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Abstract: During the last decades, learning has once again become a key topic. However, this time, not only for students and professors but also in political and economic contexts. One reason for this is that a high level of education and skills of nations, organizations, and individuals are considered both necessary and crucially competitive advantages in the present knowledge society and the globalized market. Therefore, obtaining a quality education is fundamental for all of us in today's competitive business world. In particular, adult learning within the maritime sector has been important for the success of this industry for ages. The question now is how to streamline and facilitate the learning process for the learners, the lecturers, the authors, and the learning institutions. TERP has taken on the challenge of improving this learning process by introducing Abooks, electronic textbooks based on principles of *pedagogy* (the science of learning), and *andragogy* (the science of learning focusing on adults) that adapt to the learner through artificial intelligence. Abooks also introduces the opportunity of utilizing immersive techniques. This is being developed in the AIM project; *Adapting to the Individual through Machine learning*, a research project led by the research department in TERP in collaboration with the University of Stavanger and the Norwegian Computing Center.

Introduction

Since the 1980s, the focus in education has moved from *teaching* to *learning*. This is based upon an understanding of learning as a more active process for the learner than the more passive attitude that may be associated with teaching. Teaching was supposed to be actively performed by the teacher, while the learner passively absorbed knowledge. However, this is not how we see high-quality learning today. We realize that high-quality learning can only occur with an active learner where both competence and commitment are essential.

Modeling the learning process

Learning is a complex matter, though, and there is in fact no generally accepted definition of the concept. Here, we are thinking of learning as *a process that leads to a permanent capacity to change, not solely due to biological maturation or aging*.

We believe this learning process implies the integration of two very different processes which both must be actively involved if any learning is to take place (Illeris, 2009);

- an *external interaction process* between the learner and the environment
- an *internal psychological process* of acquisition and elaboration.

Furthermore, this *internal psychological process* is a process of integrated interplay between the two psychological dimensions (Thompson & Aarset, 2012);

- *the competence dimension,* which concerns both the learner's prior competence (understanding, knowledge, skills, etc.) and the learner's ability to learn
- *the commitment dimension,* which provides and directs the mental energy that is necessary for the learning process to take place (motivation, volition, emotions, etc.).

The incentives are influenced by the content and may either be;

- *internal,* e.g., desire or interest
- *external,* e.g., necessity or compulsion.

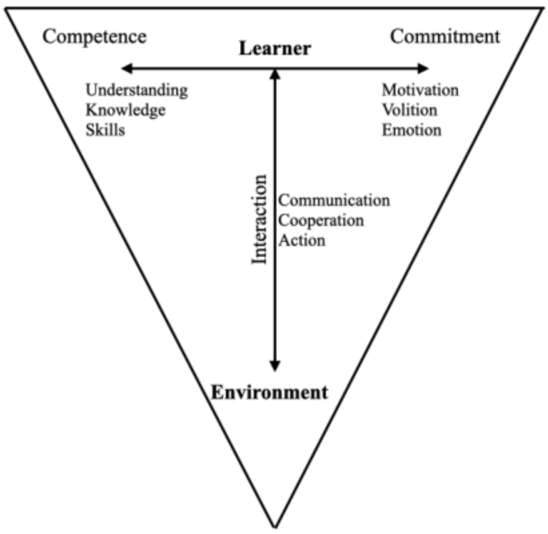

Figure 1. An illustration of the three dimensions of learning (inspired by Illeris, 2009).

How such a learning process is carried out for each individual learner varies, of course. Our goal in the AIM project is to facilitate and improve this learning process by identifying "matches" in the person and the environment concepts and utilizing this knowledge to adapt the available learning resources to the learner. We need to "observe”, characterize, evaluate, and adapt to the actual learning process autonomously for each learner.

To do this autonomously, we need to model the learning process in the language of mathematics and statistics. Let us introduce the notion
X = Learning resources
Y = Learning outcome.

We need to identify a mathematical/statistical model for how the learning resources we provide will influence the learning outcome. This may be illustrated in conceptual diagrams, as illustrated in figure 2 (Mulaik, 2009).

