The Goal - Question - Indicator Approach for Personalized Learning Analytics

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Keywords: Learning Analytics, Open Learning Analytics, Personalized Learning Analytics, OpenLAP.

Abstract: Open learning analytics (OLA) is a relatively new branch of learning analytics (LA) which emerged due to the growing demand for self-organized, networked, and lifelong learning opportunities. OLA deals with learning data collected from various learning environments and contexts, analyzed with a range of analytics methods, and for different stakeholders with diverse interests and objectives. This diversity in different dimensions of OLA is a challenge which needs to be addressed by adopting a personalized learning analytics (PLA) model. Current implementations of LA mainly rely on a predefined set of questions and indicators which is not suitable in the context of OLA where the indicators are unpredictable. In this paper we present the goal - question - indicator (GQI) approach for PLA and provide the conceptual, design, implementation and evaluation details of the indicator engine component of the open learning analytics platform (OpenLAP) that engages end users in the indicator generation process by supporting them in setting goals, posing questions, and self-defining indicators.

1 INTRODUCTION

Learning Analytics (LA) is an emerging research field that deals with the development and improvement of methodologies to support the learning process by exploiting the educational data. Recently, a new research area has emerged called Open Learning Analytics (OLA) which focuses on more open, self-organized and networked learning environments (Chatti, 2010). The aim of OLA is to improve learning effectiveness and efficiency in lifelong learning environments (Chatti et al., 2017).

The field of OLA is still not well established and the concrete conceptual and implementation plans are lacking. Thus, the solutions which could deliver the full potential of OLA are also in the early stage of development. Different solutions have been proposed in literature such as, the Apereo Learning Analytics Initiative (Apereo LAI) and the Jisc Open Learning Analytics Architecture (Jisc OLAA). However, these solutions have limitations such as addressing the goals of a limited set of stakeholders, working with a specific set of data, answering a predetermined set of objectives, and relying on a predefined set of analytics methods. To address these challenges, we proposed in earlier works the Open Learning Analytics Platform (OpenLAP) (Chatti et al., 2017; Muslim et al., 2017). In order to satisfy the requirements of different stakeholders in OLA, there is a need to involve the end user in the LA process by adopting a personalized learning analytics (PLA) model. In this paper, we explore the concept of PLA and introduce the Goal - Question - Indicator (GQI) approach for PLA. As an application of the GQA approach, we present the conceptual, design, and implementation details of the indicator engine component of OpenLAP. The main aim is to provide support for flexible definition and dynamic generation of indicators to meet the needs of different stakeholders with diverse goals.

The remainder of the paper is structured as follows: In Section 2, we present the GQI approach for PLA. In Section 3, we explain the architecture and the main components of OpenLAP. Section 4 presents the conceptual design and implementation details of the indicator engine component of OpenLAP. The evaluation results of the indicator engine in terms of usefulness and usability are discussed in Section 5. Finally, Section 6 summarizes the main findings in the paper and gives perspectives for future work.

Muslim, A., Chatti, M., Mughal, M. and Schroeder, U.
The Goal - Question - Indicator Approach for Personalized Learning Analytics.
DOI: 10.5220/0006319803710378
In *Proceedings of the 9th International Conference on Computer Supported Education (CSEDU 2017) - Volume 1*, pages 371-378
ISBN: 978-989-758-239-4
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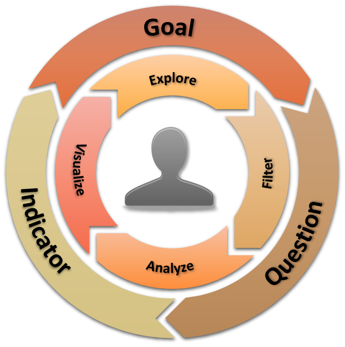


Figure 1: The Goal - Question - Indicator (GQI) approach for Personalized Learning Analytics (PLA).

2 THE GQI APPROACH FOR PLA

The aim of Open Learning Analytics (OLA) is to improve learning effectiveness and efficiency in lifelong learning environments. OLA harnesses data coming from various learning environments and contexts of different stakeholders with diverse interests and objectives, as well as multiple analytics methods to gain insight into learning processes (Chatti et al., 2017).

