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IMPLEMENTATION OF COGNITIVE VISUAL DATA ANALYTICS LEARNING SUPPORT: APPLYING MEANINGFUL RECEPTION LEARNING THEORY

Hairulliza Mohamad Judi¹, Zanaton H Iksan², Noraidah Sahari @Ashaari³

^{1,3}Fakulti Teknologi dan Sains Maklumat, Universiti Kebangsaan Malaysia, 43600 UKM Bangi,
¹hmj@ukm.edu.my, ³nsa@ukm.edu.my

²Fakulti Pendidikan, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, ²zanaton.iksan@ukm.edu.my

Abstract: The contribution of data analytics to scientific knowledge and better informed society is widely recognized but there are challenges in the traditional curriculum including the need to incorporate more meaningful computational and graphical tools and to train data analysts with agile problem solving skills. The opportunity of efficient instructional arrangement and student support method may help students with best possible information surroundings that they need. Cognitive visual support using various visual tools may help students with components that improve their communication with the lesson and enhance engagement in the action that would otherwise be outside their capacity. This research demonstrates cognitive visual support implementation in delivering data analytics topic on probability. This investigation utilizes meaningful reception learning method in the instructional arrangement to contribute learning support by perform worked-example data analytics knowledge construction and problem solutions using three useful elements: active, constructive and collaborative. The presentation may provide advisor with specific and entire references to expand an applicable task statement consistently in active data analytics learning.

Keywords: Knowledge structure; data analytics; decision making.

I. INTRODUCTION

Various new data sources emerged today that modify the ways that information is used to help policy makers, stake holders and society members making better decisions. The contribution of data analytics to scientific knowledge and better informed society is widely recognized. Data analytics aim to provide a clear description to numbers and figures to help decision makers in various fields that involve a process of examining, presenting and explaining data. Among the challenges in the traditional curriculum

include ensuring that the content meets the current needs [1]. Instructors are required to incorporate more meaningfully in the curriculum the computational and graphical tools and to train data analysts with agile problem solving skills [2]. Emphasize is given to practical and interactive integration so that analytical skills coincide with various fields such as computer science and data engineering [3].

Since complex cognitive processes involved in learning through problem solving, a dual mapping learning

environment is proposed to serve as a visual capacitor to enhance problem solving skills, improve knowledge construction processes together with the transformation between the two [4]. Considering that many data analytics students are engaged in rote learning, meaningful learning environment is needed to develop effective statistical reasoning and problem solving skills [5]. In meaningful learning, students make voluntary commitment to relate new concepts to prior knowledge, and be able to retain the knowledge to be applied in future study, daily dealings and incoming careers. Data visualization or visual data analysis is a technique for presenting data through illustrations aiming to identify trends, patterns, and contexts that are usually not easily captured in text form [6]. Visual data analysis emerged as one of the dominant technologies in higher education learning through technology integration [7]. Data visualization tools use charts and graphs by optimizing visual elements such as graphics and maps to enhance interactive capabilities to enable users to manipulate materials for learning and exploration[8].

Visual data analysis can be exploited to emphasize the relevance of concepts through concept maps. Concept map is one of the cognitive tools based on visual data analysis that has been widely implemented to help build student knowledge [9]. It demonstrates a meaningful relationship between the various concepts learned in a semantic unit[10]. The concept map was originally introduced by Novak in the 1980s as a cognitive tool and has evolved an evolutionary process to improve its function[11]. Concept maps are widely used as tools to facilitate the integration of knowledge in drawing, generating, and diffusing concepts and making knowledge relationships [12].

Although many studies have been conducted regarding the effectiveness of meaningful learning in the delivery of technical courses, the implementation of visual elements to improve understanding and problem solving skills in data analytics is not well documented [13]. Little is known about the experience and involvement of students in learning that applies visual data analysis[6]. After all, the implementation of visual data analysis in data analysis requires careful consideration of appropriate content and context to ensure a meaningful learning experience is achieved.

Therefore the researcher needs to deepen the elements in visual data analysis, to design appropriate strategies in meaningful learning. This study aims to demonstrate cognitive visual support implementation in delivering data analytics topic on probability. This research identifies important visual attributes that support the presentation of learning materials that are most readily acceptable, universal and widely known to enhance learning effectiveness. The scope of the study consider data analytics courses as widely used techniques of statistical analysis and learning outcomes focusing on statistical skills offered at higher education levels.

II. COGNITIVE VISUAL SUPPORT BASED ON MEANINGFUL RECEPTION THEORY

As an essential cognitive skill for meaning making in learning and education, modeling knowledge could be applied in the process in many different ways including organizing comprehension using concept mapping or semantic networking tool [14]. The use of cognitive visual tool supports the construction of mental models by integrating information into a progressively more complex conceptual framework.

