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Knowledge Visualization of Internet Usage Pattern to Improve Students' Academic Performance Using Prescriptive Analytic

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ABSTRACT

The knowledge discovery from graphical graphs could be challenging. Most of the time, the visual analysis cannot be done solely based on naked eyes interpretation. Therefore, knowledge visualization is vital to assist the process, especially in business intelligence and analytics to improve data insights and cognitive abilities. To effectively facilitate knowledge discovery from visual graphs, different analytical techniques should be explored in analyzing and visualizing the datasets. This study proposes an intelligent system to discover hidden knowledge from educational data by using interactive visualization and prescriptive analytic techniques. It focuses on model processing, as well as the development of an intelligent system to improve students' academic performance. The method adapted Design Research, comprising of four stages which are 1) problem definition, 2) suggestion, 3) development, and 4) evaluation. Additionally, three stages of data analytics were applied in the development stages, namely 1) descriptive-analytic on Internet usage pattern and students' academic performance, 2) predictive analytic of students' academic performance based on Internet usage pattern, and 3) prescriptive analytic to recommend the suitable action to improve students' academic performance. All these techniques involve data visualization by using the Microsoft Power BI tool. This approach is tested using a real dataset from Higher Learning Institutions, collected from 2017 to 2019. As a result, this leads to the desired knowledge visualization that facilitates the decision-making related to student performance enhancement. Theoretically, this study contributes to enhance the visualization and interpretation of data by using cognitive and reasoning components in prescriptive analytic. Besides, the proposed model enables decision maker in educational domain to make meaningful decisions regarding Internet usage management.

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1. Introduction

Good decision-making is one of the principal building blocks of success. In line with the rapid pace of technological advancement, this procedure has become even more critical nowadays [1,2]. In the current of boundaryless world era, any slight mistake in decision-making would lead to extreme criticism, profit loss, or even fatality in certain cases [3]. The same consequences are also applied in educational institutions, thus, calling for the improvement on the efficiency and effectiveness of the decision-making process [1,4]. Accordingly, the visualized information is certainly important, regardless of a high or low-level decision-maker in conveying ideas effectively. With the growing volumes of educational data, the interpretation complexity also increases [5-7]. However, a systematic representation could facilitate the transition from complex raw data into a logical stage whereby all facts, findings, and patterns become more understandable [8].

Universities are working in a very dynamic and powerfully viable environment. These institutions gather large volumes of data regarding their students in electronic form [9,10]. However, without proper data utilization, they are considered as data-rich but information poor, which could result in unreliable decision making [11,12]. The transformation of large data volumes into knowledge could be challenging. It is nonetheless a crucial part of a reliable managerial decision process [13]. At present, there are abundance studies regarding the prediction of student performance [14-21]. Several approaches, techniques, and factors concerning data mining have been highlighted by prior studies in coming up with proper predictions. However, only a few prescribe recommendations and give a better solution following the prediction analysis, especially based on student performance and internet usage patterns. Therefore, further studies are urgently needed to establish a greater degree of accuracy on this matter.

Although data analysis is considered as a complex task that is traditionally carried out by data engineers, it is currently becoming more performable by laymen within organizations [22,23]. Thanks to the current high-end data analysis tools that are now more friendly and easy to use. One of those is Power BI, an exceptional tool that pulls actionable insights instantly from data [24,25]. It also allows users to analyze, build, and visualize data metrics. These will positively facilitate the data insights at a high level and drill them down into actionable formats. Unfortunately, most of the existing studies utilized the power BI for predicting data patterns, instead of prescriptive analytics [26,27].

Therefore, the study aims to develop an intelligent model by embedding the prescriptive analytics that could recommend viable solutions in improving students' performance based on their Internet usage patterns. Next, a Prescriptive Knowledge Visualization System (PKVS) will be developed using the Power BI tools. For this purpose, the required dataset was collected from Higher Learning Institutions (HLI) that contains students' log files containing their Internet usage activities, while the academic affair department has the student profiles and academic performance. This includes their name, matric number, gender, nationality, current semester and Cumulative Grade Point Average (CGPA). The students' CGPA was used as measurement for academic performance, while the other attributes were employed in predictive analytics.

The proposed intelligent system will predict students' CGPA based on their Internet usage patterns. In other words, it will address the impact of students' Internet usage on their academic achievement. In light of this, the main goal of this system is to produce the solution and recommendation based on prediction results by using prescriptive analytics. As a result, it is expected that the system could be used to monitor students' academic performance, alert the decision-makers on the students' current achievements, and propose appropriate remedial actions in the subsequent semester.

