SEMANTIC MODEL FOR MINING E-LEARNING USAGE WITH ONTOLOGY AND MEANINGFUL LEARNING CHARACTERISTICS

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To my beloved husband and parents.

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ABSTRACT

The use of e-learning in higher education institutions is a necessity in the learning process. E-learning accumulates vast amount of usage data which could produce a new knowledge and useful for educators. The demand to gain knowledge from e-learning usage data requires a correct mechanism to extract exact information. Current models for mining e-learning usage have focused on the activities usage but ignored the actions usage. In addition, the models lack the ability to incorporate learning pedagogy, leading to a semantic gap to annotate mining data towards education domain. The other issue raised is the absence of usage recommendation that refers to result of data mining task. This research proposes a semantic model for mining e-learning usage with ontology and meaningful learning characteristics. The model starts by preparing data including activity and action hits. The next step is to calculate meaningful hits which categorized into five namely active, cooperative, constructive, authentic, and intentional. The process continues to apply K-means clustering analysis to group usage data into three clusters. Lastly, the usage data is mapped into ontology and the ontology manager generates the meaningful usage cluster and usage recommendation. The model was experimented with three datasets of distinct courses and evaluated by mapping against the student learning outcomes of the courses. The results showed that there is a positive relationship between meaningful hits and learning outcomes, and there is a positive relationship between meaningful usage cluster and learning outcomes. It can be concluded that the proposed semantic model is valid with 95% of confidence level. This model is capable to mine and gain insight into e-learning usage data and to provide usage recommendation.

ABSTRAK

Penggunaan e-pembelajaran di institusi pengajian tinggi merupakan satu keperluan dalam proses pembelajaran. Penggunaan data e-pembelajaran yang besar boleh menghasilkan pengetahuan baru dan berguna untuk golongan pendidik. Permintaan untuk mendapatkan pengetahuan dari data penggunaan e-pembelajaran memerlukan mekanisme yang betul bagi mengekstrak maklumat yang tepat. Model semasa untuk penggunaan e-pembelajaran perlombongan telah memberi tumpuan kepada penggunaan aktiviti dan mengabaikan penggunaan tindakan. Selain itu, model lain tidak mempunyai kemampuan untuk memasukkan pedagogi pembelajaran yang membawa kepada jurang semantik untuk memberi catatan data perlombongan ke arah domain pendidikan. Isu lain yang dibangkitkan adalah ketiadaan cadangan penggunaan yang merujuk kepada hasil tugas perlombongan data. Kajian ini mencadangkan model semantik untuk penggunaan e-pembelajaran perlombongan dengan ontologi dan ciri-ciri pembelajaran bermakna. Model ini bermula dengan menyediakan data termasuk penggunaan aktiviti dan tindakan. Langkah seterusnya adalah untuk menghitung hit bermakna yang dikategorikan kepada lima iaitu aktif, koperasi, konstruktif, shahih, dan disengajakan. Proses diteruskan dengan menerapkan analisis pengklusteran *K-means* untuk mengelompokkan data penggunaan ke dalam tiga kelompok. Akhir sekali, data penggunaan dipetakan ke dalam ontologi dan pengurus ontologi menghasilkan kluster dan cadangan penggunaan yang bermakna. Model ini telah diuji menggunakan tiga set data pada kursus yang berbeza dan dinilai dengan membandingkan hasil pembelajaran pelajar dari kursus. Keputusan menunjukkan bahawa terdapat hubungan positif antara hit bermakna dengan hasil pembelajaran, dan terdapat hubungan positif antara kluster penggunaan bermakna dengan hasil pembelajaran. Dapat disimpulkan bahawa model semantik yang dicadangkan adalah sah dengan aras keyakinan 95%. Model ini mampu untuk mendapatkan pemahaman daripada data penggunaan e-pembelajaran dan menyediakan cadangan penggunaan.