Personalization of the LA process is the key challenge in OLA to serve the requirements of different stakeholders with diverse goals in an effective and efficient way. The user should be in control of the LA process if LA tools are to serve the intended objective of improving learning and teaching. Most LA tools currently available provide a static set of predefined questions and indicators focusing on specific objectives of selected stakeholders. This, however, is not feasible in the OLA context where the set of required indicators is unpredictable. In order to achieve personalized learning analytics (PLA), an indicator definition process is required which can enable end user to dynamically define new questions and indicators that meet their goals in an effective and efficient way. In this paper, we present the Goal - Question - Indicator (GQI) approach for PLA which supports end users in the LA process by setting goals, posing questions, and self-defining indicators. Figure 1 shows the GQI approach consisting of three main steps.

– **Goal**: In this step, the user can specify an appropriate LA objective (e.g. monitoring, analysis, prediction, intervention, tutoring, mentoring, assessment, feedback, adaptation, personalization, recommendation, awareness, reflection) to initiate the indicator definition process.

– **Question:** In this step, the user can formulate the LA question based on the specified LA goal (e.g. how active are the students in the classroom?).

– **Indicator:** In the last step, the user can define multiple indicators to answer the formulated LA question. An indicator can be defined as a specific calculator with corresponding visualizations, tied to a specific question. Example of indicators include attendance rate in class, post rate in wikis, post rate in discussion forums. To define each indicator, the user follows the inner circle shown in Figure 1 by exploring the learning activities data, applying various filters on it, analyzing it and finally visualizing it. This would make the LA process more transparent, enabling users to see what kind of data is being used and for which purpose.

3 OPEN LEARNING ANALYTICS PLATFORM (OpenLAP)

The Open Learning Analytics Platform (OpenLAP)[1] provides a detailed technical OLA architecture with a concrete implementation of all its components, seamlessly integrated in a platform. It follows a user-centric approach to engage end users in flexible definition and dynamic generation of indicators. To meet the requirements of diverse users, OpenLAP provides a modular and extensible architecture that allows the easy integration of new analytics modules, analytics methods, and visualization techniques.

In the following sections, we present a brief description of OpenLAP through a discussion of its abstract architecture and system workflow.

3.1 Abstract Architecture

The abstract architecture of OpenLAP consists of three main components, namely *Data Collection and Management*, *Indicator Engine*, and *Analytics Framework* as shown in Figure 2.

The *Data Collection and Management* component in OpenLAP is responsible for collecting learning activities data from different sources adhering to the privacy policies of OpenLAP and generating the learner and context models from it.

The aim of the *Indicator Engine* component in OpenLAP is to achieve personalized and goal-oriented LA by following the GQI approach that allows users to easily define new indicators through an intuitive and interactive UI.

The *Analytics Framework* lays the foundation of simple yet powerful framework that is responsible for

[1]http://lanzarote.informatik.rwth-aachen.de/openlap

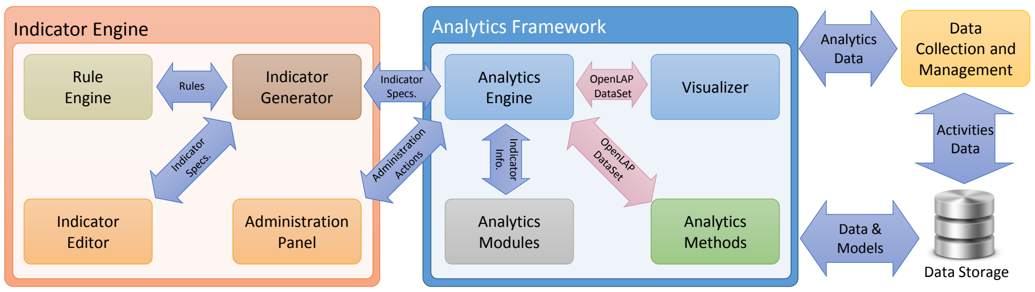


Figure 2: OpenLAP Abstract Architecture.

the management, generation and execution of indicators. It provides an easy and flexible mechanism for LA researchers and developers to add new analytics modules, analytics methods and visualization techniques to OpenLAP at runtime. It is the combination of the "OpenLAP-DataSet", the "Analytics Modules", the "Analytics Methods", the "Visualizer", and the "Analytics Engine" core components of OpenLAP (Muslim et al., 2017).