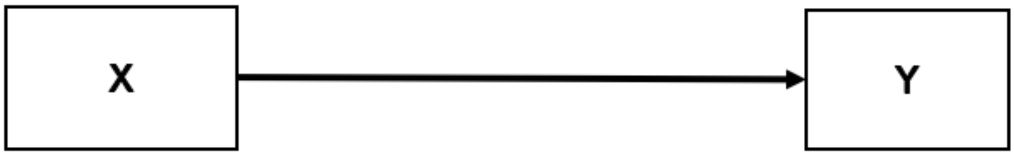

Figure 2. A simple conceptual diagram.

To get closer to a realistic model of the learning process, we need to introduce so-called *mediator variables* (Hayes, 2018). Besides the direct effect an antecedent variable X may have on a consequent variable Y, the variation in X also causes variation in one or more mediators M1, which, in turn, also causes variation in Y, as illustrated in figure 3. Here, a typical example of a mediator is motivation. The available learning resources are directly influencing the learning outcome. Still, they are also influencing the learner's motivation and are thereby also influencing the learning outcome indirectly.

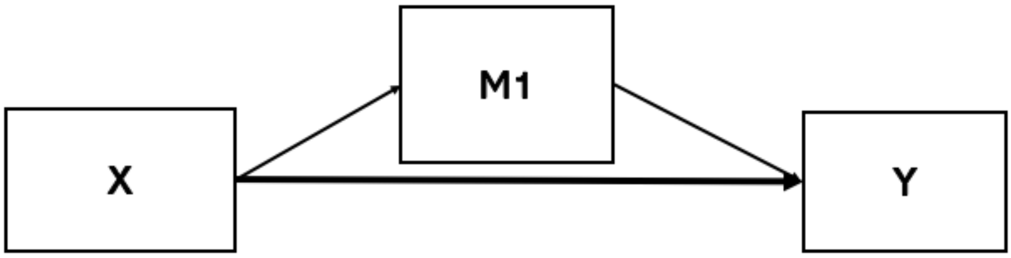

Figure 3. Introduction of a mediator variable in a conceptual diagram.

Furthermore, we need to introduce the concept of *moderator variables* (Hayes, 2018). The association between two variables X and Y is said to be moderated when the effect of an antecedent variable X on a consequent variable Y depends on a third variable (or set of variables) M2. A typical example of a moderator here is competence. We now assume that how the available learning resources influence the learning outcome depends on the learner's level of competence and ability to acquire knowledge.

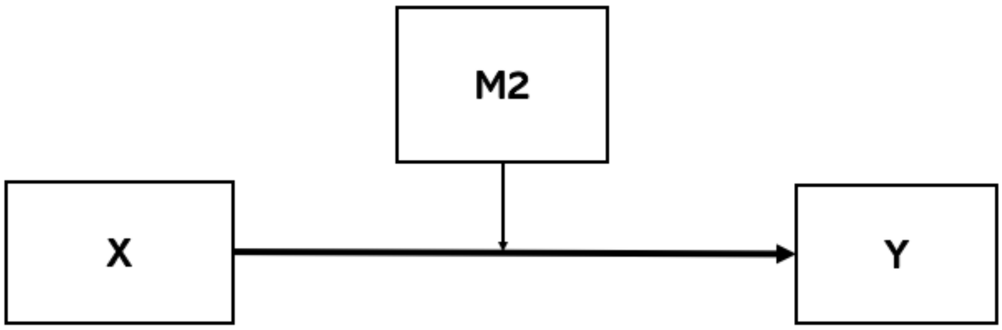

Figure 4. Introduction of a mediator variable in a conceptual diagram.

Now, we are able to identify a conceptual diagram, as presented in figure 5 below, that illustrates the main points in a learning process. A mathematical/statistical model of the learning process may directly be produced from this conceptual diagram, making it possible to characterize, evaluate, and adapt to the individual learner autonomously.

