530945-LLP-1-2012-1-GR-KA3-KA3MP

CRITON - Prediction of e-learners' progress and timely assessment of the achievement of learning outcomes in Lifelong Learning

D3.2 Deliverable Report

Selection of the appropriate pedagogical framework and specification

Research Report on Indicators for predicting success or dropout in e-learning

Project:	**CRITON** - Prediction of e-learners' progress and timely assessment of the achievement of learning outcomes in Lifelong Learning
Work package:	WP 3 Pedagogic methods' study - Selection of data from learning process
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Authors:	Katharina Resch
Document Type:	Document
Distribution:	Public
Status:	Final
Document file:	Deliverable report 3.2
Version:	V.8 after quality review
Date:	18.12.2013
Number of pages:	46

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PART I

INTRODUCTION

1 Introduction

This report gives a summary overview of indicators for prediction of learning outcomes in distance education and e-learning. These indicators are measurable variables for success or dropout ranging from login frequencies to LMS (learning management system) to age or gender of learners which in combination help to predict which learner groups will be likely to dropout or pass an online course. These indicators were derived from literature from the United States mainly where prediction is more common than in Europe. Good practice examples from Europe were also collected. All information of this report will flow into an algorithm for a prediction system – the CRITON system – which is the main output of this EU-funded project. The CRITON prediction system, which will be finished in 2014, is a system that will be used by teachers and tutors in Europe in adult education and tertiary education to predict learning outcomes and thus dropout or passing an online class. For more information, visit: www.criton.eu.

The main research questions of this report were:

- Which indicators / data are available from learners in order to predict their final grades?
- Which data is (automatically) available through the utilization of an LMS?
- Which indicators are relevant for predicting learning outcomes, thus dropout or passing a class? How can these indicators be described?
- How do current predictive systems work and what do they measure (good practice)?

Having in mind that each national education system has its own specifics, rules and access limitations in Europe, and taking into account that educational institutions have internal data policies, the current deliverable report summarizes the empirical studies and literature results which are available and accessible to the author.

2 Structure and Purpose of this report

Part II of this report describes and summarizes indicators used for the prediction of success or dropout in learning processes in previous attempts to predict dropout rates. Since predicting dropout rates is rather standard practice in the United States and Australia, but hardly anywhere in Europe, Part III of this report summarizes the rare good practice examples from Europe about predicting dropout rates in education.

Part IV summarizes the results of interviews with nine LMS experts defined as LMS developers, administrators or plug-in providers working with different LMS in different countries in Europe giving insight into their opinions about prediction systems.

Part V summarizes the deliverable report and gives concrete recommendations for the further work in CRITON in 2014.

PART II

INDICATORS FOR PREDICTING DROPOUT

3 Prediction of dropouts – theoretical perspectives

Teachers and tutors with a great amount of teaching experience typically have a lot of information in their heads in order to predict learning outcomes and whether or not a student will fail a class. This intuition – if you could call it like this – is based on analytic competences of the teachers, observation, and experience with different learner's groups. Actually you could say that they have "data" in their heads. "LMSs are providing the educational community with a goldmine of unexploited data about students' learning characteristics, behaviours, and patterns." (Abdous et al. 2012: 77) Faculties, institutions, or education providers cannot access or use this information systematically if it only exists in the heads of teachers. Thus, measuring and extracting this information, processing it through a prediction algorithm to predict learning outcomes, does make sense. In the United States this has already become standard practice for schools, universities, and colleges (see Dietz-Uhler & Hurn 2013).

Predicting learning outcomes is embedded in *learning analytics* and *educational data mining* practice.
Learning analytics involves the collection and analysis of students' data in order to predict and improve their learning outcomes (Dietz-Uhler & Hurn 2013). An increased interest in learning analytics has taken place in the last years, some of it due to the general trend for educational institutions to be more accountable for their student's success (Bienkowski et al. 2012; Campbell et al. 2007). This is sometimes perceived as pressure not to produce high dropout rates, especially in online learning, as funds might depend on pass and dropout rates.
Learning analytics can generally be used in a descriptive and a predictive way. Description would aim at giving insight into why a student failed, at what time, or how to assist him/her. Prediction would aim at giving a forecast about future scenarios of what will happen next in an online course and about best and worst cases. Learning analytics work with data extraction, analysis of performance, predictive modeling and automatic response triggers (Goldstein & Katz 2005).
According to the International Educational Data Mining Society "Educational Data Mining is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings in which they learn." In educational data mining data is taken from different processes in the educational system – this can be an

administrative process or e-learning or data from system logins – for analysis and prediction.
Baker (2009) states that there are three different types of prediction in data mining: “[…] classification, regression, and density estimation. In classification, the predicted variable is a binary or categorical variable. Some popular classification methods include decision trees, logistic regression (for binary predictions), and support vector machines. In regression, the predicted variable is a continuous variable. Some popular regression methods within educational data mining include linear regression, neural networks, and support vector machine regression. In density estimation, the predicted variable is a probability density function. Density estimators can be based on a variety of kernel functions, including Gaussian functions. “

Entry qualifications: Of course dropout rates can also be reduced by defining entry qualifications as opposed to open entry systems where there are no criteria for entry. Previous levels of education or other dimensions have the potential to reduce dropout before even the first class starts (Simpson 2006). Dropouts on a faculty level can of course also be connected to loss of student fees/tuition fees and additional work to replace the student if he/she withdraws or drops out.

Predictive indicators: The phenomenon of dropping out is described as a multi-factorial phenomenon in the literature (Simpson 2006), meaning that it needs more than just a few indicators to accurately predict success of failure. The number of indicators varies from three to over 40 in different empirical studies, but generally the more indicators the higher the accuracy.
The number of indicators partly relies on the time when the data is collected in learners. Before the first course or in the first class less data is available than in the end of a semester. Here the following rule applies to prediction: The earlier data is gathered, the more accurate prediction can be and the more can teachers’ pedagogic methods be adapted to its findings. First-year students have the highest risk of dropping out (Kovacic 2010).

Definition of success: For prediction purposes academic success needs to be defined. Success is defined here as passing the class/online course and thus failure is defined as dropout. It can be useful to divide students into low/medium/high risk groups and not only in successful and unsuccessful.

Pass rates normally vary between 40% and 95%. This variation of empirical evidence for pass rates and dropout rates in online courses can be explained with different educational levels, countries, and educational systems. Simpson describes pass rates of 44% and correct prediction rates for 65% of his learners after using a prediction system (Simpson 2006). According to Simpson (Simpson 2003) between 30% and 40% of new students withdraw from a course before the first assignment is due.

Pedagogic practice must include prior decisions whether or not learning will take place in synchronous and asynchronous ways which has consequences for learners. Learners will define their role in reaction to the course structure and accustom a more active or passive role, depending on the syllabus.
The advantages and disadvantages of prediction of final grades are discussed in the following chapters.

4 Benefits of prediction systems – rationale

There are clear benefits of predicting learning outcomes.
At the administrative level of schools or faculties it improves decision-making and resource allocation, e.g. for extra tutoring of vulnerable students etc. Also an institution's success can be highlighted by presenting low dropout rates and thus public funding can be kept. With predictive systems also enrolment processes can be adapted and changed if necessary because individual applicants can be better understood.
From the perspective of a teacher or tutor prediction can help to identify at-risk learners and especially vulnerable students. As a consequence actions can be prepared and pedagogic practices can be adapted. Atypical students' behavior can be detected and analyzed also.
From a student's perspective they gain insight into their own learning process.
These benefits only take place when data is measured and analyzed and does not merely exist in the silent observations of teachers and other staff members. Prediction systems are commonly used in consumer research indicating potential future trends and consumer decisions, but are under-used in educational research in Europe (Abdous et al. 2012).

5 Concerns with prediction systems – critical voices

Nevertheless there have also been critical voices about predicting success and dropout.

Labeling: Prediction can have a potential harmful effect if profiling is used as labeling. This means that students are stigmatized as "unsuccessful" due to the prediction system and the study population is simply divided into "successful" or "not successful" from the beginning of a course. Stigmatization has to be limited by using accurate data and algorithms and taking interpersonal problems or situations of students that have a negative impact on learning into account. Still, the danger remains to create profiles of successful and unsuccessful students and this in return creates certain expectations in teachers about the probable performance of a learner.

Limited data: Usually personal data on the social environment and personal problems are not used as indicators in predictive systems, but sometimes exactly these indicators have an effect on learning.
Also prediction systems are more accurate then more indicators for success or failure they use. If only few indicators are used and thus only limited data is collected about a learner, then prediction is likely to be inaccurate. The problem is that personal data is always limited and that learners do not always give away personal data, like distractions during learning, personal learning strategies, or amount of financial support they receive. So if the data is limited, the prediction is also limited (Dietz-Uhler & Hurn 2013). Methodological critique is also strong due to usage of only dichotomous variables (fail/pass) in prediction systems. It is recommended to enlarge the category "fail" by those who stay on the course and then fail in the end or those who withdraw early (Kovacic 2010). Better and more differentiated profiling could take place then.

