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ACCEPTANCE MODEL PREDICTION'S FOR E-ORIENTATION SYSTEMS CASE OF STUDY : PLATFORM "orientation-chabab.com"

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ABSTRACT

The orientation is the construction or development process of an educational or career plan. This process is adopting the information and the communication technologies through various platforms to help students making their own career decision. The purpose of this study is to generate an acceptance model prediction's of the e-orientation Moroccan platform "orientation-chabab.com" that can be used during the conceptual design of the future e-orientation platforms. The Technology Acceptance Model (TAM) is used as a theatrical model for early user acceptance of the e-orientation systems by evaluating an extended Technology Acceptance Model (TAM). Our experiment was conducted with the WEKA machine learning software by using five algorithms namely: NaïveBayes, J48, SMO, SimpleLogistic and OneR.According to the comparison of the accuracy rates of our simulation, the Sequential Minimal Optimization classifier gives us the best performance outcomes.

Keywords: *E-orientation, Technology Acceptance Model, Extended TAM, Machine Learning, Algorithm.*

1. INTRODUCTION

Choosing a suitable career may be difficult for students because they have to consider several criteria if they want to be on the success path. Today, the orientation is the construction and development process of an academic and career plan as it is related to the knowledge of the learner [1]. The e-orientation process is adopting the Information Technologies (IT) to automate the orientation task throughout various platforms [2] which are accessible to everyone and where the students can choose their educational and professional orientation.

Today there is a lack of current research on the acceptance of Moroccan electronic guidance systems. Thus, most of the examples focus on "Meta-model of e-orientation platforms" [3] and "Modernization of a domain e-orientation Meta-model" [4]. However, research that would focus on the acceptance prediction's model for e-orientation system has not been previously conducted.

The research on acceptance of an e-orientation systems use takes a variety of theoretical perspectives. Of all the theories, the Technology Acceptance Model (TAM) is considered the most influential and commonly employed theory for describing an individual's acceptance of information systems [5].

The TAM comprises several variables explaining behavioral intentions and the use of technology directly or indirectly (i.e., perceived usefulness, perceived ease of use, attitudes toward technology) [6]. Researchers have investigated and replicated these constructs and agreed that they are valid in predicting the individual's acceptance of various corporate information technologies [7–11]. TAM has gained considerable prominence, particularly due to its transferability to e-orientation context by extending it with mediator variables, such as perceived risk and perceived information quality [12–14].

The goal of our research is to generate an acceptance model of e-orientation systems that can be used during the conceptual design of e-orientation platforms.

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In this study we will evaluate the acceptability of an e-orientation Moroccan platform: orientation-chabab.com. The choice of these platform has been based on a previous study that evaluated Multiple e-orientation Systems [4].

The survey instruments for this study was developed using validated items from the theoretical constructs of the extended TAM model for e-orientation. The items for measuring High level of validity is ensured through extensive revision by experts and supported by previous literature review that we will discuss in more detail in the section 3. The participants were asked to be familiar with e-orientation Moroccan platform: "orientation-chabab.com" and complete the questionnaire at a convenient time for them.

Since our data is tremendously increasing, it becomes difficult for us to establish a relationship between multiple features. This makes it difficult for us to manually analyze the data for strategic decision making. Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention.[15,16].

The database included 256 samples. Using various Machine learning classifier algorithms, the best results were obtained by a SMO with accuracy rates of "98.8281%".

The rest of the paper is structured as follows. Section 2 exhibits the state of arts. Section 3 presents the TAM. Section 4 extends the TAM in the e-orientation systems based on literature review. Section 5 outlines our research methodology. Section 6 describes our exploratory results and analysis discussion. Finally, section 7 concludes the main results and gives an outline of possible future research directions

2. STATE OF ARTS

To put our research into the context, we summarize the most relevant works about some pedagogical ontologies of Orientation Domain. For example, in [4] the authors described the use of ontology in the field of orientation and defines a model of the set of domain knowledge. In this work, the authors established an ontological model and existing guidance platforms and it used a more abstract model namely meta-model to modernize the field guidance. This modernization allows us to facilitate the understanding of the orientation field, specify a core platform and simulate its operation.

In another work [3], the authors introduce a comparison and description of the existing e-orientation platforms, which is based on the WSDL[1]. The purpose of this work is to have a descriptive file enriched by features to propose a meta-model of e-orientation platforms to facilitate the guidance of students.

We notice that all the previous research has not conducted the acceptance prediction's model for e-orientation system. All these works have served as a basis for the development of our approach which is the choice of our platform based in the comparison of the existing e-orientation platforms according to the following features: • Create an account. • Look for similar profiles. • Add Parent profiles. • Manage portfolio. • Seek guidance. We choose the platform orientation-chabab.com to predict its acceptability by the users.

3. TECHNOLOGY ACCEPTANCE MODEL

TAM, proposed by Davis in 1985 [17], explains and predicts the usage of information technologies based on the Theory of Reasoned Action (TRA) of [18]. The TAM includes perceived usefulness and perceived ease of use as the main influencing variables of an individual's acceptance of information technologies [19]. Figure 1 illustrates the TAM model [20].

