An Intelligent Recommender System for E-learning Process Personalization: A Case Study in Maritime Education

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***Abstract*—The lockdown due to the pandemic of COVID-19 led to an unprecedented impact on education. Higher education institutions were forced to shift rapidly to distance and online learning. On the one hand, this fact revealed the weaknesses of adoption and utilization of e-learning strategies and technologies, but, on the other hand, it resulted in a digital revolution in education. However, the wide adoption of e-learning strategies and technologies and the complete transformation of the physical learning process to a virtual one pose the challenge of personalization of the learning process. This paper proposes a recommender system for supporting the professors in higher education in understanding their students' needs so that he/she adapts the e-learning process accordingly. To do this, it utilizes learning profile theory and it implements k-means clustering and Bayesian Networks (BN) The proposed approach was applied to a maritime educational institution.**

Keywords-learning profiles; learning styles; higher education; k-means clustering, Bayesian network; classification.

I. INTRODUCTION

According to a European Commission's report on digital skills in education in 2013, an average of 65% of students in EU countries never used digital textbooks, exercise software, broadcasts/podcasts, simulations or learning games [1]. Since then, higher education institutions have shown a persistent concern with enhancing students' academic performance through the use of innovative technologies that offer new ways of delivering and producing university education [2]. From an economic point of view, the industry of e-learning has developed considerably in the last decade. The market of e-learning all over the world will be over 243 billion dollars in 2022 [3].

The pandemic of COVID-19 led most of the governments around the world to impose lockdown, social/physical distancing, avoiding face-to-face teaching-learning, and restrictions on travelling and immigration [4]. It caused the closing of classrooms all over the world and forced 1.5 billion students and 63 million educators to suddenly modify their face-to-face academic practices [3]. This closure led to an unprecedented impact on education. Higher education institutions were forced to shift rapidly to distance and online learning. On the one hand, this fact revealed the weaknesses of adoption and utilization of e-learning strategies and technologies [4] [5]; but, on the other hand, it resulted in a digital revolution through online lectures, teleconferencing, digital open books, online examination, and interaction at virtual environments [6].

E-learning is the use of new multimedia technologies and the Internet to improve the quality of learning by facilitating access to resources and services, as well as remote exchange and collaboration [7] [8]. It has a great potential from the educational perspective and it has been one of the main research lines of educational technology in the last decades [3]. Particular attention has been given on understanding the adoption factors related to e-learning services satisfaction and acceptance by students and tutors [5] [7] [9].

However, the wide use of e-learning due to COVID-19 demonstrated inequalities as a result of previously underestimating the potential of e-learning and its exclusion from the digital education projects of educational institutions [3]. A considerable amount of literature has investigated inequalities between developed and developing countries [3] [10]. However, the wide adoption of e-learning strategies and technologies and the complete transformation of the physical learning process to a virtual one pose the challenge of personalization according to different learning profiles [11], a research area rather underexplored. E-learning provides people with a flexible way to learn allowing learning on demand and reducing the associated costs [7]. E-learning personalization is emerged as a major challenge [11] [12],

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especially in today's fast adoption of this alternative way of learning.

Despite the large amount of research works dealing with learning profiles in physical classrooms, these models should be further investigated and validated in the virtual classrooms, during the e-learning process. To this end, the contribution of e-learning to several learning factors according to the learning profiles has the potential to reveal the acceptance of e-learning by different learning profiles and to result in e-learning process personalization in order to mitigate the respective inequalities.

The objective of the current paper is to develop an intelligent recommender system for supporting the professors in higher education in understanding their students' needs so that he/she adapts the e-learning process accordingly. In addition, the proposed recommender system is able to classify new records (i.e. students) to the appropriate learning profiles, e.g., in order to support the organization of the class groups. The proposed approach was applied to a maritime educational institution. The rest of the paper is organized as follows: Section II presents the related work on methods and approaches for evaluating students' acceptance of the e-learning process as well as learning profile models for learning personalization. Section III describes the research methodology and the proposed approach for the development of an intelligent recommender system for e-learning process personalization. Section IV presents the results from the adoption of the proposed methodology on a dataset of 268 students in the maritime education. Section V concludes the paper and outlines our plans for future work.