2. Methodology

This study adapted the Design Research by Hevner *et al.,* [28] to acquire the objectives for Prescriptive Knowledge Visualization System (PKVS) prototype development. This method is suitable to design a model and prototype, which is an expected outcome of this study. Furthermore, it is a popular method in various fields, such as Human-Computer Interaction (HCI), Information Systems (IS), educational research and Instructional Design [29-34]. There are four phases in the design research, which are 1) definition of the problem, 2) suggestion, 3) development, and 4) evaluation. Figure 1 depicts the activities conducted in this study.

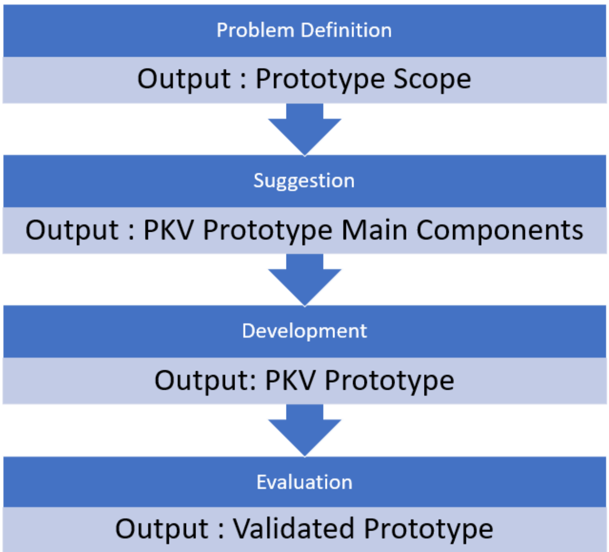

Fig. 1. Design Research (Adapted by Hevner, 2004)

2.1 Problem Definition

This stage aims to identify the domain's requirements and achieve a goal-oriented design. Domain analysis is the process of understanding the domain where the knowledge visualization will be applied. It encompasses the explicit knowledge needed to support the decision-making process in the domain work activities [35,36].

2.2 Suggestion

At this stage, the focus is to complete the description of the prototype to be developed, which includes the discussion regarding the functional and non-functional requirements. The functional requirements typically consist of the purpose, scope, user characteristics, interface, and database. On the other hand, the non-functional requirements refer to the criteria, constraint, limitation, and software performance.

The gathered information from the requirement analysis will be evaluated and an alternative solution will then formulate. This signifies the process of planning and problem solving for a software solution. It deals with choosing the appropriate algorithm design, software architecture design, database conceptual schema, logical diagram design, and data structure definition.

In prototype development, three stages analytic were suggested to applied in this study to achieve the level of intelligent system. The first stage, descriptive analytic, determined the present state of the event by gathering and analyzing the parameters related to its root causes. This stage is crucial to detect patterns of potential problems or future opportunities of the root causes.

Furthermore, predictive analytic represents the next stage that aims to predict whether an event will happen, when it is about to happen, and why it will happen. This stage is closely related to the implemented decisions and actions. As in the case of human decisions, it is very much dependent on their knowledge and experience.

Full exploitation of predictive analytic can be achieved in conjunction with prescriptive analytic for optimized decision making. Prescriptive analytic generates proactive decisions on the basis of the predictive analytic outcomes. This third stage of analytic aims at suggesting (prescribing) the best decision options in order to take advantage of the predicted future utilizing large amounts of data [23]. To do this, it incorporates the predictive output and utilizes artificial intelligence, optimization algorithms and expert systems in a probabilistic context in order to provide adaptive, automated, constrained, time-dependent and optimal decisions. In prescriptive analytic, there are two levels of action, which are (i) decision support by providing recommendations and (ii) decision automation to implement the prescribed action [37].

2.3 Development

The objective of this phase is to actualize the conceptual PKVS from the previous phase. This requires the exploration and visualization of students' Internet data to support the IHL decision-making. To achieve this, four different stages are accomplished: (i) PKVS component development, (ii) core content development, (iii) PKVS features integration, and (iv) PKVS prototype presentation.

2.3.1 PKVS component development

The objective of this stage is to design a low-fidelity prototype, especially its visual interactive interface (front-end). This can be done with paper sketching. The PKVS content development deals with the process of developing content delivery techniques using suitable programming language frameworks. This must be done to support related perceptual, cognitive, and decision supports with respective theoretical considerations. Gathering and analyzing PKVS requirements have four main components namely, organization or business requirement, infrastructure requirements, data sources requirements and document requirement specification. Business/ organizations requirements, which include the project scope, business goals and objectives. In this study, the main aim is for contribution to improve students' performance in Institution of Higher Learning (IHL).