3.2 System Workflow

In the following section, we explain the two main system processes of OpenLAP which show how the different components interact with each other (Muslim et al., 2017).

3.2.1 Indicator Generation

The indicator generation process is realized by the *Indicator Engine* component of OpenLAP to let users dynamically define their new indicators. During this process, the user interacts with the "Indicator Editor" UI of the *Indicator Engine* to specify the LA goal such as monitoring, prediction, assessment, and reflection. Afterwards, the user formulates the LA question and associates multiple indicators to answer this question. To generate a new indicator, the user performs the following steps:

1. Explore the learning activities data stored in the Learning Context Data Model (LCDM) format (see Section 4.3.1).
2. Select the appropriate dataset for the indicator.
3. Apply different filters.
4. Choose the analytics method to be applied.
5. Map the columns of the dataset to the inputs of the analytics method.
6. Choose the visualization technique to be used.
7. Map the outputs of the analytics method to the inputs of the visualization technique.
8. Preview the visualization of the indicator.

During the indicator generation process, the *Indicator Engine* remains in continuous communication with the "Analytics Engine" component of the *Analytics Framework* to get all possible dataset parameters, get the list of analytics methods which can be used, get the visualization techniques which can be applied, validate the specified mappings, and generate the indicator preview. After the indicator is finalized, the "Analytics Engine" saves it to database as a triad: indicator query ID - method ID - visualizer ID and generates an HTML and JavaScript based indicator request codes for each indicator which the user can embed in any client application (e.g. Web page, dashboard, LMS) to visualize the indicator with current data.

3.2.2 Indicator Execution

The indicator execution process is handled by the *Analytics Framework* component of OpenLAP. The indicator request code embedded in the client application request the *Analytics Framework* to visualize the specific indicator. The "Analytics Engine" intercepts the request and performs the following steps:

1. Check whether the request is valid or not.
2. Communicate with the respective "Analytics Module" to get the triad.
3. Get the query related to the requested indicator from the database.
4. Execute the query and get the raw data.
5. Transform the raw data into the "OpenLAP-DataSet".
6. Send the "OpenLAP-DataSet" and the mapping indicator query - method to the analytics method referenced in the triad for analysis.
7. Receive the analyzed data as an "OpenLAP-DataSet".
8. Send the "OpenLAP-DataSet" and the mapping method - visualization to the visualization technique referenced in the triad.

9. Receive the visualization code and forward it to the requesting client application to visualize the indicator.

4 INDICATOR ENGINE IN OpenLAP

The main focus of this paper is the *Indicator Engine* component of OpenLAP which is responsible for providing personalized and goal-oriented LA by realizing the indicator generation process of OpenLAP. It is built upon the previous work called a rule-based indicator definition tool (RIDT) for personalized learning analytics (Muslim et al., 2016). Initially, RIDT was developed as a standalone tool responsible for both indicator generation and indicator execution processes. In order to make OpenLAP modular, RIDT has been divided into the *Indicator Engine* and the *Analytics Framework* components responsible for the indicator generation and the indicator execution processes respectively. Moreover, the evaluation of RIDT revealed limitations in terms of usability which impacted the user acceptance of the tool.

In the following sections, we present the design and implementation of the *Indicator Engine* in OpenLAP - which represents an enhancement of RIDT - through a comprehensive discussion of one of the possible user scenarios, conceptual approach, implementation details, and evaluation.

4.1 User Scenario

Omer is a lecturer at RWTH University where he is teaching a Web Technologies course. In order to administer his course, he uses the university learning management system called L^{2}P. On the dashboard of the web technologies courseroom in L^{2}P, Omer has various indicators, such as, presence of students in class, most downloaded documents, and the average grades of students in assignments.

