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Development of an e-Learning Recommender System Using Discrete Choice Models and Bayesian Theory: A Pilot Case in the Shipping Industry

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1. Introduction

The field of e-learning and self-learning has rapidly evolved during the past decade mainly because of major advances in telecommunications and information technologies, in particular the widespread use of web and mobile applications. Furthermore, the work environment conditions in most industries have become extremely demanding and competitive; therefore various forms of life-long learning appear to play an important role for employees' career development, as well as for companies' productivity improvement and human resources' efficiency. The flexibility, and cost effectiveness that e-learning offers is very significant, in most cases.

In an environment with abundant educational and training institutions the development of efficient new procedures to better guide students or trainees for selecting suitable learning materials is a challenging and open issue. In particular, the development of efficient e-learning recommender systems, such as an electronic training advisor who will help individuals in choosing the appropriate e-learning courses matching their particular characteristics, preferences and needs and based on their expected professional and personal development, is an open and promising research and development area (Adomavicius & Tuzhilin, 2005; Brusilovsky, 2002; Kim et al, 2009; Ricci & Werthner, 2006; Zanker & Jessenitschnig, 2006;).

An e-learning recommender system can help trainees overcome basic constraints that e-learning users increasingly face:

- the uncertainty and insecurity of the individuals that a particular educational offer will have the best possible outcome related to their career objectives.
- the difficulty of finding and choosing courses among a large number of courses offered by different institutions, universities and organizations, based on their individual training needs;
- the perception regarding the lack of interesting content or relative courses per case;

This chapter presents an innovative methodology for the development of a training advisor for e-learning environments. We consider e-learning personalization issues and present an e-learning recommender framework based on discrete choice models and Bayesian theory (Chaptini, 2005; Greene, 1993).

2. The context

The development of the presented intelligent training advisor, took place within the scope of the SLIM-VRT E.U. research project and was applied in the shipping industry. A field study was conducted for requirements data collection, with 5000 questionnaires and 24% response rate. The techniques used offer the advantage of a comparatively detailed, user-focused e-learning attributes modelling framework (advanced choice theory) and a competent system learning capability (Bayesian theory), that improves over time the performance of the recommender system itself.

In the following, we explain development of the advisor system in the context of involved and affected stakeholders, as shown in Fig.1, including:

1. the training society;
2. the firms and organizations;
3. the learners/trainees or end-users;

These groups interact in a common environment and the actions of one group directly affect the other. Obviously, these major groups of stakeholders in a particular market, for instance the shipping industry, operate in a distinct, dynamic Economic, Technological and Legislative environment.

The methodology we propose is implemented in the shipping industry, where seafarers have specific learning needs in order to adapt and perform successfully in a continuously changing organizational, business, and employment environment (Theotokas & Progoulaki 2007; Progoulaki & Theotokas, 2008; Progoulaki et al, 2005).

Common career paths in the shipping industry may require alternate career changes and job rotation such as acquisition of different positions onboard, work on different types of ships, and employment, ashore, at an office position related with the shipping and port operations management. The training process should take into account particularities of the seafaring profession such as having long intervals between two employment periods, being far away from the family when employed onboard, experiencing alienation from the broader society, etc. Thus, the context of the maritime e-learning is highlighted by those specific characteristics underpinning the shipping market and educational environment. Today, the following features are pertinent to the shipping workforce training aspects:

- There is a decline of interest in the seafaring profession and shortage of ex-ship officers for shore-based positions
- The impact of new technologies in terms of reorganization of crew duties is important
- Maritime personnel needs to be polyvalent
- The safety of life at sea and the protection of marine environment have been a basic concern of the maritime community