In infrastructure requirements for PKVS development consist of two main sections; the software requirements and the hardware requirements. Infrastructure is an extremely important component of a PKVS prototype as it provides the underlying foundation that enables the PKVS architecture to be implemented. It includes several elements such as hardware platforms and components such as memory, server, operating systems, database platforms, connectivity and networking. For data sources requirements, datasets are identified before the integration process begins. In this context of study, students' Internet browsing activities data who used Wi-Fi connection are collected and also students' CGPA as measurement to determine students' performance.

2.3.2 Core content development

The objective of this stage is to implement the software development technologies to bring the conceptualized design and low fidelity prototype into a real state. This stage involves the core technical aspect of PKVS development. At this stage, the system architecture for PKVS prototype is identified. Four different interdependent elements of system architecture involve to build the prototype. These are the user, PKVS interface, PKVS application and database. The users are primarily the IHL decision makers and the PKVS interface is the visual-exploratory and graphical user interface. For PKVS application is the data object mapping and binding application that matches the data to be visualized. In this study, Power BI application is used to deals with visualization. Lastly, the SQL server is used for database. It is proven that this database work well with Power BI tools.

2.3.3 PKVS features integration

The aim of this stage is to complete the prototyping process by bringing the PKVS characteristics into reality using the body structure and any element of visualization tools for creating data visualization. At this stage, the core element of KV features, overview, filter, demand details, and zooming, as listed earlier, was integrated to ensure the prototype works perfectly.

2.3.4 PKVS prototype presentation

The objective of this phase is to ensure that the prototype operates in order. This is done through system checking and debugging before presenting to end user. Lastly, the summative evaluation was conducted by the end-users based on their initial exposure to the prototype. Accordingly, the end-users of this prototype are the IHL decision-makers.

2.4 Evaluation

The objective of this stage is to receive feedback on the prototype's usability. The usability testing concentrates on the data representation, correctness, and usability issues of the PKVS prototype by using designed cognitive and decision-making tasks as a guide. The input from the heuristic was used to improve both the conceptual design model and the prototype.

In this study, the usability testing was conducted to evaluate the prototype. Usability testing is one of the important quality characteristics of software systems and products [38]. The usability testing was done through the experts' interaction with the prototype using their heuristic experience [39]. The experts for this testing consist of usability experts. The choice of the disparate field experts in constituting the usability testing is to achieve reliable findings. It is noteworthy that the PKVS functionality intersects between visualization and decision support. During the usability test, 11 respondents consist of 2 academicians and 9 practitioners with IT background have participated in usability testing of PKVS prototype.

2.4.1 Develop usability testing instrument

The instrument, consisting of open-ended questions, was used to evaluate the prototype in terms of data representation correctness, usability and decision making. The measurements were made through an instrument named Q-U, which comprises of five main dimensions, visibility, flexibility, learnability, application behavior, and real-time decision making as usability attributes. It was consisted of 27 questions, which are scaled by values from 1 to 5. Scale 1 equals to strongly disagree, scale 2 equals to disagree, scale 3 equals to neutral, scale 4 equals to agree and scale 5 equals to strongly agree. The overall Q-U instrument is finalizing and send to the respondents to answer all the questions after trying the PKVS prototype. This serves as a formative evaluation for the prototype. The open-ended questions were devised so that the usability of the prototype can be objectively assessed. Table 1 presents the dimensions and definitions of usability testing instruments adopted in this study.

Table 1
Usability Testing Instrument

Dimensions	Definitions
Visibility	Display of information and interface design of the system. The ability to accurately and completely view the processes, transactions and other activities operating via using PKVS prototype.
Flexibility	Customizable and user control of the system. It is the ability of software to change easily in response to different user and system requirements.
Learnability	Easy to learn. The ease with which a user can learn to operate, prepares inputs for, and interprets outputs of a system or component.
Application Behavior	Measuring the system behavior in terms of enhance user efficiency through a consistently rapid response rate.
Real-time Decision Making	System ability to deliver live data, relevant data, and real-time data to support decision making process [40].

3. Case Study

The student data used in this case study was obtained from Higher Learning Institutions. Data contains three categories of student, namely pre-degree, undergraduate, and postgraduate. However, only the data from undergraduate students are considered in this study. Students' Internet usage data are collected from HLI, containing their Internet access log files. The access log, which records all their Internet activities were filtered and categorized into the following fields: IP Address, Web Site URL, Date and Time, and bandwidth (in and out). This is done to determine how many students are using the Internet and how it affects their academic performance. The log files were divided into 11 categories based on Web 2.0. These influencing aspects are considered as input variables.

The different sections measured include student's demographics (matric number, name, gender, citizen, semester, level of study, and college). The student performance was measured using Cumulative Grade Point Average. Cumulative Grade Point Average (CGPA) refers to the average of Grade Points obtained for all semesters and courses completed up to a given academic term. This CGPA was collected from the Academic Affairs Department. The collected students' dataset is presented in Table 2.