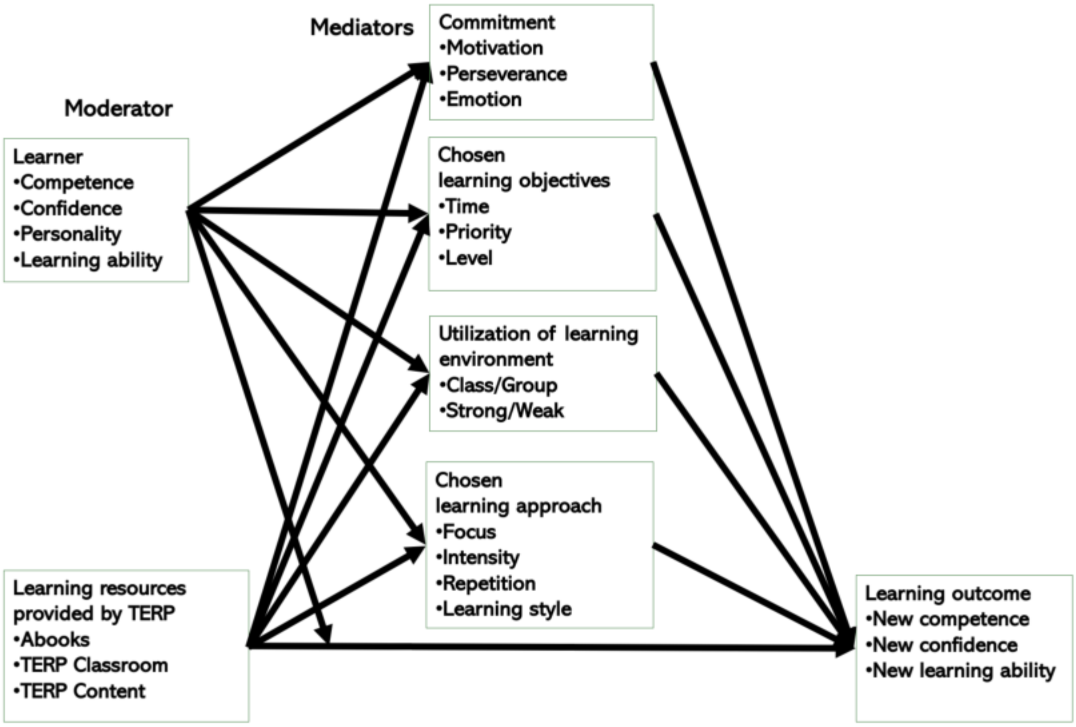

Figure 5. The learning process illustrated in a conceptual diagram.

Input to this model will partly be provided by observing learner activity. In the AIM project, individual learner activity is modeled as a discrete stochastic process where the different states of the stochastic process are defined in accordance with the available learning resources. This may be illustrated as in figure 6.