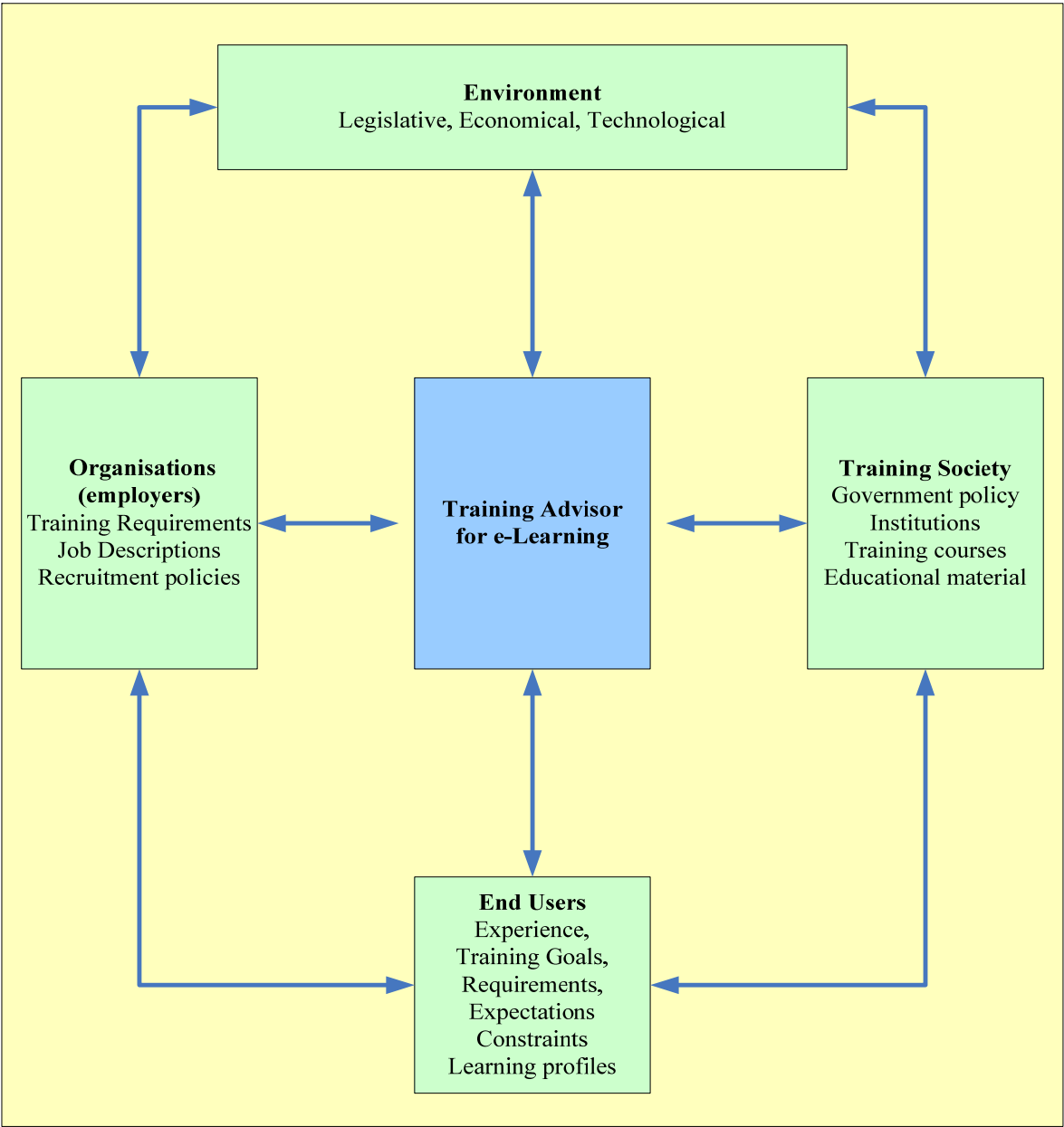


Fig. 1. Stakeholders in an e-learning Environment

- There is need to offer to the seafarers additional knowledge-skills as well the motivation to improve their soft skills, in particular (team work, leadership, communication, negotiation skills)
- There is need for applications that help the diffusion of tacit knowledge that crewmembers may have

To address these needs in a systematic and valid manner we firstly developed a tool for accumulating the basic knowledge regarding the seafaring profession and training environment, registered the information of the interviewed sample population during the data collection phase, and used statistical analysis to support the choices of each individual separately.

Four major groups of potential e-learning users are identified: a) Junior and Senior Captains; b) Junior and Senior Engineers; c) Marine students and d) Office personnel. Each group has special characteristics, interests and needs with regard to their career perspectives (continuous employment onboard, get promoted or switch career from the ship to the office), and respective training needs, which are specifically taken into account in the design of the recommender system.

Seafarers' individual preferences for course attributes and learning methodologies vary. The overall learning methodology they favour should comprise the following characteristics to meet the user needs: (a) Adaptive-blended learning (combined traditional lectures, e-learning in the office, e-learning on board with instructor); (b) Cooperative learning (practice on board, emergency drills with peers); (c) Contextual and participatory learning (via simulation, or Virtual Reality (VR) case studies); and (d) Provision of a variety of training material: textbooks, notes, videos, and VR cases.

In order to demonstrate the particular framework proposed hereafter, we developed an e-learning platform with training advisor capabilities for the shipping sector entitled SLIM-VRT. SLIM-VRT enables the existing and potential maritime students, employees, employers and authorities in the shipping industry to receive training in a way that is user-friendly, flexible, and learning effective. The overall SLIM-VRT system presents three major innovative dimensions: a) dynamic education program and content generation according to the user individual needs, especially in terms of the training advisor recommender capabilities, as explained hereafter; b) new pedagogical methodologies emphasizing collaborative and contextual learning, on the basis of case studies; and c) use of innovative and user-friendly information technologies emphasizing on VR tools.

3. E-learning recommender systems

Today, e-business applications and e-services are commonly taking advantage of advanced information and communication technology and methodologies to personalize their interactions with users. Personalization aims to tailor services to individual needs, and its immediate objectives are to understand and to deliver highly focused, relevant content, services and products matched to users' needs and contexts (Adomavicius & Tuzhilin, 2005; Brusilovsky, 2002; Ho, 2006; Kim et al, 2009; Kim et al, 2002; Ricci & Werthner, 2006;). In e-services personalization and web adaptation have been employed in many different ways: (i) the personalization service can be designed and used as an advice-giving system to provide recommendations to each individual and to generate up-sell and cross-sell opportunities (ii) personalization services are used to (dynamically) structure the index of information, product pages based on click-stream analysis to minimize the users' search efforts, where personalized content based on the user's profile is generated. The users can personalize not only the content but also the interface of the application used (Brusilovsky & Maybury, 2002; Burke, 2000; Rashid, 2002).

Applications of personalization technology are found to be useful in different domains. These include information dissemination, entertainment recommendations, search engines, medicine, tourism, financial services, consumer goods and e-learning (Adomavicius & Tuzhilin, 2005; Garcia-Crespo et al, 2011; Kim et al, 2009; Papanikolaou, & Grigoriadou, 2002).

According to (Papanikolaou, & Grigoriadou, 2002) Adaptive Educational Hypermedia Systems aim to increase the functionality of hypermedia by making it personalised to individual learners. The adaptive dimension of these systems mainly refers to the adaptation of the content or the appearance of hypermedia to the knowledge level, goals and other characteristics of each learner. Learners’ knowledge level and individual traits are used as valuable information to represent learners’ current state and personalise the educational system accordingly, in order to facilitate learners to achieve their personal learning goals and objectives. Nowadays, most e-learning recommender systems consider learner/user preferences, interests, and browsing behaviours when analyzing personalization considering different levels of learner/user knowledge. A distinctive feature of an adaptive e-learning system is a comprehensive user model that represents user knowledge, learning goals, interests, and pertinent contextual features that enable the system to distinguish among different user groups and feasible learning service solutions (Balabanovic, 1998; Lee, 2001; Sarwar, 2000).