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LIST OF ABBREVIATIONS

CMS	- Course Management System
DBMS	- Database Management System
EDM	- Educational Data Mining
HEIs	- Higher Education Institutions
HTML	- Hypertext Markup Language
HTTP	- Hypertext Transfer Protocol
KDD	- Knowledge Database Discovery
LMS	- Learning Management System
LOC	- Learning Object Context
MOOC	- Massive Open Online Course
MOODLE	- Modular Object Oriented Development Learning Environment
OWL	- Ontology Web Language
RDF	- Resource Description Framework
RIF	- Rule Interchange Format
RMSSTD	- Root-mean-square standard deviation
RS	- Root-squared
SEMME	- Semantic Model for Mining E-learning Usage with Ontology and Meaningful Learning Characteristics
SWRL	- Semantic Web Rule Language
URI/IRI	- Universal/Internationalized Resource Identifier
URIs	- Uniform Resource Identifiers
UTM	- Universiti Teknologi Malaysia
VLE	- Virtual Learning Environment
W3C	- World Wide Web Consortium
WUP	- Wu and Palmer

LIST OF SYMBOLS

$d_{Euclidean}$	-	Euclidean Distance
∞	-	Infinite
a	-	Activity
c	-	Action
H_0	-	Null hypotheses
H_a	-	Alternative hypotheses
m	-	Meaningful learning characteristic
MH_m	-	Meaningful hits for characteristic m
r	-	Coefficient correlation
$RMSSTD$	-	Root-mean-square standard deviation
RS	-	Root-squared
${}^{Sim}WUP$	-	Wu and Palmer Similarity
$W_{a,\,m}$	-	Meaningful weight between activity a and characteristic m
$W_{c,\,m}$	-	Meaningful weight between activity a and characteristic m
$\bar{x}$	-	Average value

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter provides background of the problems, statement of the problems, objectives of the study, scopes of the study, significances of the study, and thesis organization. Problem background describes the existing problems that cause the emerging of the research. Problem statement describes the research questions, whilst objectives of the study describe the research goals. Scopes of the study describe scopes and limitations of the research, whereby significances of the study describe the importance and contribution of research in theoretical, educators, and research perspectives. Lastly, thesis organization describes the structure of research documentation. The upcoming section describes the problem background of the research.

1.2 Problem Background

The internet growth has enabled the way in gathering knowledge and it has introduced a driveway for online learning. Advancements of the internet technologies later introduced an e-learning system which allow teacher to manage diverse learning resources in easier manner. E-learning has a massive recognition to connect students with learning sources limitlessly (Ranbaduge, 2013). E-learning is a great innovation of technology for education. E-learning plays various roles in a learning process including delivery tool, assessment tool, collaboration tool, communication tool which support synchronous and asynchronous communication between lecturer and students, and among students. Recent e-learning known as Learning Management System (LMS) which offers these important roles and provides convenience with its customizations.

Modular Object Oriented Development Learning Environment (Moodle) is an open source LMS (Dougiamas and Taylor, 2003), that is globally used by many universities (Henrick and Holland, 2015) due to its flexibility (Rice, 2015). Moreover, as reported by Embi (2011), Moodle is the most used LMS in Malaysia higher institutions. Dougiamas (2010) summarized the main features provided in the Moodle including communication tools, productivity tools, student involvement tools, admin tools, course delivery tools, and content development tools. However, among higher institutions in Malaysia that implementing Moodle, Universiti Teknologi Malaysia (UTM) has a lack on the use of student involvement, course delivery, and content development tools (Embi, 2011). Moodle provides variety of activities to enhance the use of student involvement and content development tools such as group work, assessment, and course template. Whilst, the course delivery tools can be used to track students' learning performance in their course.

Basically, a student is able to participate in a Moodle course by using variety of learning activities such as assignments, quizzes, resources, workshop, etc. Moreover, Moodle generates different actions as results of interaction in activities (Dougiamas, 2010). When they log in and performed activities in e-learning, they are creating usage data. For example, a student login into e-learning and access the resources page, and then downloading a lecture material. By this time, he/she is generating usage data called as "resource download", resource is the information of activity and download is the information of action performed by the student.