Table 2
Students' Datasets

No	Category	Feature
1	Students' Academic Information	Matric Number
		Name
		Gender
		Citizen
		Semester
		Level of Study
		College
		Student Cumulative Grade Point Average (CGPA)
2	Students' Internet Usage	X1 = File System (FST)
		X2 = File Transfer (FTF)
		X3 = Downloading (DWN)
		X4 = Peer-to-Peer (P2P)
		X5 = Entertainment (ENT)
		X6 = Web Browsing (WBS)
		X7 = Social Media (SCM)
		X8 = Learning (LNG)
		X9 = Online Shopping (OSH)
		X10 = Online Gaming (OGM)
		X11 = Email (EML)

3.1 Process Model of Power BI

This section describes the design architecture implementing the PKVS prototype. Figure 2 lists the four major activities of visualizing and analyzing the PKVS prototype. Each activity is discussed in the proceeding subsection. The subsequent sections elaborate on each of the activities.

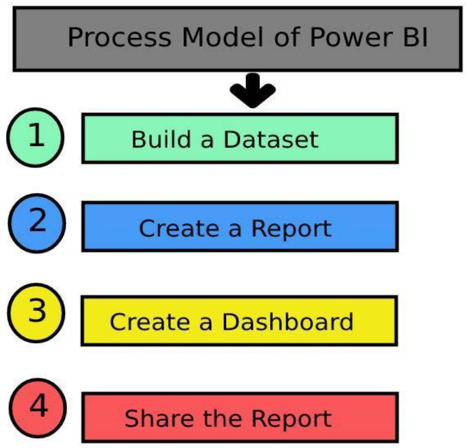

Fig. 2. The Process Model of Power BI

3.1.1 Building a data set with the input data

Data can easily be imported from Microsoft Excel and embedded in Power BI. The processing time depends on the file size. After the file has been imported, it can be transformed into a graphic format by using a visualization creation tool. In this activity, the data of students' Internet usage was mapped to their CGPA to see the relationship between the two variables. This step prepares the data to be fed to the excel format that will then be embedded in Power BI tools. The data is consolidated based on functions, attributes, features, and others. Figure 3 and Figure 4 illustrate the data in the excel format, which are embedded in Power BI with the code placed under the query form.