Omer is a pro-active lecturer who is always looking for ways to improve his teaching. Therefore, he is interested in monitoring the activities of the students in his class. To do that, he looked at the list of available indicators in OpenLAP, but did not find exactly the ones he was looking for. Thus, he uses the user interface of the *indicator engine* in OpenLAP and starts the indicator generation process by selecting 'Monitoring' as an analytics goal. Followed by entering the analytics question 'Activities of students in the Web Technologies class'. Omer reuses the existing indicator 'Most downloaded documents' and updates the filter to get the top most viewed learning materials in the Web Technologies class. He associates this indicator with the analytics question under the name 'Top 10 viewed learning materials'.

Afterwards, Omer starts creating a new indicator named "Weekly time evolution of learning resources accessed". He selects 'L^{2}P' as a data source, 'WEB' as platform, 'View' as action, and 'Learning Materials, Media Library, Shared Documents' as category to define the basic dataset for the indicator. Next, he applies a filter on the dataset to get data related to the Web Technologies class only. After that he selects the 'Item Counter - Weekly' analytics method and maps the 'Timestamp' and 'Category' columns of the dataset to the 'Timestamp' and 'Items to count' inputs of the selected analytics method respectively. Next, he uses the 'Stacked Area Chart' visualization type of the 'C3/D3.js' visualization library and maps the 'Time (Weeks)', 'Item Count' and 'Item Names' outputs of the analytics method to the 'X-Axis Items', 'Y-Axis Values' and 'Stacked Items' to the inputs of the visualization type. Finally, he previews the indicator before associating it with the analytics question. Similarly, he generates two more indicators named 'post rate in wikis' and 'rate of different resource types viewed'. After that he finalizes the question and its associated indicators to get the indicator request code which he embeds in his course dashboard for visualization. The newly created question and associated indicators are added to the list of available questions and indicators for future use by other users.

4.2 Conceptual Approach

In the following sections, we discuss the design of the *Indicator Engine* with a focus on the system requirements and the abstract architecture.

4.2.1 System Requirements

Developing a tool to support end users in dynamic generation of new indicators is a challenging task. In this section we outline the requirements for the *Indicator Engine*.

– **Modularity:** The *Indicator Engine* should adapt a modular architecture to allow easy and effective communication between loosely-coupled modules and faster adaptability of new underlying data model.

– **Extensibility:** The *Indicator Engine* should be flexible and extensible to support easy insertion of new analytics goals, analytics methods, and visualization techniques after the platform has been deployed.

– **Usability:** The *Indicator Engine* should follow standard design patterns and provide intuitive, responsive and consistent user interface (UI) to guide users through indicator generation process. Furthermore, in order to provide flexible user experience, the UI should include features to give user more control over the indicator definition process.

4.2.2 Abstract Architecture

The abstract architecture of the *Indicator Engine* is shown in Figure 2. It consists of four main components: “Indicator Editor”, “Rule Engine”, “Indicator Generator”, and “Administration Panel”. The “Indicator Editor” provides an interactive and responsive UI to realize the indicator generation process. The “Rule Engine” holds the rules which are used to generate the data query for the indicators based on the parameters defined by the users via the “Indicator Editor”. The “Indicator Generator” is the orchestrator of the *Indicator Engine* responsible for the communication between the different components within the *Indicator Engine* and with the “Analytics Engine” in the *Analytics Framework*. The “Administration Panel” provides a set of UI for administrators and developers to manage different parts of OpenLAP, such as, approving new analytics goals, uploading new and managing existing analytics methods and visualization techniques.

4.3 Implementation

The *Indicator Engine* is a Java Spring Framework[2] based web application that follows the Model View Controller (MVC) design pattern. The application makes extensive use of Web technologies, such as Servlets, JSP, Java Beans at the server side and jQuery, jQuery UI, and AJAX at the client side. In the following sections we explain the underlying data model and discuss the technical details of each component in the *Indicator Engine* using the example ‘Weekly time evolution of learning resources accessed’ indicator presented in Section 4.1.