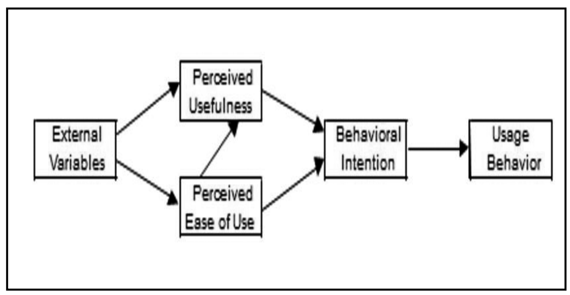

Figure 1: Technology Acceptance Model (TAM) [20].

Perceived usefulness (PU) is "the degree to which a person believes that a particular technology would enhance his or her performance". Perceived ease of use (PEOU) is "the degree to which a person believes that using a particular technology would be effortless". Behavioral intention (BI) refers to possible actions of individuals in the future, which can be based on forecasting people behavior [21].

The using of external variables depends on the type of research and reflects the flexibility of TAM[22]. According to "Li, Yuanquan, Jiayin Qi, and Huaying Shu" [22], attitude toward using

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technology is the connection between belief variables (PEOU, PU) and BI. BI is the trend of the user's cognition about likes or dislikes to use the information systems (IS). Usage Behavior (UB) is the final IS use behavior. Thus, the TAM has been verified for several information technologies by researchers and practitioners [11,23,24].

Because many information technologies have emerged since the mid-1990s, many researchers have expanded Davis' TAM, pointing out its limits. When information technology has a hedonic characteristic such as on the web and in games, studies extending the TAM [25,26] have added playfulness or enjoyment variables to the TAM. Moon and Kim [25] have extended the TAM in the WWW domain by adding perceptual playfulness variables. Van der Heijden [27] has also proposed a user acceptance model of hedonic information systems with a perceived enjoyment variable. For compulsory use of information systems or for information technologies for collaboration (e.g., groupware, instant messaging), social influence variables such as subjective norms have been added to extend the TAM with perceived usefulness and perceived ease of use variables of the TAM [28–30]. Over the last few decades, Davis' TAM has been proposed with additional and expanded factors on technology acceptance according to technological characteristics, target users, and context [19].

As shown in Figure 2, our proposed model extends the TAM by adding to the variables that exist in TAM two other variables that are: the perceived risk and quality of information.

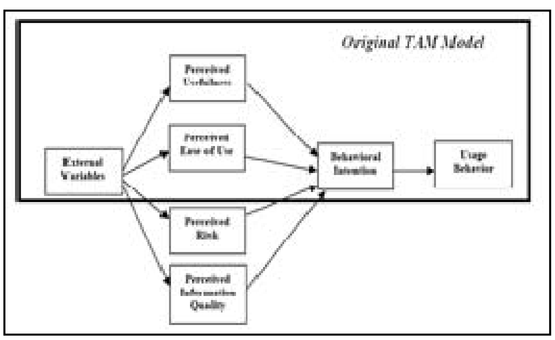

Figure 2: Extending TAM

Since the 1960s, perceived risk theory has been used to explain consumers' behavior. Considerable research has examined the impact of risk on traditional consumer decision making [31]. Peter and Ryan [32] defined perceived risk as a kind of subjective expected loss, and [33] also defined perceived risk as the possible loss when pursuing a desired result. Cunningham [34] noted that perceived risk consisted of the size of the potential loss (i.e. that which is at stake) if the results of the act were not favorable and the individual's subjective feelings of certainty that the results will not be favorable.

Information quality reflects the quality of service or product and it is related to intentions of consumers to purchase. Therefore it is plausible to assume that perceived information quality influences consumer purchase intentions [35–39].

4. EXTENDING TAM IN E-ORIENTATION SYSTEMS

Recently e-orientation platforms has been a very important tool in the students' life, so they can choose the best path of their academic and professional development [3]. Among the most used platforms in Morocco we named "orientation-chabab.com", which is a guide for high school Moroccan graduates for access to private and public universities and colleges. However, the establishment of this e-orientation platform has never been exposed to a study that shows its acceptance by users.

To develop a successful orientation system, the designer must familiarize him or herself with the specifics of that environment, as well as the typical and learned behavioral patterns that occur within it. Orientation systems need to be accessible and understandable for as many people as possible.

The acceptance and the usage of the platform "orientation-chabab.com" have been examined using Extending TAM. To understand the behavior of the individual towards the orientation systems, it is essential to research for the factors which explain the users' acceptance of e-orientation systems.

We divided our extending TAM into three categories: The explanatory variables, the mediator variables and the variable to predict (see Figure 3).