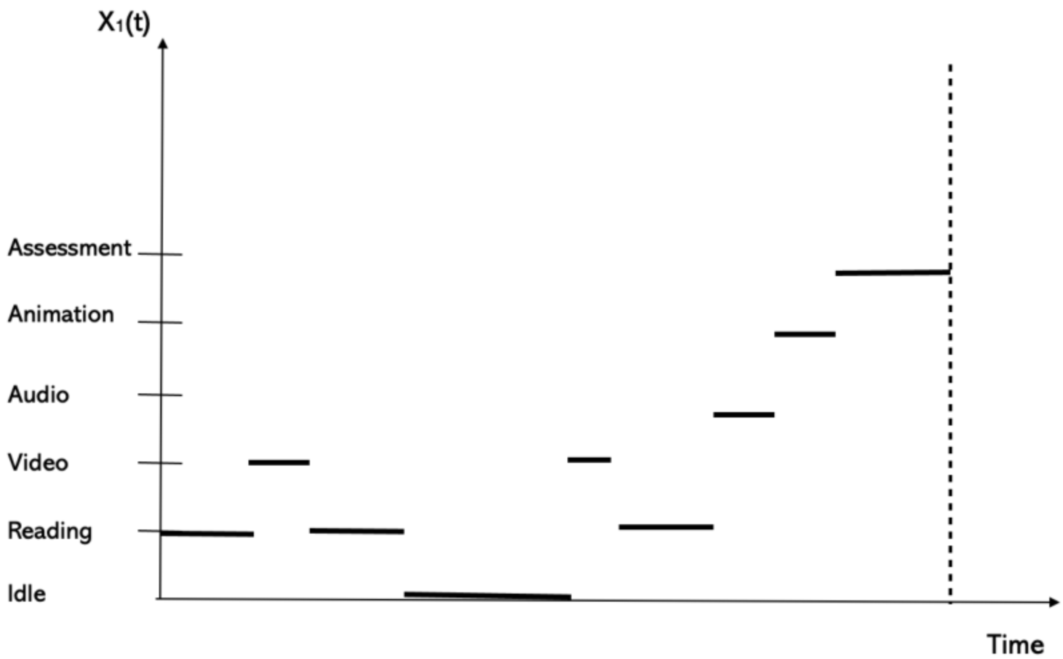

Figure 6. The learning process as a realization of a discrete stochastic process.

Utilizing artificial intelligence (AI) techniques will make it possible to acquire information "hidden" in the realizations of these stochastic processes. Machine learning techniques are utilized in the AIM project to group learners into clusters requiring similar adapted support in the learning process. This information provides input to an autonomous decision support system which in turn may provide input both to the learners, the teachers, the authors, and the educational institutions. Is it, for example, possible to identify vulnerable students who are prone to drop out or fail their courses if not an early intervention approach is initiated to mitigate their risk of failure?

Utilizing artificial intelligence

With the scientific advancements of big data and artificial intelligence, decision-makers are increasingly relying on machine learning to support decision making (e.g., Evermann, Rehse & Fettke, 2017, Bustince et al., 2013). During this development, cluster analysis, the art of finding groups in data, has reached new popularity as a technique within unsupervised learning.

As illustrated above; before any meaningful computation can be performed as part of unsupervised learning with respect to the learning process, human intervention is called for in the following four steps;

1. selection of attributes to characterize the objects (the learners)
2. selection of metrics to quantify the selected attributes
3. selection of dissimilarity to measure the distance between objects, objects and clusters, and between clusters
4. selection of algorithm to create the clusters.

The actual choice made in each of these steps will influence the final classification and thereby the reliability and validity of any decision support system. In many applied analyses, however, surprisingly little attention has been put on steps 1 - 3. As stated in Aarset et al. (2021), this should come as no surprise because of all the heuristics coming into action with respect to human attention and perception.

Kaufman and Rousseeuw (1990) illustrated this in a famous example when they characterized four persons by their attributes, height and age, as presented in Table 1.

Table 1. Four persons characterized by their height and age.

Age	Height in cm
35	190
35	160
40	190
40	160

As illustrated in Figure 7, measuring the height in centimeters would typically produce two clusters consisting of "the guys" and "the girls". Measuring the height in feet, typically would produce the clusters "the young couple" and "the old couple", while standardizing both variables would suggest no clusters at all.

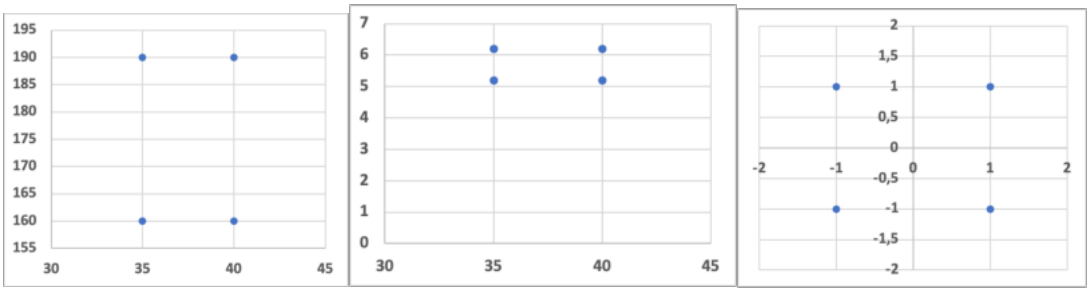

Figure 7. Measuring characteristics of objects by different metrics may produce different clusters.