II. RELATED WORK

Existing literature is quite rich on evaluating students' experience, satisfaction and acceptance of the e-learning process. In general, earlier studies focused more on content, customization and technology, while more recent studies focused on students' attitude and interaction, expectations, acceptance and satisfaction [9] [13]. To this end, there is an emerging trend towards the identification of the key factors for the adoption of e-learning strategies and technologies.

Several studies have used the original version of the classic model, the DeLone & McLean (D&M) IS Success Model [14] to measure and evaluate the success of e-learning systems [15]-[17]. The use of virtual learning environments in addition to classroom study (blended learning), were surveyed by [18]. They concluded that the students' performance of the virtual learning environment support had better results than those having only face to face learning. The identified key satisfaction factors are information quality, system quality, instructor attitude toward e-learning, diversity in assessment, and learner perceived interaction with others.

The authors in [7] identified clear governance structure and the need of organized distribution of planning responsibilities and implementation as the main adoption factors. In [19], the authors concluded that perceived usefulness, ease of use, perceived enjoyment, network externality factor, system factor, individual factors, and social factors are the main e-learning acceptance predictors. Student interface, learning community, content, and customization as well as ease of use of web courses have also been identified to have a significant impact on e-learning acceptance [20] [21].

In [22], the authors concluded that student e-learning adoption and attitudes in the university context are academic achievements mediated by digital readiness and academic engagement. In [23], the authors proposed an e-learning tools acceptance model in order to examine the level of acceptance and critical factors of virtual learning tools among university students in developing countries. Results confirm a strong relation between the perceived usefulness and the instructor preparation and autonomy in learning, as well as between the ease of use and the perceived self-efficacy perception. The reseach work of [24] developed a Technology Acceptance Model (TAM) for e-learning. The results indicated that system quality, computer self-efficacy, and computer playfulness have a significant impact on perceived ease of use of e-learning system. Furthermore, information quality, perceived enjoyment, and accessibility were found to have a positive influence on perceived ease of use and perceived usefulness of e-learning system.

The authors in [25] applied process mining methods in order to discover students' self-regulated learning processes during e-learning. They identified a high presence of actions related to forum-supported collaborative learning among the students who finally passed the exams and an absence of those in their failing classmates. The research work of [5] concluded that the main factors affecting the usage of e-learning are: technological factors, e-learning system quality factors, trust factors, self-efficacy factors and cultural aspects. Therefore, apart from the challenges related to the technological infrastructure, change management, course design, computer self-efficacy and financial support are also issues of outmost importance.

Learning personalization is an important topic in educational sciences. Since different people learn in different ways, it is important to create and adapt the e-learning process in order to maximize and speed up the learning process [11]. The need to adapt teaching strategies to the student's preferences is a reality in classrooms, be they physical or virtual [26] [27]. However, this does not mean that a method should be created for each student in a classroom, but that the best form of interaction for each of them be identified, building groups of learners with common characteristics [28]. Learning styles are cognitive, affective and psychological traits that determine how a student interacts and reacts in a learning environment [29]. The idea is to identify the marked characteristics of a given learner so that these traits influence his learning process.

Several learning profile models have been developed in the literature, such as the Myers-Briggs Type Indicator – MBTI, Kolb's Experiential Learning Model, the Hermann Brain Dominance Instrument (HBDI), the Dunn and Dunn Model, the Felder-Silverman Model, and the Honey and Mumford Model [26] [27]. With the wide adoption of e-learning strategies and technologies, there is the need for applying and validating learning profile models in the digital

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and online learning era. For example, in [11], the authors investigated the e-learning personalization aiming at keeping students motivated and engaged. To that end, they proposed the use of k-means algorithm to cluster students based on 12 engagement metrics divided into two categories: interaction-related and effort-related. The research work of [27] presented the architecture of a system that realizes an evaluation of learning profiles based on categories of student preferences. The profile models were built according to categories of student preferences based on the proposal of learning styles put forward by [29].