4.3.1 Data Model

Learners are collaborating more than ever in open, self-organized and networked learning environment. Thus, the users’ learning activities need to be collected from various heterogeneous sources in a common format for analysis. Data models provide a standard way to support interoperability and integration of data from various sources. Numerous data models have been proposed in LA literature, such as, Experience API (xAPI), IMS Caliper, Activity Streams Contextualized Attention Metadata (CAM), Learning Registry Paradata, and NSDL Paradata. OpenLAP uses the Learning Context Data Model (LCDM), proposed in the Learning Context Project[3]. LCDM represents a balance between completeness, flexibility, and simplicity as compared to other candidate data models for LA. It is a simple and easy to understand data model which holds additional semantic information about the context in which an event has been generated. As compared to other data models which are event-centric, LCDM is user-centric which is crucial to achieve personalization related tasks in LA (Lukarov et al., 2014). Nevertheless, the modular and extensible architecture of OpenLAP allows easy adaptability to different underlying data model, such as xAPI or IMS Caliper (see Section 4.3.2) (Muslim et al., 2016).

4.3.2 Indicator Engine

In the following sections we discuss the implementation details of each component in the *Indicator Engine* shown in Figure 2.

Indicator Editor

The “Indicator Editor” component is the collection of MVC Views providing a UI for the *Indicator Engine* focusing on providing high usability and user control. Following the GQI approach, the main UI has been divided into three main sections, namely Goal, Question, and Indicator.

Goal
The user starts the indicator generation process by selecting an appropriate LA goal such as monitoring, prediction, assessment, recommendation, and reflection. The user can request a new LA goal if the provided list does not contain the required LA goal. In order to moderate the creation of new LA goals, only those LA goals are made available to the users which have been approved by the administrators via the “Administration Panel”. Additionally, the user has option to reset the current indicator generation process by clicking ‘New Question’ button. For the “Weekly time evolution of learning resources accessed” indicator, the LA goal ‘Monitoring’ is selected.

[2]http://projects.spring.io/spring-framework/

[3]http://www.learning-context.de/

Question
After selecting an appropriate LA goal, the user formulates the LA question, such as, 'Activities of students in the Web Technologies class' for the 'Weekly time evolution of learning resources accessed' indicator. Afterwards, the user can associate multiple indicators with the LA question either by loading an existing indicator and altering its parameters or defining a new indicator (as explained in next section). Each associated indicator can easily be deleted or selected for editing again. After finalizing the association of the required indicators with the LA question, the user can visualize it and save it to the database. While saving, the *Analytics Framework* generates the indicator request codes for the saved question and its associated indicators which is provided to the user as shown in Figure 3. These indicator request codes can be embedded in any client application (e.g. dashboard, Web pages) to visualize them using the selected data.

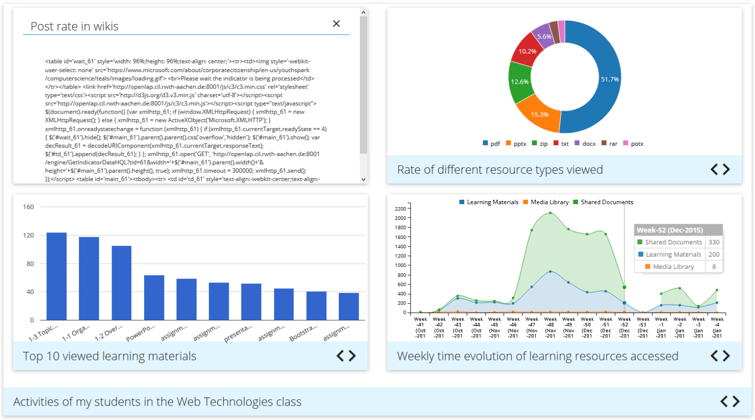
Indicator
In this section, the user can specify the parameters for the new indicator or customize the loaded indicator. The section is further divided into four parts, namely dataset, filters, analysis, and visualization.

