OBEInsights: Visual Analytics Design for Predictive OBE Knowledge Generation

Leona Donna Lumius, Mohammad Fadhli Asli*
Faculty of Computing and Informatics
Universiti Malaysia Sabah, Malaysia

***Abstract*—Gaining traction in modern higher education, outcome-based education (OBE) focuses on strategizing pedagogical approaches to help the student achieve specified learning outcomes. In the context of Malaysia, OBE is oriented towards holistic development of graduates to ensure readiness towards the working sector. To empower OBE implementation, standardized measuring instrument iCGPA was introduced to higher education institutions nationwide. With lower dependency on provided curriculum, graduate abilities and values development are also attainable via extracurricular activities. However, analyzing the curriculum results in hand with extracurricular activities can be a daunting task, albeit the potential enriched performance assessment. In addition, the current iCGPA instrument employs radar map that restricts data exploration despite its capability in visualizing multivariate information. This study aims to enable predictive knowledge generation on understanding the relationship between learning activities and performance in OBE. Therefore, a predictive visual analytics system namely OBEInsights is proposed to facilitate education analysts in assessing OBE. The system development started with the identification of crucial design and analytic requirements via a domain expert case study. The system is then built with deliberate considerations of guiding factors of a design framework conceptualized from the case study. Subsequently, the system was then evaluated in usability testing with 10 domain experts that consist of usability rating and expert validation. The evaluation and expert validation results demonstrated the effectiveness and usability of OBEInsights in facilitating OBE predictive assessment. Several design insights on constructing visual analytics for OBE assessment were also discovered in terms of effective visualization, predictive modeling, and knowledge generation. Analytic designers and builders can leverage the reported design insights to enhance knowledge generation tools for OBE assessment.**

Keywords*—Visual analytics; visualization; learning analytics; outcome-based education (OBE)

I. Introduction

Outcome-based education (OBE) has become a prominent higher education strategy and pedagogical approach around the globe. OBE focuses on organizing teaching and assessment that help students achieve specified outcomes or goals [1]. Many countries have adopted the OBE approach in their higher education structures and initiatives along with additional unique goals. In Malaysia, OBE in higher education is oriented towards the development of holistic graduates and readiness towards the working sector. To achieve this goal, an initiative and instrument namely Integrated Cumulative Grade Point (iCGPA) were introduced to Malaysian higher education institutions [2]. iCGPA helps the institutions in determining the graduate's achievement based on the program learning outcomes (PLO) set by the faculty.

The instrument also eases the recording of graduates' ability and values attainment throughout the study program duration. The recorded data is then visualized in the form of a radar map, indicating the graduate's improvement in terms of abilities and acquisition of values. However, graduate abilities and values attainments are also attainable via extracurricular activities with less dependency to the provided curriculum. Analyzing the curriculum results with extracurricular activities could provide enriched understandings towards assessing the student performance.

Despite these potentials, merging curriculum results with extracurricular activities in an analysis can cause information overload. In addition, the current radar map representation of iCGPA restricts data exploration despite its capability in visualizing multivariate information. Visual analytics is a data exploration method supported by interactive visualization [3], allowing the analyst to pursue new inquiry throughout the exploration [4]. The main motivation of this study is to facilitate education analysts in performing predictive analysis on OBE learning activities and performance. Prior studies on educational visual analytics were observed to primarily focus on visualization tool creation and system features [5], [6]. Furthermore, this study found limited visualization work that discusses OBE-specific domain users, analysis tasks, and visualization design.

This paper reports our empirical investigation on the visualization design for supporting OBE knowledge generation with regard to design requirements, development, and evaluation. To address the gap, this study proposes a predictive visual analytic namely OBEInsights that enables education analysts and practitioners to perform predictive OBE assessment. This study firstly explores the design requirements and analytic practices by interviewing 5 domain experts in a domain characterization case study. A design framework is conceptualized based on the identified requirements and analysis tasks from the case study. Next, the visual analytic OBEInsights was designed and developed with design consideration guidance of the framework. Subsequently, this study evaluated and demonstrated the effectiveness of OBEInsights in usability testing with 10 domain experts. The major contributions of this paper are as follows:

1) A novel visual analytics design framework for supporting OBE knowledge generation.
2) A visualization system namely OBEInsights for facilitating OBE predictive learning analysis.
3) Empirical evaluation report to demonstrate the effectiveness of OBEInsights in supporting knowledge generation.