III. Research Methodology

A. Data Collection and Learning Profile Model Selection

The data was collected in the form of an online questionnaire of 80 questions addressed to students of higher educational institution. Each question was in the form of Likert scale (1: Strongly Disagree – 5: Strongly Agree) and it was related to one out of the four learning styles as defined by the Honey and Mumford Model [30]: *activist, reflector, pragmatist,* and *theorist*. For example, in an ideal scenario that a student has answered 5: Strongly Agree to all the questions matching to the "activist" learning profile and 1: Strongly Disagree to all the others, he/she is classified as "activist".

Activist refers to an individual's preference for active involvement in the learning activity (through problem solving, discussion, creating their own models). *Reflector* learns best by watching and thinking about what is happening. The reflector responds more positively to learning activities where there is time to observe, reflect and think and work in a detailed manner. *Pragmatist* wants to know how to put what they are learning into practice in the real world. They experiment with theories, ideas, and techniques and take the time to think about how what they've done relates to reality. *Theorist* seeks to understand the theory behind the action. They enjoy following models and reading up on facts to better engage in the learning process.

B. Classification for Structuring the Learning Profiles

The classification of the student to the learning profiles is not straightforward (like in the aforementioned ideal scenario) since they may have characteristics of more than one profile. Therefore, according to the given answers, the k-means clustering algorithm was applied in order to assign the respondents to 4 clusters ($k=4$) matching to the aforementioned learning profiles.

k-means clustering is a method of vector quantization that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid) [31]. k-means clustering minimizes the within-cluster variances (squared Euclidean distances). Given a set of observations $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$, where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k $(\leq n)$ sets $\mathbf{S}=\{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS) (i.e. variance). Formally, the objective is to find:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x}\in S_i} \|\mathbf{x}-\boldsymbol{\mu}_i\|^2 = \arg\min_{\mathbf{S}} \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i \tag{1}$$

where $\boldsymbol{\mu}_i$ is the mean of points in S_i. This is equivalent to minimizing the pairwise squared deviations of points in the same cluster:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \frac{1}{2|S_i|} \sum_{\mathbf{x},\mathbf{y}\in S_i} \|\mathbf{x}-\mathbf{y}\|^2 \tag{2}$$

The equivalence can be deduced from the identity:

$$\sum_{\mathbf{x}\in S_i} \|\mathbf{x}-\boldsymbol{\mu}_i\|^2 = \sum_{\mathbf{x}\neq\mathbf{y}\in S_i} (\mathbf{x}-\boldsymbol{\mu}_i)(\boldsymbol{\mu}_i-\mathbf{y}). \tag{3}$$

Because the total variance is constant, this is equivalent to maximizing the sum of squared deviations between points in different clusters (Between-Cluster Sum of Squares, BCSS), which follows from the law of total variance.

C. Modelling the Relationships between Learning Profiles and E-learning Preferences

Subsequently, the proposed approach models the relationships between the learning profiles and e-learning contribution to learning factors as derived from the questionnaire. To do this, a Bayesian Network (BN) is applied aiming at identifying these causal and uncertain relationships. A BN, also known as belief network, is defined as a pair $B = (G, \Theta)$. $G = (V, E)$ is a Directed Acyclic Graph (DAG) where $V = \{v_1, \ldots, v_n\}$ is a collection of n nodes, $E \subset V \times V$ a collection of edges and a set of parameters Θ containing all the Conditional Probabilities (CP) of the network [32]. Each node $v \in V$ of the graph represents a random variable X_V with a state space $\boldsymbol{X_V}$ which can be either discrete or continuous. An edge $(v_i, v_j) \in E$ represents the conditional dependence between two nodes v_i, $v_j \in V$ where v_i is the parent of child v_j. If two nodes are not connected by an edge, they are conditional independent. Because a node can have more than one parent, let π_v the set of parents for a node $v \in V$.