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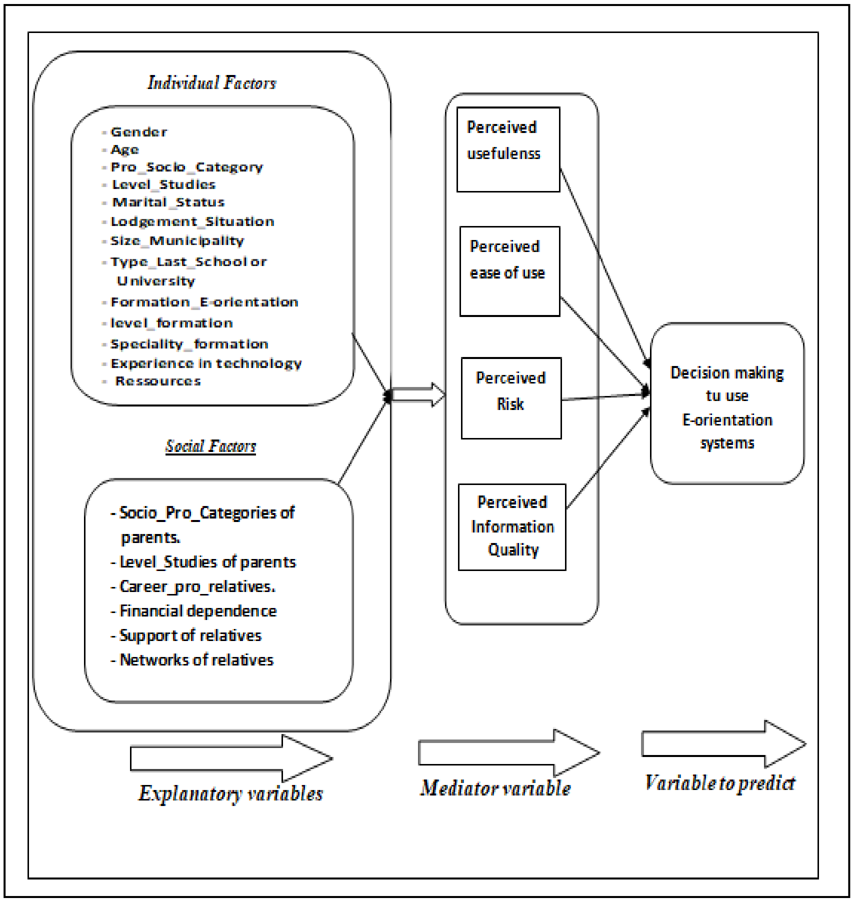

Figure 3: theoretical model of acceptance of E-orientation systems

Explanatory variables: Presents the external variable that affects the decision making of an e-orientation: Individual and Social factors.

Individual factors: It consists on individual variables characteristics (gender, age, level education, formation educational, experience and resources) [40–42].

Social factors: The concept of social influence is based on the subjective norm proposed in the TAM, and describes the influence of people who are important to the subject making decisions. In our study context, we are talking about the social factors that affect the acceptance and use of an e-orientation (influence of : professional categories and study's level of parents, career professional of relatives, support of relatives, effect of relative's and networks financial dependence) [40].

As Mediator Variables, we positioned four factors:

Perceived usefulness (PU) The influence of user perception on the usability of the e-orientation Platform (Behavior Intention) [5].

Perceived ease of use (PEOU) The influence of perceived ease of using E-orientation platform on users' intentions to use the e-orientation platform (Behavior Intention) [5].

Perceived risk: Perceptions of risk in using the e-orientation platform (in Perceived Risk) affect the intention to use this platform (Behavior Intention).

The research of Wang [43] has demonstrated in "Understanding the effects of trust and risk on individual behavior toward social media platforms: A meta-analysis of the empirical evidence' that risk are theorized and approved to have effects on individuals' behaviors toward SMPs.

Perceived information quality: Perceptions of users' information quality in the e-orientation platform (Behavior Intention).

As a Variable to predict we have the user's prediction of decision to accept or not using the e-orientation platform.

The variables cited in our theoretical model (Figure3) are supported by previous literature review by experts as seen in (table1).

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Table 1: Literature related to factors affecting intention to use e-orientation systems.

Factors determine e-orientation platform intention to use	Supported literature	References
Individual factors	Hung et al.2006	[44]
Social factors	Hung et al.2006 Van Dijk et al (2008).	[44,45]
Perceived usefulness	Hung et al.2006, Davis, Fred D(1989)	[44,46]
Perceived ease of use	Hung et al. 2006; CDavis, Fred D(1989)	[44,46]
Perceived risk	(Featherman & Pavlou, 2002; Gefen et al., 2002; Sitkin & Weingart, 1995)	[33,47]
Perceived information quality	Parasuraman et al. 1988; Lee et al. 2002; Kumar et al. 2007; Prybutok et al. 2008; Nicolaou, A. I., & McKnight, D. H. (2006).	[48,49] [13,50]

5. METHODOLOGY
4.1 Data collection

The study was conducted in MOROCCO and our field of study is predicting the utilization acceptance of the platform "orientation-chabab.com". We first distribute the questionnaire for the interviewers and then asked them to use the platform of Moroccan e-orientation during a period of one month. The questionnaire was accompanied by a covering letter explaining the research objectives. By the end of the examination period, the interviewers return to us the answered questionnaire.