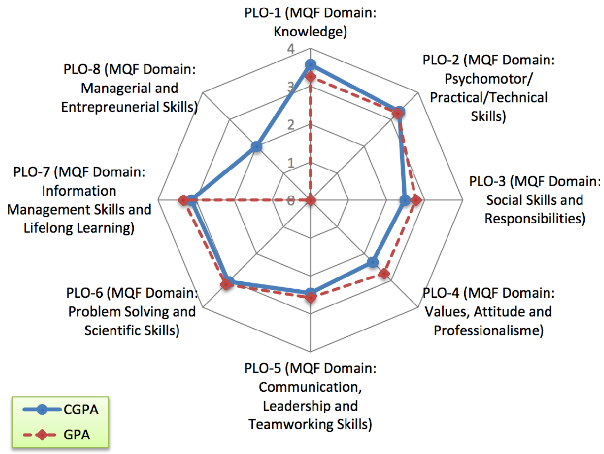

Fig. 1. iCGPA's Radar Map of Student's Achievement based on Specified LOD.

The remaining content of this paper is organized as follows. Section 2 introduces the fundamentals of OBE predictive analysis and visual analytics. Next, Section 3 describes the methodology in deriving the design framework, visualization system development, and design evaluation. Section 4 then presents and discusses the results of empirical design evaluation in a user case study. Finally, the conclusions and future work are presented in Section 5.

II. BACKGROUND

This section introduces the background of this study by summarizing the underlying principles and fundamentals of outcome-based education (OBE), predictive analytics, and visual learning analytics. The adoption of OBE in modern higher education calls for efforts in developing new analytics to support OBE-oriented analysis.

A. Outcome-Based Education and Predictive Analytics

Outcome-based education (OBE) is an educational approach or pedagogical perspective that emphasizes curriculum choices based on student performance [7]. Apart from the core approach, OBE implementations in many countries can be different with additional goals or structures. OBE implementation in Malaysia's higher education is oriented towards producing graduates equipped with relevant expertise, morals, and social skills.

Malaysia practices top-down approach for organizational management and decision-making process [8], [9]. To standardize OBE in Malaysian higher education institutions, the Malaysian Qualifications Agency (MQA) has set 8 specific Learning Outcome Domains (LOD). In 2015, the Malaysian Ministry of Higher Education introduces the Integrated Cumulative Grade Point Average (iCGPA), an evaluation instrument for Malaysian OBE [2]. iCGPA records and reports on the students' holistic attainment throughout the study duration as per specifications of LOD set by the MQA. Currently, iCGPA report of students' holistic achievement throughout each semester is visualized as a radar map as shown in Fig. 1.

Education analysts can analyze the OBE datasets like iCGPA by using predictive modeling to identify future patterns and trends [10]. Parameters like the students' knowledge levels, performance, scores, or marks are commonly analyzed and assessed in higher education [11]. Predictive models are applied against the dataset to automatically learn and generate predictions based on recorded historical data. However, there are limited advances in OBE evaluation platforms and tools, particularly in integrating student learning performance with extracurricular activities. In addition, there is limited work that clearly describes the OBE analytic practices and users specifically in Malaysia.

B. Visual Learning Analytics

Visual analytics combines the prowess of automated analysis with interactive visualization, allowing the user to gain efficient understanding, reasoning, and decision-making on large and complex datasets [12]. Applied into the education domain, visual learning analytics is defined as the use of computational tools and methods for understanding educational phenomena via interactive visualization [6]. Educators leverage visual analytics to understand or measure students' progress for diagnostic pedagogical decision-making in real-time [13].