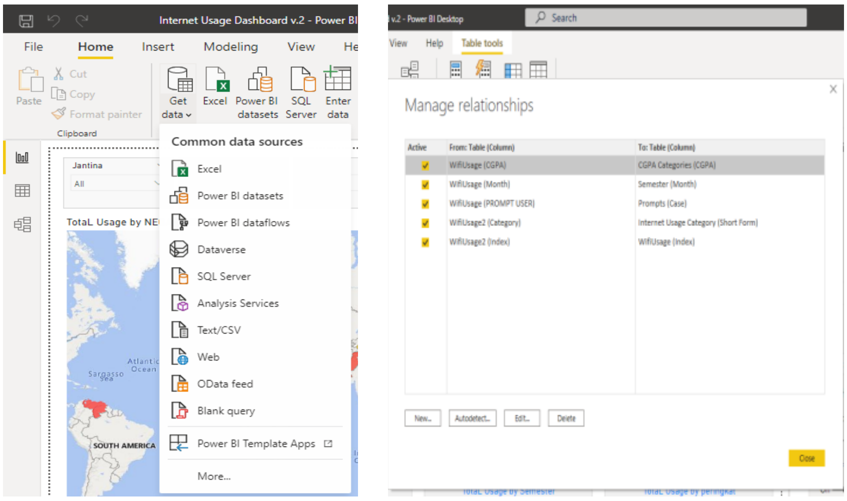

Fig. 3. Data from Microsoft Excel Embedded in Power BI

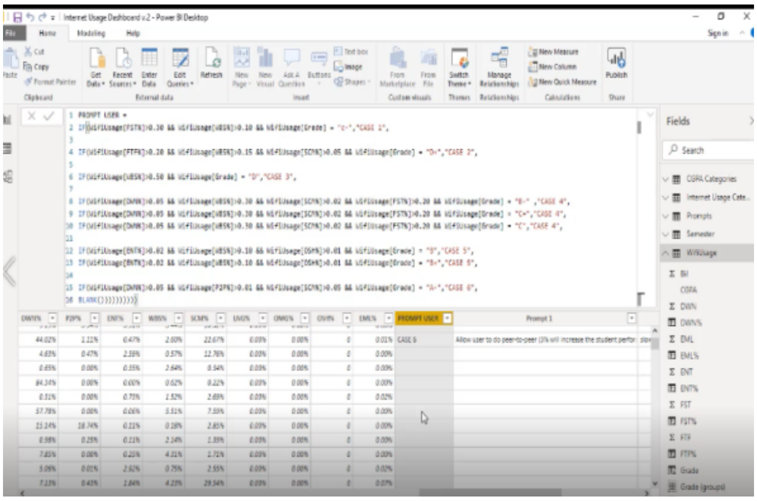

Fig. 4. Coding Form

3.1.2 Create report

Once a dataset is ready, reports can be created by adding a choice of multiple visualization elements. Visualization elements in Power BI range from showing a single number to a gradient-colored map. These visuals help to present data in a way that provides context and insights. Filters can be applied to the reports so that relevant data is surfaced for users interested in analyzing the data. Such reports can be created manually or by using the Quick Insights feature, which uses various algorithms to analyze the data and returns a report that is automatically generated.

3.1.3 Create dashboard

Once produced, the whole report or some of its elements can be included in the dashboard. A Power BI dashboard shows a 360-degree view of the data by enabling users to keep their most important metrics in one place. It also allows users to modify the report by filtering and querying the data or even allowing natural language queries. It is, however, limited to a single page, thereby surfacing only the relevant portions of the data to make it easy for users to draw insights. It is possible to constantly update the report and dashboard data in real-time and make it available on all devices, such as PCs and smartphones.

3.1.4 Share the report

Power BI enables various options to share reports and dashboards [41]. Once the report is ready, users can publish the results to a website or blog and share it with other users within the organization or groups with confidence that those sharing rules will be applied effectively.

4. Results and Discussion

This section provides the results and discuss the objectives of this study. The prototype was developed by using Power BI, a well-known tool that supports visualization as shown in Figure 5. After completing the development process, the prototype was transformed into web-based system. When the web-based version is accessed, the landing page will show the system. The best thing about this system is that it only consists of one page that contains the whole information about the results. The system applied two visualization techniques, which are Geo Chart (e.g., Map view) and motion chart (e.g., bar chart and pie chart).

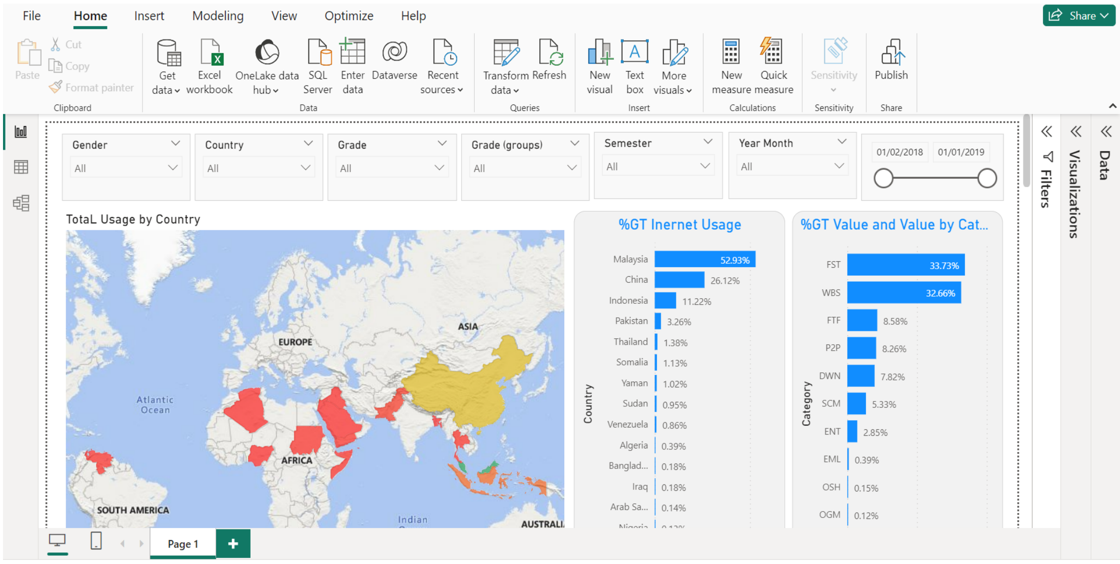

Fig. 5. PKVS User Interfaces

The Geo Chart is placed at the top of the system. The visualization embedded in the system enables the presentation of colorful content that can attract viewers. Users can click on the Geo Chart menu and the results will appear automatically. The Geo Chart gives a population distribution of the students’ Internet usage based on their nationalities. The graph of the Internet usage percentage is placed on the right side of the system. The system will automatically separate the Internet usage based on 11 categories.