Over the last 10 years, researchers in adaptive hypermedia and Web systems have explored many user modelling and adaptation methods, whereas a number of them already have been applied to the e-learning domain. The pre-Web generation of adaptive hypermedia systems explored mainly adaptive presentation and adaptive navigation support and concentrated on modelling user knowledge and goals. Empirical studies have shown adaptive navigation support can increase the speed of navigation and learning, whereas adaptive presentation can improve content understanding. The Web generation emphasized exploring adaptive content selection and adaptive recommendation based on modelling user interests. The mobile generation is now extending the basis of the adaptation by adding models of context and situation-awareness (location, time, computing platform, quality of service).

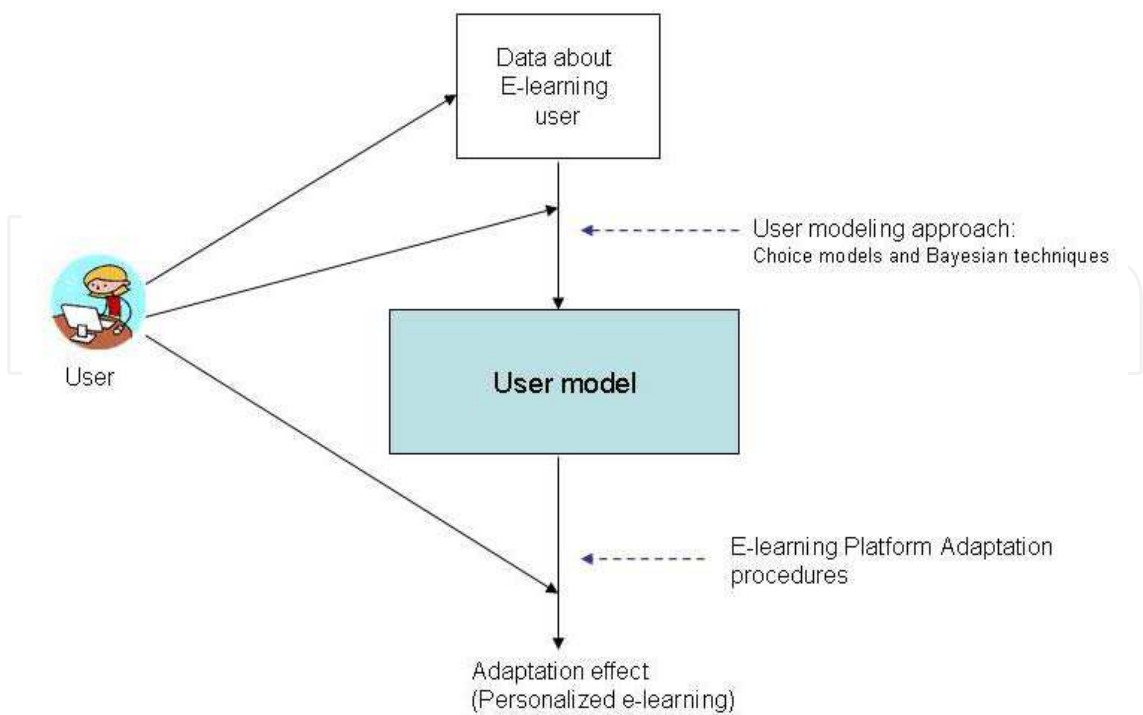


Fig. 2. Adaptive e-Learning System

An adaptive system collects data for the user model from various sources that can include implicitly observing user interaction and explicitly requesting direct input from the user (Brusilovsky & Maybury, 2002). The user model is used to provide an adaptation effect, that is, tailor interaction to different users in the same context. Adaptive systems often use intelligent technologies for user modelling and adaptation.

In specific, user modelling could be considered as the key process that enables recommendation systems to generate offers to users according to their needs, using content-based, filtering based and hybrid techniques (Adomavicius & Tuzhilin, 2005). More analytically, in the case of recommender system based on an intelligent system, the recommendation process is commonly implemented by a rule-based system that maintains a collection of knowledge facts, also denoted as the knowledge base (registering attributes such as student's preferences, interests and knowledge levels). The knowledge of an intelligent system can be expressed in several ways. One common method is in the form of "if-then-else" type rules. A simple comparison of the input to a set of rules will implement the desired actions, in order to deduct the recommendation. An intelligent system platform can be utilized for an e-learning recommendation system, such as the Java Expert System Shell (JESS), which represents its knowledge not only in the form of rules but also as objects. This allows rules to use pattern matching on the fact objects as well as input data.

In the following, we present a particular e-learning recommender framework based on advanced choice models and Bayesian techniques (Chaptini, 2005; Greene, 1993), which is considered as an intelligent recommender system. The presented e-learning recommender model is applied and tested in the shipping e-learning environment, it is though proposed for adaptation and use in different e-learning settings, also e-service environments favouring intense personalization and recommendation value-adding features. The techniques used in our system offer the strong competitive advantage of a comparatively detailed, user-focused e-learning attributes modelling framework (advanced choice theory) and a competent system learning capability (Bayesian theory), that improves over time the performance of the recommender system itself.