Moodle uses log file to record the usage data (Henrick and Holland, 2015). The more e-learning being used during learning process, the more usage data stored in the log file (Yunianta, 2015). The log file contains huge of e-learning usage data which could produce a gold mine of educational data, there might be information is worth extracted by educator actors (Mostow and Beck, 2006). Each activity in which student is participating in a course indicates significant information of learning capacity (Ranbaduge, 2013). Thus, e-learning usage data has sufficient details for tracking the use of e-learning and learning performance (Romero and Ventura, 2010). However, Moodle e-learning produces statistics report to track e-learning usage, which has lack to exploit acquired information and deduce useful conclusion on the course or students (Valsamidis *et al.*, 2011). Moreover, it does not offer concrete tool to perform e-learning usage assessment (Valsamidis *et al.*, 2012).

Hence, apart from the success of its implementation, evaluation of e-learning usage is crucial to allow teachers to track and assess students' activities (Zorrilla *et al.*, 2005), investigate student's performance and behavior, assisting teachers for detection of possible errors (Cash *et al.*, 2011), learning strategy improvements (Ranbaduge, 2014), or define the facts about students such as virtual interaction or knowledge gained (Zhang *et al.*, 2004). According to Zaiane and Luo (2001), data mining is a promising field to tackle these issues. Data mining derived from multiple fields including statistic, database, pattern recognition, machine learning, and visualization (Romero *et al.,* 2008). This field contributing several techniques for mining e-learning usage data, including prediction, clustering, personalization, relationship mining, or pattern mining (Baker, 2010). Application of data mining in education field later known as 'Educational Data Mining (EDM)' research area. EDM aimed to discover new patterns in data and help in developing new model (Romero and Ventura, 2013).

E-learning usage collected contains many variables from explicit activities and actions such as taking quiz, completing assignment, online interactions, posts on discussion forum, and getting course materials. These data can be explored for model building. The model aims to answer important questions towards student learning, and to generate recommendation which referring to the model's predictions (Bienkowski *et al.*, 2012). Moreover, Johnson *et al.* (2012) added that the model also beneficial to assess academic progress, predict future learning performance, and spot risky students, and other potential issues (Cash *et al.*, 2011).

Data mining techniques has been used in several works to study e-learning usage including grouping of students based on their e-survey and feedback answers (Beal *et al.*, 2006; Castro *et al.*, 2005), browsing behavior (Su *et al.*, 2008; Wang, 2006), number of navigation access (Khribi *et al.*, 2008), forum usage (Cobo *et al.*, 2012; Ratnapala *et al.*, 2014), course interest (Aher and Lobo, 2013; Bienkowski *et al.*, 2012; Hung and Zhang, 2008), resource interest (Chuan, 2016; Govindarajan *et al.*, 2013; Hogo, 2010; Valsamidis *et al.*, 2014), and overall e-learning activities (Burgos *et al.*, 2017; Despotovic-Zrakic *et al.*, 2012; Kock and Paramythis, 2010; Preidys and Sakalauskas, 2010; Romero *et al.*, 2008; Valsamidis *et al.*, 2012).

However, existing works for mining e-learning usage are focusing on the activities usage and ignoring the actual actions behind activity. Bienkowski *et al.* (2012) stated that issue in the analysis scope is one of concern when applying data mining in e-learning domain. Moreover, there is a need to incorporate pedagogical domain knowledge towards data mining tasks to realize the effectiveness and efficiency of e-learning usage (Wang, 2006). Educators find difficulties to interpret mining results and therefore the necessity of mining e-learning usage data cannot be perceived. Due to data collected from different domains, the generic data mining tasks have lack ability to identify and make use semantic interpretation across different domain (Dou *et al.*, 2015).