4.1 Descriptive Analytic

The purpose of the descriptive analytic is to visualize raw data and facilitate users' interpretations. The raw data will be analyzed using the Knowledge Data Discovery (KDD) technique. The KDD process was conducted in four stages; data selection, data pre-processing, data transformation, and data interpretation. In this analysis, the pie and bar charts were used to envision the percentage of each category. Figure 6 depicts the example of the descriptive analysis visualization results.

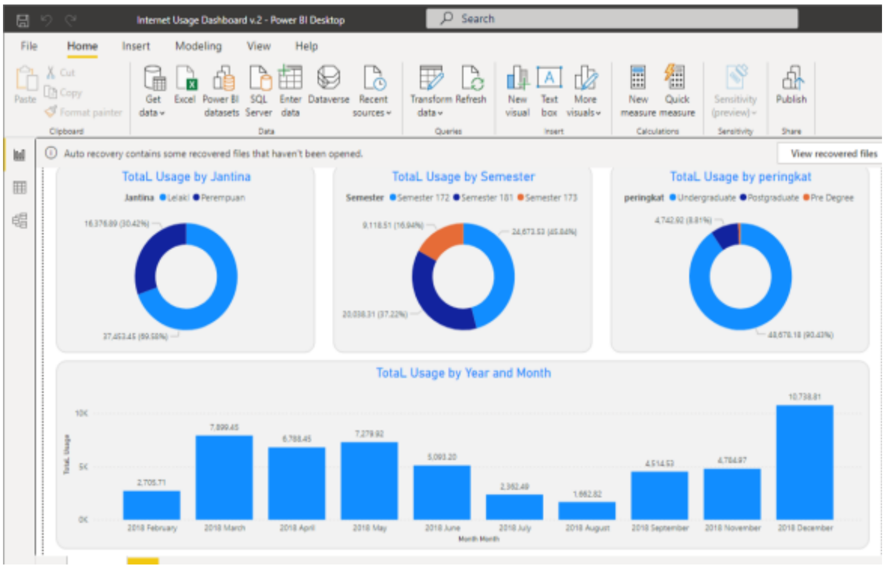

Fig. 6. Descriptive Results in PKVS Prototype

This section contains the pie charts to visualize the total usage per semester, based on gender and level of study. Finally, the bottom part of the dashboard displays a graph showing the total Internet usage by month and year.

4.2 Predictive Analytic

Three main Data Mining techniques: clustering, classification, and correlation, were performed to achieve the objective of predicting student performance. These techniques were also applied to examine the relationship between students' Internet usage and performance based on the CGPA. The relationship between these two variables is presented in the form of a graph. The system also mapped the relationship between the Internet usage pattern and CGPA.

From Figure 7 and Figure 8, the website list down the students' Internet category based on their browsing activities. By just clicking the graph, a user will know which category affects students' performance. The results automatically visualize through the process of predictive analytic.

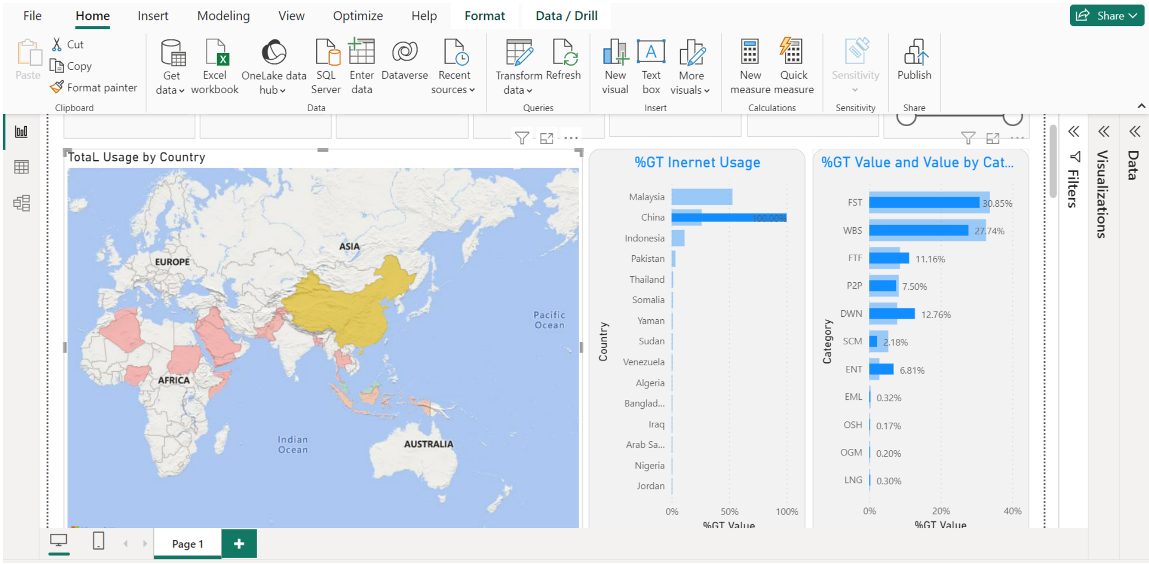

Fig. 7. Predictive Results in PKVS Prototype (Students' Internet Usage Category)

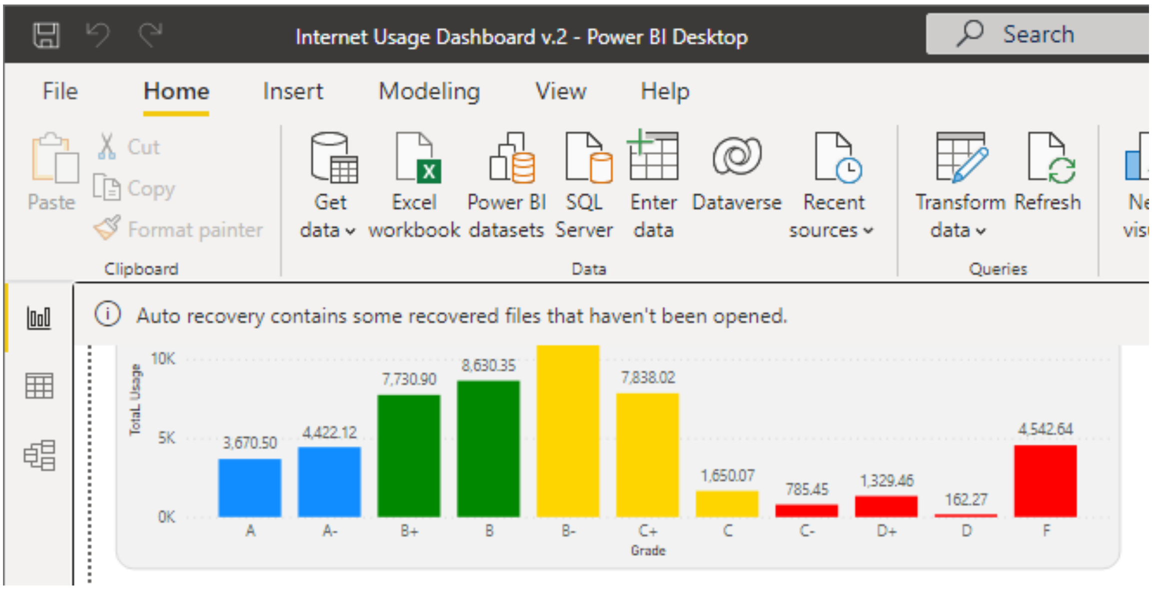

Fig. 8. Predictive Results in PKVS Prototype (Students' Performance)

4.3 Prescriptive Analytic

To achieve the objective of prescribing the recommendations based on students' Internet usage activities, prescriptive analysis was conducted by using the regression techniques. Each of the predictive models was evaluated using the R Square criteria, which represents the percentage that a model can explain about its output based on a training dataset. The higher the R-square value, the better is the model. In this study, the forecast model for the students' performance was tested and predicted against their Internet usage. Figure 9 visualizes the recommendation based on the predictive results.

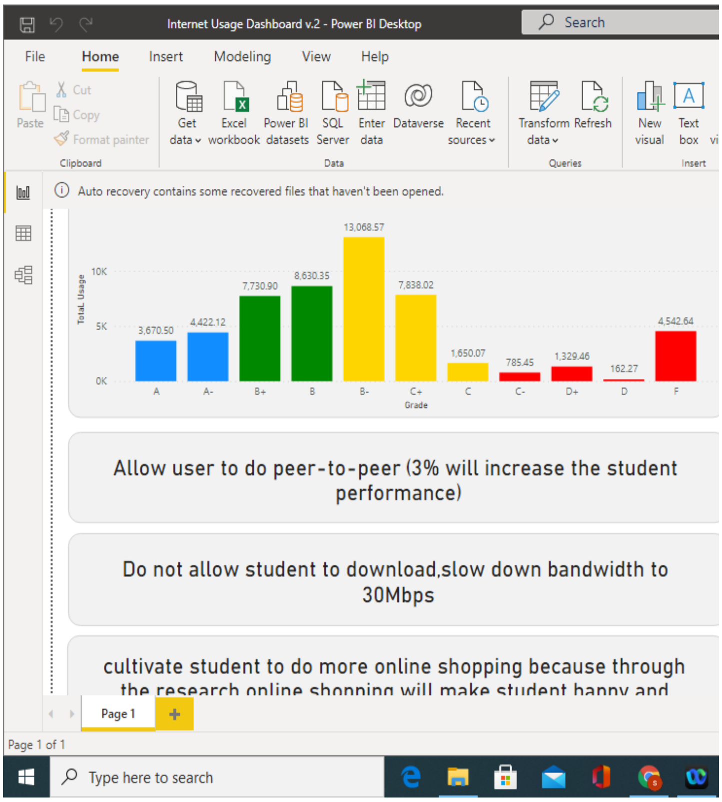

Fig. 9. Prescriptive Results in PKVS Prototype

From the Figure 9, the system tries to propose a solution and recommendation to the decision maker by giving three options to decide on improving students' performance. The system will list down the formulated proactive recommendations along with the weighted percentage to recommend to users (decision makers).