4. Training advisor development: A pilot case in the shipping industry

As mentioned above, the particular training advisor framework proposed hereafter, was developed as integrated with the SLIM-VRT e-learning platform for the shipping sector.

4.1 Methodological framework

The training advisor we developed is primarily characterized by a detailed, user-focused modelling approach, as denoted in Fig. 3. The user model that is the employees' preferences for e-learning is a function of (a) the Trainees Profile, which includes their socioeconomic characteristics, educational profile, working experience, and learning profile; and (b) The Training Package characteristics. Each training package is composed of one or more courses with specific attributes such as training method, duration of training, location of training, assessment method, training material, training institution, and training cost.

Individuals' preferences with regards to the training package are formed based on their training objectives and career expectations. That is, individuals may want to be promoted, change career, or stay in the current position, but enhance certain skills or improve their

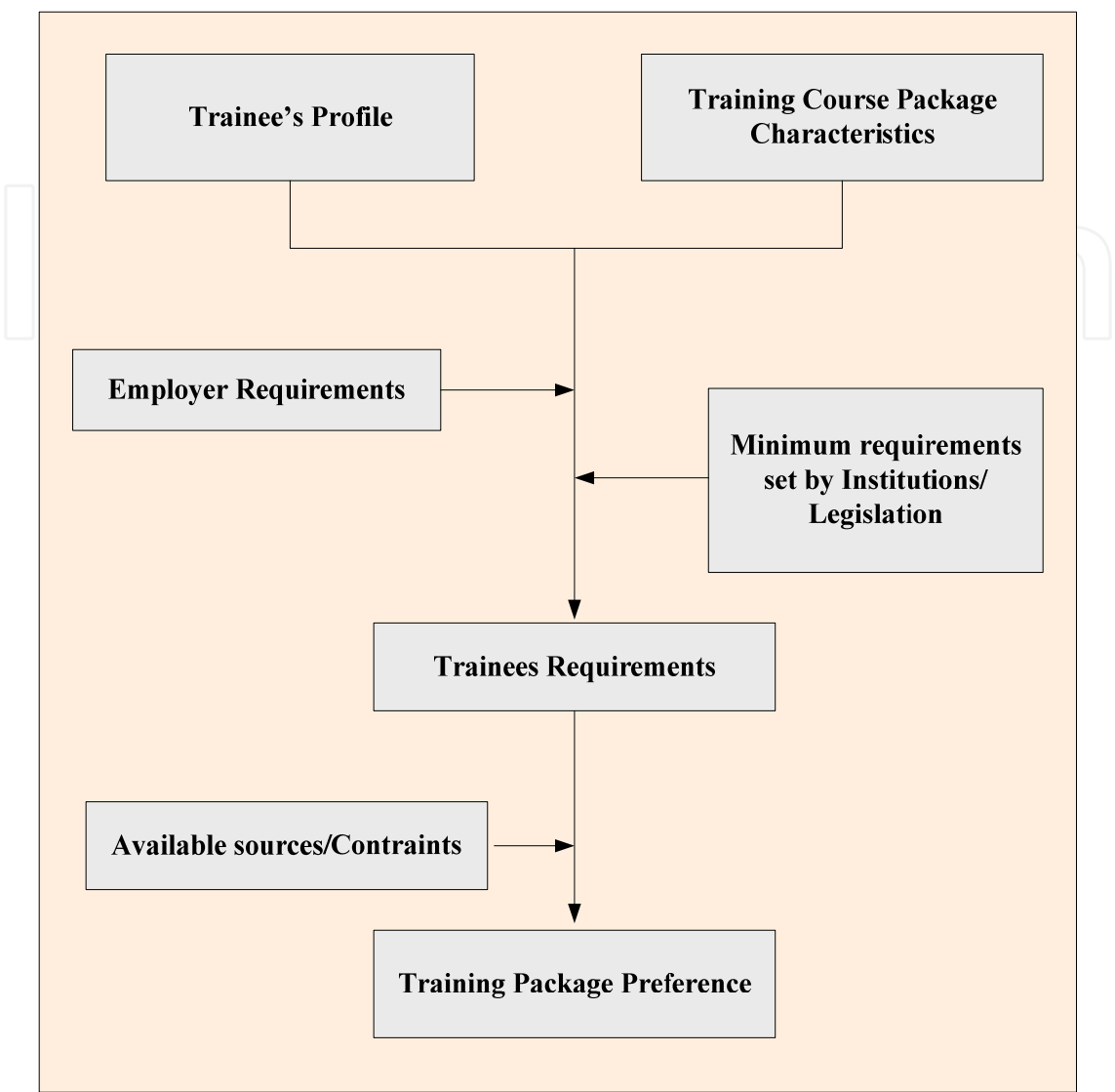


Fig. 3. E-learning Recommender Methodological Framework

knowledge on specific topics. The choice to adopt a “self-training for work” package is a function of these objectives, as well as of the resource availability and of situational constraints.

Resource availability includes training institution and course offerings, as well as job position openings by shipping companies and institutions. The situational constraints include the Employers’ Requirements and the Institutional-Legal Minimum Requirements for each job position.

The underlying assumption in this recommender model framework is that employees try to choose the training package with the maximum utility. Thus, assuming a motivation to follow a “self learning for work course”, they choose, among all the courses offered, the one that maximizes their utility, given their characteristics, the course attributes and the motivational and situational constraints. Given the source of motivation, employees select

for consideration, from the menu of all –at present- available and non available courses, the ones that best address their needs. For example, based on the utility maximization assumption, an increase in flexibility is expected to increase the preference for the training package, while an increase in costs should decrease its preference.