Literature indicates many advances of visual analytics approaches in the educational context especially in enhancing learning analytics and decision-support tools [6]. In addition, prior work also explores the educational analytic practices via design study to characterize analysis scenarios, target users, and viable visualization. Several design studies have investigated visualization design for different focus like online classroom [14], [15] and massive open online courses (MOOC) [16], [17], [18]. Prior work also reported that the visual form of graphs, maps, and dashboards have greater potential to generate effective visualization especially for performance assessment [19].

Despite many advances in visual learning analytics, there are limited discussions for facilitating knowledge generation of specific learning pedagogy like OBE. Therefore, this study was carried out to investigate and offer insights in constructing predictive visual analytics for OBE assessment. This study then designed and developed OBEInsights, a visual analytics system for supporting OBE assessment as described in the following section.

III. VISUAL ANALYTICS SYSTEM: OBEINSIGHTS

This section presents OBEInsights, a visual analytics system to support education analysts in performing OBE predictive analysis. Detailed descriptions of requirement analysis leading towards the conceptualization of its design framework are also presented. Furthermore, the specifications and features of OBEInsights including data sources, automated data analysis, and visualization are explained.

A. Domain Characterization and Design Framework

To identify the visualization design requirements for facilitating OBE analysis, this study adopted part of the design study methodology [20], specifically the problem characterization. Related to requirements analysis in software engineering [21], problem characterization serves as a discovery stage in understanding domain-specific analysis tasks. Understanding the domain analysis helps the designer to translate and fit it

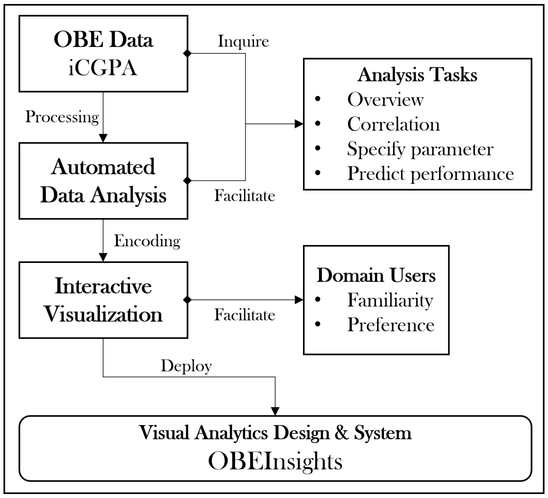

Fig. 2. Visual Analytics Design Framework for Supporting OBE Predictive Analysis.

TABLE I. BACKGROUND OF DOMAIN EXPERTS

Expert	Qualification	Teach Experience	Expertise Area
Exp1	PhD	30 years	Natural Science
Exp2	PhD	20 years	Tourism, Entrepreneurship
Exp3	PhD	30 years	Higher Education
Exp4	PhD	35 years	Engineering
Exp5	PhD	20 years	Accounting

into generic visualization language and create actionable visual metaphors. 5 domain experts from the higher education field with different expertise but have considerable proficiency and experience in OBE were interviewed as described in Table I. A semi-structured interview was carried out with the aim to learn and discover OBE-specific analysis tasks and nature from the experts. The interview helps the study to understand these major requirements: domain analytic practices, domain user's visualization knowledge, and domain user's analysis interests.

Based on the identified requirements, a visual analytics design framework was conceptualized for facilitating OBE predictive assessment as shown in Fig. 2. The purpose of this framework is to guide visualization designers in translating domain analysis tasks and considering appropriate visualization to facilitate OBE analysis. Referring to the visual analytics model [22], this study mapped the visual analytics components for the context of predictive OBE assessment. The interview results reveal interesting insights on OBE analytic practices in Malaysia, specifically in pedagogical decision-making and analysis interests. The experts explained the major factors that need to be considered in determining the faculty's program learning outcomes: curriculum revisit, external feedback, and standard compliance. Based on the interview, 3 major analysis tasks in OBE predictive analysis were identified:

1) Overview on student curriculum results and activities.
2) Correlation between student performance and extracurricular activities.
3) Prediction on student progression and achievement based on activities.