4.4 Usability Testing

The result of the questionnaire's reliability showed good internal consistency with Cronbach alpha, α = 0.60 for all the usability dimensions. The acceptable value for Cronbach alpha is between 0.6 to 0.7 as suggested by Hair Jr *et al.,* [42]. In this study, all dimensions in the questionnaire showed acceptable internal consistency with Cronbach alpha, α = 0.69. The overall result of the usability evaluation is presented in Table 3.

Table 3
Overall Usability Testing Results

Usability Dimensions	N	Mean, M (Percentage Score)	Std. Deviation
Visibility	11	4.43 (88.6%)	0.58
Flexibility	11	4.16 (83.2 %)	0.13
Learnability	11	4.52 (90.4%)	0.51
Application Behavior	11	4.58 (91.6%)	0.41
Real-Time Decision Making	11	4.53 (90.6%)	0.58

Calculating the average value for each dimension, the results showed that for each dimension the majority of respondents agree that the PKVS prototype provides data visibility, is flexible, easy to learn, behaves as expected, and allows real-time decision making. All the dimensions have a mean value of more than 68% and it indicates that the PKVS prototype is eligible to be implemented in the real world based on the accepted value in System Usability Scale [43].

From the results, the highest mean value is in application behavior with 91.6%. The respondents have a positive reaction about the PKVS prototype in terms of its ability to enhance user efficiency, consistency, effectiveness in completing user tasks, easy to find needed information, and capability to complete the task quickly. Therefore, it strengthens the conclusion that the prototype is applicable to be used in the real world.

Furthermore, all the respondents are strongly affirming that the PKVS prototype provides data on time to take suitable actions and decisions with a mean value of 90.6%. The respondents agreed with the statement for each measurement item, hence, affirm that the data provided by the PKVS prototype are always live data and up to date, which means PKVS proposed model and its prototype provides fully supported for real-time decision-making, and thereby strengthens the conclusion of this study.

Obviously, the findings show that research objective were successfully answered through the design model and the usability testing that have been evaluated in IHL environment. The objectives feedback from the participants suggested that the PKV prototype supports decision making activity. The prototype has ability and functionality that produce actionable insights thus support decision making process. Therefore, it showed that the conceptual model is usable in designing PKV prototype that supports visibility, flexibility, learnability, application behavior and real time decision making.

5. Conclusion

This study has successfully developed a Prescriptive Knowledge Visualization system (PKVS) using a Design Research method [28]. Data of students' Internet usage were classified into 11 categories based on Web 2.0 and later mapped with students' CGPA to see the correlation and the impact of Internet usage activities on their performance. The prescriptive analytic was applied to transform the predictive analytic results into meaningful action by recommending suitable action to the decision-maker. The system was develop using Power BI tools. A dataset consisting of HLI undergraduate students' Internet usage and CGPA from 2017 to 2019 was used to visualize and predict students' performance. Based on the results, the system will automatically produce the recommended solutions for the decision-makers by using the prescriptive analytic. This would facilitate them to make accurate decisions in improving students' academic performance. The system includes all the previous phases of data analytics and delivers not only insights into the future, but foremost presents a set of alternative actions or decisions that may significantly improve student performance [44]. This method has enabled users to view and perform complex decision-making processes within the native application.

In the end, a set of questionnaires has been used to validate the PKVS prototype. The results revealed positive feedbacks from the users on five dimensions in terms of visibility, flexibility, learnability, application behavior and real-time decision making of the PKVS prototype. It showed that the knowledge visualization tools and prescriptive techniques that are embedded in this intelligent system are certified and suitable techniques to support decision-making. The objectives of this study are achieved from the usability testing results. Feedback from the participants affirmed that the PKVS prototype supports decision-making activity. This is evidenced in decision-making results, with a high percentage (90.6%) that the prototype support decision making. The prototype has the ability and functionality that produce actionable insights thus support the decision-making process. The results were obtained, showing enough evidence to conclude that the proposed PKVS prototype is workable in the IHL environment as well as a guideline to improve students' academic performance.

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