Different groups of individuals are expected to have a different level of sensitivity to each of these attributes. In particular, it is expected that middle aged professional seafarers (captains and engineers) are to demonstrate higher willingness to pay for increased flexibility for courses that “lead” to shore positions. However, the extent to which an employee is willing to incur “training costs” depends on how much these costs are affected by the available income or expectations for promotion or reorientation of her/his career.

The characteristics of the job, particularly the available free time onboard may also constrain the consideration set of courses. Age, gender, marital status, profession and previous working experience are considered to have a strong effect on the perceived impact of “self training for work”. For example, older learners are likely to be well-established in their career and have minimal preferences for new courses. On the other hand, young individuals (students in marine academies and personnel of shipping companies) are expected to appreciate more the flexibility and the “internet facilities” allowed by a “self learning for work” package. The training advisor developed provides as recommended training package, the one that maximises the utility of the user.

4.2 Training advisor logic

This section describes the e-learning recommender workflow implemented based on advanced choice models and Bayesian techniques for its core computational part. The proposed system architecture can be thought of as divided into two main parts according to system operation procedures, which is the front-end and back-end parts. The front-end part manages the interaction and communication with learners and records learner behavior, whereas the back-end part performs the analysis of learner preferences, skills and selects appropriate course materials for learners based on estimated learner ability. A main component of the latter subsystem is the *Training Advisor*, the logic and capabilities of which is detailed in the following section.

More specifically, our training advisor’s structure and workflow can be seen as composed of 9 main steps, depicted in Figure 4.

First, at the entry of the trainee in the system a registration process is made (step 1). After the successful completion of registration, the user follows a series of steps (step 2-5) in order to receive detailed advices from the system regarding the educational package which suits in his/her needs (step 6).

In the end of the process, a trainee can review certain elements of the proposed courses (objectives, level, cost, etc.) and he/she can decide if he/she will attend one or more courses of the proposed package (step 7). Provided that the trainee has completed a full educational life cycle (step 8) this education process can be evaluated as well as the advisor usefulness (step 9).

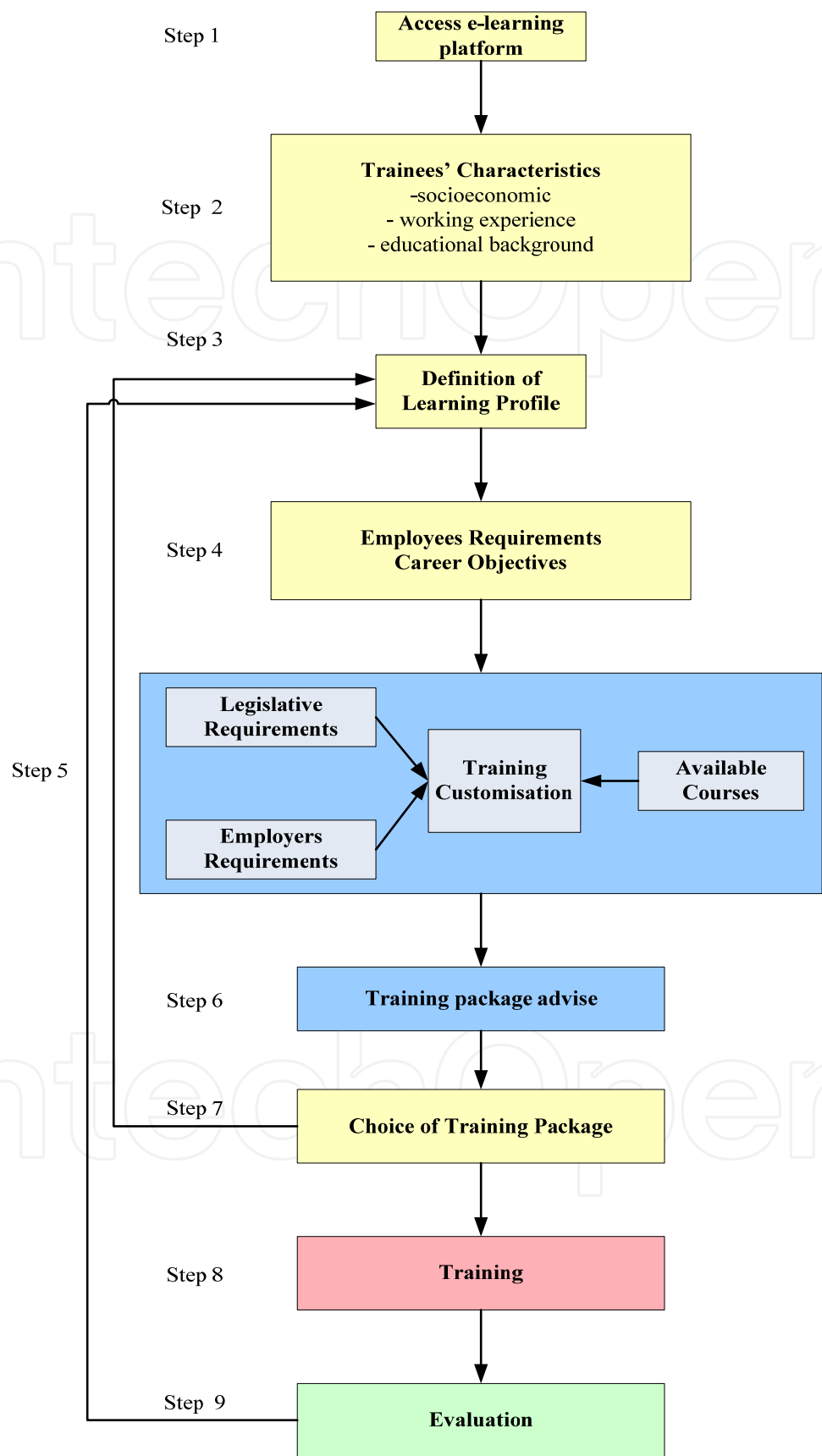


Fig. 4. Workflow of the Training Advisor

5. The model

In order to develop the *Training Advisor*, we used theories of individual choice behaviour analysis (Ben-Akiva & Lerman, 1992; ChoiceStream, 2004; Chaptini, 2005). Discrete choice analysis is the modelling of individuals' choices from a set of mutually exclusive and collectively exhaustive alternatives. A decision maker is modelled as selecting the alternative with the highest utility among those available at the time the choice is made. An operational model consists of parameterised utility functions in terms of observable independent variables and unknown parameters the values of which are estimated from a sample of observed choices made by decision makers when confronted with a choice situation.