Therefore each random variable is independent of all nodes $V \setminus \pi_v$. For each node, a Conditional Probability Table (CPT) contains the CP distribution with parameters $\theta_{xi|\pi i} := P(x_i|\pi_i) \in \Theta$ for each realization x_i of X_i conditioned on π_i. The joint probability distribution over V is visualized by the BN and can be defined as:

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|\pi_i) \tag{4}$$

With BN, inference for what-if analysis can be supported, either top-down (predictive support) or bottom-up (diagnostic support). If a random variable which is represented by a node is observed, the node is called an evidence node; otherwise, it is a hidden node [33]. Based on

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the learning profiles derived from the questionnaire, a BN with two layers was developed: at the top layer (i.e. learning profiles), there are 4 parent nodes matching to the respective clusters of students.

At the bottom layer (i.e. e-learning contribution to learning factors), there are 9 child nodes referring to 9 e-learning factors grouping the questions. In this way, the model identifies the preferences of each learning profile by assessing the impact of e-learning on the learning process of each profile. Therefore, according to the learning profile, the user is able to select the appropriate learning strategies aiming at personalizing the e-learning process.

D. *Predicting the Class Attribute of E-learning Impact*

At any time, the user of the recommender system is able to make queries in order to investigate particular relationships along with their associated CPTs. Moreover, the model incorporates a Naïve Bayes classifier for predicting the class attribute of a learning profile as soon as new records of students' responses are inserted into the database.

Naïve Bayes classifier is highly scalable, requiring a number of parameters linear in the number of variables in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers [34]. Prediction of the class attribute can be performed even if the questionnaire is not completely answered.

IV. RESULTS

The proposed approach was applied on a dataset of 268 students of a maritime higher educational institution in Greece. The transformation of maritime from highly labour- to capital-intensive industry contributed to the presence of tertiary education in maritime studies [35]. However, the learning process in maritime education faces additional challenges due to the structure of their programs, the tendency of undergraduate students to combine studies and work, the internationalization, specialization, and standardization [35]-[37]. These make maritime education an interesting case study for the validation of e-learning process personalization.

The implementation and execution of the experiments were performed using the sklearn.cluster library of Python [38] for the k-means clustering algorithm and the BN functionalities of the pgmpy (Probabilistic Graphical Models using Python) package [39]. After having structured the learning profiles of the respondents, the BN is created and the CPTs are calculated, as shown in Figure 1. Table I presents the highest and the lowest CPs of the e-learning contribution to learning factors given the learning profiles. Therefore, the highest CP is the one of a student being activist given the answers of the second row that is 38.6%. The lowest CP is the one of a student being activist given the answers of the last row that is 5.6%. According to the queries posed by the user, various calculations can be done. As already mentioned, the model can also serve as a classifier for predicting the class attribute of learning factors as soon as new records of students are received and classified through the k-means clustering algorithm.

TABLE I. CPS OF THE E-LEARNING CONTRIBUTION TO LEARNING FACTORS GIVEN THE LEARNING PROFILES

	E-learning contribution	Learning profile	CP
Highest CPs	F1={Neutral}, F2={Agree}, F3={Disagree}, F4={Agree}, F5={Strongly Disagree}, F6={Disagree}, F7={Neutral}, F8={Strongly Disagree}, F9={Agree}	Activist	0.386
	F1={Disagree}, F2={Disagree}, F3={Agree}, F4={Strongly Disagree}, F5={ Disagree}, F6={Agree}, F7={Neutral}, F8={Neutral}, F9={Disagree}	Theorist	0.295
Lowest CPs	F1={Stongly Agree}, F2={Disagree}, F3={Strongly Agree}, F4={Neutral}, F5={ Disagree}, F6={Strongly Disagree}, F7={Neutral}, F8={Strongly Disagree}, F9={Disagree}	Reflector	0.081
	F1={Agree}, F2={Strongly Disagree}, F3={Agree}, F4={Strongly Disagree}, F5={Strongly Agree}, F6={Neutral}, F7={Agree}, F8={Agree}, F9={Strongly Disagree}	Activist	0.056