- **Dataset** In this part of the UI, the user can specify the name and explore the learning activities data to define the basic dataset for the indicator. The dataset is defined based on the parameters selected by the user, including the list of Sources from where the data should be used (L2P, Moodle, etc.), data coming from which Platforms should be included (web, mobile, etc.), data related to which Action types should be used (add, update, delete, post, begin, end, etc.) and which Category should be used (Wiki, Discussion forum, Assignments, etc.). These parameters represent the attributes of the 'Event' table in the LCDM data model, as discussed in Section 4.3.1.
- **Filters**
  This part allows the user to specify additional filtering parameters on the defined dataset. Three different types of filters can be applied, namely 'Attribute', 'Time', and 'User'. The 'Attribute' filters are applied on the additional semantic information related to each event stored in the 'Entity' table of the LCDM (see Section 4.3.1). Using the 'Time' filter the starting and/or ending dates can be specified to define the range of time for which the data should be used. Finally, the 'User' filter allows the user to specify whether only his/her data or anonymized data of the whole class should be considered.
- **Analysis**
  Analysis is the crucial part of the indicator generation process where the user can specify which analytics method should be performed on the filtered dataset. The user can select an analytics method from a provided list containing methods from the domain of statistics, data mining (DM), and social network analysis (SNA). Afterwards, the user can define the mapping between the filtered dataset and the selected analytics method by specifying which column of the dataset should go into which input of the analytics method. A statistics analytics method called 'Item Counter - Weekly' is used for the 'Weekly time evolution of learning resources accessed' indicator. The selected analytics method expect two inputs, 'Items to count' and 'Timestamp' which are mapped to 'Category' and 'Timestamp' data columns respectively.
- **Visualization** The final step in the indicator generation process is to define the visualization for the indicator. In this part, the user can select an appropriate visualization library and visualization type for the indicator. Afterwards, the user can define the mapping between the outputs of the selected analytics method and the expected inputs of the selected visualization type. For the 'Weekly time evolution of learning resources accessed' indicator, the 'Stacked Area Chart' of the 'C3/D3.js' visualization library is used. The selected visualization type requires three inputs, 'X-Axis Items', 'Y-Axis Values' and 'Stacked Items' which are mapped to 'Time (Weeks)', 'Item Count' and 'Item Names' outputs of the selected analytics method respectively.

Rule Engine

The "Rule Engine" component is responsible for managing the rules to generate data queries for indicators during the indicator generation process. The *Indicator Engine* uses a rule engine called Drools[4]. Each rule accepts a list of selected dataset and filtering parameters and generates an appropriate data query. Drools rule consists of three main clauses, a 'Header' clause which contains a human readable name of the rule, a 'When' clause where the condition for executing the rule is specified and a 'Then' clause describing the actions which needs to be taken when the specified conditions are satisfied. After the user has finalized defining the indicator using the "Indicator Editor", the "Indicator Generator" requests the Drools to generate the data query for the indicator using the

[4]http://www.drools.org/



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xmlhttp_61.onreadystatechange = function (xmlhttp_61) { if (xmlhttp_61.currentTarget.readyState == 4)
{ $('#wait_61').hide(); $('#main_61').parent().parent().css('overflow','hidden'); $('#main_61').show(); var
decResult_61 = decodeURIComponent(xmlhttp_61.currentTarget.responseText);
$('#td_61').append(decResult_61); } }; xmlhttp_61.open('GET', 'http://openlap.cil.rwth-aachen.de:8001
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});</script> <table id='main_61'><tbody><tr> <td id='td_61' style='text-align:-webkit-center;text-align:-
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Figure 3: Indicator request code generated for the question.

dataset and filtering parameters provided by the user. The data query is used to fetch the raw data from the database during indicator generation and indicator execution processes by the *Analytics Framework*.

The core benefit of following a rule-based approach in the *Indicator Engine* is that the LCDM can easily be replaced with other data models such as xAPI, IMS Caliper by changing 'When' and 'Then' clauses in the rules to accommodate the attributes of the new data model. Additionally, rules make it easy to adapt a different database technology (e.g. NoSQL) by defining appropriate actions in the 'Then' clause.

Indicator Generator

The "Indicator Generator" acts as a mediator between different components of the *Indicator Engine*. It is responsible for generating the data queries by communicating with the "Rule Engine", providing data to different sections of the "Indicator Editor" by communication with the *Analytics Framework* as shown in Figure 2.

Administration Panel

The "Administration Panel" provides a set of UI to enable extensibility in OpenLAP by allowing managers to administer different parts of it. It helps administrators to approve or reject the newly requested LA goals by the end users. OpenLAP is a modular and extensible framework which allows developers to develop and easily integrate new analytics methods and visualization techniques (Muslim et al., 2017). The "Administration Panel" provides an intuitive interface to allow developers to upload newly developed components to OpenLAP which are made available to users after validation by the *Analytics Framework*.