Ethical issues: Ethical issues are often stated as problems with predictive systems. Teachers' and students' activities in an LMS are watched and observed and their data is stored for prediction purposes. This can be threatening to those involved. Students have to be informed about which data is stored. There are also ethical concerns as to who the collected data belongs to and who can access it (Campbell et al. 2007). Research suggests that most students are not aware of the fact that prediction data is collected and that is exists (Simpson 2006). They usually have the right by the law to see the data if requested by them.

6 Indicators for predicting learning outcomes

As already mentioned dropout is a multi-factorial phenomenon depending on a range of issues. The number of indicators in articles and empirical studies varies considerably (Kovacic 2010).
Also it has to be considered that a great number of courses are carried out with blended learning, using online and offline course structures in a combination (Abdous et al. 2012). Prediction systems often only take into account online indicators in online courses.

6.1 Structure, Dialogue, and Autonomy

According to Moore's theory of transactional distance, which evolved in the 1970ies and first stated that distance education was not only defined by a geographical distance between teachers and learners, but also a pedagogic concept, three dimensions are important: structure, dialogue, and autonomy. (Andrade 2012) These can be seen as prerequisites to any prediction system.

6.1.1 Structure

The teacher gives the learner a structure by defining objectives, assignment dates or schedules. These organizational elements help to structure the online course and thus also the learning activities.

6.1.2 Dialogue

The communicative element is called “dialogue” in Moore’s theory and involves the interaction of learners with teachers, peers and the faculty. It also involves all elements of communication in e-learning environments: emails, postings, video conferences etc.

6.1.3 Autonomy

The element of autonomy has two components: choice and capacity. Choice refers to learners’ choices about their learning strategy, the place where they learn, their personal goals or how and when they study. Capacity means the learners’ abilities to learn at all: taking control of learning processes, awareness of learning strategies or the capacity to learn independently from others.

6.2 Socio-demographic data about the learner

The indicators used most often for prediction are indicators like gender, age, and socio-economic-status if available. In the United States or Australia also ethnicity plays a role. To what extent this is an issue in Europe will be explored.

Algorithms are mostly based on statistical information about learners, such as age, gender, ethnicity, socio-economic-status measuring the education level, the number of children, and marital status. Age, gender, and educational level have found to be good in explaining variation between dropout rates (Simpson 2006). Concerning work status of learners, those employed between 1 and 10 hours/week had the highest chance of success while those who were unemployed or worked more hours had fewer chances to pass.

According to Woodman (1999) the most important factors for academic success are: previous educational qualifications, high socio-economic-status, being a woman, and being middle-aged as well as the level of course that is chosen (the lower the course level the better the pass rate). For previous educational qualifications sometimes high school grades and the type of school attended were taken into account. Age does have a positive effect on success and diminishes dropout. Disability came out to rather increase dropout so it is a disadvantage for the learner. Also, those students who work and study in parallel are more likely to pass the class (Kovacic 2010) than those who only study.

However, socio-economic data has not performed well to predict learning outcomes in the case of traditional students (regular fulltime students), but have performed well for non-traditional students in distance and open education (Kovacic 2010). Gender and ethnicity have said to have less influence than previous educational qualifications, although they can still be significant depending on the context.

When *only* socio-demographic information is used to predict learning outcomes the

accuracy rate lies between 58% and 65%. When other variables (see chapter 6.4 and 6.5) are included, the accuracy rates of prediction increase.
However, there is mixed evidence on how strong each socio-economic factor applies to prediction in specific settings.

6.3 Structural indicators

Structural indicators for prediction are indicators which are determined by both the teacher and the learner. Teachers have to structure their online course and learners have to be able to learn within this set structure.
One aspect of structure is the capability of learners to fulfill formal requirements of the online course (attendance rates, having tasks ready on deadlines etc.). The literature suggests that a concrete study guide including a schedule of tasks and deadlines helps learners to structure the learning process themselves.

6.4 Self-regulated learning

In online learning courses learning is a self-regulated activity.
Learning is an activity students perform for themselves. Self-directed learning means setting goals for oneself in a learning process, something that is meaningful and challenging at the same time. Self-regulation was identified as a predictor for learning outcomes in the 1980ies already.

Self-regulating practices include (Andrade 2012):

- Motives: purposes for learning
- Methods: use of learning strategies
- Time: time management
- Physical environment: management of the immediate environment while learning
- Social environment: utilization of social resources while learning incl. communication and help seeking behavior
- Performance: grades within an online course

Learners can be self-motivated or in real classrooms be motivated by peers or teachers. Self-motivation does lead to better performance levels, thus to better grades and a reduced risk of dropout. Many learners choose distant learning because of a higher level of independence, convenience (not having to go anywhere), and self-paced learning (learning in one's own pace).
Methods of learning which are said to be less beneficial to final grades are rehearsal, copying notes, reciting, or underlining. Better methods for learning are elaboration, paraphrasing, summarizing, creating analogies, posing and answering questions as well as mapping and outlining. One indicator is also additionally important for prediction, namely the use of course materials. The familiarity with textbooks, study guides or supplemental resources to the online course are predictors for success.

Managing one's time in an online course involves avoiding procrastination and the ability to prioritize activities and tasks. A record of time used can be helpful in which students note for which tasks they have already used time and prioritize new tasks. In online courses learners are more than in offline courses confronted with high autonomy, low structure, and a high risk of procrastination. It is therefore recommended to set a regular time for studying as if the learner was really attending a class (e.g. each Monday from 4 pm to 5pm), to determine beforehand what to work on and to evaluate to level of difficulty of the next tasks and if the time for the task is sufficient or not.
The ability to structure one's physical environment is crucial for online learning since it should be quiet and free from distractions. This involves turning off phones, email alerts, music or television. But also personal concerns and problems play a role and can hinder the learner from learning effectively. Learners need to choose physical places where learning is possible, which is free from noise, comfortable in terms of light, temperature and furniture, and where physical needs can be taken care of.
Social environment means the use of resources and help seeking behavior through asking peers, tutors, or instructors for assistance. It also includes non-social resources like using textbooks or searching the internet. Help-seeking is seen as a positive strategy to successfully complete a course rather than a behavior showing weakness. Some online courses have live tutorials which is a necessary resource in online learning.

6.5 Behavioral indicators (incl. dialogue)

Many studies reporting about predictive systems in their educational institutions measure behavioral indicators in order to predict success or dropout. At least three levels can be differed: the level of participation in the online course, delivering contents, and e-learning behavior of learners. All aspects of what Moore (see chapter 6.1) calls "dialogue" fall into behavioral indicators.

6.5.1 Level of participation in the online course/class

The most important is the level of participation of learners in online courses.
Sometimes social network tools are used to quantify the level of participation of learners in online networks of learners.

Typically the level of participation of learners is measured by using the following indicators:

- Login frequency to LMS
- Site engagement
- Read messages
- Posted messages
- Online interaction in forums and number of emails sent
- Offline interaction with teachers and peers
- Level of participation in group work

The login frequency in a LMS, site engagement, read and posted messages can be easily collected in an online system. Also online interaction can be measured in terms of quantity of forum postings or emails sent, but the quality of postings cannot be analyzed. It is harder to indicate success in offline interaction and group work, since normally these types of interaction are not automatically covered in an LMS and have to be collected separately.

6.5.2 Delivering contents

Of course grades on tests or interim exams predict final grades as well. While some classes only have one final grade, other classes are structured along different assignments and tests before the final exam. Taking into account that a lot of online courses are embedded into blended learning, other offline indicators might also influence the final grade of learners. So grading is a complex task and for prediction the method of grading has to be taken into account.

Interestingly, the time of delivery of assignments has an impact on the reliability of prediction. Dietz-Uhler and Hurn (2012) found out that the performance on the first two exams in a class and tests taken before the start of the class successfully predicted learning outcomes. This again stresses the fact the entry criteria for online classes are important (see chapter 3). For pre-assessment, formative, and summative assessment forms see also D2.1 report.

6.5.3 E-learning behavior

In online courses some indicators for prediction can already be stored and collected by the use of a LMS. The advantage is that this data about e-learning behavior is automatically collected in a lot of cases and does not have to be gathered by interviews or questionnaires. As Amazon for example also collects data about your purchases and then predicts possible future purchases, an LMS stores data about current engagement in the LMS, frequency of login or times of login, which can be used to predict dropout rates (Dietz-Uhler & Hurn 2013).