The extending TAM model has been used for identifying suitable items. The questionnaire was divided into two parts, one is the demographic information and other is the structured questionnaire as seen in Table2.

The structured questionnaire part includes the different variables presented in the extending TAM. There are 27 questions and each item is measured on a 5-point Likert scale [51]. The targeted individuals are between 18 years and 60 years or older invited to take part in this survey and we asked them to use the platform of e-orientation during a month and to make an evaluation by answering our questionnaire survey.

Table 2: Demographic Information.

Measure	**Item**
Gender	– Male – Female
Age	– 18-20 – 21-24 – 25-45 – 46-60 – >60
socio-professional categories	– Student – Farmer – Merchant, artisan, Entrepreneur – Senior, Professor, Intellectual, Supervisor – Intermediate Occupation – Employee – Worker – Unemployed – Inactive – Other
Education level	– College – High school – Baccalaureate – Baccalaureate+2 – University degree, Mastery(Bac+3or4) – Master, DEA, DSS – PhD – No diploma
Marital Status	– Single – married – divorced – widowed
Lodgment Situation	– At my parents – I live alone – I live with other students – I live in a couple
Commune Size	– Big City – Small Town – Campaign – Town

The distribution of the questionnaire was administered online by mail or by SMS and distributed among groups, forums and social networks, and paper form by realizing direct interviews. Their returns are recorded on an Excel file in Google drive. The data collection was then carried out in April 2018 which lasted 6 months. We received 256 Returns.

In this study 140 respondents were male (54.69%) as shown in figure 4. Those who sent more returns are those who live in big cities (72%)

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as seen in figure 5. About 237 of the respondents are between the ages of 18-45, and only (7, 42%) of the respondents are 60 years or older. Most respondents had higher education (96, 48%).

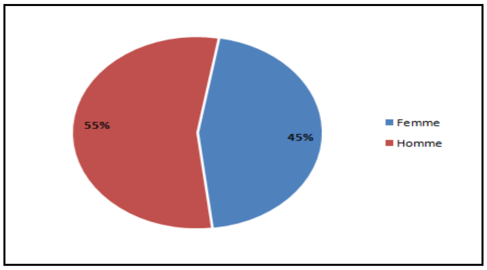

Figure 4: The returns of women and men

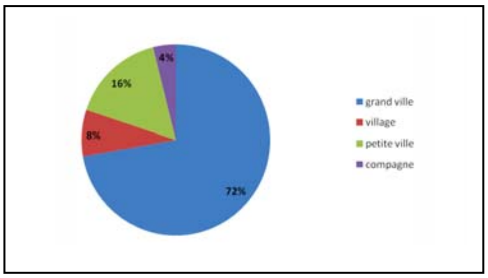

Figure 5: The size of the municipality of responders to the survey

Once we have collected our data, we start to examine it and work out what we can do with it. The objective we have is one of prediction: given the data we have, predict what the next person will make the decision form the e-orientation platform.

Prediction models were developed through rigorous comparative study of important and relevant machine learning classifier algorithms techniques namely: NaiveBayes, SMO, J48, SimpleLogistic and OneR. Performance comparison was also carried out for measuring unbiased estimate of the prediction models using full-training set method. We conducted experiment in the WEKA environment.

Machine learning (ML) is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task [52–54].

4.2 Material

The WEKA (Waikato Environment for Knowledge Analysis) is a popular suite of machine learning software written in Java, developed at the University of Waikato, New Zealand. It was first introduced by [55] as a workbench designed to aid in the application of machine learning technology to real world data sets.

In our data analysis, we have downloaded and installed the software "WEKA" version 3.9 which is available from WEKA University of Waikato website[2].

We have exported in CSV format our data file in the "WEKA" tool which will in turn show us the 27 attributes that will allow us to implement a model to predict the acceptation of the e-orientation systems (see table 3).

Table 3: List of attributes from our data.

Attribute
Form_Presentation
Contents
Perceived_Usefluness
Perceived_Ease_Use
Perception_Risk
Qualiy_Information
Age
Pro_Socio_Category
Level_Studies
Formation_E-orientation
Influence_Level_Formation
Influence_Speciality_Formation
Influence_Formation_Relatives
Experience_Information_Technology
Influence_Career_Pro_Relatives
Ressource_Rate
Financial_Dependence
Support_Relatives
Influence_Networks_Relatives
Decision_Orientation
Type_last_School_University
Marital_Status
Lodgement_Situation
Size_Municipality
Level_Studies_Parents
Socio_Pro_Categories_Parents
Gender

4.3 Classification Algorithms

Our research study uses different well-known classifiers, such as NaïveBayes, SMO, J48, SimpleLogistic and OneR for validating the output of "decision making for using the platform "orientation-chabab.com".

[2] http://www.cs.waikato.ac.nz/ml/weka

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Decision tree algorithm J48: J48 classifier is a simple C4.5 decision tree for classification. It creates a binary tree. The decision tree approach is most useful in classification problem. With this technique, a tree is constructed to model the classification process. Once the tree is built, it is applied to each tuple in the database and results in classification for that tuple. The basic idea is to divide the data into range based on the attribute values for that item that are found in the training sample. J48 allows classification via either decision trees or rules generated from them [56].