The framework for choice theories can be viewed as an outcome of a sequential decision-making process that includes the following steps: 1) Definition of the choice problem; 2) Generation of alternatives; 3) Evaluation of attributes of the alternatives; and 4) Choice Model.

5.1 The choice problem

In our case, the decision makers are seafarers and employees of the shipping industry. These decision makers face different choice situations and have widely different tastes.

The recommender system acts as an automated training advisor. It facilitates a bundle of courses choice selection task by recommending courses that would satisfy employees' personal preferences and suit their abilities and interests.

The underlying hypothesis is that trainees perceive courses as a bundle of attributes. The utility of a course to a particular individual is a function of its attributes. Once those attributes are defined, discrete choice models can be used to calculate the utility of a set of courses, and the bundle of courses with the highest utilities would be selected.

5.2 Generation of alternatives

All the courses offered at various training institutions define the universal choice set of alternatives. This includes courses that are feasible during the decision process. The feasibility of an alternative is defined by a variety of constraints such as course offering and scheduling requirements and prerequisites.

The additional complexity of the problem stems from the fact that the training advisor needs to recommend a combination of courses that may be offered by different institutions.

5.3 Identifying attributes of the alternatives

The main hypothesis is that a course can be represented by a set of attributes that would define its attractiveness to a particular trainee (see Table 1). Courses are considered to be heterogeneous alternatives where decision makers may have different choice sets, evaluate different attributes, and assign diverse values for the same attribute of the same alternative.

ATTRIBUTES	LEVEL 1	LEVEL 2	LEVEL 3
COURSE	Compulsory (STCW/95, IMO Model Course, National Education Authority)	Non Compulsory	
INSTITUTE	Governmental (Marine, Academy, University)	Non Governmental (Helmepa, Private Training, Manufacturer)	
ASSESSMENT PROCEDURES	Exams	Without Exams (Self Evaluation, Practice)	
COST	Fees (Paid By Trainee)	Without Fees (Cost Paid By Government Or/ And Employee)	
LOCATION OF TRAINING	Ashore (Institute’s Quarters, In-house Training)	Onboard	Ashore And Onboard
DURATION OF TRAINING	Academic Semester	Short Courses / Seminars	Flexible
TRAINING METHODOLOGY	Classic Lectures (In Class, In Office, Onboard With Instructor)	Self Learning (By Distance Or E-Learning With The Support Of Training Multimedia, Virtual Case Studies Etc)	On The Job Training (Practice Onboard, Emergency Drills, Simulation)
TRAINING MATERIAL	Printed (Textbooks, Notes, Manuals)	Digital (C.D, Diskettes, Internet, Virtual Equipment)	Audiovisual (Video, Audiocassettes)

Table 1. Attributes of the Alternative Choice

5.4 Choice model

The choice model involves the estimation of a preference function, based on the attributes presented above. The estimation is based on stated preferences data, which are expressed responses to hypothetical scenarios presented to the employees.

With regards to the development of the training advisor it is important to estimate models in a relatively short time frame in order to deliver online recommendations.

Therefore, two models are developed:

Training Needs Module - An offline model system: that relies on advanced choice models to estimate the base parameters for different trainee’s profiles; and

Training Advisor Module - A real time model system: that is based on the above models and in real time, estimates and customizes the parameters to each individual using Bayesian Techniques, and give fast recommendations. Bayes's theorem calculates the probability of a new event on the basis of earlier probability estimates which have been derived from empirical data. A key feature of Bayesian methods is the notion of using an empirically derived probability distribution for a population parameter. The Bayesian approach permits the use of objective data or subjective opinion in specifying a prior distribution. With the Bayesian approach, different individuals might specify different prior distributions. Bayesian methods have been used extensively in statistical decision theory. In this context, Bayes's theorem provides a mechanism for combining a prior probability distribution for the states of nature with new sample information, the combined data giving a revised probability distribution about the states of nature, which can then be used as a prior probability with a future new sample, and so on. The intent is that the earlier probabilities are then used to make ever better decisions. Thus, this is an iterative or learning process, and is a common basis for establishing computer algorithms that learn from experience (Greene, 1993).

5.5 Training needs module

This section presents the development of the training needs module and estimation results of the training advisor offline models that are used in our approach.

5.6 Data collection

In order to identify the seafarers' needs and develop the SLIM-VRT training advisor a field study was conducted. The target sample included members of seafarer's unions, shipping office's personnel and people working at shore based activities related to shipping sector. A total of 5000 questionnaires were sent to crew and shore based personnel, as well as to students of marine academies. 1195 completed questionnaires were received, corresponding to a 24% response rate. From these completed "employee's questionnaires", 59% (710 seafarers and employees) were Greek, 10% (115 seafarers and employees) were from the U.K, 7% (85 seafarers and employees) were from Spain and the rest 24% (285 seafarers and employees) were from other countries (Norway, Ukraine, Egypt, the Philippines, India, etc.). The multinational and multicultural character of the sample represents the decision making behaviour of major nationality groups in the shipping industry. The questionnaire included one to two Stated Preferences Experiments for Self-Learning for work. In each scenario individuals were presented with a course, described by several attributes and were asked to state their preference for following such a course.