Indicators that successfully predict learning outcomes are:

- Login frequency to LMS
- Site engagement
- Read messages
- Posted messages
- Time spent with one online task
- Dates and times of access
- Number and types of resources accessed

Smith et al (2012) found out that the following indicators predict the performance in a course: login frequency, engagement in online material, pace, and grades.

The most relevant advantage of LMS data measuring e-learning behavior for prediction purposes is that it is available to teachers without additional work. In addition to LMS data the teacher also generates data for prediction, such as assignment grades, grades on discussion forums, number of questions asked in a forum or number of emails sent to the teacher. One study found out that learners' participation in discussion forums was the best predictor for their final grades (Falakmasir & Jafar 2010).

These results suggest that e-learning behavior should be analyzed for prediction purposes as well.

6.6 Autonomy indicators = individual learning

A lot of indicators lie within the learner, which means that they are hardly measurable or visible by faculty staff or the school. This data normally has to be collected separately for prediction purposes. However, there are validated questionnaires for some of these indicators. These are goal orientation of the learner, individual learning strategies, e-learning and computer self-efficacy and self-efficacy in general.

6.6.1 Intrinsic and extrinsic goal orientation

The degree to which a learner participates in learning activities is oriented towards personal goals (intrinsic motivation) and the fact if learning or passing an online course is seen as a personal challenge or not. Intrinsic goals can be more knowledge, meeting a personal challenge, or curiosity in something.
Extrinsic goal orientation refers to doing a course as means to an end and so much for personal development, but for a job promotion, rewards, or approval from others. Studies agree that intrinsic goals have a higher likelihood for leading to success than only extrinsic goals (Sharma et al. 2007).

There are reliable and validated tests for measuring motivation in learning, like the Motivated Strategies for Learning Questionnaire (MSLQ).

6.6.2 Individual learning strategy

Indicators for individual learning can be derived from the Metacognitive Learning Strategy Questionnaire in nine subscales:

- Organization of learning: clustering, outlining, selecting main ideas
- Peer learning strategies
- Metacognitive thinking: the ability to reflect, understand, and control own learning
- Help seeking
- Time and study environment
- Rehearsal
- Elaboration
- Critical thinking
- Effort regulation

These scales can be answered with 1 to 7 (1 meaning totally wrong and 7 meaning totally true). Tok et al. (2010) found out that only the first three indicators have an effect on academic success. Organizations of learning and peer learning strategies have a significant effect on the final grade. Additionally they found out that if students are explicitly taught metacognitive thinking, their academic success is likely to increase. Rehearsal, elaboration, critical thinking and effort regulation are rather poor indicators for success.
Help seeking behaviour and time and study environment management have found to have positive effects on learning outcomes in other studies:
Help seeking: Help seeking behavior of students also predict learning outcome (Sharma et al. 2007). Help seeking behavior decreases frustration in an isolated e-learning environment and not employing help seeking strategies means a higher likelihood of failing. For help seeking the faculty or school should provide different paths of assistance.

Time and study environment: Time and study environment are said to be crucial indicators for dropout or success in e-learning environments. In the study environment the presence of children is one important factor and if they live together with the learner or not. Learners need to be able to (a) avoid distractions while doing an online course and (b) control distractions if they appear. Since the controlled environment of a classroom is missing in e-learning environments, learners themselves need to make a study environment – in an internet café, at home, at a friend's house – etc. and control study time and place (Sharma et al. 2007). Time planning involves scheduling of tasks, goal-setting for certain time periods, and prioritizing capability of the learner. Time management indicators can be derived from the time management behavior scale.

6.6.3 E-learning and computer self-efficacy

E-learning takes place without the teacher and the student being in one geographical place. So there is no direct interaction between teacher and student. However, other factors are important for prediction in this case: motivating factors in the e-learning environment and family or social pressure or motivation to learn.
Computer self-efficacy and e-learning self-efficacy are key factors in achieving one's goals in an online course.
E-learning self-efficacy refers to the confidence in the ability to learn via e-learning and have success doing so. It includes the ability to use the computer and to be able to perform with it (computer self-efficacy). Previous studies show that older learners have lower e-learning self-efficacy on average than younger ones (Whisler 2004). Competences needed in this case include being able to use a virtual learning environment, using html, using chat rooms, understanding copyright information, using instant messenger, integrating videos, graphics or sound into tasks (Kosak et al. 2013).
E-learning self-efficacy is probably closely linked to e-learning behavior (see chapter 6.4).

Computer self-efficacy can be measured with a validated scale: the Computer self-efficacy scale.

6.6.4 Self-efficacy

Self-efficacy is described as beliefs about the effectiveness of regulating one's own learning. This involves the:

- confidence in minimizing disruptions when learning
- confidence in finishing e-learning course by the set deadlines
- confidence in planning course work on one's own

Self-efficacy can be measured with the self-efficacy for self-regulated learning scale.

6.7 Other indicators

Offline data: A considerable number of courses happen online and offline in a blended learning approach. Teachers can in this case also use indicators from the offline classroom experience into account.
Level of financial support: Some empirical studies – mostly from the United States where students have to pay large amounts of money for studying – the level of financial support a student receives plays a role for prediction. Those who receive financial support need to show that they have successfully passed courses – so they have a higher extrinsic motivation – to keep their financial support.
LMS specific data: Depending on the LMS used, other indicators of the LMS can be taken into account, depending on what is measured and stored in the LMS anyway. This is country-specific and depends on the educational institution.

7 Full List of Indicators for Prediction

Taking into account all indicators used in previous studies, the following list can be generated listing 6 main indicator groups and 30 sub-indicators with a total number of 52 indicators[1] for predicting learning outcomes:

1. Socio-demographic information of the learner
    a. Age
    b. Gender
    c. Ethnicity
    d. Marital status
    e. Number of children
    f. Educational background
    g. Previous grades

[1] Some indicators overlap.

   h. Working status
   i. Financial status
   j. Chosen course level

2. Structural indicators defined by teachers
   a. Course structure
   b. Study guide availability

3. Self-regulated learning indicators
   a. Motives of learners (see also 5a and b)
   b. Learning methods
      i. Rehearsal
      ii. Copying notes
      iii. Reciting
      iv. Underlining
      v. Elaboration
      vi. Paraphrasing
      vii. Summarizing
      viii. Creating analogies
      ix. Posing and answering questions
      x. Mapping
      xi. Outlining
   c. Time management
      i. Avoiding procrastination
      ii. Prioritizing tasks
   d. Management of the physical environment
      i. Eliminating distractions
      ii. Solving personal problems before learning
   e. Management of the social environment and help seeking behaviour
      i. Seeking real help from peers, tutors or instructors
      ii. Seeking help in material and resources (written material)
   f. Final grades

4. Behavioural indicators of the learner
   a. Level of participation in the course
      i. login frequency
      ii. site engagement
      iii. read and posted messages
      iv. online interaction
      v. participation in group work
   b. Delivering contents
      i. passing entry qualifications
      ii. delivering assignments in time

      iii. passing interim tests
      iv. passing final exams
   c. E-learning behaviour
      i. login frequency
      ii. site engagement
      iii. read and posted messages
      iv. dates and times of access to LMS

5. Autonomy indicators of the learner
   a. Intrinsic goal orientation
      i. Learning as a personal challenge
      ii. Learning to gain knowledge
      iii. Learning for personal development
   b. Extrinsic goal orientation
      i. Job promotion after course completion
      ii. Financial or other reward after course completion
      iii. Approval from others after course completion
   c. Individual learning strategy
      i. Organization of learning
      ii. Peer learning strategies
      iii. Metacognitive thinking
      iv. Help seeking behaviour (see also 3e)
      v. Time and study environment management (see also 3c and 3d)
         1. Avoiding distractions
         2. Controlling distractions
   d. E-learning self-efficacy
      i. Confidence to learn via e-learning
   e. Computer self-efficacy
      i. Confidence and ability to use the computer for learning
      ii. Using a virtual course environment (LMS)
      iii. Using html
      iv. Using chat rooms, instant messenger and forums
      v. Understanding copyright information
      vi. Using sound, graphics and videos
   f. Self-efficacy
      i. Confidence in minimizing disruptions (see also 5c)
      ii. Confidence in finishing e-learning course in time
      iii. Confidence in planning own work load

6. Other indicators
   a. Offline indicators in the classroom
   b. Level of financial support
   c. LMS specific indicators

8 Indicators with significant importance for prediction

Obviously all listed and described indicators can have an impact on learning outcomes. The question is which are most common and can be applied in different educational levels and systems across Europe. This question is not a trivial one and cannot be answered without applying some complexity to the answer.