Many learning issues dealing with presenting new concepts to students consider the application of concept mapping as powerful cognitive tools that could help learners remember information in visual format [15]. Cognitive visual support is accepted as an interactive tool to attract students' attention and to enhance concepts connection as it allows the separate encoding of information in memory in visual and well as non-visual form, or better known as dual coding [16]. Using cognitive visual support, students are encouraged in student-centered learning environment by providing scaffolding and guidance for a significant task[17].

Meaningful Reception Learning Theory proposes that students be supported with appropriate information to enhance learning [18]. This may include cognitive visual support such as concept maps to integrate main ideas with previously gained knowledge. In meaningful learning, students are able to unite new concepts to their prior knowledge in cognitive structure [18]. The most important element in teaching and learning process would be prior knowledge [19]. Students are also encourage to apply their understanding in daily practice [20].

Knowledge Subsumption Theory provides further description to Meaningful Reception Learning. Knowledge Subsumption Theory was also presented by David Ausubel, proposes a process of linking and combining new learning materials with established concepts in cognitive structure [21]. The incorporation of new elements with existing elements in cognitive structures contributes to the creation of a meaning. David Ausubel argued that learning was the process of discovering meaningful connections between new events and information with previous concepts in new neural network structure. Signs, symbols, concepts illustrations, or representations that are meaningfully associated with certain individual structures are clearly and substantially retained.

This relevance benefits learning including acquiring new meanings, higher retention rates, and stronger knowledge organizations.

In rote learning, concepts and elements are associated with cognitive structures without any rules and bases verbatim without any relationship establishment. On the other hand, the learning of tethering techniques ensures new material is tied to relevant and well-established entities in cognitive landscapes. This theory holds a new material into the mind of one's mind by adapting it to the larger and more inclusive conceptual system. Climbing action through the construction of new information links to a stable structure

triggers a meaning. In order to create a positive learning environment, creative methods including visual approaches are suggested to help students build relationships to link the concepts learned [22].

In order to build knowledge shutting down, several important steps need to be followed [23]. It starts with students identifying the relevant knowledge domain they are proficient. Furthermore, students identify key concepts in the domain, which are the most common and the most comprehensive. The most common concept (super ordinat) is placed above the affinity followed by a specific relevant concept or subordinate concept below it. New concepts associated with existing constructs often have relationships that can parse common meanings[24]. For example, an explanation of the probability calculation is explained by the relative frequency concept that describes the comparison of the value of an event.

An example of the use of knowledge propagation in probability topics, as in Figure 1, ensures that understanding of the probability count is pegged to a relevant and steady existing entity, i.e. an understanding of the frequency of events associated with the outcome of the experiment in the classic approach. Furthermore, the concept of probability calculation is reinforced in a stable structure through adaptation after training and consolidation. New concepts such as conditional probabilities enter the space of thought by associating them based on a comprehensive and inclusive conceptual system through meaningful relationships.

Important visual attributes that support the presentation of learning materials are identified to provide guidance on graphical features that are most readily acceptable, universal and widely known to enhance learning effectiveness [25]. The visuals are expected to be able to influence, stimulate curiosity and attract students to explore learning revealed in relevant images, info graphics, charts and matching characters. The visual framework for learning is intended to help designers organize learning materials to explain abstract ideas with clear structures [26]. There are six essential elements in the framework listed in Table 1.

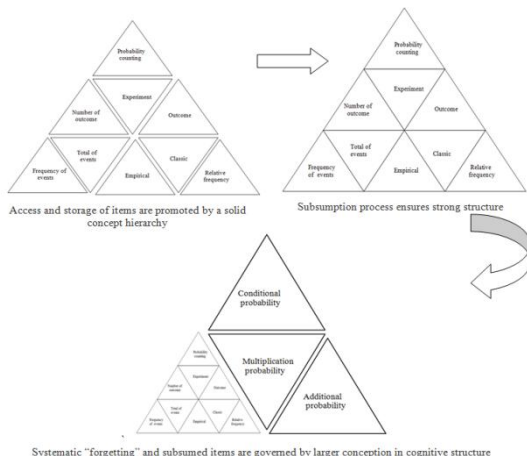


Figure 1: Knowledge Subsumption schematic

TABLE I: ELEMENTS IN COGNITIVE VISUAL FRAME

Element	Description
Concept label	Short term refers directly to the concept
Concept types and domains	Present the concept of either scientific or practical application or a combination of both, as well as areas commonly associated with concepts such as math (for scientific type) or operating management (for practical application types)
Concept definition	Describe the main idea behind the concept
Concept Element	Lists different substructure or sub-concepts i.e. important elements in key concepts
Manifestation	Provide examples of real-life use of concepts
Implication	Summarize the practical consequences of the concept i.e. how it is important and usable

