Intelligently derived features that influence students' perceptions on e-textbooks

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ABSTRACT

In today's digital age of ubiquitous computing the role of portable resources has changed the ways we perform many tasks in education such as the use of e-textbooks. One would assume that e-textbooks for the learning environment would be demanded in today's tech driven society. This paper investigates relevant experiences of tertiary students in using e-textbooks and whether their attitudes about using them has swayed the need of physical books. To accomplish the aim, 71 IT students at Auckland Institute of Studies (AIS) have been surveyed in a single semester to gain a better understanding of reasons students may resist adopting e-textbooks. The methodology used to achieve the aim is based on computational intelligence by determining small yet relevant features that directly affect students' perceptions. The experimental results on the data collected from the survey revealed new features that can reveal reasons behind students' decisions on adopting e-book as part of their course curriculum.

Keywords: E-Textbooks, Classification, Data Mining, Feature Selection

1. INTRODUCTION

In tertiary education, the textbook is one of many resources used for learning. Some courses make the textbook central to the course structure, while others just as a supplementary resource that acts as a guide. Regardless of how a textbook is used, lecturers and students consider the textbook an essential learning tool within the course. In today's digital age, the nature of the textbook is changing since about 80% of tertiary students own laptops, and even more are using tablets, smart phones, and other portable devices (Smith & Caruso, 2010). Recognizing the mobile driven generation, publishers are nowadays offering more textbooks in digital format. These digital texts are called e-textbooks, which are accessed through the Internet to be downloaded on portable devices with up-to-date specifications.

Though with many technological advances in the ways digital content is being designed, developed and provided, "digital natives" are still exposed to the pre-digital era of paper textbooks and paper textbooks are still a preference for many students. Therefore, this paper investigates features that may influence students' perception about e-textbooks as part of their course at Auckland Institute of Studies. To be exact, we seek to find out what it takes students to adopt or reject e-textbooks by investigating different features related to student, course delivery and the course itself. To accomplish the goal, we utilized a survey that consisted of thirty-eight questions, some of which are binary and others are multivalued. The survey was distributed to 71 students from the Information Technology programme at AIS, and hence a dataset with 71 instances has been formed.

The methodology adopted to figure out the most influential features was based on two main approaches. Initially, we used computational intelligence methods to reduce the original 38 features and choose smaller subsets of features based on both mutual information and wrapping methods (Quinlan, 1986; Kohavi & John 1997). Then these subsets have been verified using data mining methods to measure their effectiveness with respect to different evaluation measures such as classification accuracy and false positive rates. Data mining based on classification was used that involves building a predictive classifier from the subsets of features (Thabtah, et al., 2015). The data mining algorithms that processed the features' subsets are decision trees and Fuzzy Unordered Rule Induction Algorithm (Furia) (Hühn & Hüllermeier, 2009; Quinlan, 1993) (more details are given in Section 4). We show that there are four effective features that are influential on the problem of adopting e-text book. These features have been identified after processing the distinctive features' subsets chosen by the computational intelligence techniques. When using such features, the academic department and its different stakeholders can understand reasons behind students' perception toward the issue of e-textbooks in course delivery and hence are able to better accommodate their academic needs.

This paper is organised as follows: Section 2 briefly reviews the literature on presents related research works. Section 3 is devoted to the research methodology used and Section 4

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presents the data, results and their analysis. Finally, the conclusions are given in Section 5.

2. LITERATURE REVIEW

One of the earliest studies (Selinda et. Al 2010) on e-book usage at Columbia University assessed user experiences to shed light on their perception to this digital content move. The authors discovered that despite the growth in e-book circulation there was still a high preference of physical books over e-textbooks. This particular study showed that, when faced with information-finding tasks, students are more successful with paper text than e-texts, simply because of their familiarity with paper text format (Selinda et. Al 2010). However, for the same students, the study reported that the interactivity of e-text was easier over paper text especially when utilizing features such as hyperlinks, and search capabilities.

Jamali et. al 2009, categorized the advantages of using e-textbooks into the following categories: Online access, ability to search, cost, and portability. This study concluded that problems of using e-textbooks for students was printing, saving and carrying among others. Moreover, technological issues or difficulties with certain platforms caused user frustration. Some students ended up wanting to print portions of the e-text for reading, annotating and highlighting text, obviously tasks they found difficulty in doing with the e-text. However 15.4% of students in Jamali et al., (2009) study admitted that the advantage of e-textbooks are easy search for relevant content, which can be quicker when using keywords and phrases in an e-text. In addition, 10.8% of the students stated that e-textbook are more cost effective compared to physical books.

A research team at the University of Central Florida (DeNoyelles et. al 2015) conducted two surveys, one in 2012 and one in 2014, that investigated tertiary students' attitudes in regards to e-textbooks. One of the aims was to discover the most influential factors of e-textbook acceptance over time. Results of their survey showed that lower cost remained the top factor influencing the preference of e-textbook from 2012 to 2014 and the second most important factor that influenced the preference of e-textbooks for students was convenience, in particular the search capability was the most praised feature over printed textbooks.

A study by Grajek et.al (2013) found that most students did not alter their study habits when using e-texts, students still preferred print over digitised content (Howard et.. al 2013). During a University of Washington pilot study (Giacomin et. al. 2013), though, in which students were given free e-textbooks, over 25% still purchased a physical textbook. In the same study Giacomin et. al. (2013) found student issues with e-texts such as unpleasant reading experiences due to difficulty reading text on screens and preferences for print.

3. METHODOLOGY

Large numbers of features were derived from the e-Book Satisfaction survey. These features plus the class variable represent student's background and indicators of student's attitudes and experiences with the use of e-textbooks at AIS for a single semester. The data collection used was based on assessing these features using computational intelligence methods in particular, Information Gain (IG) and Wrapper Subset Evaluation (WSE) (Quinlan, 1986; Kohavi & John, 1997) in order to determine the most effective features on student perceptions of e-textbooks. Hence multiple distinctive features sets are evaluated based on data analysis using two predictive techniques (Furia, J48) and using different evaluation metrics. The data analysis techniques were applied on real data collected from AIS students via the e-Book survey.

The survey included twenty-five questions: twenty-three were close-ended and two were open-ended. Closed-ended, categorical, and Likert-scale questions collected data about the subjects' demographic information, prior knowledge, issues faced about their prescribed e-texts. The two open ended questions sought the students' reasons behind their answers about e-texts (See Table 1 for the complete features / questions). Moreover, the desired target subjects for this study were the seventy-two Information Technology students at Auckland Institute of Studies (AIS), and the survey was conducted during the second semester of 2017.

The methodology used in this paper consisted of two phases

a) The use of filtering and wrapping methods to decide small yet non-redundant features that may directly have an impact on the student's decision (class variable) in the survey data
b) The use of data mining methods to evaluate the features selected at the first phase. This phase is necessary since we can identify whether the features chosen by IG and WSE are effective enough so the academic department are able to understand students' needs in e-textbooks.

More details on the filtering and wrapping methods details are given in Section 3.1.

3.1 Computational Intelligence Methods Used

A *Wrapper* method works when the predictive classification algorithm evaluates subsets using a testing method like cross-validation to produce a predictive model from each subset of features (Abdelhamid and Thabtah, 2016). As a result, an optimal subset of features is presented to the end user. Wrapper Subset Evaluation (WSE) was selected to run the wrapping method (Kohavi & John 1997) and FURIA was selected as the predictive algorithm to construct the classification models. When using the WSE, the input data get processed by examining very large numbers of feature sets based on the plugged predictive model and the subset that yields the best accuracy is offered to the end user (Abdelhamid and Thabtah, 2014).

IG is one of the popular filtering methods that assesses features by computing their relevancy with the class. Any variable that has a gain higher than a predefined threshold is relevant and therefore preserved for further data processing. This method works by ranking features according to their gain score.

$$I(C,A) = H(C) - H(C|A) \quad (1)$$

where C is the class variable, A is the attribute variable, and $H()$ is the entropy. Features with higher IG scores (gain) are ranked above the features with lower scores.

$$I(C,I) = -\sum_{c\in C} p(c)\log p(c) + p(a)\sum_{c\in C} p(c|a)\log p(c|a) + p(\bar{a})\sum_{c\in C} p(c|\bar{a})\log p(c|\bar{a}) \quad (2)$$

4. DATA AND RESULTS

4.1 Preliminaries

This section describes the experimentation on the features collected via the survey using the wrapping and filtering methods. The aim is to measure the effectiveness of these features utilizing data mining so we can determine which features have directly effect on the student's perception in e-textbook adaptation. To achieve the aim, we examined the below distinctive sets of features:

a) Set 1: The set of features derived by WSE method
b) Set 2: The set of features derived using IG filtering method.
c) Set 3: The complete set of features (the original 38 features in the input dataset).

Since the e-text survey data is a binary classification problem (Table 2), having two class labels in the dataset, then binary classification evaluation measures are used. These measures are employed to evaluate the impact of the features sets (Sets 1, 2 and 3) including classification accuracy and false positives (See Equations 3 and 4). The evaluation measures evaluate the influence of the features sets and their corresponding predictive models generated by the data mining algorithms. The classification accuracy (Equation 3) assesses the predictive performance of the classifiers and denotes the number of correctly classified instances in the test dataset from the total number of instances on the test dataset. False Positive rate (FP) (Equation 4) is the percentage of the test examples that are "yes", but have been predicted as "no".

Table 1: The original dataset

Student Background Features	**Description**
Gender	Male/female
Nationality	Japan, Domestic, China, India, etc..
Qualification	This denotes which qualification they are pursuing at AIS
Specialisation	Student's major, one of: • Information Systems, • Software Development • Computer Networking
NumofSemesters	How many semesters they've enrolled in AIS so far
NumberofCourseEnrolled	Number of courses enrolled in currently
AwareOfAISEText	Aware that AIS provided e-texts before they enrolled
PriorSkillEText	Any previous knowledge/skill with e-texts prior to AIS.
EText Experience Features	**Description**
NumberOfCourseswithEText	How many of their courses have e-texts
NumberOfETextDownloads	How many e-texts download have they done
MethodOfReceivingMoodle	Did they receive an e-text via Moodle?
MethodOfReceivingviaEmail	Did they receive an e-text from the IT admin via email?
BrowserIncompatibility	While downloading, browser incompatibility?
downloadIssue	Download issues encountered?
ProblemsWhileusingETexts	Problems while using the E-text?
IssuewithNavigation	Navigation issues while using an e-text?
IssueWithSizeOfFont	Issues with size of e-text font?
HardtoRead	Difficulty in reading the e-text
HardtoUse	Difficulty overall in using the e-text
HardToScroll	Difficulty in scrolling e-text pages
ThoughtETextUseFor_Courses	Knowledge of extent of e-text use at AIS
FrequencyOfUse	How often do they use the textbook
UserFiendly	Easy to use overall
ETextSatisfaction	Feeling about the E-Text courses overall
Usability Features	**Description**
UseAISlaptop	Do they use AIS laptop to access the e-texts?
Usetablet	Do they use a Tablet to access the e-texts?
UseofPersonalLaptop	Do they use their personal laptops for e-texts?
Usesmartphone	Do they use smartphones to access the e-texts?
LecturerEncouragement	Do their lecturers encourage students to use e-texts?
Preference	Do they prefer Physical or e-text?
insertngNotes	While using e-texts do they use the "Insert Note" feature?
HighlightText	While using e-texts do they use the "Highlight" text feature?
Use of Hyperlinks	While using e-texts do they use the "Hyperlink" feature?
Text Search	While using e-texts do they use the "Text Search" feature?
Changefont/zoom	While using e-texts do they use the Change Font/Zoom feature?
EtextComments	General comments about e-texts
Reason	Purpose for comment
FinalPreference	What is their final preference about e-texts?

$$Accuracy(\%) = \frac{|TP + TN|}{|TP + TN + FP + FN|} \quad (3)$$

$$FalsePositive(\%) = \frac{|FP|}{|TN + FP|} \quad (4)$$

The initial raw data of the surveys was processed to remove noisy instances such as those that are missing or incomplete. A sample of ten data instances using seven features plus the class label are shown in Table 3. Some of the features are binary and others are multi-valued. Two data mining algorithms named Furia and J48 have been utilized to measure the impact of the features on accepting or rejecting e-textbooks (Hühn & Hüllermeier, 2009; Quinlan, 1993). J48 is a known decision tree algorithm that has shown superiority in different application domains with respect to predictive accuracy so we adopt it in the data processing phase. On the other hand, Furia was chosen because it generates simple "If-Then" rules that different stakeholders can easily understand and manage. These rules will be used as a goodness measure to validate the effectiveness of the features that are selected hence, a higher assurance in features performance will be confidently adapted by Department Supervisors and Academic Admin to make more informed decisions. Moreover, the rules derived by Furia correspond to useful correlation among influential features that can be exploited to make decisions on how to adapt a specific e-text come into light, and therefore academic managers are able to interpret the reasons behind the rules derived.

The WEKA software tool (Hall, et al., 2009) was used to run the experiments of the data mining algorithms and the feature selection techniques on the dataset collected. WEKA is an open source Java platform developed at the University of Waikato in New Zealand that contains different implementations for data mining and filtering methods. Ten-fold cross-validation testing was used in training Furia and J48 to produce classifiers from the student e-text dataset. Lastly WSA and IG filters that were built within WEKA and were applied to derive the features subsets.

features leaving 28 features in its results set. Based on the selected features by WSE, it seems that "previous experience" and the "frequency" of using e-textbook are highly influential features. In addition, the platform of the course delivery in which the e-textbook is offered to the students is also vital. In this case, Moodle was the platform utilised by the student's course material and submit assignments and most of students seem comfortable in accessing the text book using this platform.

Table 2: Confusion matrix for the student e-textbook problem

	Predicted Class	
Actual Class	**YES**	**NO**
YES	True Positive(TP)	False Negative (FN)
NO	False Positive (FP)	True Negative (TN)

To measure the influence of the 4 and 28 features sets derived by the WSE and IG methods respectively on students' perception we conducted different experiments. Figure 1 shows the predictive performance in terms of classification accuracy generated by Furia and the decision tree (J48) algorithms over the three distinctive sets of features. The results clearly show that Furia fuzzy rule induction algorithm consistently generates better predictive models than decision trees especially from the features chosen by the WSE wrapping method. To be exact, and for the sets of features chosen by WSE feature selection method, Furia produced a classifier with 21.12% higher classification accuracy than that of J48. The fact that only four features could classify students' perceptions with over 21% accuracy than the original 38-features collected through the survey is a definite advantage. This is since not only the data dimensionality has been substantially reduced but also redundant features that negatively contributed to accuracy have been discarded. Now, the different stakeholders including academic staff, academic student support unit as well as academic managers are able to determine the key features that impact adopting e-text book by learners. The results of Figure 1 also show that IG has only pruned three features keeping 31 features and without any significant classification gain, hence we can say the IG is not suitable filtering method at least for this dataset. Overall, it's been observed that Furia when processed WSE features set has outperformed the other distinctive features' sets by almost 15% accuracy besides reducing the search space significantly to just four features. This result pinpoints to redundancy in the features collected through the survey and this is clear when we measured the

Table 3: Sample ten instances with seven features plus the class

Gender	**Nationality**	**Qualification**	**Specialisation**	**PriorSkill**	**ReceivedViaMoodle**	**LecEncourage**	**Class**
f	Pacifica	GDIT	SD	no	t	no	No
f	Japan	BIT	CN	no	f	yes	Yes
f	India	GDIT	IS	no	t	yes	No
f	Palestine	GDIT	IS	no	t	yes	No
f	Domestic	BIT	IS	no	t	yes	Yes
f	India	GDIT	IS	yes	t	yes	No
f	India	GDIT	SD	yes	t	yes	Yes
f	China	BIT	CN	yes	f	yes	No
f	China	GDIT	SD	yes	f	yes	Yes
f	Domestic	GDIT	SD	no	f	yes	Yes

4.2 Results Analysis

Table 4 depicts the features subsets selected by both IG and WSE. It is clear from the feature selection results that WSE was able to substantially reduce the initial dataset dimensionality by only selecting four features out of 37. This is an equivalent of 89% reduction of the search space of features and hence this wrapping method was able to prune the majority of the questions in the survey. On the other hand, IG only discarded 9 impact of the features sets using data analysis using Furia in terms of classification accuracy.

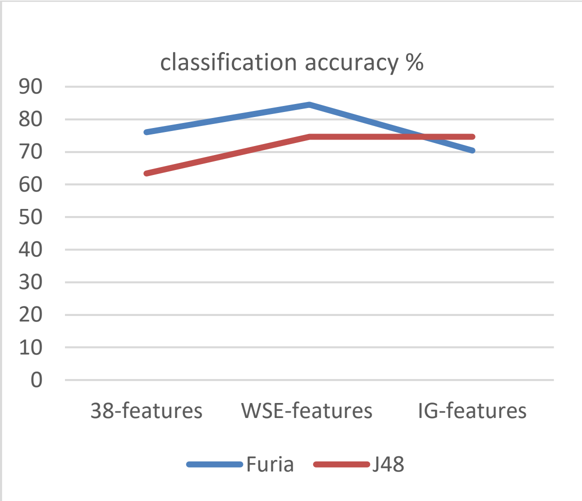

Figure 1: Classification accuracies generated from the distinctive sets of features using the classification algorithms

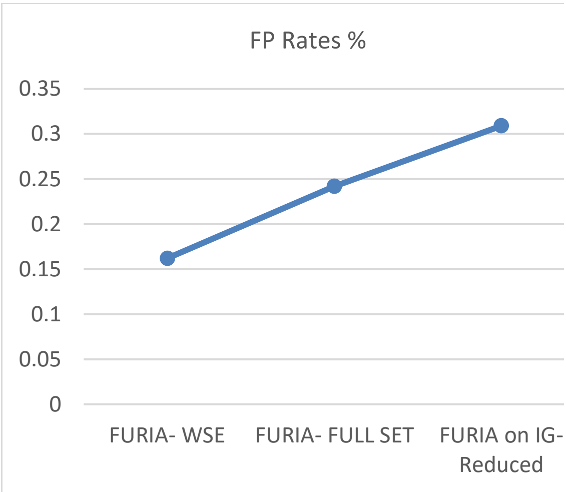

Figure 2: FP rates generated from the distinctive sets of features using Furia fuzzy induction algorithm

We further investigated Furia on the three distinctive sets of features using False Positives (FPs) as shown in Figure 2. FPs, according to Table 3, denote the data instances that are actually classified as "yes" but have been incorrectly classified by Furia to class "no". Figure 2 reports that Furia on WSE features has a lower rate than that of on the original dataset features and the IG-selected features. The FP rate generated by Furia from the WSE features are lower by 8% and 14% from those generated from the complete features set and IG-features set respectively. Overall, predictive models derived from the WSE features seem to have lower FP rates than models derived from the remaining features set for at least these Furia algorithm. This is consistent with the classification accuracy results generated earlier.

Lastly, we investigated the rules derived by Furia and its use for decision making in regards to student e-text adaptations. The highest ranked rule simply implies that students who found e-texts "hard to use" did not prefer e-textbooks, students that found the e-texts "convenient" said "yes" to e-texts. An interesting piece of knowledge was that students who have at least two courses with e-texts and had only "some" frequency of use, were likely to say "no" to e-texts and the rule, if frequency of use is "never" then students say "no" to e-texts. This could indicate that frequency of use could play a role in students preferring e-texts more. Department administrators could maybe try and make sure that instructors constantly make students use the e-texts in all their classes, therefore increasing the frequency of use, which would increase familiarity, hence these students may end up saying "yes" to e-texts. The summary of the rules are shown below.

Table 4: WSE and IG chosen features

WSE chosen Features Set	Information Gain Chosen Features Set
NumberOfCourseswithEText	Reason
MethodOfReceivingMoodle	Nationality
FrequencyOfUse	FrequencyOfUse
Reason	HighlightText
	ThoughtETextUseFor_Courses
	Changefont/zoom
	Use of Hyperlinks
	HardToScroll
	Usetablet
	ProblemsWhileusingETexts
	IssueWithSizeOfFont
	UserFiendly
	IssuewithNavigation
	Text Search
	NumofSemesters
	insertngNotes
	downloadIssue
	HardtoUse
	HardtoRead
	Usesmartphone
	Qualification
	Specialisation
	PriorSkillEText
	UseofPersonalLaptop
	MethodOfReceivingMoodle
	LecturerEncouragement
	BrowserIncompatibility

Rules derived from FURIA-WSE

- If (Reason = hard to use) Then FinalPreference=No
- If (NumberOfCourseswithEText in [2, 3, inf, inf]) and (FrequencyOfUse = some) => FinalPreference=No (CF = 0.81)
- If (FrequencyOfUse = never) => FinalPreference=No
- If (Reason = hard to read) => FinalPreference=No
- If (Reason = easy to use) => FinalPreference=Yes

- If (Reason = convienient) => FinalPreference=Yes
- If (Reason = helpful) => FinalPreference=Yes

6. CONCLUSION

In this paper, we have investigated students' perceptions on the adaptation of e-textbooks by identifying certain features related to students, students' experience and courses. To achieve this aim 38 features including a target class were designed in a survey and distributed to AIS ITP students. After collecting the data, feature selection methods based around wrapping and filtering methods were applied to choose a small yet effective features set that can determine why some students resist the adoption of e-textbooks. Experimental results revealed that the WSE wrapping method was able to select the least number of features but still achieve the highest predictive accuracy. Frequency of using e-textbook in previous courses, the experience students have in using e-textbooks and the platform that accommodated the e-textbooks were some of the significant features that impacted the perception of students on the use of e-books. The data analysis was conducted using two well know data mining algorithms called Furia and J48, but Furia gave more accurate results. The results of the Furia algorithm showed that if students find it easy to use, convenient and helpful that they are more likely to accept e-books. These rules can be exploited by academic managers and academic student support services to better understand what it takes to improve the utilisation of e-textbook in course delivery. In the near future, we are going to investigate larger datasets to enhance and generalise our findings.

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