Some indicator groups from chapter 7 have strong overlaps and some sub-indicators can be found in several categories. Therefore the list of indicators has been diminished to 4 main indicator groups:

- Socio-demographic indicators
- Individual learning and efficacy indicators
- Behavioral indicators
- Management indicators

Socio-demographic information will stay as a main category since many studies determine it as a basis for prediction.
Self-regulated learning indicators were separated into management indicators and indicators based on individual learning strategies.
Behavioural indicators remained a main category. Autonomy indicators were summarized under individual learning and efficacy indicators.
Other indicators and structural indicators were deleted.
From all main indicator categories those sub-indicators with small empirical evidence for prediction were deleted or summarized.

Also, when developing a predictive system, two types of indicators have to be taken into account:

- Indicators which are available to teachers and tutors
- Indicators which are not available to teachers and tutors

Indicators do not differ across educational levels, except for socio-demographic indicators (e.g. working status is not a relevant indicator in secondary school).

Table 1: Prediction Indicator Model

CRITON Integrated Prediction Indicator Model

MAIN INDICATOR 1

Socio-demographic indicators:

1.1Age
1.2Gender
1.3Number of children
1.4Educational background
1.5Previous grades
1.6Working status
1.7Chosen course level

MAIN INDICATOR 2

Individual learning and efficacy indicators:

2.1Intrisic goal orientation
2.2Extrisic goal orientation
2.3Individual learning strategy
2.4E-learning self-efficacy
2.5Computer self-efficacy
2.6Self-efficacy

MAIN INDICATOR 3

Behavioural indicators:

3.1Level of participation in the online course
3.2Delivering contents
3.3E-learning behaviour

MAIN INDICATOR 4

Management indicators:

4.1Time management
4.2Management of the physical environment
4.3Management of the social environment and help seeking behaviour

Sub-indicators for individual learning:
2.1
Learning as a personal challenge
Learning to gain knowledge
Learning for personal development
2.2
Job promotion after course completion
Financial or other reward after course completion
Approval from others after course completion
2.3
Organization of learning
Peer learning strategies
Metacognitive thinking
Learning methods
2.4
Confidence to learn via e-learning
2.5
Confidence and ability to use the computer for learning
Using a virtual course environment (LMS)
Using chat rooms, instant messenger and forums
2.6
Confidence in finishing e-learning course in time
Confidence in planning own work load

Sub-indicators for behaviour:
3.1
Online interaction
Participation in group work
3.2
Delivering assignments in time
Passing interim tests
Passing final exams
3.3
Login frequency
Site engagement
Read and posted messages
Dates and times of access to LMS

Sub-indicators for management:
4.1
Avoiding procrastination
Avoiding distractions
Controlling distractions
Prioritizing tasks
4.2
Eliminating distractions
Solving personal problems before learning
4.3
Seeking real help from peers, tutors or instructors
Seeking help in material and resources

PART III

GOOD PRACTICE EXAMPLES

9 Examples for the use of prediction systems across Europe

In the following section good practice examples are described for educational institutions which already use predictive systems in their faculty or school in order to predict final grades. The search was conducted in Europe, but only a few good practice examples were found. Prediction systems are more in use in the United States than in Europe, so some examples here are from the United States in order to show in which direction developments could go in Europe.

Example 1: Predicting success in video-live streaming courses

No.	Title	Description
1	Country	United States, Virginia
2	Educational level	Tertiary level (university)
3	Organisation / Project of good practice	A university in Virginia (US) offers distance learning courses which work with 1) face-to-face, 2) satellite broadcasting or 3) video-live streaming. 138 courses with more than 1100 learners were evaluated, measuring behaviour of learners using video-live streaming. This good practice example wanted to predict final grades by analysing video-live streaming behaviour.
4	Problem the good practice is based on	Individual behaviour could be better predicted with higher accuracy if behaviour of learners using video-live streaming were analysed. Students' learning performance could be improved and atypical students' behaviour could be identified.
5	Pedagogic approach	☐ Blended learning ☒ Online learning only, if yes, describe it: video-live streaming Learners from all over the country watch video-live streaming in real time from their own computer. They can interact with the teacher by sending messages which are displayed on a monitor for the teacher. The teacher answers in real time or send answers later on via email. Participants can also chat with each other during video-live streaming.
6	Description of the good practice	In this case four indicators for prediction were used: check-in time to the LMS (video-live streaming), meeting deadlines and managing the schedule, grades and exams, and the use of course material. Additionally the university wanted to find out which questions learners ask in LMS forums and if the type of question could predict final grades or not. Learners whose questions concerned the contents of the course had higher odds to get a good grade than those only asking administrative or technical questions during video-live streaming. The final grade depended on many factors: demographics and behavioural indicators. Those who chatted often with peers also asked the instructor more questions. Learners were more likely to discuss technical problems among peers and to discuss questions concerning the exam with the instructor. Those with a high number of logins to the LMS also asked more questions in general (high level of participation). Those who logged in only a few times

		did not chat as much either.
7	Contact, website, sources	Abdous, M. & He, W. & Yen, C. (2012): Using data mining for predicting relationships between online question theme and final grade. In: Educational Technology & Science, 15(3), 77-88.
8	Application for CRITON	This example clearly shows that behavioural indicators are most important for predicting final grades. E-learning behaviour has a predictive function and also the level of participation (chat and discussion forums). Only behavioural data was used for prediction, since other data about individual learning strategies or socio-demographic information was not available.
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☐ Structural indicators Course structure ☐ Study guide availability ☐ ☒ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☒ Final grades ☐ ☒ Behavioural indicators Level of participation in the course ☒ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☐ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☐ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐ ☐ Other indicators, please describe:

Example 2: Monitor Student Progress and Encourage Lagging Students

No.	Title	Description
1	Country	Pennsylvania (USA)
2	Educational level	Tertiary level (university)
3	Organisation / Project of good practice	Pennsylvania State University / Monitor Student Progress and Encourage Lagging Students
4	Problem the good practice is based on	Although some students may do better in an online environment than in a face-to-face classroom, it should not be expected every student to succeed in an online environment; therefore, instructors should recognize and work with those who are not successful in the online class
5	Pedagogic approach	☐ Blended learning ☒ Online learning only, if yes, describe it: ANGEL Course Management System (CMS)
6	Description of the good practice	There is a module that provides strategies for monitoring students' progress in an online environment. This module is part of the Online Teaching Course created by Penn State University World Campus as a guide for faculty who

		are new to teaching in an online environment. While recognizing different student learning styles, instructors monitor student progress, identify lagging students, and help them minimize their procrastination through appropriate monitoring and encouragement.
7	Contact, website, sources	http://cnx.org/content/m15059/latest/
8	Application for CRITON	This example clearly shows that behavioural indicators are most important for predicting students' dropout or not. E-learning behaviour has a predictive function and also the level of participation through tools tracking student progress in course activities. Moreover autonomy indicators play significant role since students sometimes cannot participate due to technical problems.
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☐ Structural indicators Course structure ☐ Study guide availability ☐ ☐ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☐ ☒ Behavioural indicators Level of participation in the course ☒ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☒ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☒ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☒ Self-efficacy ☐ ☒ Other indicators, please describe: technical difficulties or problems with course content, team communications

Example 3: Introduction to Artificial Intelligence

No.	Title	Description
1	Country	Ireland
2	Educational level	Tertiary level (university)
3	Organisation / Project of good practice	School of Computer Science and Informatics, College of Engineering Mathematical and Physical Sciences, University College Dublin/ Students' Continuous Assessment through Discussion Threads within Blended Teaching Method (face-to-face and e-learning)
4	Problem the good practice is based on	In contrast to traditional forms of assessment such as, the unseen end of the year examination, the link between the students' learning activities, the resources and the assessment had to be emphasized clearly. Lectures took place only once a week for three consecutive lecturing hours. The Moodle web-based e-learning environment was used for on-line activities such as,

