guidance provided and performing reflective remedying actions. Our hypothesis is that this process can be effectively supported by appropriate Teaching and Learning Analytics methods and tools.

B. Teaching and Learning Analytics

The concept of ***Teaching and Learning Analytics*** refers to the process of data-driven reflective teaching practice [16]. More specifically, it comprises the processes of (a) analyzing and transparently modeling the teachers' practice (e.g., their educational designs) and (b) utilizing Learning Analytics tools for collecting evidence towards on-the-fly reflection as well as summative (re)design of subsequent educational designs [16]. In this way, teachers can receive insights through the analysis of students' delivery data (e.g., level of engagement in activities or time spent on each activity) in order to reflectively re-design the specific elements of their teaching practice which affected student performance.

However, research in this field is still scarce in terms of designing tools to afford explicit analysis and mapping of the educational design to the educational data harvested during its delivery to facilitate targeted reflection of teachers [9], [17]. Such holistic tools are identified as a significant challenge in technology-enhanced teaching and learning [10]. In particular, in technology-enhanced STEM education there is a lack of tools to explicitly model and analyze IED as well as collect and process relevant students' educational data to support targeted reflective (re)design.

Therefore, further research in the field of Teaching and Learning Analytics in STEM education is required to facilitate teachers to *analyze* and *reflect* on their teaching practice using data-driven insights. The contribution of the work presented in this paper (as part of an on-going agenda) is to tackle the first aspect of this challenge, by reporting on the design and preliminary evaluation of an IED Teaching Analytics tool (TAt). The proposed TAt aims to facilitate visual analysis and evaluation of teachers' IED, at the design level, in terms of the level of technology-supported guidance they offer.

III. Teaching Analytics Tool for Inquiry-Based STEM Education

A. Description

The core engine of the TAt is a mechanism used to measure the *degree of Guidance* potentially offered by the online labs and guidance tools in an IED. As aforementioned, online labs usually accommodate only sub-sets of the Guidance Instances required in an Inquiry phase, and guidance tools are utilized to complement these design shortcomings. Therefore, the proposed mechanism aims to calculate the level in which the selected guidance tools effectively ***complement*** the Guidance Instances already provided by the online lab of the IED, which could potentially be only a sub-set of the overall Guidance Instance requirements of the IED and its phases. Overall, the mechanism identifies inconsistencies between (a) the Guidance Instances that are provided by the specific guidance tools selected by the teacher and (b) the Guidance Instances that each inquiry phase requires (elicited from the training set used to configure the mechanism) and which are not addressed by the online lab used. Additionally, each guidance tool is also assessed based on whether its specific functionalities (as captured through keyword descriptions provided by tool developers) match the specific textual description of the learning activities described within a given Inquiry phase (as captured through text-based outlines provided by the teacher). Based on these, the proposed algorithm for performing this process requires two types of **input data**, namely:

- Teachers' provided text-based outlines of the specific learning activities to be performed in each inquiry phase of their IED structured following the Inquiry cycle.
- The Guidance Instance profiles[1] and (keyword) descriptions of the online labs and guidance tools that have been used in the given IED. The latter descriptions are typically provided by the developers of the online lab and guidance tool and aim to depict their main functionalities and affordances.

These two types of input data are exploited for assessing the ***Degree of Guidance*** as a function of:

- The *completeness degree* between the Guidance Instances offered by each guidance tool selected to complement the online lab of the IED, against the Guidance Instances required by the specific inquiry phase. More specifically, the guidance tools are assessed in terms of the level that their Guidance Instance profile effectively complements the Guidance Instance shortcomings of the online lab. The completeness degree is calculated using the Jaccard similarity co-efficient, which is a widely used and highly accurate statistical method to compare elements between attribute sets (e.g., [18]).
- The *similarity degree* between the teacher-provided textual outline of each inquiry phase and the descriptions of the guidance tools. This is calculated using a mechanism based on the ***tf-idf*** information retrieval factor [19]. The rationale for using this text-based similarity is that guidance tools should be selected not only based on their capacity to complement Guidance Instance shortcomings of the online lab, but also in terms of how well their specific functionalities (as captured through their keyword descriptions

[1] These profiles depict the Guidance Instances afforded by each online lab and guidance tool and are generated offline. For the scope of this work these profiles were generated by the researchers following the detailed guidelines described in [11]

provided by tool developers) match the specific textual description of the learning activities described within a given Inquiry phase (captured through the descriptions of the teacher). Therefore, the tf-idf mechanism aims to capture this text-based similarity between each guidance tool and the Inquiry phase descriptions.