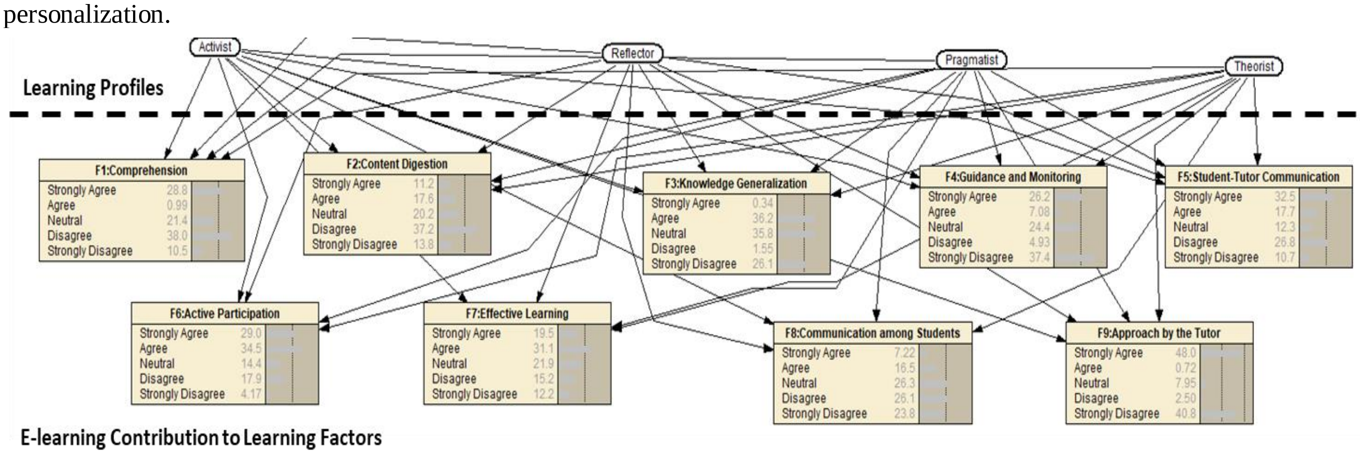

Figure 1. The Bayesian Network structure for modelling the relationships between learning profiles and e-learning contribution to learning factors.

In order to evaluate its classification effectiveness, we inserted additional records, derived from more questionnaires addressed to students of the maritime educational institution, and we created the confusion matrix according to Table II in order to estimate the precision and the recall of the classifier using the (5) and (6) [40].

TABLE II. CONFUSION MATRIX

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP) = 31	False Negative (FN) = 6
Actual Negative	False Positive (FP) = 4	True Negative (TN) = 22

$$Precision = \frac{TP}{TP + FP} = \frac{31}{31 + 4} = 88.57\% \quad (5)$$

$$Recall = \frac{TP}{TP + FN} = \frac{31}{31 + 6} = 83.78\% \quad (6)$$

The Precision results are quite satisfactory, while the Recall results can be further improved. We should also take into account that modelling human behavior, such as the learning process, has a high degree of uncertainty [41]. Moreover, the BN model sticks to the initially identified relationships, i.e., the ones that have been mined during the model training. Therefore, when new relationships, not previously identified, are added, they are not classified correctly. These records include values that are not frequent, so they are not critical for decision making.

V. CONCLUSIONS AND FUTURE WORK

During the last years, e-learning has been gaining an increasing attention in higher education. Especially during the last months, higher education institutions were forced to shift rapidly to distance and online learning. On the one hand, this fact revealed the weaknesses of adoption and utilization of e-learning strategies and technologies, but, on the other hand, it resulted in a digital revolution in education. A major challenge was to apply e-learning strategies and technologies for supporting e-learning personalization. In this paper, we proposed an intelligent recommender system for e-learning process personalization.

The proposed approach is based on the Honey and Mumford Model of learning profiles and utilized k-means clustering and BNs in order to classify the students to learning profiles and to reveal relationships with the contribution of e-learning to several learning factors. The proposed approach was applied to a dataset of 268 students in maritime education and we presented indicative examples of queries. We also validated the model in terms of its precision and recall in predicting the learning profile when new records are inserted into the database.

Regarding our future work, we plan to incorporate additional learning factors with respect to the e-learning impact. Moreover, we plan to apply more machine learning and data analytics methods, with an emphasis on fuzzy methods, in combination with different learning profile models. Finally, we will plan to expand our research to various universities in order to obtain more generalized results.

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