As e-learning used in educational field, thus it is necessary to incorporate learning pedagogy towards data mining tasks (Wang, 2006). Meaningful learning is a pedagogy which involves active, cooperative, constructive, authentic, and intentional learning characteristics (Howland *et al.*, 2012). Jonassen (2000) stated the rapidly development and utilization of technologies in education can foster meaningful learning. However, there are still limited work that incorporate meaningful learning pedagogy onto data mining tasks.

Semantic technology and ontology allowed to represent relationship between meaningful learning and Moodle e-learning concept, and then to be used in data mining tasks. Dou *et al.* (2015) believed that ontology is capable to reduce semantic gap by annotating mining data with semantic manner. Integration of data mining, ontology, and learning pedagogy in e-learning is not a novel approach. Some integration works have been used to provide resource recommendation (Gomes *et al.*, 2008; Jovanović *et al.*, 2007; Shamsi and Khan, 2012; Tarus *et al.*, 2017; Zhuhadar *et al.*, 2009), to study user's profile behavior (Fernandez and Ponnusamy, 2016), to predict learning outcome (Grivokostopoulou *et al.*, 2014), to group students based on activities usage (Firdausiah Mansur, 2013), and user profiling (Ferreira-Satler *et al.*, 2012).

However, most of researchers limit the scope onto resource data (Fernandez and Ponnusamy, 2016; Ferreira-Satler *et al.*, 2012; Gomes *et al.*, 2008; Jovanović *et al.*, 2007; Shamsi and Khan, 2012; Tarus *et al.*, 2017; Zhuhadar *et al.*, 2009). Besides, the studies by Firdausiah Mansur (2013) and Grivokostopoulou *et al.* (2014) have lack on data integration between data mining results and ontology, which is the issue faced when apply data mining in e-learning (Elaal, 2011). Data mining results generated and yet being stored in the database schema, is not shareable nor reusable. There is a need to include relational database onto ontology (Press, 2008), and thus interpretation of data mining results able to enrich the domain knowledge bases (Dou *et al.*, 2015). Besides, the absence of learning recommendation towards mining results is another lack from current works. As suggested by Hogo (2010), there is a necessity for mechanism of oriented towards students which is a recommendation of e-learning usage. It allowed to improve learning experience based on model's recommendation to be realized as stated by Bienkowski *et al.* (2012). Hence, aimed to tackle the aforementioned issues, this research integrates ontology and meaningful learning to propose a model for mining e-learning usage.

1.3 Problem Statement

According to the discussion on the problem backgrounds, the main research problem for further exploration is: *"How ontology and semantic technology can improve data mining for e-learning usage?"*

Referring from the main research problem, the following statement of the problems are addressed as follow:

i. What are the e-learning usage aspects and existing techniques applied for mining e-learning usage?

ii. How to improve data mining for e-learning usage with ontology and meaningful learning characteristics?

iii. How to establish relationship between meaningful e-learning usage and learning outcome?

1.4 Research Objectives

Referring from the statement of the problems, this research has addressed the following objectives:

i. To identify e-learning usage aspects and existing techniques applied for mining e-learning usage.

ii. To propose a semantic model for mining e-learning usage with ontology and meaningful learning characteristics.

iii. To establish relationship between meaningful e-learning usage and learning outcome.

1.5 Scope and Limitations

The following scopes are included in this research:

i. The e-learning usage were studied in this research based on the activities and actions from Moodle e-learning system, in Universiti Teknologi Malaysia (UTM).

ii. The data mining technique applied in this research is K-Means clustering with cluster validation using Root-Mean-Square Standard Deviation (RMSSTD) and Root-Squared (RS) (Halkidi *et al.*, 2001; Han *et al.*, 2011; Wu, 2012).

iii. The characteristics of meaningful learning pedagogy used in this research namely: active, constructive, cooperative, authentic, and intentional (Howland *et al.*, 2012).

iv. The similarity weight between keywords of e-learning usage and keywords of meaningful learning pedagogy measured with Wu Palmer similarity technique and WordNet database (Wu and Palmer, 1994).

v. The experiment data used in this research based on the Moodle e-learning usage data and student result data in UTM. The subjects involved as experiment data including SCJ2303_Section3 for the year 2010, SCJ2153_Section4 for the year 2011, and SCJ4553_Section1 for the year 2012.