		discussion forums, during which I could be in contact with the whole class, despite the fact that there was face-to-face contact only once a week. Apart from assignments and a final examination, assessment tasks included contributions to the on-line discussion threads. These mixed modes of assessment reflected the blended approach to teaching (i.e., face-to-face and e-learning). This blended type of lecturing had to be linked with the assessment criteria by which the students are evaluated in terms of their personal achievement at the conclusion of the module. The assessment of students helps the teacher to evaluate the students' performance and the effectiveness of the teacher's effort
5	Pedagogic approach	☒ Blended learning ☐ Online learning only, if yes, describe it:
6	Description of the good practice	Introduction to Artificial Intelligence The marking scheme for each module is constructed as follows: 50% exam paper, 20% assignment, and 30% weekly participation and forum questions. The students were informed, during the first lecture, of the standard rules concerning plagiarism and copyright issues. They had to read the announcements and postings for each module on a weekly basis, attend lectures, study the lecture notes and the recommended chapters from the textbook and answer the initial question in the forum posted from the lecturer by the end of the third day of classes. A maximum of three contributions to each discussion thread was allowed from each student, taking into account that one-liners would not be counted as participation. The discussion threads proved to be knowledge constructive for the students. Especially for the topics related to the software development, the students could share concerns and solve problems through the e-collaborative environment that they created though their postings in the forum. The assessment of the quality of the students' participation in the online discussions was based on the evaluation of the three most important criteria in discussion threads: 'Participation in Discussion' (level of interaction and provision of new information for the discussion thread), 'Content of Posting' (level of understanding of the topic and provision of responses based on research) and 'Critical Thinking' evidenced by posting (level of critical analysis of a posted idea and justification/explanation of any comments posted). This assessment took place at the end of each week and the e-moderator (lecturer in this case) reviewed the students' overall participation.
7	Contact, website, sources	http://www.aishe.org/readings/2007-1/No-02.html eleni.mangina@ucd.ie
8	Application for CRITON	This example shows that structural indicators, behavioural indicators and feedback are most important for predicting students' final marks. Good student performance, measured by student assessment results, depends on effective teaching strategies and module organization and the learning styles of the individual students.
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☒ Structural indicators Course structure ☒ Study guide availability ☒ ☒ Self-regulated learning indicators Motives of learners ☐ Learning methods ☒ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☒

		☒ Behavioural indicators Level of participation in the course ☒ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☒ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☐ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐ ☒ Other indicators, please describe: Student feedback

Example 4: Prediction-enabled content display and routing service

No.	Title	Description
1	Country	Finland
2	Educational level	VET/Secondary school and above
3	Organisation / Project of good practice	EU project's VCP-based SCENARIO Engine / ADE (Application Development Engine). This VCP-Engine is also available to the Criton project partners via Criton.EUproject.org, with Guest or User Member level for application usage, and information provider membership-level for application design.
4	Problem the good practice is based on	Production of highly personalised as well as evidence-based learning such as those making use of learning analytics and prediction indicators in LMSes, as well as in inquiry-based and Game-based learning mostly require programming, and/or are restricted to a more limited set of prediction indicators, learning analytics components and consequence actions, taken based on the indicators for facilitating personalized learning experiences.
5	Pedagogic approach	☒ Blended learning ☒ Online learning only, if yes, describe it Can be used in both modalities, in which online learning can be either conventional modalities or particularly geared to game-based learning.
6	Description of the good practice	The Scenario engine enables design and production of highly sophisticated and personalised online learning services, which can make use of both prediction indicators and learning analytics data from both within a scenario-application as well as from its surrounding e-learning/collaborative environment (i.e. any other accessible VCP-based learning community data). Flow and conditional actions are blocks of actions, or individual content elements, or individual page- or question/query presentations, defined and operated via a process/flow-chart, which includes different process components like displays, questions and decisions. Each such flow-element is defined through a set of forms, indicator manipulations and conditionality statements. Asset values can be used within or across different applications can be imported and used in advanced calculations. The conditional statements can be defined with separate or combined if-then statements as a series of and/or combinations. The content in each flow-element can be text and images, web-links and multimedia presentations, as well as file displays. Smaller scenarios can be made part of larger meta scenarios, as well as being in-built into other applications, such as LMSes and other e-learning services.
7	Contact, website, sources	Example available from e.g. from the following site: http://www.vcp.biz/services/Forms/formdata.cfm?FormID=56

		(Prior usage of the tool for a previous collaboration project/online service)
8	Application for CRITON	The tool can be used for collection and usage of a wide range of indicators, choices and preferences being used and acted upon as prediction indicators.
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☒ Structural indicators Course structure ☒ Study guide availability ☐ ☒ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☐ ☒ Behavioural indicators Level of participation in the course ☐ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☐ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☒ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐ ☐ Other indicators, please describe:

Example 5: Experience and Knowledge-exchange – A tool/solution for social media-oriented assessment and social media interactions

No.	Title	Description
1	Country	Finland
2	Educational level	VET/Secondary school and above
3	Organisation / Project of good practice	The EKE tool, developed on basis of the VCP-based Inquiry Engine / ADE (Application Development Engine). This VCP-Engine and the EKE solution are also available to the Criton project partners via Criton.EUproject.org, with Guest or User Member level for application usage, and with an information provider membership-level for application editing/re-design.
4	Problem the good practice is based on	Assessments are far too often an 'individual affair' between the learner and the assessor/e-learning programme/learning service facilitator. Today's 'digital realities' includes large components and strong focus on social media and more collaborative approaches and peer interactions. The practice of assessment and the utilisation of assessment data in social/collaborative settings have a great potential now when many are 'riding on the digital wave'.
5	Pedagogic approach	☒ Blended learning ☒ Online learning only, if yes, describe it Can be used in both modalities, in which online learning can be either conventional modalities and especially geared towards learning communities, LLL and informal learning with collaborative components.

6	Description of the good practice	The EKE tool is a unique user-centred online assessment and social interaction service. The service operates as an integrated part of VCP-based membership services and operated within any of the VCP-based learning community environments, and makes use of the Inquiry ADE for the service design and the back-stage application management. The content structure is hierarchical in its format and can make use of basically any such competency framework (an early example is the assessment of Learning to Learn competencies). The assessment/inquiry process is carried out in form of a number of screen dialogues where position statements are collected via multiple-choice options. The social component of the tool interconnects the user to other peers that either have the capabilities that the user is missing, or with other users that are missing the capabilities that the EKE user has. The follow-ups are making use of the member collaboration and interaction services being part of the VCP-environment's membership services. The EKE tool is also providing a profile statement both for the EKE users as well as for the peer that the user decides to contact based on their profile complimentarily. More than one peer can be contacted by the user for one and the same profile component, and user can also contact different peers for each of his/her profile components and interact with them separately about one or more of the different EKE-components in their profiles.
7	Contact, website, sources	Example available from e.g. from the following site: http://www.vcp.biz/services/Forms/formdata.cfm?FormID=56 (Prior usage of the tool for a previous collaboration project/online service)
8	Application for CRITON	The tool can be used for collection and usage of a wide range of needs-based and structural indicators. The 'Inventory of Learner capabilities' example can be modified to fit Criton project's application more precisely and be geared towards a wide range of predictor indicators, as well as be in-built as an add-on to different kind of LMS solutions.
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☒ Structural indicators Course structure ☒ Study guide availability ☐ ☒ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☐ ☒ Behavioural indicators Level of participation in the course ☐ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☐ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☒ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐ ☐ Other indicators, please describe:

Example 6: Personalized Assessment tool/service

No.	Title	Description
1	Country	Sweden
2	Educational level	LLL / Adult Education / professional development training
3	Organisation / Project of good practice	EUproject.org/net VCP based services in which the FORMS ADE (Application Development Engine) is a part. The tool/services are also available to the Criton project partners via Criton.EUproject.org
4	Problem the good practice is based on	Provide as an assessment service that is mediated online and facilitates high level of personalisation of dialogue content based on previous performance, competencies, selected choices, options and routs, and the individual learner's interaction pattern
5	Pedagogic approach	☒ Blended learning ☒ Online learning only, if yes, describe it Can be used in both modalities, in which online learning can be either conventional modalities as well as in connection with game-based learning.
6	Description of the good practice	The personalised assessment solution/tool enables users to define single page or multi-page assessment pages with questions and options in multiformats, and where both individual questions on a page is altered as well as the pages are being displayed selectively depending on a predefined set of variables derived from present or previous responses/interactions with the present or previous assessments using the same tool, or even in combination with indicators derived from other applications within the same learning environment. The collected indicators define the personalisation action that is taken for each service user/learner base on different conditionalisations.
7	Contact, website, sources	Example available from e.g. from the following site: http://www.vcp.biz/services/Forms/formdata.cfm?FormID=56 (Prior usage of the tool for a previous collaboration project/online service)
8	Application for CRITON	The tool can be used for collection a wide range of indicators, choices and preferences subsequently being used as predictability indicators.
9	Indicators for prediction	☒ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☒ Structural indicators Course structure ☒ Study guide availability ☐ ☒ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☐ ☒ Behavioural indicators Level of participation in the course ☐ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☐ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☒ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐

		☐ Other indicators, please describe:

Example 7: 'Facilities for Conditionalized' presentation and routing of learning activities and content presentation in e-learning courses/modules