Sequential Minimal Optimization* classifier (SMO)*:) is an algorithm for efficiently solving the optimization problem which arises during the training of support vector machines. It was invented by John Platt in 1998 at Microsoft Research. SMO is widely used for training support vector machines and is implemented by the popular libsvm tool. The publication of the SMO algorithm in 1998 has generated a lot of excitement in the SVM community, as previously available methods for SVM training were much more complex and required expensive third-party QP solvers. SMO is an iterative algorithm for solving the optimization problem described above. SMO breaks this problem into a series of smallest possible sub-problems, which are then solved analytically. Because of the linear equality constraint involving the Lagrange multiplier, the smallest possible problem involves two such multipliers [57].

Naive Bayes classifier: The Naive Bayes algorithm is a simple probabilistic classifier that calculates a set of probabilities by counting the frequency and combinations of values in a given data set. The algorithm uses Bayes theorem and assumes all attributes to be independent given the value of the class variable. This conditional independence assumption rarely holds true in real world applications, hence the characterization as Naive yet the algorithm tends to perform well and learn rapidly in various supervised classification problems [6]. Naïve Bayesian classifier is based on Bayes' theorem and the theorem of total probability [56].

Classification One Rule algorithm (OneR), short for "One Rule", is a simple, yet accurate, classification algorithm that generates one rule for each predictor in the data, and then selects the rule with the smallest total error as its "one rule". To create a rule for a predictor, we have to construct a frequency table for each predictor against the target. OneR Algorithm for each predictor, For each value of that predictor, make rule as follows [57] :

- Count how often each value of target(class)appears
- Find the most frequent class
- Make the rule assign that class to this value of the predictors
- Calculate the total error of the rules of each predictor.
- Choose the predictor with the smallest total error.
- Find the best predictor which possess the smallest total error using OneR algorithm

Classification JRIP algorithm (JRip): JRip (RIPPER) is one of the basic and most popular algorithms. Classes are examined in growing size and an initial set of rules for the class is generate using incremental reduced error JRip (RIPPER) proceeds by treating all the examples of a particular decision in the training data as a class, and finding a set of rules that cover all the members of that class. Thereafter it proceeds to the next class and does the same, repeating this until all classes have been covered [36].

The choice of the learning algorithm that we should use, is a critical step. Once the preliminary testing is judged to be satisfactory, the classifier is available for routine use. The classifier's evaluation is most often based on prediction accuracy (the percentage of correct prediction divided by the total number of predictions) [16].

4.4 Classifier Accuracy Measures

There are some parameters on the basis of which we can evaluate the performance of the classifiers such as TP rate, FP rate, Precision and Recall F-Measure areas which are explained below.

The Accuracy of a classifier on a given test set is the percentage of test set tuples that are correctly classified by the classifier.

The Confusion Matrix is a useful tool for analyzing how well your classifier can recognize tuples of different classes. A confusion matrix for two classes is shown in Table 3.
Given m classes, a confusion matrix is a table of at least size m by m. An entry, $CM_{i,j}$ in the first m rows and m columns indicates the number of tuples of class i that were labeled by the classifier as class j.

Table 4: Confusion Matrix.

	C_1 Predicted Class	C_2 Actual Class
C_1 C_2	True positives False positives	False negatives True negatives

A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. Some standards and terms [37]:

1. True positive (TP): If the outcome from a prediction is p and the actual value is also p, then it is called a true positive.
   True positive rate = diagonal element/ sum of relevant row
2. False positive (FP): However, if the actual value is n then it is said to be a false positive.
   False positive rate = non-diagonal element/ sum of relevant row.

Precision and recall: Precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance. Precision can be seen as a measure of exactness or quality, whereas recall is a measure of completeness or quantity. Recall is nothing but the true positive rate for the class [56].

- Precision = diagonal element/sum of relevant column.
- F-measures =2*precision*recall/(precision + recall)

In this paper, we have used WEKA (Waikato environment for knowledge analysis) tool for comparison of NaïveBayes, SMO, J48, SimpleLogistic and OneR algorithm and calculating efficiency based on accuracy regarding correct and incorrect instances generated with confusion matrix.

6. RESULTS AND DESCUSSION

We have performed classification using NaïveBayes, SMO, J48, SimpleLogistic and OneR algorithm on our data of 256 instances in WEKA tool which provide us with inbuilt algorithms. We obtained the following results:

Table 5: Classification accuracy test results

Instances(256) / Algorithms	Correctly classified instances	Incorrectly Classified instances
NaiveBayes	184(71.875%)	72(28.125%)
SMO	253(98.8281%)	3(1.1719%)
J48	194(75.7813%)	62(24.2188%)
JRip	199(77.7344%)	57(22.2656%)
OneR	138(53.9063%)	118(46.0938%)

Table 5 demonstrates the classification accuracy results of five classification algorithms. It is evident from the table 5 that SMO has the highest classification accuracy (98.8281%) where 253 instances have been classified correctly and 3 instances have been classified incorrectly. The Second highest classification accuracy for JRip algorithm is (77.7344%) in which 199 instances have been classified correctly. Moreover, the J48 and NaiveBayes showed respectively a classification accuracy of (75.7813 %) and (71.875%). The OneR results in lowest classification accuracy which is (53.9063%) among the five algorithms. So the SMO outperforms the NaiveBayes, J48, JRip and OneR in terms of classification accuracy.