In terms of domain users, the experts stated that most education analysts and practitioners possess limited knowledge and familiarity with visualization. Therefore, the factors of familiarity and preference need to be considered in generating appropriate visualization. The presented framework is a refined iteration of prior work [23], added with additional focus on design development. Driven by the identified requirements and factors, a visual analytics system was designed and developed for facilitating OBE predictive analysis. The following subsection presents detailed descriptions of the visual analytics system including specifications and development process.

TABLE II. INTEGRATED RELEVANT ATTRIBUTES IN ICGPA DATASET

Attribute	Remarks
`student_id`	Identifier for student information
`sem`	Identifier for semester sessions
`igpa`	Grade point average
`icgpa`	Cumulative grade point average
`po_value`	Program learning outcomes (PLO)
`po_this_sem_course`	PLO per semester
`po_igpa`	Student PLO achievement per semester
`po_courses`	No. of courses contribute to PLO
`po_grade_pointer`	Grade point obtained per PLO
`po_achievement`	Achievement distribution

B. Visual Analytics Design and Development

Guided by the conceptualized framework, this study designed and built OBEInsights, a predictive visual analytic system for supporting OBE assessment. The system was built with specifications and considerations as follows.

Data Sources: In this study, two different OBE datasets generated by iCGPA consisting of the 'Accounting' program of our institution that contains students' PLO information were used. These datasets were selected after thorough consideration of easier access and its uniformity with many OBE datasets. The dataset consists of students' PLO results and extracurricular activities in each semester. The datasets were prepared for automated analysis by integrating key relevant attributes as shown in Table II.

Automated Data Analysis: Based on identified analysis requirements, this study designed the automated data analysis particularly for facilitating student achievement prediction. Literature recommends the following algorithms for modeling prediction due to model flexibility and customizable parameters: random forest, gradient boosting, neural network, and support vector machines [24], [25]. An experiment was conducted upon these algorithms in terms of lower and upper intervals to determine the most precise predictive modeling for OBE assessment. Before the experiment, the variable correlation within the dataset was firstly identified by using best subset classification. The classification result shows that `igpa`, `icpga`, `po_igpa`, `po_value`, and `sem` to be the impacting variables on the prediction modeling. Furthermore, the classification result indicates linear dependency towards `po_grade_pointer` that could lead to poor accuracy measures. Next, the prediction accuracy of the trained models was measured in an experiment with additional validation by using misclassification error. The results of the prediction models' performance are shown in Table III.

The experiment result shows that the random forest algorithm to be the best model for predicting student achievement.

TABLE III. Lower and Upper Intervals of Prediction Accuracy

Algorithms	Accuracy (Low)	Accuracy (High)
Random Forest	91.0%	94.9%
Gradient Boosting	88.2%	93.0%
Neural Network	45.2%	53.2%
Support Vector Machines	46.4%	54.4%

This study infers that the lower performance by neural network and support vector machine is due to sharpened model flexibility that overfits prediction. Moreover, random forest and gradient boosting use sequential model training, simulating and refining decision tree based on prior accuracy. Therefore, the random forest prediction technique was incorporated into our automated data analysis design for OBE prediction assessment.

Interactive Visualization: With the constructed automated data analysis component, this study needs to assess the appropriate visualizations and interfaces to display it. Upon deliberate consideration of the critical factors of user familiarity and preference, simple visual metaphors and layouts are selected. The visual analytics is then deployed in a form of simple dashboard front-end integrated with predictive modeling back-end. The front-end was developed using HTML, CSS, and Javascript, while the back-end was developed using Phyton. OBEInsights incorporates the existing radar map iCGPA to ensure continuous familiarity towards further OBE prediction analysis. The interfaces of OBEInsights are as shown in Fig. 3.