A total of 1664 observations were used for estimating the preference models. Table 2 presents the distribution of the observations of the course attributes included in model estimations as independent variables.

We can see a very good distribution of the observations among the levels of attributes. This suggests a successful distribution of the stated preferences experiments between subjects.

Table 3 presents the distribution of observations of the dependent variable, or preference rating, taking the value of 1 if the individual is most unlikely to take the course and 7 if the individual is most likely to take the course.

Attributes	Levels	Distribution of Observations
Training methodology	Classic lecture	552
	Self learning	682
	On-the-Job	430
Training material	Printed	811
	Digital	548
	Audiovisual	305
Duration of Training	Academic semester	432
	Flexible	795
	Short seminars	437
Institute	Governmental	1355
Cost	No fee	705
	100-500 Euros	528
	>=500 Euros	431
Location	Ashore	739
	On-board	476
	Both ashore and on-board	449
Certification	Certificate	1123
Assessment procedure	Exams	783

Table 2. Number of Observations Administered at Each Level

Preference Rating	Level	Frequency	Percent
1	Most Unlikely	159	9,6
2	More Unlikely	112	6,7
3	Unlikely	137	8,2
4	In The Middle	413	24,8
5	Likely	298	17,9
6	More Likely	269	16,2
7	Most Likely	276	16,6
	Total	1664	100,0

Table 3. Choice of Course

5.7 Model estimation results

Regression models were run with as dependent variable the choice of course and as independent variables the attributes of the course.

These result in regression-type models of the following form:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + + \beta_k X_k$$

or

$$y = \beta_0 + \beta_1 SelfLearning + \beta_2 OnTheJob + \beta_3 VR + \beta_4 Govermental + \beta_5 Flexible + \beta_6 NoFees + \beta_7 GT500Euros + \beta_8 Certificate + \beta_9 Exams + \beta_{10} Ashore \& \ onBoard$$

Table 4 presents a generic model estimated with all the available observations.

Coefficient Number	Variable	Estimated Coefficient	t-stat
0	Constant	3.54	10.9
1	Self-Learning	0.36	1.8
2	On-the-job Training	0.42	2.0
3	Digital	0.25	1.5
4	Governmental	0.31	1.6
5	Flexible	0.23	1.7
6	Without fees	0.10	1.0
7	Greater than 500 Euros	-0.84	-2.8
8	Certificate	0.78	5.3
9	Exams	-0.26	-1.8
10	On Board and Ashore	0.35	1.6
Summary Statistics			
Number of observations: 1664			
Rho-bar squared = 0.2			

Table 4. Model Estimation Results

The estimated results demonstrated the following:

- Individuals prefer self-learning and on-the-job training over classical lectures
- Digital material are favoured over printed ones
- Trainees prefer studying at governmental institutions, such as universities
- There is a preference over flexible courses adjusted to the user needs rather than courses offered for a full academic semester
- Individuals prefer not to pay for receiving the courses and are especially negative towards following a course with cost more than 500 Euros
- Getting a certificate is very important for the trainees
- There is negative attitude towards courses that have exams as the assessment procedure
- Individuals would prefer courses that are offered both on-shore and off-shore.

The above-mentioned results have been tested by a panel of experts and were found consistent with the current situation and emergent trends in the maritime education and employment environment, and our a priori hypothesis regarding the behaviour of seafarers.

The equation implemented with regards to the preference rating of each course (y) is therefore the following:

$$y = 3.54 + 0.36SelfLearning + 0.42OnTheJob + 0.25VR + 0.31Govermental + 0.23Flexible + 0.10NoFees - 0.84GT500Euros + 0.78Certificate - 0.26Exams + 0.35Ashore \& \ onBoard$$

Similar equations are estimated for different user groups. These groups were defined based on the opinion of the experts’ panel used for this purpose. The categorization is based on the following characteristics: (1) Age; (2) Education; (3) Years of working experience; (4) Current Job (Engine, Deck, other); (5) Learning styles; and (6) Soft skills.

5.8 Training advisor module

The basic models developed for each group of trainee, as described in the previous section, need to be customized for each respondent. Bayesian theory is used to provide the suggestions of the courses that match the preferences of the individuals.

For each Group the following information, the following outputs of survey regressions are saved to be used in the Training Advisor:

$$s = \begin{cases} \bar{\beta}_g = \text{estimated coefficients for each group } g \\ s_g = \text{standard deviation} \end{cases}$$

$\Sigma_{\bar{\beta}}$ = variance-covariance matrix of the prior $\bar{\beta}_g$

The steps followed are:

Step 1. Subject profile

A number of questions are asked at the beginning of the session regarding the characteristics of the trainees. A number of these characteristics (the X 's) define the Group in which each individual belongs.

Assume $g = 1, \dots, G$ number of groups.

Step 2. Elicitation

The individual is presented with a sample of courses (using always the same attributes) and is asked of his preferences.

Assume:

N = number of experiments presented to the individual, and

y_n ($N \times 1$ vector) = the ratings of course n .

Step 3. Creation of Individualized Data

The new data is (y_n, X_n) where:

y_n ($N \times 1$ vector) = the ratings of the courses.

X_n ($1 \times K$ matrix) = attributes of course n

K = number of attributes

In the new table the respondent has N ratings. To each rating the K attributes of the course are appended.