Overall, the proposed mechanism utilizes the aforementioned data to generate the **Guidance Degree Index** (***GDI***) of the inquiry phase (**IP**), depicting the level that the Guidance Instances required by the **IP** have been addressed by the guidance tools (on top of the utilized online lab). For each Guidance Instance required by the phase (as defined by the training set), the proposed mechanism calculates the ***GDI*** using the following formula:

$$\boldsymbol{GDI_{t,IP}} = \boldsymbol{\lambda} * \left(\boldsymbol{w_{GI}} * \boldsymbol{Jaccard_{t,IP}}\right) + (\boldsymbol{1} - \boldsymbol{\lambda}) * \left(\boldsymbol{tf\_idf_{t,IP}}\right) \quad (1)$$

where:

- $\boldsymbol{Jaccard_{t,IP}}$, is the Jaccard index which depicts the degree of similarity between the Guidance Instances offered by guidance tool $\boldsymbol{t}$ and the ones required by the $\boldsymbol{IP}$.
- $\boldsymbol{w_{GI}}$, is a weighting factor that aims to consider the "significance" of each Guidance Instance $\boldsymbol{G_I}$ for the given $\boldsymbol{IP}$. This significance factor is derived from the training set selected to train the mechanism, and is calculated based on the past frequencies of each Guidance Instance for the corresponding inquiry phase. The rationale for this is related to the assumption that some Guidance Instances are more "important" for a specific inquiry phase (e.g., guidance for hypotheses formulation during a hypothesis formulation task).
- $\boldsymbol{tf - idf_{t,IP}}$, is the degree of similarity of the keyword description of guidance tool $\boldsymbol{t}$ to the textual description of the $\boldsymbol{IP}$ based on the ***tf-idf*** factor.
- $\boldsymbol{\lambda}$, is a parameter introduced in order to calibrate the significance of each factor contributing to $\boldsymbol{GDI_{t,IP}}$. The 'optimal' value of $\boldsymbol{\lambda}$ (in terms of the accuracy of the classifying mechanism) is obtained in an experimental manner and is the focus of the preliminary evaluation presented in this paper.

Additionally, the proposed TAt also generates a **Consolidated Guidance Degree Index** (***CGDI***) for the overall IED ***j*** (comprising ***N*** inquiry phases), modeled as the mean value of the individual ***GDI*** of each inquiry phase $\boldsymbol{IP}$ (Formula 2):

$$\boldsymbol{CGDI_j} = \frac{\sum_{i=1}^{N} \boldsymbol{GDI_{IPi}}}{\boldsymbol{N}} \quad (2)$$

Finally, the proposed TAt allows for directly feeding the analysis results in visual dashboards, in order to assist teachers to gain visual overviews of their designs in terms of the degree of tool-supported guidance they have included or missed compared to the 'optimal' Guidance Instance requirements of each inquiry phase (as these are defined by the training set been used to configure the mechanism). An exemplary proof-of-concept depiction of the dashboards utilized in the TAt is presented in the following section.

B. Exemplary Proof-of -Concept Dashboard Visualizations

This subsection describes three proof-of-concept exemplary dashboards of the proposed TAt, in order to briefly depict the different types of visualizations offered. These dashboards were included in the TAt based on the emerging understanding that visual dashboards can facilitate teachers to gain insights from educational data [20].

Fig. 1a depicts the visualization of the ***CGDI*** offered by the overall IED, aiming to provide an overarching view of the level of Guidance offered. Fig. 1b provides a higher level of granularity, by visualizing the cardinality of the sets of Guidance Instances which were accommodated or neglected for each inquiry phase of the IED (based on the training set) (the Fig. 1b shows the results for one exemplary inquiry phase). More specifically, the mechanism can be trained (using training datasets - see Section IV) to identify which Guidance Instances are 'optimally' required in each Inquiry Phase. This configuration is used as a benchmark to evaluate the teachers' design and identify potential shortcomings. Finally, Fig. 1c depicts the highest level of granularity offered by the proposed TAt, namely the set of specific Guidance Instances that have not been incorporated in each inquiry phase, but should have been based on the training set (the Fig. 1c shows the results for one exemplary inquiry phase). As aforementioned, the Guidance Instances are not equally weighted for each inquiry phase. Therefore,

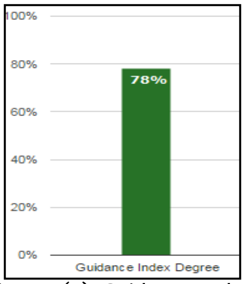

Figure 1(a): Guidance Index Degree offered in IED

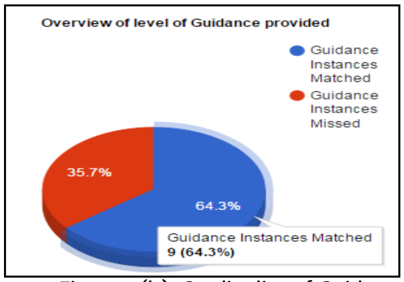

Figure 1 (b): Cardinality of Guidance Instances provided and neglected

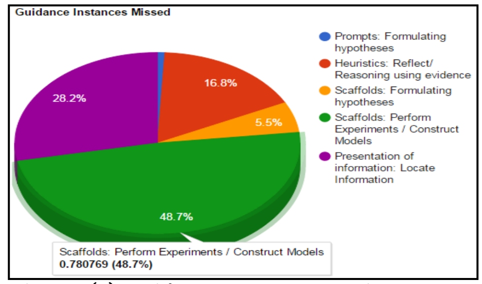

Figure 1(c): Guidance Instances not incorporated in an inquiry phase

the proposed TAt assigns different weights of "significance" to each Guidance Instance (based on the training set selected) and visualizes them accordingly. In this way, the TAt aims to provide feedback on not only the specific Guidance Instances that have not been accommodated, but also on their "importance" for the given inquiry phase. The following section presents the evaluation methodology and preliminary evaluation results of the proposed TAt.

IV. Preliminary Evaluation

A. *Evaluation Methodology*

The evaluation methodology consisted of preliminarily evaluating the accuracy of the proposed mechanism on calculating the appropriateness of guidance tools to address the Guidance Instance requirements of online lab-supported IED and their phases. Furthermore, the evaluation also aimed at configuring the mechanism of formula (1) in terms of the value of parameter λ to achieve highest accuracy. In order to perform the preliminary evaluation, data from a major European project, namely "Global Online Science Labs for Inquiry Learning at School" (Go-Lab) (http://www.go-lab-project.eu/), were used as a case study. The Go-Lab online repository [http://www.golabz.eu/] contains a vast pool of 301 online labs and 35 guidance tools[2]. The training and test sets utilized in the preliminary evaluation are as follows:

- The **training set** for the context of this preliminary evaluation comprised a Guidance Instance model derived from a state-of-the-art literature analysis. More specifically, towards formulating the Guidance Type requirements of each inquiry phase, the work of [21] was exploited, which performed a systematic literature review and quantitative analysis of the Guidance Instances utilized in technology-supported phases of IED (also consistent with the work of [3]. Future evaluations will focus on training the TAt using also teacher-created IED.
- The **test set** comprised a manually harvested dataset from the publicly available repository of Go-Lab, containing 37 "best-practice" IED created by expert project partners in the field of Inquiry-based STEM education. These "best-practice" IED (which were populated with online labs and guidance tools) were used as a means to evaluate the accuracy of the mechanism to correctly classify guidance tools as appropriate for given IED and its phases.