Table 6: The performance results of five models

	Naïve Bayes	SMO	J48	Simple Logistic	OneR
Precision	72,8%	98,8 %	75,6 %	80,3%	54,6 %
Recall	71,9%	98,8 %	75,8 %	80,5%	53,9 %
F-measure	71,9%	98,8 %	75,5 %	80,2%	52,9 %
TPR	71,9%	98,8 %	75,8 %	80,5%	53,9 %
FPR	8,5%	0,6%	8,5%	7,5%	15,9 %

As can be seen from Table 6, the precision, recall, Fmeasure of SMO algorithms performed better than NaïveBayes, J48, SimpleLogistic and OneR. Furthermore, the points of bagging algorithms are near the perfect point than the point of the four remaining algorithm which means this machine learning algorithm can identify a prediction of an e-orientation system acceptation with very high precision, reliability.

A distinguished confusion of SMO (sometimes called contingency table). SMO is applied on the data set and the confusion matrix is generated for class “Decision of E-orientation” having five possible values: Totally agree, not at all, agree, mostly agree, and more or less agree.

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Confusion Matrix:

a	b	c	d	e	<-- classified as
39	0	1	0	0	a = Totally agree
0	30	0	0	0	b = Not at all
1	0	104	0	0	c = Agree
0	0	1	42	0	d = Mostly agree
0	0	0	0	38	e = More or less agree

For above confusion matrix, true positives for class a='Totally agree' is 39 while false positives is 1 whereas, for class b=' Not at all', true positives is 30 and false positives is null. True positives for class c="Agree" is 104 while false positives is 1. Whilst True positives for class d=" Mostly agree" is 42 while false positives is null. And True positives for class e=" More or less agree" is 38 while false positives is null. Diagonal elements of matrix 39+30+104+42+38 =253 represents the correct instances classified and other elements 1+1+1 = 3 represents the incorrect instances.
Many different metrics are used in machine learning and to build and evaluate models. In SMO We employed four performance measures TP rate, FP rate: precision, recall, F-measure.

In Table.3 SMO shows a high accuracy and true positives Rate (TP Rate) as well as false positives Rate (FP Rate). In general, the performance of SMO is evaluated in term of Precision, TP Rate, and FP Rate.
The proposed model with SMO classifier can be used as a predictive tool for researchers, instructional designers and expert of e-orientation systems. The results of this study can be used during the conceptual design of e-orientation platforms. The proposed model is also useful as a practical tool to test user's acceptance, which would provide early clues to risks of user rejection of the e-orientation system. The knowledge of risks at this stage would enable designers and responsible of e-orientation to take preventive measures to ensure user's acceptance of the e-orientation system.

In this study, a model is proposed based on TAM model associated with social and individual external factors to determinate the factors of user's acceptance of an e-orientation Moroccan platform: orientation-chabab.com, by extending it with variable mediator, as perceived and perceived quality.

The goal of our research is to generate an acceptance model of e-orientation systems that can be used during the conceptual design of e-orientation platforms.
The survey instruments for this study was developed using validated items from the theoretical constructs of the extended TAM model for e-orientation platform. And we use machine learning classifier algorithms techniques for elaborate our predictive model.

7. CONCLUSION

The goal of this study is to generate an acceptance model prediction's for the e-orientation systems that can be used during the conceptual design of e-orientation platforms. For that we have evaluated the acceptability of an e-orientation Moroccan platform: orientation-chabab.com by using a survey instruments that was developed using validated items from the theoretical constructs of the extended TAM model for e-orientation and we apply machine learning classifier algorithms techniques in our data for elaborate our predictive model.

In this research we have performed the experiments in order to determine the classification accuracy of five algorithms in terms of which is the better predictive algorithm of user's decision making via the e-orientation platform "orientation-chabab.com", with the help of an attractive data mining tool known as WEKA.

Five algorithms namely NaïveBayes, SMO, J48, SimpleLogistic and OneR were compared on the basis of different percentage of correctly classified instances. All these four come under the classification methods of data mining which makes a relationship between a dependent (OUTPUT) variable and independent (INPUT) variable by mapping the data points. It is clear from the simulation results that the highest classification accuracy performance is for the SMO classifier (98.8281%) for our datasets containing 27 attributes with each 256.

Furthermore, the Second highest classification accuracy for JRip algorithm is (77.7344%). Moreover, the J48 and NaiveBayes showed respectively a classification accuracy of (75.7813 %) and (71.875%). The OneR results showed less accuracy as compared to the previous four mentioned which is (53.9063%). This indicates that SMO classification algorithm should be favored over NaïveBayes, J48, SimpleLogistic and OneR classifiers where classification accuracy performance is important.