No.	Title	Description
1	Country	Sweden
2	Educational level	LLL / Adult Education / professional development training
3	Organisation / Project of good practice	EUproject.org/net VCP based services in which the PAGES and DISPLAY ADEs (Application Development Engine) is a Designer service. These tool/service-combinations are also available to content/service developers for Criton project partners via Criton.EUproject.org (Access are assuming minimum Information Provider membership level).
4	Problem the good practice is based on	Most LMS learning service providing environments have no or very limited capabilities for conditions display of pages or content components on a personalized learning service basis, which also means that the flexibility and options for generating higher levels of personalised learning e.g. based on predictability indicators and other learning Analytics information collected prior to and/or during the learners engagement in a particular learning service, often leading to less than desired utilisation of prediction and evidenced based learning management.
5	Pedagogic approach	☒ Blended learning ☒ Online learning only, if yes, describe it Can be used in both modalities, in which online learning can be either conventional modalities as well as in connection with learning communitybased learner services.
6	Description of the good practice	The Page ADE facilitates partial modification, replacement, re-routing as well as other conditional actions, manipulation of indicator data, and formulation as well as triggering of actions based on conditional statement based on one or more if-then and and-or statement combinations. The Display ADE facilities acts as a 'partner to the Page ADE , and is ised to enable control, select and steer strings of Page presentations, external applications and media presentation in a highly personalised manner, based e.g. on the users prediction indicators, 'electronic footprints' and actions.
7	Contact, website, sources	Example available from e.g. from the following site: http://www.vcp.biz/services /Pages/ and /Display/ (New and prior usage of the tools 'front-pages' provided access to own/access-entitled application examples)
8	Application for CRITON	The tool can be used for generating a wide range of indicators usages, choice display-and preference handling of VCP-based predictability indicators.
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☒ Structural indicators Course structure ☐ Study guide availability ☐ ☒ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☐ ☒ Behavioural indicators

		Level of participation in the course ☐ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☐ (delivering assignments in time and passing tests and exams) E-learning behaviour ☒ (login frequency, site engagement, read and posted messages, dates and times of access) ☒ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐ ☐ Other indicators, please describe:

PART IV

INTERVIEWING LMS EXPERTS

10 Short introduction to the expert interviews

The purpose of the expert interviews was to discover how existing LMS can be technically enhanced by a prediction system. While previous work in the EU-project CRITON have a pedagogic focus and want to explore the opinions of teachers and tutors as well as students of all educational levels about predicting drop-outs, this part of the research wants to put a focus on **technical feasibility**. The interviews were technically focussed and can be seen as an add-on to the empirical work done with a pedagogic focus.

An "expert" was in this case defined as someone with expertise in LMS development or administration or plug-in providers for LMS who might have experience with prediction systems, although rarely used in Europe.

In sum eight experts were interviewed using a semi-standardized questionnaire that was developed in the project partnership of CRITON (see Annex 1). The interviews were conducted by project partners in their national languages and then summarized in English for analysis.

The essential questions asked were:

1. What type of e-learning system are you currently working with /developing / administering?

2. If you think about the assessment features of that LMS, what are the main problems you face with it?

3. Have you, as a developer/administrator ever thought about an electronic prediction system and which prediction systems do you know of that already exist?

4. Which technical features do we need to take into account in your opinion when developing such a prediction system?

5. In terms of prediction what would you say are important prediction indicators in e-learning environments for success or failure? (e.g. time used for one task, experience with the computer etc.)

6. What would we have to take into account in Austria / other country in order to use such a prediction system in university or adult education?

The following table summarizes the interviews and gives details about the country it took place in, the date, the duration and the expert status of the interviewed person.

Table 2: Interviewed LMS experts

No.	LMS Expert	Gender	Date of interview	Length of interview in min.	Country
1	LMS developer	m	21.6.2013	20	Greece
2	LMS administrator at university level	f	26.6.2013	30	Greece
3	LMS experts	m, m	20.8.2013	120	Sweden
4	LMS specialists	f, m	21.8.2013	80	Finland
5	LMS development and maintenance in a public university	m	4.9.2013	50	Lithuania
6	LMS developer at university level	m	9.9.2013	20	Greece
7	Plug in provider of LMS	m	9.9.2013	20	Greece
8	LMS administrator in an adult education institution	m	16.9.2013	45	Austria

11 Results of the expert interviews

The following section summarizes the results of the expert interviews in four main chapters.

11.1 Type of LMS in use, level of modification and data storage

Five of the interviews experts stated working with moodle, which is an open source solution, for e-learning and two experts stated working with OpenEclass, which is also an open source LMS. External apps/add-in components are used also. The interviewed experts stated modifying the LMS for it to fit the needs of their institutions. The expert from Austria mentioned changing design and size of data restrictions (Int. 8), two experts from Greece mentioned editing existing features and developing new ones, like new modules (Int. 6, 7). The reasons for modification might lie in the following: "the main problem with assessment features of OpenEclass is that these feature are not flexible enough in order to meet the different pedagogical needs of each organization, for example the same LMS is used in primary and secondary school and in higher education. It is obvious that each educational level has different needs and students' role varies in each educational level." (Int. 7)
One expert working with the OpenEclass platform modifies the subsystem of Exercises and Assignments, since they need improvement. In the future the Exercises will obtain more nice characteristics e.g. new type of exercises, better interface and an integrated rating system for grades (Int. 1). The OpenEclass platform was also recently enriched with web 2.0 tools such as blog, wall, commenting, rating, and tags. The expert believes that these tools can also help in students' evaluation.

Data storage procedures are different in each country and institution and vary from one year to five years. The Swedish expert mentioned that data is stored up to one or two years after completion of the learner usage of the services provided or a maximum of five years, depending on client requests (Int. 3). The Lithuanian expert of a university stated that all students' data is collected and stored for up to five years (which is assumed to be the average learning period of a student at university level) (Int. 5). Data can also be stored for project purposes only, the Finish expert explained (Int. 4). For commercial clients data is stored in accordance with contractual agreements, which in most cases is up to one year after the online training/course has been completed.

About the type of data that is stored, experts say that this mainly focuses on the student. The Greek expert states that students' tasks and grades are stored (Int. 6). The Austrian expert says that login frequency of users and also login times are stored, if and which documents they download and the results of online quizzes (Int. 8). Also each student has a profile which means he or she can enter personal data, but this is optional. The Lithuanian expert also mentions that student's statistical data is stored (Int. 5) in addition to tasks accomplished during their period of studies, e.g. assessment results, e-portfolio etc.

11.2 Assessment features of the LMS in use

Two experts (Int. 6, 7) believe that the assessment features of LMS are not very popular among teachers. They seem to prefer traditional means of assessment.
Another expert (Int. 4) underlines this by saying that most teachers do not make full scope usage of all the assessment options available in either of the two online learning solutions being used. Often very limited assessment components are built into teacher-generated applications, even if the LMS have assessment capabilities beyond their initial expectations/requirements.

The assessment features which are used by teachers described by several experts are quite basic (e.g. Int. 4). Basically assessment is based on three features in the adult education institution working with moodle: download of online documents (80% of documents have to be downloaded to pass the class), results on quizzes (50% have to be reached in order to pass the class) and uploading homework (50% of homework has to be done to pass the class). The assessment features are used by all teachers once for a final quiz and as tests during the course (Int. 8). According to another expert (Int. 5) the results of assessment make up 50-60% which is done either online or face-to-face, but is accomplished in more secure ways – for example using video conferencing. The assessment features in moodle extensively mirror the kind of assessments that take place in the classroom (Int. 4). The assessment in the VCP/scenario engine are more geared towards facilitating personalized learning, and as such has substantially wider and more flexible assessment capabilities besides also having capability to integrate into learning services extensive 'conditionality features'.
Another expert explains in detail how the assessment via LMS works (Int. 1): He believes that teachers use the subsystems of OpenEclass for the evaluation of the students, and

that the most popular subsystems are the Assignments, then the Exercises and then the Learning Path. OpenEclass provides the possibility for teachers to assess their students. First of all there are *Assignments*. The teacher is able to specify a task that requires students to upload files to it within a specified period of time and after completion the teacher can now grade his/her student. Students receive this rating and teachers can also add comments.
Another way for students' assessment is with the module of *Exercises*. This subsystem provides two scenarios for assessment: In the first scenario the teacher can specify exercises only for assessment. The students enter into the system, do their exercises and at the end they see their grade. In the other scenario the teacher can set exercises and at the end of the exercises see the grade of his/her student, download it and understand if the student did it well or not. Another way of assessment is to see the active participation of the student through the LMS platform. First of all the teacher can watch the movement as well as the traffic of students through the *statistics* of the platform and how much time a student spends with each subsystem. So the teacher has a picture of whether the student participated in the course or not. Another tool for assessing is the *Learning Path*. The teacher can establish a Learning Path using already existing subsystems of the platform. For example if a teacher wants to have a successful learning lesson he/she must determine to go through some steps and combine some subsystems. So the teacher sequentially determines all the steps required to establish an educational goal and through it the teacher can observe if the students clicked on the subsystems, which exercise he/she performed, which and how many documents he/she uploaded, etc.