B. *Evaluation Metrics*

In order to evaluate the accuracy of the proposed mechanism, a diverse set of widely utilized metrics was exploited, defined as follows [22]:

- **[M1] - Recall.** This metric is aimed to evaluate the sensitivity of the mechanism to identify elements of the "positive" class.
- **[M2] - Specificity.** This metric is aimed to evaluate the sensitivity of the mechanism to identify elements of the "negative" class.
- **[M3] – AUC (Area Under Curve).** This metric is aimed at evaluating the capacity of the mechanism to avoid wrong classification of elements.

C. *Preliminary Evaluation Results*

The results of the preliminary evaluation are shown in Fig. 2, comprising the performance of the mechanism in terms of the evaluation metrics for an increasing value of **λ**.

[2] Data from 20 April 2016

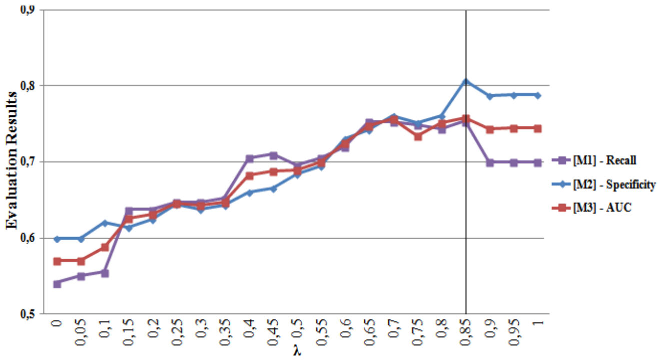

Figure 2: Preliminary evaluation results for the proposed TAt

As the Figure 2 depicts, the proposed mechanism obtained its highest value for all three evaluation metrics for λ =0.85. Moreover, as the Fig. 2 depicts, the accuracy results of the TAt are considerably high (i.e. more than 0.54) for all λ values. More specifically, the obtained results on the *Recall* metric, signify that the proposed mechanism is highly sensitive in identifying guidance tools that are appropriate for supporting Guidance needs of a given inquiry phase. Additionally, these results are complemented by the insights gained from the *Specificity* metric, which attest to the capacity of the proposed mechanism to identify guidance tools whose Guidance Instance affordances and descriptions do not address the specific Guidance requirements and outline of the corresponding inquiry phase. Finally, the results from the *AUC* metric show that the proposed mechanism is highly sensitive in highlighting guidance tools which better complement the guidance instances provided by online labs for each inquiry phase and, therefore, avoid erroneous classifications.

Overall, it is evident that the evaluation results for all evaluation metrics are significantly high, especially in the 'optimal' point of λ =0,85. These results attest to the overall high levels of accuracy of the proposed mechanism of the TAt, providing evidence of its capacity to correctly identify guidance-related oversights in IED at the design level.

V. Conlusions and Future Work

This paper presented a first step towards a Teaching and Learning Analytics tool for supporting teachers in evidence-based reflective (re)design of STEM IED. The design of a novel IED TAt was presented, which aims to facilitate STEM teachers (especially novices) in identifying and visualizing the level of technology-supported guidance they offer in their IED. Moreover, the paper presented preliminary evaluation results towards configuring the proposed TAt as well as assessing its accuracy using a diverse set of metrics.

Future work in this agenda should focus on extending this TAt to address significant challenges in the area of reflective (re)design for teachers. More specifically, Teaching and Learning Analytics tools should be designed and evaluated in order to provide holistic support to teachers to not only analyze their educational designs, but also relate them to students' educational data from the delivery of these designs (for example students' access patterns in the different phases of the educational design (e.g., [8]) and students' time spent on each phase (e.g., [23]). In that way, the Teaching and Learning Analytics tools could process these data in combination and provide the teachers with insights on potential correlations and interdependencies to alleviate for prior shortcomings in a targeted manner and enhance students' learning experiences.

Acknowledgment

The work presented in this paper has been partially funded by the European Commission in the context of the Go-Lab project (Grant Agreement no. 317601) under the Information and Communication Technologies (ICT) theme of the 7th Framework Programme for R&D (FP7). This document does not represent the opinion of the European Commission, and the European Commission is not responsible for any use that might be made of its content.

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