5 EVALUATION

We conducted a user evaluation based on a custom questionnaire to assess the usability of the *Indicator Engine*. The System Usability Scale (SUS) was employed as a general usability evaluation method. During the evaluation process, the users were briefly introduced to the concept of personalized LA and the objectives of the *Indicator Engine* in OpenLAP. 10 participants were asked to follow the steps of the indicator generation process and perform various tasks. Subsequently, the participants were asked to fill out the questionnaire which consisted of 28 questions divided in four sections.

5.1 Participants' Background

The first section of the questionnaire gathered the participants' backgrounds. 70% of the participants were in the 18-30 age range and had at least Bachelor's degree in computer science. 40% of the participants were professionals working in software development industries whereas the rest were either students or researchers in universities. The male to female ratio in the participants was 1:1.

5.2 Usefulness

The second section of the questionnaire focused on capturing the usefulness of the *Indicator Engine*. Around 94% of the participants found the different steps of the indicator generation process easy or very easy as shown in the Figure 4. Only one of the participants found the steps 'Define Filters' and 'Define Mappings' to be difficult. In general, the participants

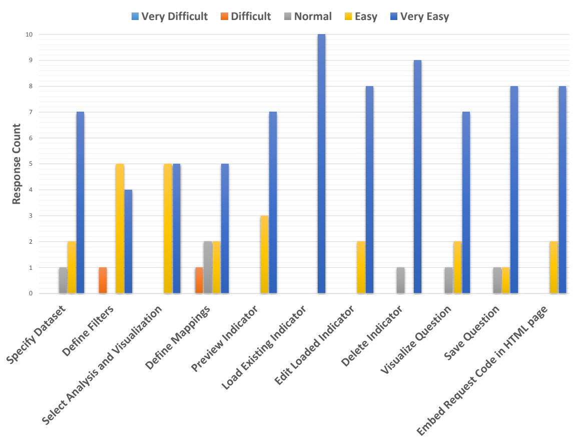

Figure 4: Usefulness evaluation of the *Indicator Engine*.

reported that the *Indicator Engine* was useful. However, some participants requested to provide suggestions for defining mappings to further improve the user experience for non-technical users. Additionally, a feedback was given to include a step by step guide including screencast for the indicator generation process.

5.3 Usability

The third section of the questionnaire captured the usability of the *Indicator Engine*. It consisted of 10 questions required to compute the usability score of the *Indicator Engine* using the System Usability Scale (SUS) method. The questions were designed to capture the intuitiveness, simplicity, feedback, responsiveness, efficiency of the UI, user's comfort level in using the UI, and the steepness of the learning curve which a user must go through to successfully use the UI. Based on the provided feedback, the usability score of the *Indicator Engine* is calculated to be 81.75 which is above the average SUS score of 68. Overall, the participants found the system intuitive, responsive, and easy to learn.

5.4 General Remarks

The last part of the questionnaire aimed at collecting the general user remarks related to the *Indicator Engine*. The feedback revealed that all participants liked the concept of defining their own indicators following the GQI approach. The most appreciated feature was flexibility in customizing the visualization parameters and previewing of the indicators at runtime. Additionally, the participants pointed out that the feature of mapping dataset to the input of analytics method and then output of analytics method to the input of visualization is a very strong feature which allow high end indicator customization. However, the power of customization can increase the complexity of the system for non-technical users which is evident from the evaluation results.

6 CONCLUSION

In this paper, we proposed the goal - question - indicator (GQI) approach for PLA that engages the end users in a continuous inquiry-based LA process. We presented the theoretical, design, implementation, and evaluation details of an indicator engine component of the open learning analytics platform (OpenLAP) that illustrates the GQI approach in action by supporting users in setting goals, posing questions, and self-defining indicators that help them achieve their objectives. The evaluation results are promising and show high user satisfaction with the usefulness and usability of the indicator engine. Additionally, the evaluation revealed that OpenLAP has the potential to support a personalized learning analytics experience. Future work includes the implementation of new analytics methods, visualization techniques and improvements in providing recommendation for the mapping which would guide end users through the indicator generation process.

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