1.6 Significance of Study

In general, this research is conducted to discover solutions to certain questions when applying data mining in e-learning. This research expected to be significant as it aimed to propose a semantic model for mining e-learning usage. Referring to the problem backgrounds, there is a necessity to incorporate learning pedagogy in data mining task (Dou *et al.*, 2015) and to provide usage recommendation (Bienkowski *et al.*, 2012; Hogo, 2010). Thus, the model incorporated ontology and meaningful learning pedagogy in order to gain insight of e-learning usage data and to tackle the issues. Accordance to the research, the outcome of the research will benefits in educational data mining area. The other significances of the research are in terms of theoretical and practical.

In theoretical contributions, this research integrates activities and action usage, data mining, ontology, and meaningful learning characteristics to develop the proposed model. This research also provides semantic meaningful weight for e-learning activities and actions. The enhancements of Moodle ontology along with its mechanism to perform data mapping to integrate mined data into ontology with auto instantiation are accomplished.

In practical contributions, the semantic model helps in gain new knowledge from e-learning usage data. The model also provides meaningful usage cluster and usage recommendation to improve online learning performance. In addition, the model used as guideline to plan and design online learning strategies and to promote meaningful learning.

Lastly, this research opens the opportunity to researchers whom would like to expand the expertise in educational data mining especially with the engagement of semantic technology, ontology, and learning pedagogy.

1.7 Thesis Structure

This thesis is organized in six chapters including introduction in Chapter 1, literature review in Chapter 2, research methodology in Chapter 3, development of semantic model for mining e-learning usage with ontology and meaningful learning characteristics in Chapter 4, results and discussion in Chapter 5, and Conclusion in chapter 6. The brief description of these chapters are explained as follows:

Chapter 1 introduces background of problems, follow with the statement of problems, research purpose, objectives of study, scopes of study, and significances of study. Chapter 2 investigates aspects of e-learning usage, activities and actions in Moodle e-learning, concepts of data mining techniques, ontology, similarity calculation, mapper tools, meaningful learning characteristics, and existing models for mining e-learning usage.

In Chapter 3, the activities of research methodology including planning and preparation, development, implementation, and validation of model for mining e-learning usage are presented. Moreover, this chapter includes description of operational framework which consists of data source layer, semantic mining layer, semantic mapping layer, and usage representation layer.

Chapter 4 describes development of semantic analysis model for mining e-learning usage including development of components in data source layer, semantic mining layer, and semantic mapping layer. Whilst Chapter 5 describes results and discussion of semantic model for mining e-learning usage toward case studies. This chapter including identify datasets, describe results of usage hits calculation, results of meaningful weight and meaningful hits calculations, results of meaningful usage cluster and recommendation. In addition, results of validation and verification are also presented in this chapter. Lastly, Chapter 6 describes the conclusions and limitations of this research, and future research opportunities.

1.8 Summary

The chapter describes background of the problems, statement of the problems, objectives of study, scopes of study, and significances of study. The problem background describes the lacks on the existing works in mining e-learning usage data. Moreover educational data mining offers significant promise in improving and assessing the use of e-learning system. However, e-learning system often driven by it functions to generate large and complex data, which is lead to many concerns. The aspect of e-learning usage including activities and actions, learning pedagogy, and necessity of a way to automatic access and deeper observation into analysis results bring new challenges when mining e-learning usage.The research statemens, research objectives, and significance of study are described to strengthen the importance of the research. This research endeavor to propose a semantic model incoporated with ontology and meaningful learning characteristics for mining e-learning usage. The next Chapter 2 investigates the reviews of related studies in this research including existing models for mining e-learning usage.

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