The user can select students to observe from the student list on the left sidebar, and the main window updates the visualization as per students' information. The main window can be scrolled down to show more analysis items like student activities in Fig. 4 and the prediction panel in Fig. 5. The user can access 'Predict & Analyze' tab to open the prediction assessment panel for specific program outcomes (PO). User can customize the parameters like student achievements or extracurricular activities, and the predictive model generates results. The prediction result for the selected PO then can be interpreted based on achievement distribution categories.

IV. Design Evaluation with Domain Experts

This section presents and discusses the design evaluation of our OBEInsights visual analytics system. This study demonstrates and evaluates the effectiveness of OBEInsights

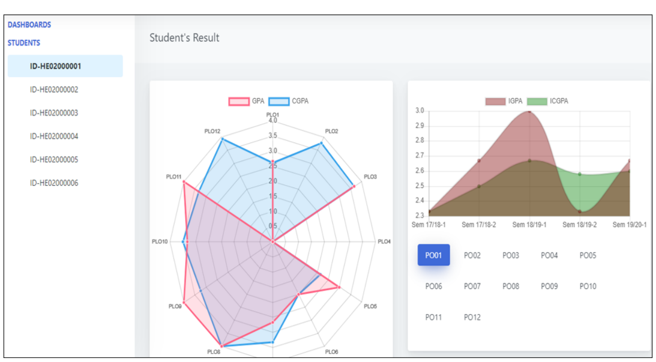

Fig. 3. Overview Layout of OBEInsights.

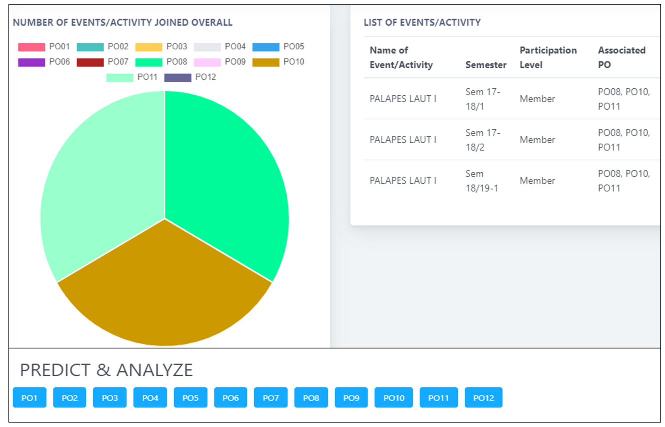

Fig. 4. Student Activities and Achievements from Extracurricular Activities.

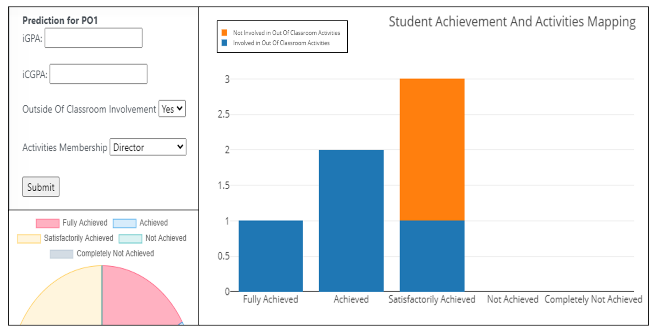

Fig. 5. Prediction Assessment Panel for Student Achievement and Activities.

in visualization system usability testing with domain experts. Subsequently, this section discusses the significant findings from usability testing in terms of effective visualization, modeling, and knowledge generation.

A. *Case Study with Domain Experts*

To evaluate and demonstrate the effectiveness of the system, this study conducted a usability testing with the domain experts. This test specifically measures OBEInsights' usability effectiveness in visualizing OBE predictive assessment. 10 domain experts from the higher education field with great proficiency and expertise in OBE participated in the test. The test was performed in an observation session with each expert for approximately 1 hour. The session starts with a brief introduction of the features of OBEInsights with an allocated 15 minutes for the experts to use the system.

After the introduction, the test began with inquiring the experts to perform several OBE analyses tasks as followings.

1) Display the overall performance of a student.