There are plenty of possible pitfalls while introducing an autonomous decision support system for analyzing a learning process. No such system will have complete information, which on the other hand, neither any learner nor teacher will have. All experience with human behavior tells us that it is not at all clear that a learner (nor a teacher) necessarily will follow advice they don't understand. Therefore, to be successful, we believe such a decision support system will need to be based on what has been named XAI (*Explainable Artificial Intelligence*) in contrast to AI (*Artificial Intelligence*).

Explainable AI is artificial intelligence where the feedback from the autonomous system can be understood and meaningfully be evaluated by humans. It contrasts to the concept of the "black box" principle, where even the system designers cannot explain why an AI algorithm arrives at a specific result. In the AIM project, we believe we need to present results in a «white box» setting where the XAI algorithms are following the principles of

- *transparency*, i.e., presenting which data and procedures the calculations are based upon in an understandable way to the user
- *interpretability*, i.e., presenting the underlying basis for the analysis in an understandable way to the user
- *explainability*, i.e., presenting the underlying basis for how decisions are made in an understandable way to the user.

There is so far no generally accepted definition of these concepts in the scientific literature.

Introducing learning resources

To provide the learning resources both to the learners, the teachers, the authors, and the educational institutions, TERP has developed and is developing further, four apps. They are;

- **Abooks**, which gives learners access to the abooks, including assessments, and provides guidance to optimize learning
- **TERP Classroom**, where knowledge gaps are identified and where teachers and learners are allowed to interact
- **TERP Content,** where it is possible for both learners and teachers to become content developers and create new or update and improve already existing learning material into abooks and assessments
- **TERP Analytics,** where dashboards are provided to the educational institution for monitoring of the ongoing learning processes.

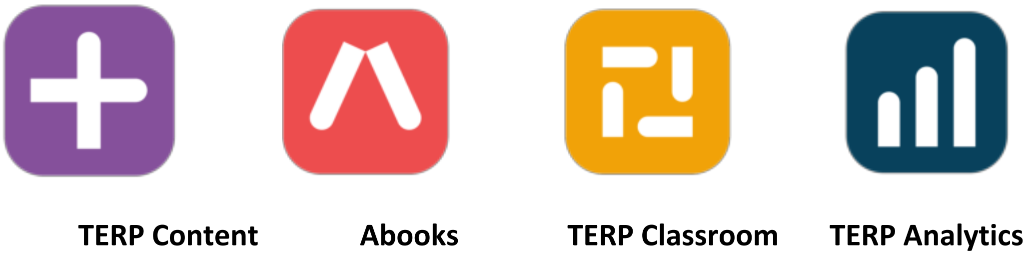

Figure 8. TERP's four interactive apps.

Combined, these apps provide a tool for improving the learning process. The focus is both on the individual learners, the teachers, the authors, the educational institutions, and the (sometimes almost forgotten) important interaction between them. Furthermore, there is no need to leave these apps and log into any other e-learning facility. All features are available here. The Abooks themselves are easy to update, which also makes them environmentally friendly.

Conclusion

When the learners use Abooks and the other learning resources, data on the individual learner from e.g. the realization of the stochastic process in Figure 6 will be registered and the learner classified based on the results from a cluster analysis. The characteristics of this cluster will give input to the learning process illustrated in Figure 5 and a gap analysis will be conducted to identify the difference in performance between what is expected based on the model and actual performance. Then, the learner will receive feedback in the form of a “nudge” based on generic results from andragogy and experience from gaming, and the teacher and the educational institution receive information as decision support for the upcoming activities.

By the introduction of Abooks and the other learning resources available through the apps mentioned above, we hope the results from the AIM research project will provide future learners with both

- new competence
- new confidence reflecting their own abilities
- new ability to learn and acquire knowledge.

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