In Lithuania teachers and tutors at university always combine e- and traditional modes of assessment (face-to-face) (Int. 5).
One expert from Greece (Int. 2) names the following assessment features of the LMS:

- Questionnaires (open questions and multiple choices)
- Uploading of assignments (it is the most important characteristic, since the students have to upload the assigned tasks within a specific period)
- Wikis (students write their task)
- Observation of students' traffic (the administrator is able to see how much time each student spends in each module, how many times the students visited the LMS, etc.)

In Finland the game-based assessment features often use more sophisticated assessment forms and include closer monitoring of actions and predictability indicators, branches, etc. (Int. 4).
A Greek expert believes that if teachers or tutors want to have a clear picture of their students' performance when they use an e-learning platform they have to use it very systematically. She assigns tasks every week to her students and she also uses questionnaires, wikis and forums in every lesson (Int. 2).
From her point of view the most popular moodle feature for her course is the wiki, since the students do their tasks in groups and it seems easier and funnier to them. The second

most popular feature are questionnaires end especially those with multiple choice questions. She rarely observes students' traffic and she does not use the electronic rating system.

Problems mentioned which explain the low usage of assessment features are: the main problem is that the assessment features are not flexible enough in order to meet the different pedagogical needs of each organization, for example the same LMS is used in primary and secondary school and in higher education (Int. 6). It is obvious that each educational level has different needs and students' role varies in each educational level.
The main e-assessment limitations according to another LMS expert (Int. 5) are:

- Security limitations
- Plagiarism
- Ensuring equivalence
- Dependence on the e-literacy of the learners (and test-creators and assessors).

11.3 Opinions about an electronic prediction system

Four of the experts had no interest or experience with predicting learning outcomes or drop-out rates. One argument against the need for prediction is the existence of tuition fees, which makes students want to pass classes (Int. 6).
One expert (Int. 7) does not know any electronic prediction system, however he finds the idea very attractive, which could help teachers prevent learners from failing an e-learning class or course. Assessing data from the usage of an LMS could be helpful in predicting students' performance. He believes that there is a need to take into account how easy or not is to collect the required data and probably the privacy implications when developing such a prediction system.
In the Nordic countries (Int. 3, 4) prediction systems are in use, facilitated through the VCP environment. One expert states making use of a combination of 'electronic footprints' of the user interaction with the online learning service as well as in application-specific usages with 'barometers' that keep track of the accumulated characteristics of the learning service usage. These production indicators then influence different 'conditionalities' built-into the learning routes in the online learning services. Another expert states using different forms of prediction, especially in game-based learning development. The VCP/Scenario engine provides a wide range of predictability options, enabling the institution to build online learning services with a high level of personalization. The VCP based services include 'electronics footprints', page and content display conditionality, detailed monitoring of performance and behavior as well as choice and predictability indicators.
One expert states that prediction is a tracking process (Int. 8). Before working with LMS he used to work with CMS for tracking processes how customers buy products. A prediction system in education is very similar to marketing. Students' actions are tracked to see which results they have and how successful they are.

11.4 Technical features that need to be taken into account

The experts raise the question how easy it will be to collect relevant data for the prediction system (Int. 6). Privacy policies also have to be taken into account. Also a prediction system's design should have an appealing user interface and should be tailored to the needs of teachers in order to engage them in the data collection and entering process (Int. 6, 7). Moreover, the system should provide accurate predictions since then teachers will use it or regularly get improved in the course of usage.

The experts from Lithuania and Austria agree that data collection procedures are important (Int. 5, 8). Enough data has to be collected in order to have a sufficient analysis and data dynamics. It is extremely important to define the processes you need for prediction in the educational institution. It means setting up a standard process which data is needed for prediction and where do you get it from.

One expert proposes the following sequence (Int. 5):

- data collection
- piloting the prediction system with one group of teachers
- link data to diagrams and analyse dynamics
- draw conclusions if possible

Teachers' involvement in this process is a must. If students are under-age, parents should be involved as well (Int. 5).

Most important is a powerful capability, solid operation and visibility of settings/definitions of the predictabilities to designers/administrators, and possibly even individual users, partially or in full (Int. 3).

Two experts are concerned about the connectedness of LMS to the prediction system (Int. 4, 8). The prediction system should be connectable to the LMS. Standard formats should be used to store data and analyse it. You could make the user fill in some questions using indicators for prediction in a doc file online, then the LMS sends the file to the prediction system and then the prediction system sends it back to the LMS with an analysis. The user is informed via email about his drop-out rate. This could be one way of doing it (Int. 8). The question needs to be solved how existing and desired prediction services can be built-in or interconnected to the online learning services, and the long-term usage as well as the stability/maintenance of the prediction services.

The predictability indicators should be both application/module specific as well as generic for overall use of the learning service environment, and the indicators should be both accumulative, able to calculate and to make 'conditionalized choices', make automated decisions, and track routes. A predictability-enabled ought to have, besides the automated rerouting and prediction, also capability for tutors/support staff to influence conclusions drawn from the automated system, as well as possibly even for the learners themselves to influence the routing and choices made. (Int. 4)

The predictability indicators need to act as an application-specific or generic 'barometers' that measures one single or combined indicator and be influential on one conditionality statement or a combination of these. The actions could e.g. be route changes, screen/content manipulation or content replacement, with recording and tracking that can be analyzed post-facto. (Int. 3)

One important aspect to consider is how easy it is to get historical data. In most cases prediction algorithms take into account historical data, however it could be difficult to acquire them since teachers could be reluctant to provide them or they are not recorded at all. (Int. 7)

11.5 Opinions about prediction indicators

The interviewed experts mentioned a number of prediction indicators which are important from their perspective.
If compared to the indicator framework mentioned earlier in this report (see chapter 7 and 8), the following indicators are mentioned.

Table 3: Prediction indicators mentioned by experts

No.	Name of mentioned indicator by experts	Interview	Indicator group	Corresponding specific indicator
1	Past learning performance of students	3, 4	Socio-demographic indicators	-
2	Learner`s characteristics such as age, educational level, occupational status	4, 5	Socio-demographic indicators	-
3	Motivation for learning	5	Individual learning and efficacy indicators	2.1
4	Computer skills	5	Individual learning and efficacy indicators	2.5
5	Self-efficacy	3, 4	Individual learning and efficacy indicators	2.6
6	Self-management skills	4	Individual learning and efficacy indicators	2.6
7	Skills to learn	5	Individual learning and efficacy indicators	2.6
8	Participation in social networking activities (forums, chats etc.)	6, 7	Behavioural indicators	3.1
9	Time used for one e-learning task	6, 7	Behavioural indicators	3.2
10	Time used to compete one task	7	Behavioural indicators	3.2
11	Login rates/dates	8	Behavioural indicators	3.3

The table above shows which indicators the interviewed experts rated as important for prediction of learning outcomes. Three indicator groups were touched by them: socio-demographic indicators of the learner, efficacy indicators and behavioural indicators.

The experts mentioned the time used for specific tasks, the degree of participation in social networking activities (e.g. forum, chat) (Int. 6, 7), or log in rates and dates (Int. 8). If an administrator sees that someone only logged in to the LMS two days before the final quiz, the prediction is clear that the student is going to fail the class. So regular logins tell the LMS administrator or the teacher something about the possible success rate.
Also past learning performance has to be taken into account (Int. 4). Also self-efficacy might vary depending on the educational level of the student. Firstly a difference might occur between e-learning in formal education and more informal adult learning as the learners` self-management and the rationale for engaging in learning might be different. In adult education the learners` self-management is more important than the 'tutor control' in school education.

PART V

CONCLUSIONS

12 Conclusions from previous CRITON deliverables

The CRITON project has not only brought forth this deliverable report at hand, but also other deliverable reports:

- D2.1 about documented assessment practices of teachers in e-learning environments
- D2.2 about the results of a teacher's and student's survey and their assessment experiences in e-learning
- D2.3 about concrete recommendations about assessment practices across educational levels based on D2.1 and D2.2
- D3.1 about the results of a teacher's survey about pedagogy and assessment methods

These deliverable reports also have impact on the prediction indicators to choose for the piloting of the prediction system.

D2.1 concludes that for assessment the teacher has to define learning objectives and if these objectives are somewhat complex, then standard formats of assessment, like closed questions in multiple choice formats, will have to be supplemented by open ended questions and these have to be analyzed by teachers.

D2.2 summarizes the results of a survey with 1.254 learners and teachers across Europe and across educational settings about their assessment preferences and experiences. The report comes to the conclusion that multiple choice answer formats, short answer formats, games, and tables and charts in e-learning assessment are dominant across Europe. The majority of teachers measure participation of learners in discussions for assessment, which underlines that e-learning behavior is important for success (see indicator group 3 below). Also the survey shows that learners with a high socioeconomic status are more computer literate than those with a lower socioeconomic status. This supports the usage of socioeconomic indicators for prediction of success or drop-out (see indicator group 1 below). In order to meet the needs of teachers with the prediction system to be developed behavioral and socioeconomic indicators should be taken into account.