TABLE IV. SUS Score Interpretation

SUS	Grade	Adjective
>80.3	A	Excellent
68 - 80.3	B	Good
68	C	Okay
51 - 68	D	Poor
<51	F	Awful

TABLE V. USABILITY SCALE RATING OF OBEINSIGHTS

Usability Scale	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
I will use this system frequently.	5	3	5	4	3	5	3	4	4	5
The system is unnecessarily complex.	2	2	1	2	2	3	1	1	1	2
The system is easy to use.	4	4	5	4	4	4	4	3	4	4
I will need technical support to use this system.	2	2	1	2	2	3	2	2	2	1
The system functions are well integrated.	4	3	4	4	4	3	4	3	4	3
The system has too many inconsistencies.	3	3	2	3	3	2	2	2	3	1
I can learn to use the system quickly.	4	4	5	4	3	4	4	5	3	4
The system is cumbersome to use.	2	1	1	2	2	1	2	1	3	2
I feel confident in using the system.	4	4	4	4	4	4	4	4	3	4
I need to learn many things to use the system.	2	2	1	2	5	3	4	2	1	1
Total Scale (x/50)	32	29	29	31	32	32	30	27	28	27
SUS Score (%)	**75**	**70**	**75**	**72.5**	**70**	**75**	**70**	**77.5**	**70**	**82.5**

TABLE VI. VISUALIZATION SCALE RATING OF OBEINSIGHTS

Visualization Scale	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Featured visualizations offers different perspectives.	4	4	5	5	5	5	4	4	4	4
Interactivity features helps my ability in data exploration.	4	3	4	4	4	5	4	4	5	3
Visualizations displays OBE performance data effectively.	5	4	4	5	5	4	4	3	5	4
Featured visualizations allows me to discover new patterns.	4	4	5	4	5	3	4	5	4	5
Visualizations enables me to explore and discover insights.	4	5	4	3	5	4	4	5	3	5
Total Scale (x/25)	21	20	22	21	24	21	20	21	21	21
SUS Score (%)	**84**	**80**	**88**	**84**	**96**	**84**	**80**	**84**	**84**	**84**

2) Find the relationship between the student's PLO achievement and extracurricular activities.
3) Review a student's iCGPA progression for specific PLO over the study duration
4) Predict a student's future performance for specific PLO with customized parameters for extracurricular activities, position, iGPA and iCGPA.

The purpose of inquiring about these tasks is to allow the users to practically utilize the featured interactive visualization to perform major OBE analysis. Furthermore, the effectiveness and limitation of OBEInsights in facilitating the analysis from the direct perspective of the domain user can be observed. Upon completing the tasks, the experts were then asked to answer two sets of questionnaires that were designed based on the system usability scale (SUS) [26]. The resulting scores can be interpreted based on rating as shown in Table IV. The questionnaires inquire the experts' perception towards the usability and visualization of OBEInsights by scale rating. The results of the usability testing are shown in Table V and Table VI.

B. Discussion

Based on the presented results, this study further discusses and reflects on the significant findings from the conducted design evaluation. This study found several visualization design insights that can be explored in three spectrums: visualization, predictive modeling, and knowledge generation as discussed as follows.

1) Effective Visualization Design for Student's Holistic Development: Referring to earlier domain characterization, this study identified three major analyses in OBE assessment: (1) Overview of student results and activities, (2) Student's PLO results over the semesters, and (3) Relativity of student extracurricular activities with performance. The domain characterization helps specify the analysis interests and practices from OBE analyst and practitioners to identify crucial design requirements. The factors of visualization familiarity and preferences plays a role in enhancing the learnability of the system [27]. The evaluation result in Table V and Table VI indicates that the featured interaction and visualization encodings applied into OBEInsights are effective in facilitating OBE predictive analysis. With average SUS score of 84.8%, the experts' rating demonstrates and validates the effectiveness of the design in visualizing OBE predictive assessment. The inclusion of visualization literacy into the design consideration greatly affects the perceived effectiveness of presented visualization to the users [28]. Despite the positive results, the implemented design only employs basic visualization that can be limited when visualizing advanced or complex analysis scenario. This study are interested to explore the implementation of advanced visualization into OBEInsights to facilitate complex OBE analysis. Furthermore, we intend to reiterate and refine the current design especially on main interfaces and deployment by incorporating user experience design.