Step 4. Develop the personalized preference equation for each individual

Bayesian updating is used to calculate the personalized coefficients of the preference equation as follows:

$$\tilde{\beta} = \left[s_g^2 \Sigma_{\bar{\beta}_g}^{-1} + X'X \right]^{-1} \left[s_g^2 \Sigma_{\bar{\beta}_g}^{-1} \bar{\beta}_g + X'y \right]$$

where:

$s = \bar{\beta}_g, s_g, \Sigma \bar{\beta}_g$ = outputs of the survey – regressions of group g, and

(y , X) = the new data

y is Nx1

X is NxK

- Calculate new coefficients
- Update preference equation with new coefficients
- Calculate Course Ratings
- Calculate the rating of each course by applying the personalized equation of Step 3.

Step 5. Preference Score of Bundles of Courses

A number of potential bundles of courses exist based on expert judgment. Apply ratings to each course of the bundle. Sum-up the ratings.

Step 6. Recommend

Present to the trainee the bundle of courses with the highest rating (Fig. 5).

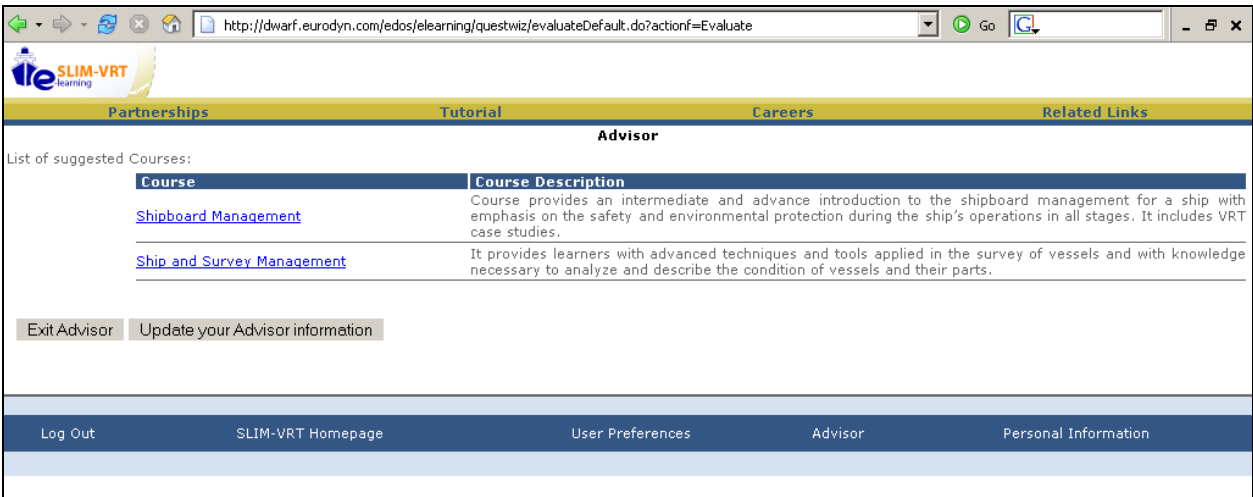


Fig. 5. E-learning system recommendation

6. Conclusions

This chapter presents a modelling methodology for developing an e-learning recommender system. The proposed methodology includes the definition of a mathematical user model, as formulated in the context of the shipping industry and its employment and training environment. The implementation of the central component of this recommender system, namely the Training Advisor, is explained as based on discrete choice models and Bayesian theory. In particular, the development of an e-learning recommender system, such as the electronic training advisor proposed will help trainees in choosing the appropriate e-learning courses matching their particular characteristics, preferences and needs and based on their expected professional development. The training process as assisted by the proposed training advisor; it takes into account the peculiarities of the seafaring profession,

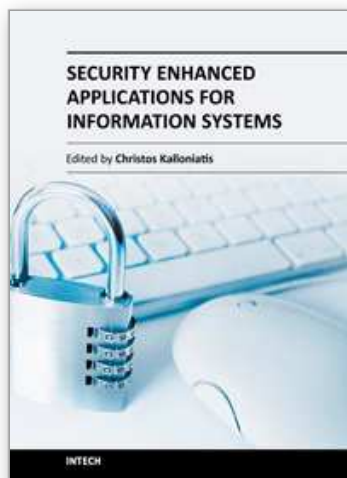
applicable career paths and respective seafarers' training needs. To formally model these requirements we developed a knowledgebase for accumulating the basic knowledge regarding the shipping work and training environment and registered the information of a 5000 users- sample population, furthermore we used statistical analysis to support the choices of each individual separately. In specific, our e-learning recommender framework is based on advanced choice models and Bayesian techniques and is considered as an intelligent system that can be tested and reused in different e-learning settings, favouring intense personalization and recommendation value-adding features. The foundational techniques used in our system offer the strong competitive advantage of a comparatively detailed, user-focused e-learning attributes modelling framework (advanced choice theory) and a competent system learning capability (Bayesian theory), that improves over time the performance of the recommender system itself .

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Every day, more users access services and electronically transmit information which is usually disseminated over insecure networks and processed by websites and databases, which lack proper security protection mechanisms and tools. This may have an impact on both the users' trust as well as the reputation of the system's stakeholders. Designing and implementing security enhanced systems is of vital importance. Therefore, this book aims to present a number of innovative security enhanced applications. It is titled "Security Enhanced Applications for Information Systems" and includes 11 chapters. This book is a quality guide for teaching purposes as well as for young researchers since it presents leading innovative contributions on security enhanced applications on various Information Systems. It involves cases based on the standalone, network and Cloud environments.

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