We conclude that the SMO classification algorithm is the best algorithm for generating an

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acceptance model prediction's of the e-orientation Moroccan platform "orientation-chabab.com" that can be used during the conceptual design of the future e-orientation systems.

In future work, we can include the extension of the simulation performed in the WEKA environment by increasing the number of instances in a given dataset and comparing the classification accuracy performance of the proposed algorithms. Moreover, other factor can also be taken for instance the time requirement to compare the accuracy of the proposed algorithms which we believe shall surely bring out certain important aspects about the different algorithm which can prove usefulness in the research field.

REFRENCES:

[1] Guerss F zahra, Aitdaoud M, Douzi K, Talbi M, Namir A. Implementation of a computerized system for the orientation of the Moroccan student in the university. Procedia-Social and Behavioral Sciences 2015;182:381–387.

[2] Guerss F, Aitdaoud M, Douzi K, Guemmat K, Namir A. Towards a new ontology of the Moroccan Post-baccalaureate learner profile for the E-orientation system "MMSyOrientation." Dx Doi Org 2015.

[3] Adib J, Moutachaouik H, Marzak A, Hain M. The Generation of the Components Meta-Models of an E-Orientation System Using the WSDL-UML Transformation 2018.

[4] Fatima-zahra G, Khadija D. Modernization of a domain E-orientation metamodel. 2016 11th International Conference on Intelligent Systems: Theories and Applications (SITA), IEEE; 2016, p. 1–6.

[5] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 1989:319–340.

[6] Zhang X, Prybutok VR, Koh CE. The role of impulsiveness in a TAM-based online purchasing behavior. Information Resources Management Journal (IRMJ) 2006;19:54–68.

[7] Ariff MSM, Yeow S, Zakuan N, Jusoh A, Bahari AZ. The effects of computer self-efficacy and technology acceptance model on behavioral intention in internet banking systems. Procedia-Social and Behavioral Sciences 2012;57:448–452.

[8] Chin WW, Todd PA. On the use, usefulness, and ease of use of structural equation modeling in MIS research: a note of caution. MIS Quarterly 1995:237–246.

[9] Doll WJ, Hendrickson A, Deng X. Using Davis's perceived usefulness and ease-of-use instruments for decision making: a confirmatory and multigroup invariance analysis. Decision Sciences 1998;29:839–869.

[10] Mathieson K. Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. Information Systems Research 1991;2:173–191.

[11] Segars AH. Pie-Examining Perceived Ease of Use and Usefulness: A Confirmatory Factor Analysis. MIS Quarterly 1993:517.

[12] Roy SK, Balaji M, Kesharwani A, Sekhon H. Predicting Internet banking adoption in India: A perceived risk perspective. Journal of Strategic Marketing 2017;25:418–438.

[13] Nicolaou AI, McKnight DH. Perceived information quality in data exchanges: Effects on risk, trust, and intention to use. Information Systems Research 2006;17:332–351.

[14] Legris P, Ingham J, Collerette P. Why do people use information technology? A critical review of the technology acceptance model. Information & Management 2003;40:191–204.

[15] Michie D, Spiegelhalter DJ, Taylor C, others. Machine learning. Neural and Statistical Classification 1994;13.

[16] Kotsiantis SB. Supervised Machine Learning: A Review of Classification Techniques. Informatica (Lithuanian Academy of Sciences) 2007;31:249–268.

[17] Davis FD. A technology acceptance model for empirically testing new end-user information systems : theory and results. Journal of Multivariate Analysis 1985.

[18] Fishbein M, Ajzen I. Belief, attitude, intention, and behavior: An introduction to theory and research 1977.

[19] Yoon C. Extending the TAM for Green IT: A normative perspective. Computers in Human Behavior 2018;83:129–139.

[20] Venkatesh V, Davis FD. A model of the antecedents of perceived ease of use: Development and test. Decision Sciences 1996;27:451–481.

[21] Molinari LK, Abratt R, Dion P. Satisfaction, quality and value and effects on repurchase and positive word-of-mouth behavioral

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

intentions in a B2B services context. Journal of Services Marketing 2008;22:363–373.
[22] Li Y, Qi J, Shu H. Review of relationships among variables in TAM. Tsinghua Science & Technology 2008;13:273–278.
[23] Adams DA, Nelson RR, Todd PA. Perceived usefulness, ease of use, and usage of information technology: A replication. MIS Quarterly 1992:227–247.
[24] Hendrickson AR, Massey PD, Cronan TP. On the test-retest reliability of perceived usefulness and perceived ease of use scales. MIS Quarterly 1993:227–230.
[25] Moon J-W, Kim Y-G. Extending the TAM for a World-Wide-Web context. Information & Management 2001;38:217–230.
[26] Ha I, Yoon Y, Choi M. Determinants of adoption of mobile games under mobile broadband wireless access environment. Information & Management 2007;44:276–286.
[27] Van der Heijden H. User acceptance of hedonic information systems. MIS Quarterly 2004:695–704.
[28] Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science 2000;46:186–204.
[29] Lou H, Luo W, Strong D. Perceived critical mass effect on groupware acceptance. European Journal of Information Systems 2000;9:91–103.
[30] Glass R, Li S. Social influence and instant messaging adoption. Journal of Computer Information Systems 2010;51:24–30.
[31] Lin W-B. Investigation on the model of consumers’ perceived risk-integrated viewpoint. Expert Systems With Applications 2008;34:977–988.
[32] Peter JP, Ryan MJ. An investigation of perceived risk at the brand level. Journal of Marketing Research 1976;13:184–188.
[33] Featherman MS, Pavlou PA. Predicting e-services adoption: a perceived risk facets perspective. International Journal of Human-Computer Studies \/ International Journal of Man-Machine Studies 2003;59:451–474.
[34] Cunningham MS. The major dimensions of perceived risk. Risk Taking and Information Handling in Consumer Behavior 1967.
[35] Wang RY, Strong DM. Beyond accuracy: what data quality means to data consumers. Journal of Management Information Systems 1996;12:5–33.
[36] Parasuraman A, Grewal D. The impact of technology on the quality-value-loyalty chain: A research agenda. Journal of the Academy of Marketing Science 2000;28:168–174.
[37] Patterson PG, Spreng RA. Modelling the relationship between perceived value, satisfaction and repurchase intentions in a business-to-business, services context: an empirical examination. International Journal of Service Industry Management 1997;8:414–434.
[38] Tam JLM. Customer Satisfaction, Service Quality and Perceived Value: An Integrative Model. Journal of Marketing Management 2004;20:897–917.
[39] Zeithaml VA. Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence: Journal of Marketing 1988;52:2–22.
[40] Venkatesh V, Morris MG. Why don’t men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. Management Information Systems Quarterly 2000;24:115–139.
[41] Radif^1 M, Fan^1 I-S, McLaughlin^1 P. EMPLOYMENT TECHNOLOGY ACCEPTANCE MODEL (TAM) TO ADOPT LEARNING MANAGEMENT SYSTEM (LMS) IN IRAQI UNIVERSITIES. Inted2016. 10th international technology, education and development conference, 2016, p. 7120–7130.
[42] Kim DJ, Ferrin DL, Rao HR. A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems 2008;44:544–564.
[43] Wang Y, Min Q, Han S. Understanding the effects of trust and risk on individual behavior toward social media platforms: A meta-analysis of the empirical evidence. Computers in Human Behavior 2016;56:34–44.
[44] Hung S-Y, Chang C-M, Yu T-J. Determinants of user acceptance of the e-Government services: The case of online tax filing and payment system. Government Information Quarterly 2006;23:97–122.
[45] Van Dijk JA, Peters O, Ebbers W. Explaining the acceptance and use of government Internet services: A multivariate analysis of 2006 survey data in the Netherlands.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Government Information Quarterly 2008;25:379–399.
[46] Davis FD, Bagozzi RP, Warshaw PR. User acceptance of computer technology: a comparison of two theoretical models. Management Science 1989;35:982–1003.
[47] Sitkin SB, Weingart LR. Determinants of risky decision-making behavior: A test of the mediating role of risk perceptions and propensity. Academy of Management Journal 1995;38:1573–1592.
[48] Parasuraman A, Zeithaml VA, Berry LL. SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. Journal of Retailing 1988;64:12–37.
[49] Lee YW, Strong DM, Kahn BK, Wang RY. AIMQ: a methodology for information quality assessment. Information & Management 2002;40:133–146.
[50] Prybutok VR, Zhang X, Ryan SD. Evaluating leadership, IT quality, and net benefits in an e-government environment. Information & Management 2008;45:143–152.
[51] Joshi A, Kale S, Chandel S, Pal D. Likert scale: Explored and explained. British Journal of Applied Science & Technology 2015;7:396.
[52] Hu H, Li J, Plank A, Wang H, Daggard G. A comparative study of classification methods for microarray data analysis. Proceedings of the fifth Australasian conference on Data mining and analystics-Volume 61, Australian Computer Society, Inc.; 2006, p. 33–37.
[53] Shipp MA, Ross KN, Tamayo P, Weng AP, Kutok JL, Aguiar RCT, et al. Diffuse large B-cell lymphoma outcome prediction by gene- expression profiling and supervised machine learning. Nature Medicine 2002;8:68–74.
[54] Mair C, Kadoda GF, Lefley M, Phalp K, Schofield C, Shepperd MJ, et al. An investigation of machine learning based prediction systems. Journal of Systems and Software 2000;53:23–29.
[55] Garner SR, others. Weka: The waikato environment for knowledge analysis. Proceedings of the New Zealand computer science research students conference, 1995, p. 57–64.
[56] Patil TR, Sherekar S, others. Performance analysis of Naive Bayes and J48 classification algorithm for data classification. International Journal of Computer Science and Applications 2013;6:256–261.
[57] Nasa C, Suman S. Evaluation of different classification techniques for web data. International Journal of Computer Applications 2012;52:34–40.