2) Modeling Accuracy on Predicting Student's Performance: Based on the earlier accuracy experiment, we learn that the 'Random Forest' algorithm yields the highest accuracy rate on low-prediction (91%) and high-prediction (94%) for OBE prediction assessment. The prediction results were also validated with misclassification errors. Our findings correlate with other studies that also found 'Random Forest' and 'Gradient Boosting' to produce accurate prediction results. However, the predictive algorithms that were investigated in this study were typical in handling structured datasets. Future research can investigate further on predictive machine learning algorithms with regards to flexibility in handling unstructured datasets. Despite the positive accuracy result, our study has not included human-user confidence in its design consideration and evaluation. Further investigation on human-user confidence towards the automated OBE analysis output helps curate the prediction reliability. In addition, the datasets used in this study only pertain information limited to one study program and limited extracurricular activity variables. Analyzing many different OBE datasets from other institutions using the visual analytics system may yield different results or reveal interesting insights.

3) Framework Supports on Knowledge Generation: OBEInsights was built based on deliberate guided consideration towards many factors in the conceptualized design framework in Fig. 1. Inspired by the visualization mantra "Overview, zoom and filter, then details-on-demand" [29], the framework was designed to support analysis tasks in each step in the top-down decision-making process [30]. Starting from raw data, the domain user first overviews the entire OBE information from the dataset with no specific analysis subject. Next, the user specifies their analysis by selecting subjects and parameters for the automated data analysis to process. The automated analysis design needs to facilitate the user's potential OBE analysis interest throughout their data exploration. Finally, the generated output needs to be encoded into appropriate visualization and interaction features to be displayed to the user. Currently, OBEInsights facilitate knowledge generation in a linear way, having the user select or customize specific analysis subjects and parameters. We intend to reiterate the design framework to support multifaceted analysis that allows for the inclusion of multiple subjects and parameters. Enabling multifaceted analysis could enrich the knowledge generation on pedagogical consideration for attaining learning outcomes. The presented design framework and system only cover the OBE assessment scenario that involves standardized parameters and specific stylized pedagogical decision-making in Malaysia. Other researchers can pursue further investigation on designing visual analytics for many different OBE analyses with regards to unique geographical contexts or variants.

V. Conclusion and Future Work

This paper has presented the empirical investigation in designing visual analytics for supporting OBE predictive assessment on learning activities and performance. The findings from this study offer insight into visual analytics design development for OBE analysis particularly in automated prediction and interactive visualization. This paper also presented the predictive visual analytics system namely OBEInsights along with elaborate descriptions of its design conceptualization and development. The effectiveness of OBEInsights is demonstrated and validated via a design evaluation study with domain experts. Design evaluation results indicate the system's effectiveness in facilitating OBE predictive assessment with great usability rating. Moreover, this study also learns the impact of crucial factors like visualization familiarity and preference towards the system usability. For constructing automated analysis components, several recommended algorithms were experimented with to determine the best predictive modeling for OBE assessment. The experiment result reveals the Random Forest model as the highest performing technique for OBE predictive modeling. In terms of supporting knowledge generation, a visual analytics design framework was conceptualized to guide visualization development for OBE assessment. The design evaluation results also demonstrated the framework capability via the deployed OBEInsights in supporting major OBE analysis tasks. The scope of this study is limited to OBE predictive assessment with specific parameters and pedagogical decision-making. This study recommends further investigation on visualizing many advanced OBE analysis that handles different context, variables, or users. Future research can also explore the potential of incorporating human-confidence design and unstructured handling capabilities. In our future works, we intend to reiterate the design and explore its performance against many different datasets that possess different structures and complexity. Furthermore, this study intends to enable multifaceted analyses to augment the knowledge generation process for OBE predictive assessment.

Acknowledgment

This work is supported by the Ministry of Education Malaysia under the research grant FRG0499-2018.

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