2 TYPES OF COMMENTS:
Bold comments describe the content of that paragraph.
Italic comments indicate that a piece of text should be moved to somewhere else.

1 Introduction

General introduction 1st paragraph, i.e.: general context (introduction to the field of 'technology-enhanced learning'):
With the rise of technology-enhanced education, in particular when software-based, large and diverse groups of students are interacting with the learning materials (REF). These interactions usually take place in an online environment, such as 'Massive Open Online Courses' (MOOCs), where the role of teachers in tutoring and assessment is limited compared to the traditional classroom setup. Therefore, intensive support for increasing students' learning effectiveness and feedback to students from an educator is of limited availability. These online learning environments however can, and have been to a certain extent, augmented with techniques such as automatically keeping track of students' characteristics and interactions with the software, which open up new possibilities for (automated) feedback to students and teachers, instructors and trainers. Being able to identify personal learning styles, goals and indications for student progress is therefore an integral part of data-driven approaches used in intelligent learning environments (ILE's). When monitoring on an individual level, these approaches are being called 'Student Models' in the literature. When gathering and interpreting aggregated data of all students in an ILE, we generally use the phrase 'Learning Analytics'.

General introduction 2nd paragraph, still general context, but focusing on 'data', as we will later see that we have a 'data-driven' approach (Machine Learning):
Student characteristics can be obtained through interviews or as a form that is part of the ILE. Features such as age, motivation and pre-knowledge may be indicative features for an outcome variable such as learning effectiveness or the possession of certain related knowledge. The interactions with the software can be logged and exported and be used for the same purpose.

This doesn't belong here, can be mentioned when we start talking abour our research
In this paper for example, we want to check which features and interactions are useful predictors, and in what way, for the end result on the exam of the students using our software.

These predictions can be useful as feedback to either the instructor or the student. A teacher might for example choose to give students with a low end-grade prediction extra attention. Students themselves might get more motivated to intensify their learning due to knowledge of their predicted grade.

This doesn't belong here (to early to already talk about our application), move to end of specific context introduction, or even as separate paragraph after the 'specific introduction':

Our application will include an 'analytics dashboard' that can be accessed by either the instructor or the student (with an individual view-mode for the student), which should present clear and incisive graphical feedback on the aforementioned aspect of end result predictions.

Specific introduction, i.e.: specific ('1 level more zoomed in') context (introduction of 'stereotyping' and 'machine learning (in context of ILE's ofcourse):
Machine Learning, with its ability to recognize patterns from data, is a natural candidate for tasks dealing with learning from student's interactions in an ILE. It is shown by [6] that historically, machine learning has been mostly used in two important areas of research in student modeling: automatically extending or constructing from scratch the bug library of student modelers as in PIXIE [8] and MEDD [7] and for building a consistent and insightful student model by induction from student interaction data such as in DEBUGGY [1] and THEMIS [5]. More recently, machine learning techniques have been combined with the approach of stereotyping to cluster all possible users of an adaptive system into several groups according to certain characteristics that they typically share [3]. In [2] Dynamic Bayesian Networks were used to select the appropriate learning resources for each student alongside stereotyping to classify students based on their learning style. In [9] stereotypes are used to classify a new learner based on initial assumptions. The student is then compared with the k-means algorithm to students in the same group to estimate the knowledge the learner already has.

Problem:
Although the approach of stereotypes as a student model has matured and many effective and interesting possibilities have been explored, some difficulties remain unsolved. In a literature review paper about student modeling in general [3], the authors note two problems with stereotyping:

> First, in order to use them, the set of system users must be divisible into classes; however, such classes may not exist. Second, even if it is possible to identify classes of system users, the system designer must build the stereotypes; this is a process that is both time-consuming and error-prone. [4]

Furthermore, [9] focusses on the effect of manually creating stereotypes:

> The stereotype approach is quite inflexible due to the fact that stereotypes are constructed in a hand-crafted way before real users have interacted with the system and they are not updated until a human does so explicitly. [9]

% **Motivation (naar aanleiding van probleem): Machine Learning combineren met stereotyping is handig want...**

—einde introductie voor nu—

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