III. DESIGN AND DEVELOPMENT

The implementation of cognitive visual support is planned as part of research activities using ADDIE instruction model. As a systematic design framework, ADDIE model serves as dynamic and flexible approaches to build effective teaching modules [27]. The main activities in analysis phases include in-depth literature review and preliminary study to identify research direction. In design phase, the main activities include modeling scaffolding for data analytics learning, identifying component attributes and frames for relevant ML strategies, and designing scaffolding implementation for the strategy. In this phase, three meaningful learning strategies are selected due to its close relevancy to data analytics learning, i.e. active, collaborative and constructive to be implemented in the study.

IV. IMPLEMENTATION OF COGNITIVE VISUAL SUPPORT

Cognitive Visual support model focuses on data analytics knowledge construction and problem solving. Figure 2 presents the visual frame in the probability topic by detailing the identified elements. Six elements were clarified in the topic to enhance learning by explaining abstract ideas with clear structures. Figure 3 offers the concept map of probability distribution to allow students to explore association between concepts and organise related information systematically.

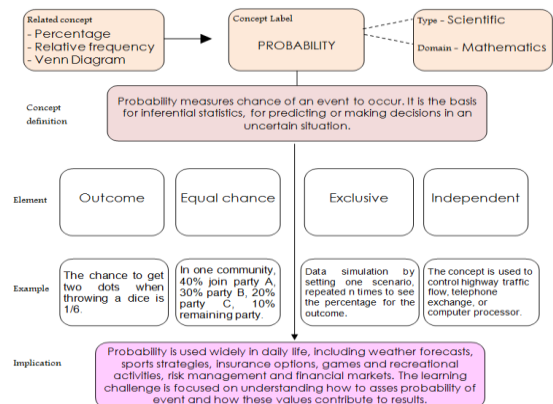


Figure 2: Knowledge structure as advance organizer

V. CONCLUSION AND DISCUSSION

The design of cognitive Visual support using active, constructive and collaborative strategy in data analytics learning has considered a list of important visual attributes. The list of attributes includes concept label, concept types and domains, concept definition, element, manifestation and implication. The series provide a allusion structure to break large and complicated problem lesson into several small segments that are convenient for students to accept the concepts and applications [28].

The concept map presents useful visual for a group of conceptualization that result in easily understandable and comparable points. Thus, concept maps aim to support the design of instructional materials and successful instructional activities [29]. The concept maps also provide the support needed by students in their learning using specific scaffolding to enhance problem solving skills and knowledge construction [30], [31]. These visual tools were emphasized in meaningful learning to organize knowledge by linking new information with existing concepts in strong cognitive structure [32]-[34].

This study identifies six visual attributes that support the presentation of learning materials that are most readily acceptable, universal and widely known to enhance learning effectiveness. This research demonstrates cognitive visual support implementation in delivering data analytics topic on probability. This research utilizes meaningful reception learning approach in the instructional arrangement to implement information support by perform worked-example data analytics knowledge construction and problem solutions using three useful elements: active, constructive and collaborative. The presentation may provide advisor with specific and entire references to expand an applicable task statement consistently in active data analytics learning.

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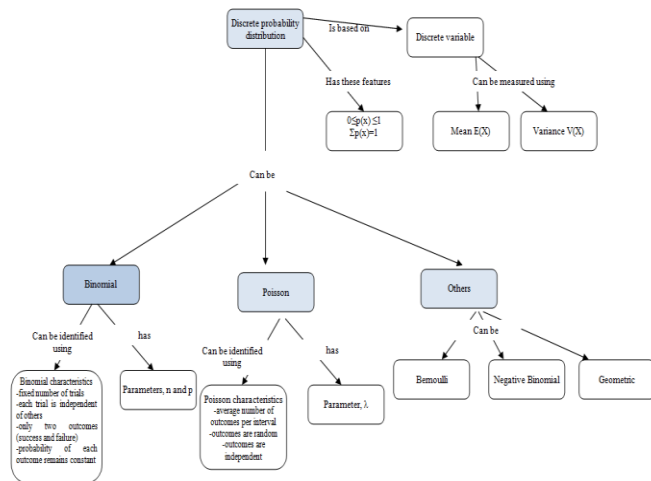


Figure 3: Concept map of probability distribution

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