D2.3 is a summary of recommendations from D2.1 and D.2.2.

D3.1 is the concrete result of a pedagogic survey with 252 teachers in four European Member States about assessment practices in e-learning. The report comes to the conclusion that between 60% and 80% of teachers assess their students' progress twice per semester and that what learners know after the course is more important to them than formal requirements or participation in online discussions (this corresponds to indicator 3.2 below). Teachers see the main target groups for failing or dropping out as those: those who do not fulfil formal requirements (73.5% Greece, 54.3% Lithuania, 27.3% in Austria, and 25% in Germany), and those who are lazy (51.5% Greece, 27.3% Austria, 35.7% in Germany, and 77.7% Lithuania).

D3.2 is the deliverable report at hand about prediction indicators in education. As already mentioned in this report dropout is a multi-factorial phenomenon depending on a range of issues. The number of indicators in articles and empirical studies for prediction purposes varies considerably. For a full list see chapter 8 of this report. Nevertheless, at least four indicator groups have been identified to measure dropout and success rates in e-learning.:

- Socio-demographic indicators
- Individual learning and efficacy indicators
- Behavioral indicators
- Management indicators

Socio-demographic information will be a main category since many studies and the expert opinions (see chapter 11 of this report) determine it as a basis for prediction.
Individual learning and efficacy indicators are not stressed so much in the literature, but more in LMS expert interviews. These indicators can only be collected by asking the learners themselves.
Behavioural indicators remained a main category for prediction which is supported by previous CRITION deliverable reports, good practice examples of prediction, LMS expert interviews, and literature.
When developing a predictive system, one issue has to be taken into account: Indicators need to be available to teachers and tutors, who are defined as the main users of a prediction system in CRITON, or a separate survey format has to be developed to collect the respective indicators from learners.

So from all the above mentioned deliverable reports of the CRITON project it is recommended – based on this deliverable report and the others – that the necessary indicators for the prediction of drop out and success rates in e-learning are four indicator groups, which are described below (chapter 13).

13 Final Conclusions and Recommendations

Recommendations concerning **prediction indicators**:

- Prediction of drop-out rates is a complicated task that has to take account several indicator groups in order to be accurate or as accurate as possible.
- The prediction system should be built upon all four indicator groups proposed in chapter 8 in order to be most accurate.

The main result of this deliverable is the indicator model with four indicator groups and 19 sub-indictors the CRITON prediction will rely on.

MAIN INDICATOR 1

Socio-demographic indicators:

1.1Age
1.2Gender
1.3Number of children
1.4Educational background
1.5Previous grades
1.6Working status
1.7Chosen course level

MAIN INDICATOR 2

Individual learning and efficacy indicators:

2.1Intrisic goal orientation
2.2Extrisic goal orientation
2.3Individual learning strategy
2.4E-learning self-efficacy
2.5Computer self-efficacy
2.6Self-efficacy

MAIN INDICATOR 3

Behavioural indicators:

3.1Level of participation in the online course
3.2Delivering contents
3.3E-learning behaviour

MAIN INDICATOR 4

Management indicators:

4.1Time management
4.2Management of the physical environment
4.3Management of the social environment and help seeking behaviour

Application to different educational levels:
All these indicators apply to the educational levels of tertiary education and adult education. For primary and secondary education modifications would have to be made.
For learners from primary and secondary educational levels, socioeconomic indicators for prediction will have to be reduced (deleting 1.3 number of children, 1.4 educational background, and 1.6 working status) or have to be replaced by socioeconomic indicators of their parents. The chosen course level (indicator 1.7) can in primary and secondary education be deleted as an indicator since this typically corresponds to age (e.g. all 11-year olds are in the same class). So for primary and secondary education indicator group 1 can be reduced to 1.1, 1.2 and 1.5. All other indicators also apply to primary and secondary education.
For CRITON prediction only adults will be piloting the prediction system.

Recommendations concerning the **process of the piloting** CRITON in 2014 (→ WP 4):

- A next step must be the operationalisation of indicators and the development of a standard questionnaire for prediction data collection in adult education, VET and higher education for piloting.
- The process of data collection for prediction purposes needs to be defined in a standard procedure and contain: which data is collected, how often, with which instruments, and by whom.
- A selection of sub-indicators has to take place in order to alleviate the process of data collection for institutions and teachers, since teachers will not be able to fill in 19 questions about each of their students and time efforts have to be reduced. The balance between keeping time efforts for teachers low and accurate prediction on the basis of as many indicators as possible has to be found.

- It is recommended to ask students directly about their individual learning, efficacy, and management indicators (indicator groups 2 and 4). Socio-demographic information and behavioural indicators might be known to the educational institution or documented in LMS anyway (indicator groups 1 and 3).
- Each partner country has to set up a procedure of how the data will be collected. The instrument (questionnaire) for data collection has to be developed as soon as possible in a standard format without open questions.
- Teachers who are the end users of the prediction system need to be involved in the process of development and thus paid or refunded something for their effort.
- Then piloting groups have to be chosen and incentives set for them to provide historical data from past courses and classes. Privacy and ethical issues of data collection have to be solved.
- Collection of historical data for the prediction algorithm – this is seen as a difficult task, since teachers might be reluctant to providing it or do not have it. Incentives should be found in order to cover teachers' efforts to provide data of previous courses or classes. Privacy policies of educational institutions might not allow giving away historical data for prediction purposes.
- It could be difficult to practically implement a prediction system based on assessment in an LMS since many teachers do not use LMS assessment features.

General recommendations:

- Since there are few good practices of prediction systems in use in Europe, a collection of good practices according to the template above in the CRITON test phase is recommended. It is recommended to use a good documentation system for the CRITON piloting phase in order to be able to collect as much transparent data as possible.
- All technical LMS experts stated modifying their LMS in use on a regular basis and thus modifying it for the purpose of prediction should not be a technical problem. LMS administrators and developers are used to modification work.

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ANNEX 1

Interview guide for LMS experts

1. What type of e-learning system are you currently working with /developing / administering?

➔ Is it an open source or are you modifying / editing the LMS? If yes, how?

➔ Which data is stored in your current LMS? (for how many years etc.)

2. If you think about the assessment features of that LMS, what are the main problems you face with it?

➔ If you compare different LMS you know, which differences are there in the assessment features?

➔ What can you tell us about the frequency teachers use these features for assessment? How would you rate their popularity or importance?

3. We are currently working in an EU project that wants to develop a prediction system to help teachers prevent learners from failing an e-learning class or course.

   Have you, as a developer/administrator ever thought about an electronic prediction system and which prediction systems do you know of that already exist?

   ➔ How do existing prediction systems or add-ons or plug-ins work?

4. Which technical features do we need to take into account in your opinion when developing such a prediction system?

   ➔ Which other features are important in your view for developing such a system? e.g. involving teachers in the process, etc.

5. In terms of prediction what would you say are important prediction indicators in e-learning environments for success or failure? (e.g. time used for one task, experience with the computer etc.)

6. What would we have to take into account in your country in order to use such a prediction system in university or adult education?

ANNEX 2

Template for collecting good practice in predicting dropout

No.	Title	Description
1	Country	
2	Educational level	
3	Organisation / Project of good practice	
4	Problem the good practice is based on	
5	Pedagogic approach	☐ Blended learning ☐ Online learning only, if yes, describe it
6	Description of the good practice	
7	Contact, website, sources	
8	Application for CRITON	
9	Indicators for prediction	☐ Socio-demographic information of the learner Age ☐ Gender ☐ Marital status ☐ Children ☐ Educational background ☐ Previous grades ☐ Ethnicity ☐ ☐ Structural indicators Course structure ☐ Study guide availability ☐ ☐ Self-regulated learning indicators Motives of learners ☐ Learning methods ☐ Time management ☐ Management of the physical environment ☐ Social environment and help seeking behaviour ☐ Final grades ☐ ☐ Behavioural indicators Level of participation in the course ☐ (login frequency, site engagement, read and posted messages, online interaction, participation in group work) Delivering contents ☐ (delivering assignments in time and passing tests and exams) E-learning behaviour ☐ (login frequency, site engagement, read and posted messages, dates and times of access) ☐ Autonomy indicators Intrinsic goal orientation ☐ Extrinsic goal orientation ☐ Individual learning strategy ☐ E-learning self-efficacy ☐ Computer self-efficacy ☐ Self-efficacy ☐ ☐ Other indicators, please describe: