



Goal-oriented student motivation in learning analytics: How can a requirements-driven approach help?

Omar Talbi¹ · Abdelkader Ouared¹

Received: 21 February 2022 / Accepted: 1 May 2022 / Published online: 25 May 2022

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Abstract

Determining student motivation within the context of Learning Analytics is fundamental for academic students to realize their educational goals. We aim to perceive the student's motivation state at a high level of abstraction and act accordingly to deal with motivation issues. We investigate how Model-Driven Engineering paradigms capture the essence of a motivation domain and provide deep automation in stimulating students' tasks. In this paper, first, we propose a Conceptual Modeling Approach that provides a unified environment in which all dimensions of students' motivation are explicitly defined. Secondly, a guideline, allows educational stakeholders to perceive the states of change in students' motivation. Third, the issue of student motivation is addressed by making a mechanism that stimulates students. Finally, to stress our approach and to prove how it is useful, we present a global usage scenario for our system called *Hafezni*. Sixteen Master's students of the computer science department of the Ibn Khaldoun University of Algeria participated in the experiment. Results showed that our approach allows educational actors to perceive the motivational state of the student. The Hafezni mobile app is useful according to learners and educational stakeholders. Finally, the student motivation makes sense on the causality of failure/success with an acceptable percentage of correctly classified instances increased from 69.23% to 96.13%.

Keywords Conceptual modeling · Goal-oriented modeling · Learning analytics · Mobile application · Machine learning · Student's motivation

✉ Omar Talbi
omar.talbi@univ-tiaret.dz

Abdelkader Ouared
abdelkader.ouared@univ-tiaret.dz

¹ Computer Science, Ibn Khaldoun University, Tiaret, Algeria

1 Introduction

The widespread dissemination of information and communications technology in the education field, especially in Higher Education (HE) gave rise to virtualize face to face courses using the Learning Management System Platforms (LMS) (Sarker et al., 2019), e.g. Moodle¹. It should however be noted that due to the HE massification and the Covid-19 pandemic, HE is now witnessing a wide rise in the use of online learning. These learning situations generate digital traces² that would be interesting to collect and analyze to improve learning and help educational stakeholders in their decision-making. This process is referred to as Learning Analytics (LA) and is defined as: “*the measurement, collection, analysis and reporting of data about learners and their context, for purposes of understanding and optimizing learning and the environments in which it occurs*” (Siemens & Gasevic, 2012). The modeling community aims to improve the incorporation of end user human aspects (e.g. age, gender, culture, language, educational level, personality, emotional reaction) into software engineering (Grundy, 2021; Hidellaarachchi et al., 2021). In this perspective, the LA community meets Learning behavior Analytic Dashboards (i.e. behavior LADs) as an opportunity to analyze and keep track of the student motivation/behavior based on Learners “Digital Traces”. Recently, Mussbacher et al. (2020) discuss the challenge of intelligent modeling assistance during modeling activities.

In the same direction, Tlili et al. (2019) developed an automatic modeling learner’s personality using the LA approach in an intelligent Moodle learning platform. This work paved a new way for modeling personality instead of resorting to traditional methods that use self-reports, such as Big Five Inventory (BFI)(John et al., 1991). In the context of smart educational decision support systems, tracking students’ online learning activities such as doing tests, assignments, forums, quizzes, etc. to *perceive* not only their personality but also their motivation to prevent churn rates using conceptual modeling tools has become crucial and a challenging task. Indeed, according to (Zimmerman, 2008; Sun et al., 2018; Jansen & et al., 2015), motivation in the field of education is one of the most important pillars through which we can achieve the educational goals.

Our study was based on two main perspectives: **(i)** HE massification and **(ii)** the tracking and monitoring of students’ learning activities in online learning environment. In this context, perceiving the motivation state, often implicit, for a given student to address his/her motivation issues is a complex task for educational stakeholder. Indeed, in a digital learning environment, the educational stakeholders have difficulty spotting the state of students’ motivation reflected in their behaviors in the real world. Simplifying the representation of one or many aspects of the motivation

¹ Moodle is a global-standard LMS that allows users to develop useful teaching material for online courses

² xAPI (for Experience API) xAPI is an eLearning specification that makes it possible to collect data about the wide range of experiences a person has within online and offline training activities: <https://xapi.com>

state in a human understandable way provides a visual mental image that facilitates understanding and building smart educational decision support systems. However, we identify a lack of use of conceptual modeling approach dealing with the student's motivation state in an LMS environment that should provide a more accurate view of the reality of student behavior. On the other hand, there is no standard language enabling to have a student's motivation state as an abstract description in a machinable format. This situation penalizes the educational actor, in terms of spotting and understanding the motivated students' behaviors from their digital learning activities, prompting them investigating empirical studies of comparison and interpretation of valuable indicators. In this study, we strongly motivate the modeling behavior thoughts into conceptual modeling languages and so that automation becomes attractive.

Every motivation technique is not valid for every student or group of students and it is not adequate for every context. Indeed, according to Seli and Dembo (2019), each student has his/her own personality characterized by a set of beliefs and perceptions related to the importance he/she attaches to his/her success or failure.

Our study puts the focus on the customizable motivation states and leads us to consider more entries to determine the motivation specification.

As we said before, the previous work does not provide interdependency between the students' learning interactions that represent motivation behind their complex behavior and its design at the high level of abstraction. Moreover, this work does not explicit the synchronization between the visual representation (i.e. LAD) and the core APIs of LMS used for computation of the digital interaction learning activity obtained from xAPI.

The goal is to perceive the student's motivation state at a high level of abstraction and act accordingly to deal with motivation issues. Our study is based on the point of view of the educational stakeholder in the context of Master's students in computer science. We formulated three research questions (RQs):

- RQ1. How to perceive the student motivation aspects at a high level of abstraction?
- RQ2. How to customize the boost of student motivation according to the student's digital learning activities?
- RQ3. Does Motivation State Model make sense on the causality of failure/success?

The subjects of the experiment were 16 Master's students of the Computer Science Department of the Ibn Khaldoun University of Algeria³. We have used a dataset containing the student profile with information about demographics, available modules, assessments, available materials in LMS, results of student's assessments, types of indicators that reflect the student learning motivation in the LMS, namely: (i) CPI (e.g. Completed course activities, Submitted discussion prompts, Current course grade), and (ii) LBI (e.g. Engagement in discussions, Timing of starting

³ <https://www.univ-tiaret.dz/fr/>

activities, Timing of completing activities). In the experiment we had to (1) see if educational stakeholders can perceive Student's Motivational State, (2) identify the perceived Usefulness of our assistant tool, and (3) test if Motivation State Model makes sense on the causality of failure/success.

To tackle the problems presented above, we propose a conceptual modeling approach for to explain and to conceptualize the entries of the motivation throughout the students' learning activity. Our approach is based on Model Driven Engineering (MDE) (Kent, 2002) that provides a unified environment in which all aspects of students' motivation are explicitly defined. In addition, Goal-Oriented Modeling makes guidelines analysis of student profile regarding his/her learning behavior and his/her content progress to understand his/her different learning activities using Learning Behavior Indicators (LBI) and Content Progress Indicators (CPI) in line with (Jivet et al., 2020). Our approach transforms digital interaction learning activity (obtained from xAPI⁴), in a motivation state. This approach is based on three different models: (i) Goal-oriented Requirements Model based on goal-oriented modeling for representing information of educational stakeholders' requirements, (ii) Learning Activities Model that abstracts the required information related to the learning activities and, (iii) Learning Motivation State Model that enables user to specify the dimensions of students' motivation and its characteristics. A Prototype implementation demonstrates the feasibility and practical utility of the approach in HE. To stress our proposal, our approach is engineered by a system called *Hafezni* (i.e. word in Arabic means in English "*Motivate Me*"). In fact, this latter includes a LAD dedicated for educational stakeholders and a mobile application system dedicated for students stimulation.

The paper is organized as follows: Section 2 reviews background, Section 3 introduces our Requirement-Driven Approach of students' motivation, while Section 4 presents the proof of concept and Section 4.3 shows in detail the stages of the experiment. We conclude with a summary and outlook in Section 5.

2 Background and related work

In this section, we present what does the student's motivation to learn means, we illustrate it by a motivation example, and we address the most related works with our.

2.1 Student motivation in learning analytics

According to Gopalan et al. (2017), motivation is the process that triggers and maintains goal-oriented behaviors.

Is the reason that makes people do what they do (e.g. the reasons for studying). Sherria & Stephen (2009) identify three reasons for studying: (i) Means to an end as

⁴ The Experience API (Experience API (xAPI) is common standard to describe learning activity data across multiple sources.

improving standard of living, (ii) Personal development as improving life skills, (iii) Stopgap as avoiding work or laziness that corresponds respectively to the three main types of motivation that Ryan & Deci (2000) distinguish in their theory of self-determination, (i) extrinsic motivation, (ii) intrinsic motivation, and (iii) amotivation.

In the context of learning, according to Viau (2006), motivation is based on the relationship between three following most important sources of motivation: (i) The judgment made by the student on the importance, interest, and relevance of an activity according his/her reasons for studying, namely “Value”, (ii) The student’s believe on his/her competence in achieving an activity, in other words, the student asks himself whether or not he/she is effective in a given activity, namely “Competence”, (iii) Do the learning strategies adopt by the teacher offers control to the student in the development of the activity? Namely “Control”. These student’s perceptions directly influence the cognitive engagement and the perseverance in a certain activity.

The perceptions that students have towards failure and success in their studies as cited by Seli & Dembo, (2019), will lead them to have different motivated behaviors in: (i) Choosing and starting an activity, (ii) Level of activity and involvement, and (iii) Persistence and management of effort which will enable to spot a motivate student based on his/her learning activity.

In Seli & Dembo, (2019), the authors have identified four types of students to be in line with motivation state: (i) Success-Oriented Student (i.e. this student has more motivation for success than fear of failure (Low-High $L - H$)), (ii) Failure Avoider Student (i.e. this student has more fear of failure than motivation for success (High-Low $H - L$)), (iii) Overstriver Student (i.e. this student is high in both motives (High-High $H - H$)), and (iv) Failure Acceptor Student (i.e. this student is low in both motives (Low-Low $L - L$)).

In the context of LA, the student’s motivation state is perceived through his/her learning behavior estimated by LBI such as Timing of starting activities, Timing of completing activities, Engagement in discussions, etc. and his/her CPI such as completed course activities, current course grade, completed graded assignments, etc.

We illustrate the Student State Motivational Dynamics as a state machine diagram model as it is shown in Fig. 19. A learning behavior reflects a motivational state (i.e. the different states as shown in Fig. 19). Any change in a student’s learning behavior reflects a change in his/her motivational state. This change in behavior is caused by a positive stimulus (i.e. motivational affordances like badges, points, feedback) or negative stimulus (i.e. inhibitors learning like feelings of inferiority, uncompetitive practices) that is indicated by both the LBI and the CPI (i.e. the different transitions as illustrated by Fig. 19). For instance a stimulus impacts the timings of starting and completing activities indicators correlated to both completed course activities and current course grade indicators thus generating a new motivational state that must be maintained to achieve success (Fig. 1).

2.2 Motivation example

Consider now an example that describes the motivation of our work referring to what frequently happen between students and their professor imposing activities in

It is a state of a H:High
Success-Oriented Student and a
L:Low Failure Avoider Student

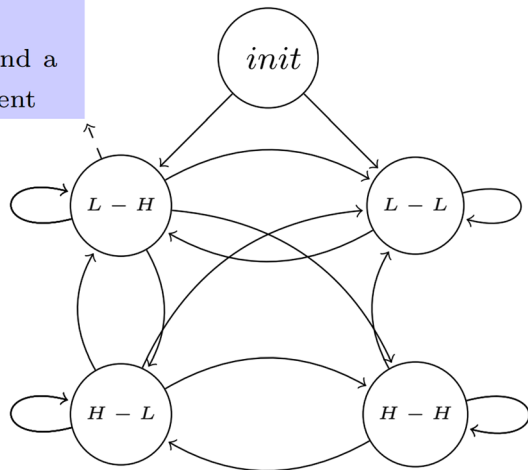


Fig. 1 Student State Motivational Dynamics

LMS. We present a use case example on how a teacher proceeds to perceive student motivation. Given a teacher that comes to add a forum activity as Optional Subscription mode about a fundamental unit with Interactive Video Content -H5P. Hence, the teacher wants to perceive an engaged student in discussion. When student engage early and regularly in this activity can indicate the aspect of choosing and starting an activity within the meaning of Seli & Dembo (2019) and can be evaluated for example by indicator such as the number of questions/responses posted by student in this discussion. These indicators relative to activities objectives and thereby enabling stimulus where there are deviations. Also, teacher analyzes a generate digital traces expressed on xAPI (e.g. number of visits, average time, and something related to grades). On the other hand, engaging in this activity by a student one day before the ending activity can be interpreted as a lack of motivation. Basing on Viau, (2006), teacher decides to change his strategy as follow : (i) Encouraging active and practical learning by making connections to real-world applications of the course material with the aim to show the interest that this activity covers and consequently increases the first and third determinant of motivation (i.e. Value and Control), (ii) Convince students of the feasibility of the activity and that they have the required skills and they can spend reasonably time and effort to do it, which will allow him to increase the second determinant of motivation (i.e. Competence). In the LMS environment, the teacher can for instance consider different kinds of LBI that are defined over a teaching strategy (i.e. Forced Subscription with digital Badge for best answer). This strategy can be seen as a source of motivation according to calculated indicator to identify and predict failing students earlier and push them to achieve success. We can cite, an example of the scale for Deep Motivations and Strategies and Surface Motivations and Strategies is: “The Reflection Page Relevant to YOU’ take-home exam made me work hard because I found the material interesting.” (Young, 2018). The step which consists of perceiving motivation students from the real world is laborious and error-prone (often *implicit*). As shown in Fig. 2, in this paper, we

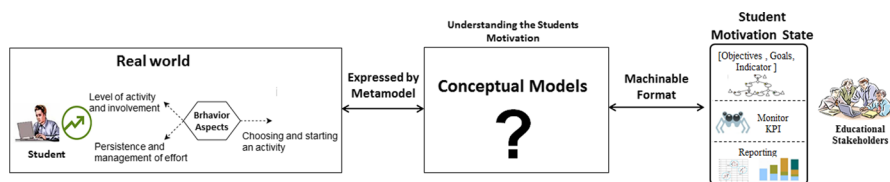


Fig. 2 Understanding student motivation

focus on the transition from the behavior of students and providing a context for its motivational states by conceptual modeling for understanding the students motivation, we perceive this determinant as conceptual model, next, convert a conceptual model in a machinable format analyzed by educational stakeholders.

2.3 Related work

Many researchers have put forward various theories, models, and approaches to demystify motivation (e.g., Sherria & Stephen, 2009; Harter, 1981; Karaoglan Yilmaz, 2021; Keller, 1987; Barron & Hulleman, 2015; Deci et al., 1994; Valle et al., 2021). As we said before, the work of Tlili et al. (2019) showed modeling learner’s personality can be automatic using Learning Analytics approach in an intelligent Moodle learning platform. In the same direction, (Beheshti et al., 2020) propose a Cognitive Recommender Systems. In Young (2018), the authors propose Integrating the two learning theories leads to hypothesized relationships among reflection, students’ motivation, strategies, and learning outcomes.

Recent advances in cognitive computing (Modha et al., 2011) and Machine Learning (Ian & Eibe, 2005) techniques could be introduced in automated conceptual modeling. Keller (1987) considers the motivation as an essential aspect in the field of instructional design. The Keller’s ARCS Model of Motivation (Attention, Relevance, Confidence, and Satisfaction) (Keller, 1987) gives instructional strategies to develop motivational learning systems in the cases of work and learning settings. Other models of motivation theory are considered in literature, we can cite Expectancy - Value - Cost Model (Barron and Hulleman, 2015) and Self-Determination Theory (Deci et al., 1994). Previous work can be roughly classified into three categories: Empirical studies in Learning Analytics, Learning analytics dashboard for motivation, and From the perspective studies of Model-Driven Engineering for Learning Analytics. In the following, we survey these two categories of work.

2.3.1 Empirical studies in learning analytics

In the domain of LA, the community meets statistical analysis of empirical data and behavior LADs as an opportunity to analyze and keep track of the student motivation/behavior based on Learners “Digital Traces”. In the empirical studies, several works investigate the analysis and the interpretation of student motivation/behavior using empirical analysis (e.g., Sun et al., 2018; Karaoglan Yilmaz & Yilmaz, 2021;

Valle et al., (Valle et al., 2021)). The empirical studies rely on learner data using xAPI, metrics and results rather than theories about students' intrinsic/extrinsic motivation. For instance, in Sun et al. (2018), the authors show that reading time is a telltale indicator of low motivation and online reading time was a significant indicator of motivation to take an online course. In the same direction, Karaoglan Yilmaz and Yilmaz (2021) show that the motivation of students increases by providing them with feedback on the results of the learning analytics. The Empirical studies in LA investigates correlation between parameters that impact motivation student in simulation level rather than model level.

2.3.2 Learning analytics dashboard for motivation

Other recent research has been geared towards techniques that aim to provide a visual strategy to support the eye-tracking and monitoring of motivation aspects commonly referred to as LA Dashboards (LAD) based on motivation theories and models. In Valle et al. (2021), the authors conduct an experimental study based on achievement goal theory, where they explore the influence of predictive and descriptive LAD on students' motivation and statistics anxiety in an online course. To do this, authors use Questionnaires and Individual semi-structured interviews. Similarly, in (Fleur et al., 2020), the authors analyze student motivation/behavior using LAD for establishing a relationship between LAD and the learning sciences by using a conceptual model. This LAD visualizes providing cognitive and behavioral process-oriented feedback to learners and teachers to support regulation of learning. However, the previous work does not provide interdependency between the students' learning interactions that represent motivation behind their complex behavior and its design at the high level of abstraction. Moreover, this work does not explicit the synchronization between the visual representation (i.e. LAD) and the core APIs of LMS used for computation of the digital interaction learning activity obtained from xAPI.

A conceptual modeling is needed to analyze student behavior motivation by designing at the high level of abstraction to mitigate the gap between real data of digital learning trace and LAD. Thanks to the conceptual modeling tools that simplify the representation of the motivational aspect in real phenomena in a human understandable manner. The studies of this category are not explicit how to derive the student profile from the digital interaction of learning activity obtained from xAPI. Furthermore, the previous work does not provide interdependency and explicit synchronization between the student's learning interactions and complex behavior and its design at the high level of abstraction.

2.3.3 Model-driven engineering for learning analytics

The Learning modeling is a crucial task in the emerging research area of LA, recently studies (e.g., Pérez-Berenguer & García-Molina 2019; 2020; Nouira et al., 2019; Costa et al., 2020) conducted by the LA community identify the needs in order to Leveraging the MDE paradigm (Schmidt, 2006) (e.g., meta-modeling, model transformation and code generation) to improve the learning process using the conceptualization and explanation in the context of learning

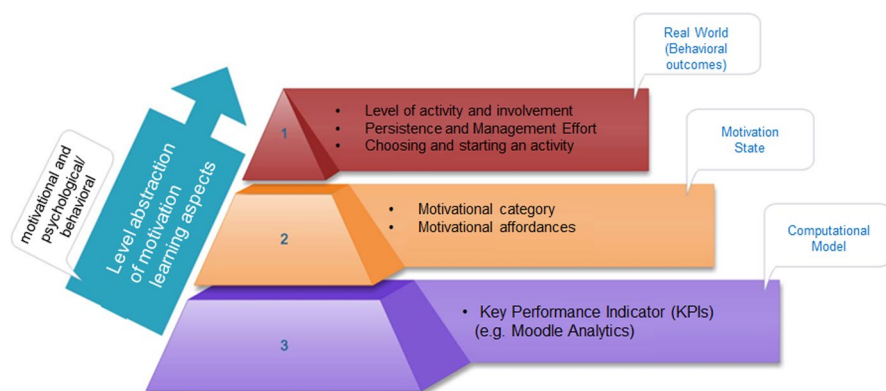


Fig. 3 The abstraction level view: learning indicators, motivational state, and further behavioral outcomes

analytic. In (Costa et al., 2020), ontology-driven conceptual modeling is adopted in coordinated way with Learning Analytics in purpose of academic performance monitoring, in which, the conceptual models are independent of underlying digital trace interactions (known as xAPI data). This vision increases the interdependencies between driven data approaches presented in first category and provide personalized and meaningful information (Nouira et al., 2019) at model level. The works of this category discuss different aspects of the learning data representation with models in the analyzing courses (Pérez-Berenguer and García-Molina, 2019), acting proactively, and personalize the training course according to learner profile (Nouira et al., 2019). However, perceive the student's motivation state at the model level, has not been addressed in the literature.

Our work falls in this category, In general, it is necessary to elaborate a model-based analysis of the motivation state by following three abstraction level views: learning indicators, motivational state, and further behavioral outcomes (see Fig. 3).

We aim to perceive the student's motivation state at a high level of abstraction and act accordingly to deal with motivation issues to assist support staff perceiving and customizing motivational orientations according to the student's digital learning activities.

Therefore, in this study we argue that we can spot a motivated student based on these three different motivation behaviors in an intelligent Moodle learning platform using LA approach (Tlili & et al., 2019). Regarding the first type of student, it would be interesting to maintain their motivation. The last three types of students respectively have Defensive, Anxious and Hopeless attitudes, it would be interesting to address their motivation issues.

We would like to emphasize the originality of our line of contribution by proposing our Conceptual Approach for learning student motivation, which is based on the MDE paradigm. By exploring the literature, the previous works have not addressed this issue to enable educational stakeholders to perceive a student motivation aspect,

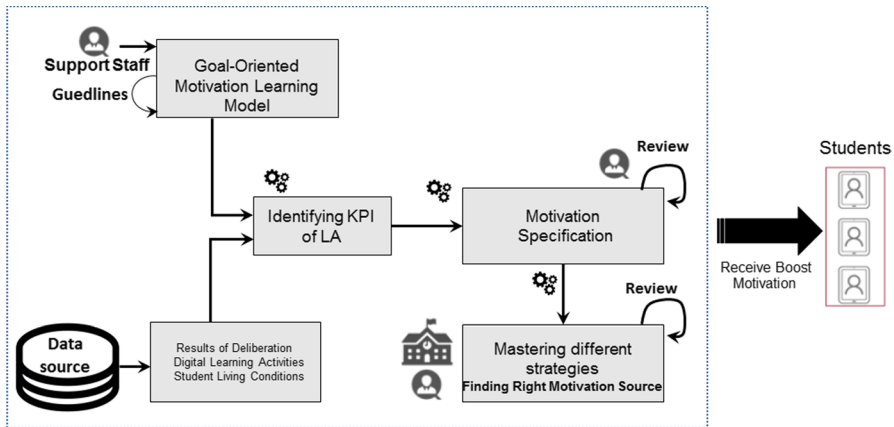


Fig. 4 Overall view of the process proposed

nor an assistant that helps teacher/support staff to customizable boost motivation in online learning. The major contributions of this paper can be summarized as follows:

- We expand the concept of motivation by considering different aspects of students' motivations covering any kind of students' profile, their context, their teaching techniques, etc.
- We provide a guideline for educational stakeholders to drive them to get a detailed mental image of student behavior.
- We make an online system to efficiently motivate students in HE by a customizable boost of motivation working with an existing LMS (e.g., Moodle).
- We develop tool support of our approach as smartphone platforms to demonstrate how it helps address the student motivation (e.g., emotion, risk level, mental challenges).
- We test if Motivation State Model makes sense on the causality of failure/success.

3 Our proposal

As previously introduced in the paper, perceive the students' motivational state in e-Learning platform is a challenging task. To explicit the students motivation state and act accordingly to maintain or improve his/her motivation, we propose a Conceptual Approach (see Fig. 4) based on the Model-driven engineering (MDE) paradigm (Schmidt, 2006). Our main goal is to help educational stakeholders to spot the state of students' motivation that are represent their behavior during online learning activities. We need to explicit the dimensions of students' motivation based on the Domain Specific Modeling Language (DSL) which is conceived as a DSL for motivation of students learning. Thanks to the facilities of model-driven engineering

paradigm (e.g. meta-modeling, model transformation and code generation). Moreover, MDE studies Domain Specific Modelling Languages (DSL) best suited for describing specific human and business activities. As every DSL, our language is defined by three elements:

- Abstract syntax: it is the structure of the language based on elements and their relationships. This structure corresponds on the meta-model. We have used a diagram class to express our meta-model. It is one of various MOF implementations.
- Concrete syntaxes: they correspond to specific representations of the design language in order to instantiate its meta-model. A syntax may be graphical or textual.
- Semantic: which means the meaning of meta-model concepts and how can be represented on the instantiation.

Hereafter, we focus on the elements of our meta-model and its semantics.

Our approach starts by collecting data from Data Sources that is the history of events related to the activities (i.e. xAPI tracked on LMS like Moodle) and student’s profile. In the second phase, users use a Goal Oriented Model to track student from the collected data to identify and monitor the important LBI related to LMS e-Learning that considered on the student’s behavior aspect: *activity choice*, *activity engagement*, *activity involvement* and *perseverance*. Based on these LBI, we identify a motivation state of student and their profile. This result used by user to determine the most proper strategy which are used to describe the boost student motivation. In summary, the learning motivation state perceive and the student profile extraction problem to produce a detailed mental image about student behavior is described below:

Automatic Providing of Student Motivation State

Input:

- A digital learning activity (obtained from xAPI).

Output:

- Extract target motivation State, i.e. Motivation State synthesis from Learning Behavior indicators (LBI).

In the following, we present the Conceptual Organization of our approach and its process on two vision support staff and student.

3.1 Conceptual organization of our approach

Our proposal is based on three models: (i) **Goal-Oriented Requirements Model:** Allows users to capture their information needs and certain learning motivation aspects related to a student learning, (ii) **Learning Activities Model:** Abstracts the required information related to learning activities from the data sources to aid in

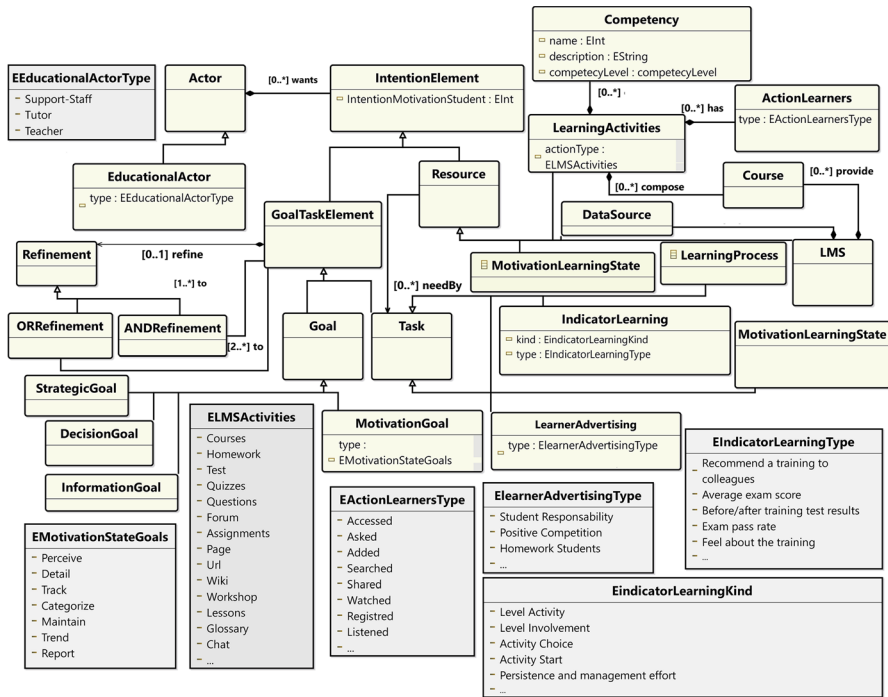


Fig. 5 Requirement Model of the Student's Motivation Analysis

determining the most learning activity and competency will be achieved with its indicators, and (iii) **Learning Motivation State Model**: Enables users to specify the dimensions of students' motivation and its characteristics. In the next we detailed each model.

3.1.1 Goal-oriented requirements model

Our approach starts from a Goal-Oriented Requirements Model that allows us to capture information needs. To describe the coordinates required to build a motivation context (*Goal*, *Perception*, *User*, *Profile*, *Motivation State*, *Activities Type*, and *Indicator Type*) we follow the specification to automate perceived motivation state in e-Learning, in this way, we make sure that the motivation specification is addressed in HE issues.

Our metamodel shown in Fig. 5 is an extension of *i** (Maté et al., 2014). Existing elements in the *i** core are extended to specify by a metamodel to describe the concepts of the motivation. The first element is the *EducationalActor*, which models the user of the system. There are three types of Learning Motivation Actors: *Teacher*, if he/she has no knowledge of students motivation, and *Tutor* or *Support staff*, if he/she has previous tutoring experience. Next

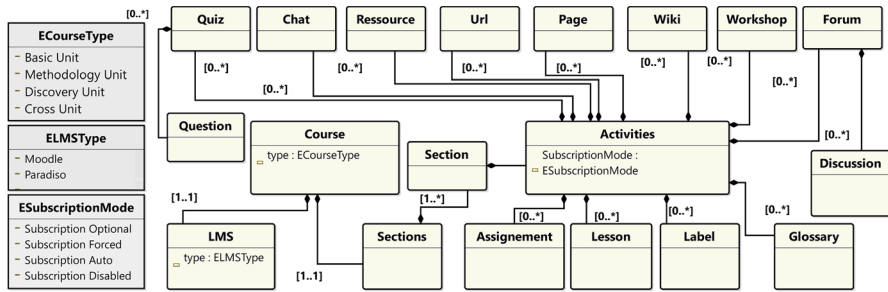


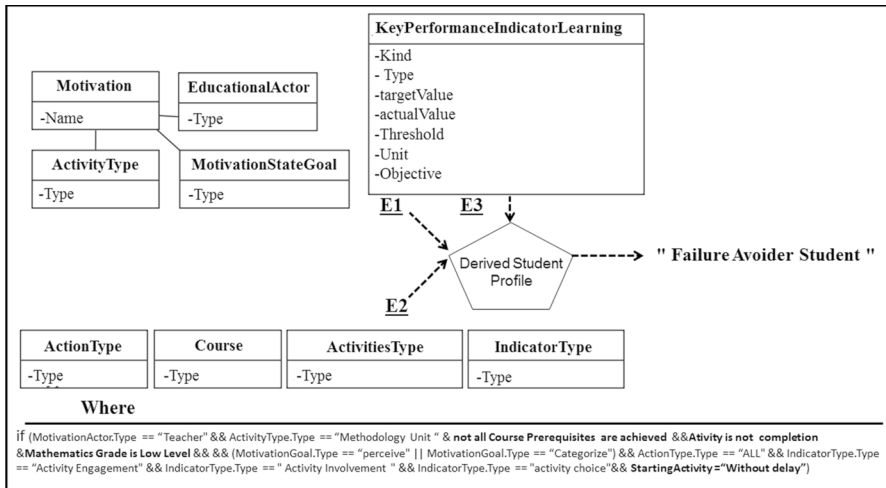
Fig. 6 Excerpt of LMS learning activities Metamodel

is the *LearningProcess* on which users will focus their analysis. The learning process will serve as the guideline for the definition of Goals. The *MotivationAnalysisType* allows users to express which kind of analysis they wish to perform. The type of analysis can be determined by selecting which aspect from the following ones (Liaw, 2008) to be analyzed: Level of activity and involvement (Engagement), Persistence and management of effort (perseverance) or Choosing and starting an activity (activity choice). Next, a *MotivationState* represents a specific motivation of student that will be need addressed by one or more *MotivationGoals*. Each *MotivationGoal* describes an aspect of the student that the motivation should reflect. These goals can be *Perceive*, *Detail*, *Track*, *Maintain*, *Trend* or *Report*. Along with *MotivationGoals*, Motivation has one or more *EIndicatorLearningKind*, that capture the aspect learning behavior of students, as considered in (Liaw, 2008). The different kinds of LBI are *Engagement*, *Involvement*, *Perseverance*, or *Activity Choice* on demand as consider to student motivation in HE. Finally, a Motivation makes use of one or more *Resource* elements that include *Competency*, *Course*, *LearningActivities* and *ActionLearners*. This is providing the data to the motivation state.

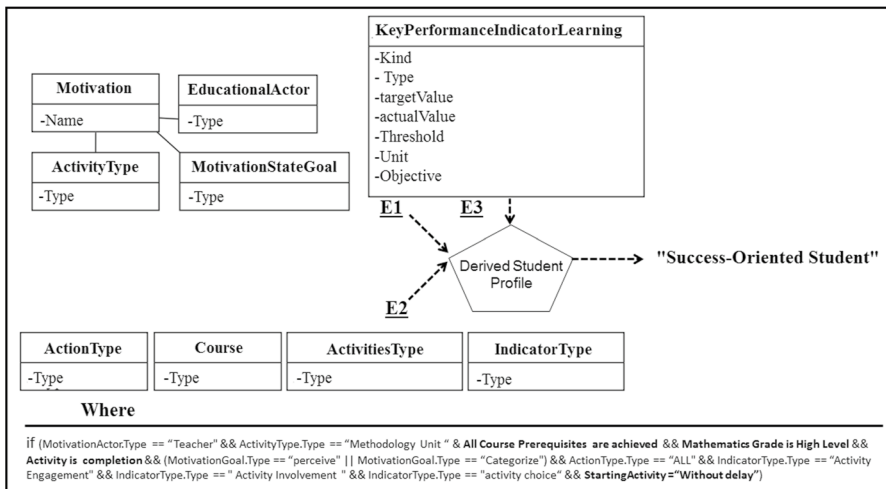
3.1.2 Activities learning model

Our second model is the Activities Learning Model. This model captures the activities and its human-machine interaction actions interacting with the LMS (i.e. xAPI verbs) that are relevant to the learning and is generated through an LRS process. Firstly, users will connect to the data sources that they want to be represented in the motivation state of students. This process needs identifying their profiles and their digital practices from LMS. As depicted in Fig. 6, a LMS is composed of several courses, which consist of a list of sections. The other sections are made by the teacher containing activities.

To know how to identify the LBI type for each instance of requirement model and collected data. In this way we classify the flowing elements: *CourseType*, *Activity-Type*, *InteractionType* and *IndicatorType* as follows (see Fig. 7):



(a) Example of DerivedStudentProfile = "Failure Avider Student "



(b) DerivedStudentProfile = "Success-Oriented Student"

Fig. 7 Generation of the motivation state behind student behavior based on Goal-model

- **CourseType:** represents the type of the course that is categorize in four main categories of teaching units arranged in a coherent pedagogical manner which is as follows: Basic Unit, Methodology Unit, Discovery Unit, and Cross Unit.
- **ActivityType:** represents the activity type of the course or section. It can either be Quiz/tests, exams, Assignment, engaging students in discussion etc... And has four Subscription Mode: Subscription Optional, Subscription Forced, Subscription Auto and Subscription Disabled.

- **InteractionType:** is used to declare the type of each human-machine interaction to be analyzed. It is the actions of students on content, url, video and document like *registered*, *accessed*, *asked*, *added*, *searched*, *shared*, *watched*, etc. Listing 1 shows the xAPI JSON representation of an edX video resumed event.
- **IndicatorType:** represents the LBI, that is used to measure an educational objective (i.e. The target of the present indicator) thereby enabling corrective action where there are deviations. Specifically, it can be in category of activity choice, activity engagement, activity involvement and perseverance.

Figure 7 shows two examples of generation of the student behavior behind the state of motivation from user requirements, respectively an example of Derived Student Profile = “Failure Avoider Student ” (see Fig. 7a) and an example of Derived Student Profile = “Success-Oriented Student” (see Fig. 7b).

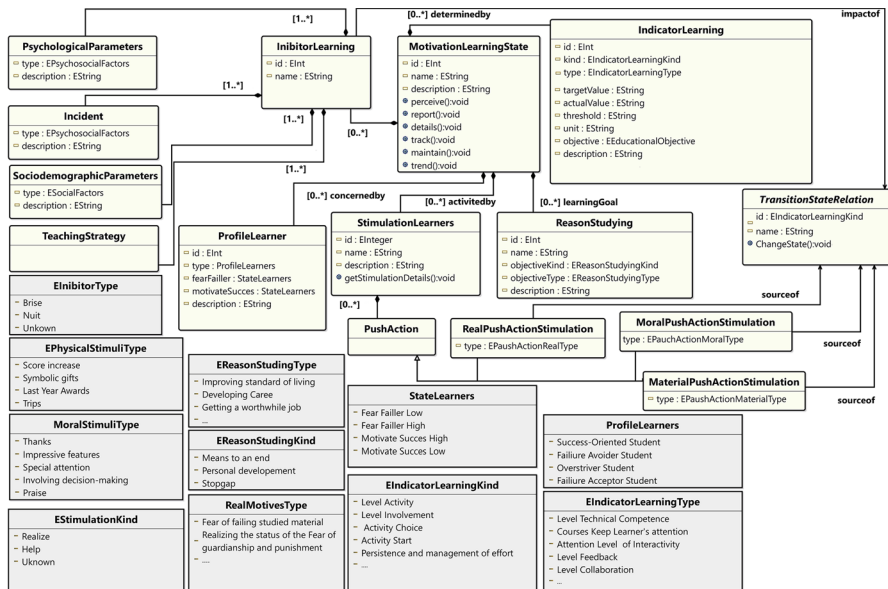
3.1.3 Learning motivation state model

We introduce a metamodel to represent the Student State Motivation. We focus on the elements of *LearningMotivationState* of meta-model and its semantics. Figure 8 depicts the core elements of the meta-model, which its root element is *Motivation-StateLearning* class (i.e. the instantiating starts from this class). Every *Motivation-LearningState* instance is composed of (1) *IndicatorLearning* describes the learning activity through its metadata and shows the student’s behavior towards the achievement of that activity.

However, this is a very long and complex task. For the first version of our proposal, we provide a solution via the user answer of the BFI a questionnaire has also been distributed to the participating students to understand their students’ personalities. (2) *Stimulation*: it integrates different Push-Action of student in the learning such as Physical stimuli (e.g. Score increase, Last Year Awards), Moral stimuli (e.g. Thanks, Special attention) or the real motives behind students’ dedication (e.g. fear of failing, realizing the status of the studied material, fear of guardianship and punishment) , (3) *inhibitorsLearning*: its

```
{
  "actor": {
    "mbox": "mailto:554433@example.edu",
    "name": "554433",
    "objectType": "Agent"
  },
  "verb": {
    "id": "http://adlnet.gov/expapi/verbs/resumed",
    "display": {
      "en-US": "resumed"
    }
  },
  "object": {
    "id": "https://youtu.be/hFz6uHznMA?t=94",
    "definition": {
      "name":
        "description":
      "objectType": "Activity"
    }
  },
  "context":
}
```

Listing 1 Example JSON fragment illustrates xAPI representation of an edX video resumed event

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3.2 Process of our approach

The use of our conceptual approach also is used to boost of motivation students. The Goal Model proposed in the Section 3.1.1 use to highlight a multiple goal to boost of motivation students also to mastery goal orientation elements were used the perceive the student's motivation state process (as shown in Fig. 9 ⑥). Mastering different strategies or finding the right motivation source is depend on engagement provided by learners that is expressed in xAPI level to tracking its activities (Fig. 9 ①)..

This latter, is transformed in behavioral outcome (Fig. 9 ④) based on LMS learning activities model (Fig. 9 ②) and learning Motivation State Model (Fig. 9 ③). Users can specify boost of motivation process features through SPL (Software Product Lines) instantiation (Presented after in Section 3.2.2). This customization concerns the students' profiles that includes a motivational category (e.g. Cognitive, emotional, social) and motivational affordances (e.g. Challenge, progress bar, Achievements (Fig. 9 ⑤)).

In this section, we present the process of our approach from two different angles: first, "Support staff view", and second, "Student view".

1. Perceiving the student's motivation state based on their learning activities.
2. Customizing the boost of motivation to positive changes in the individual and collective behaviors of students, soliciting their participation and engagement in learning activities a long periods of time.

3.2.1 Perceive the student's motivation state process

Figure 10 shows the process of our approach. Our contribution is based on the facilities of the MDE, its core components and the different links between it and

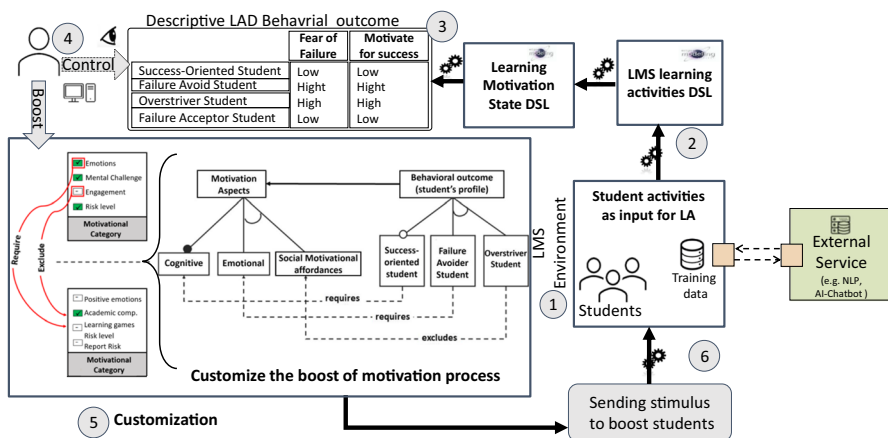


Fig. 9 Process of perceive and boost the student's motivation

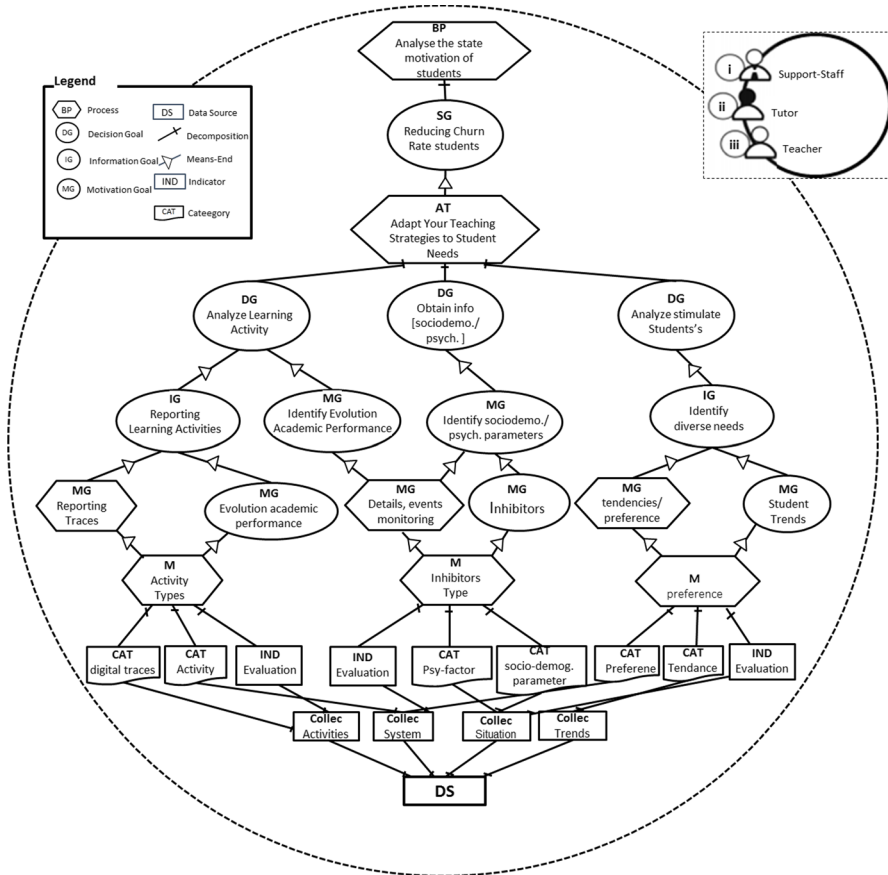


Fig. 10 Perceive the student's motivation state process

MotivationLearningState (Fig. 7) and Goal-oriented requirements model (Fig. 4). Users need to analyze the student's motivation state to Reducing Churn Rate students that means in the end of adapt teaching strategies to student's needs. This proposed approach is a multi-step process primarily consists of 8 phases:

1. During the first phase, we collected information of target students from our Data Source.
2. During the second phase, user starts by select a particular goal from list of goal (e.g. *Perceive, Detail, Track, Maintain, Trend* or *Report*).
3. For each student, we have defined three dimensions analysis: analyze learning activity, obtain her/his profile, her/his demographically, and her/his analyze stimulate student.
4. For analyze learning activity, we identified evolution academic performance that organize in activity, category, and evaluation.

5. In the fifth step involves socio-demographic/psychological parameters. We proceeded to analyze details, events monitoring (e.g. humiliations) and Inhibitors Type (e.g. psychological factor, socio-demographic parameter).
6. In the sixth step, we associated the diverse needs such as tendencies/preference and Student Trends. Defining a preference student process helps determining the student oriented s and the goals pursued.
7. In the seventh step, from the different dimensions, we started to visualize the indicators: LBI and CPI. Once user have defined the LBI and motivation state from our goal oriented model and data source, it is possible to profile student according to motivation for success than fear of failure. We focus on the actual LBI achieved by student on learning activities, these indicators identify from our Goal-Oriented model. The indicator provide the level of fear of failure and motivation for success.
8. Finally, step of specify the motivation state and student profile for which the student should be receive a boost motivation.

Overall, the motivation specification obtained through Goal-Oriented Requirements model and Learning Activities Model that allows to capture information about *Stimulation*, *Inhibitors*, *ReasonStudying*, *Student Profiling*, etc. With the definition of this motivation specification, by applying our motivation specification transformation, the profile type of student is generated. We illustrate an example of requirements learning scenarios where we want to determine the type of motivation of the student. Let consider that “Success Oriented Student” is either “Low” or “High” and “Failure Avoiding Student” is either “Low” or “High” and that student’s motivation specifications have been defined as follows:

- **Motivation Goal:** perceive, categorize.
- **xAPIActions:** registered, accessed, asked, added, watched.
- **User:** Support staff.
- **Course Type:** Methodology Unit.
- **Learning Behavior Indicators:** Timing of starting activities, Timing of completing a activities, and productivity.
- **Activity Type:** exam quiz, forum with Optional subscription mode.

With the definition of this motivation specification, by applying our motivation specification transformation, the motivation type generated is “Success-Oriented Student” is “Low” and “Failure Avider Student” is “High”.

3.2.2 Customize the boost of motivation process

The stimulus to boost student with reward mechanisms are categorized according to his/her behavioral outcome spotted by a LBI. In this section, we present how to customize the boost of motivation process.

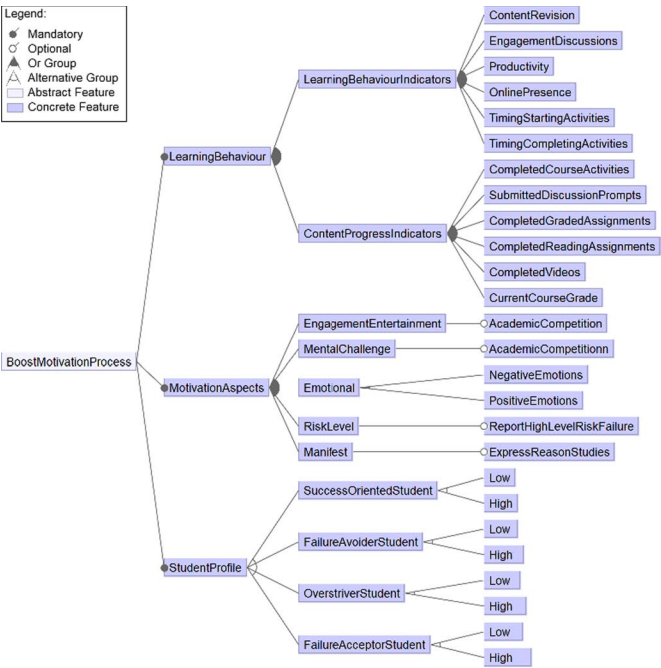
For this, we define Software Product Lines (SPL) (Pohl et al., 2005)) allows description of variability on the students’ profiles, the motivation aspects, and their behavior learning indicators (see Fig. 11). Thanks to the variability facilitated by

Fig. 11 Excerpt of our SPL: The variability on the students' profiles, the motivation aspects, and their behavior learning indicators

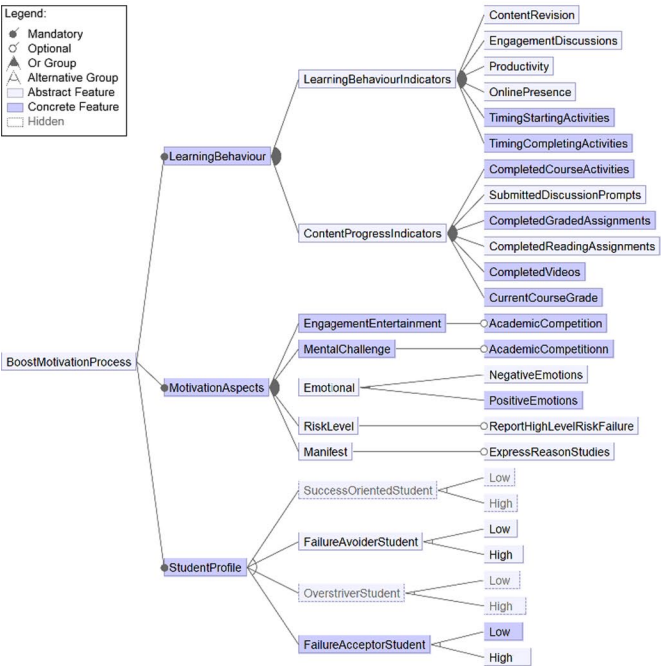
SPL to instantiate the boost's customization of motivation process. Our approach generates positive and negative (i) **Emotions** in different student. By providing a feeling of students, as display today's word (positive and negative reactions). These reactions can have a major impact of students' motivation and use of aggregated emotions serving to influence a given student by the major emotion of most individuals. This is based on using a $x\%$ threshold for aggregation. (ii) **Mental Challenges**. The second aspect that has been developed in our system helps students to overcome cognitive challenges like an academic competition with the aim of improving their performance in the learning activities. These challenges include good mental health to boost students and overcome digital living barriers and obstacles. (iii) **Risk Level**. The high level of risk of failure gives more motive to defiance challenges and motivate students to succeed. For instance, our system displays for some students a level of risk on the prediction of the results of the second submitting one banding on the linear regression. This value is encoded in colors to identify a risk level related to the results of the exams for a given students. The impact of this mobile functionality on Failure Avoider Student (i.e. this student has more fear of failure than motivation for success) can be achieved by stimulation of a student. (iv) **Engagement and Entertainment**. This service helps a many students profile that are highly driven by enjoyment, entertainment and “*fun*” aspects of using Learning Games Activities. Our system shows the engagement of users in cultural and science activities. This movuance of active user influences a student he must engage in this activity type. This latter can help more a Overstriver Student (this student is high in both motives) to the change strategy of learning that move this student into a Success-Oriented Student (i.e. this student has more motivation for success than fear of failure). (v) **Manifest**. This service allows students to outsource and express a Manifest as an instance of personalized learning inhibitors or information that indicates for instance the reason for studying (i.e. the objective motivated by the educational situation such as *personal development*). Every manifest is related to different categories, enumerated in our approach. Student may access this service to get assistance and the appropriate response that fits his/her manifest. We believe that this service aims to strengthen a feeling of belonging to the group that plays an important role in motivation.

In the following we show the Process of our system - Student vision step by step as follows:

- **Step (1):** The App requests a login after a 3 seconds splash screen, the user will have to enter his UserID and Password.
- **Step (2):** The user will be asked to report his reason of studying once every 6 months, otherwise the user will just have to enter his mood which is asked once a day. The data will be collected to be used for predictions.



(a) Variability space of the boost of student motivation



(b) Example of Customize the boost of motivation for given student

- **Step (3):** The Main Activity shows a Navigation Bar, where we can reach every other Activity, it also shows the user's grades and compare them to it is whole Class.
- **Step (4):** The Announcements Activity shows the user it is latest announcements, there are three types of announcements (Reminders, Awards, Challenges and Motivational Sayings).
- **Step (5):** The Chat Activity will allow the user to have real and human-like conversation with an AI-Chatbot . Since we are unable to communicate such a high number of students due to the HE massification. Indeed, to ensure the scalability of the communicate, it is preferable to call an external service software programs that interact with users via natural language (NL) conversation (e.g. AI-Chatbot).
- **Step (6):** The To-Do Activity shows a list where the user can add new tasks, delete them, and mark them as Done. The tasks will also be stored in the system database where it will be used for predictions.
- **Step (7):** The Challenge Activity gets activated by the system, the user will play a quiz game and their rank will be shown after.
- **Step (8):** Collected data will go through AI Models to (Predict motivation, Generate answers, Recommend activities...), Crowd data will be used to influence the users and stimulate motivation at Different parts of the Application.
- **Step (9):** A *Hafezni* widget will be shown at the end of every class to ask for feedback inside or outside the application to collect data about (user's mood, feelings, their classes, Motivational quotes..)

4 Proof of concept

To stress our approach according to our research questions (RQ1, RQ2, RQ3) and to prove how it is useful and helpful, we have developed a support tool that allowing to perceive and visualize the students' motivation states. The Service-based pipeline our approach is organized as it is shown in Fig. 12. Service 1: Data Source, Service 2: Data Curation Process, and Service 3: is frontend service responsible for displaying the right content on the different actors, i.e. teachers/support staff and students. To show how our system works, we have implemented a demonstrator application into two sides (i) a single-page applications stack is developed as dashboard to more understand visual perception and perceive visual changes states to each student (i.e. the facet related to RQ1), and (ii) oriented motivation learning by a mobile application system (i.e. the facet related to RQ2). The last experimental tests on motivation make sense on the causality of failure/success (i.e. the facet related to RQ3).

4.1 Student behavioral motivation analysis dashboard (RQ1)

We remained that our first goal according to RQ1, is How to perceive the student motivation aspects at a high level of abstraction?. To answer the first research question, a LAD is dedicated to educational stakeholders. Our LAD provides visual

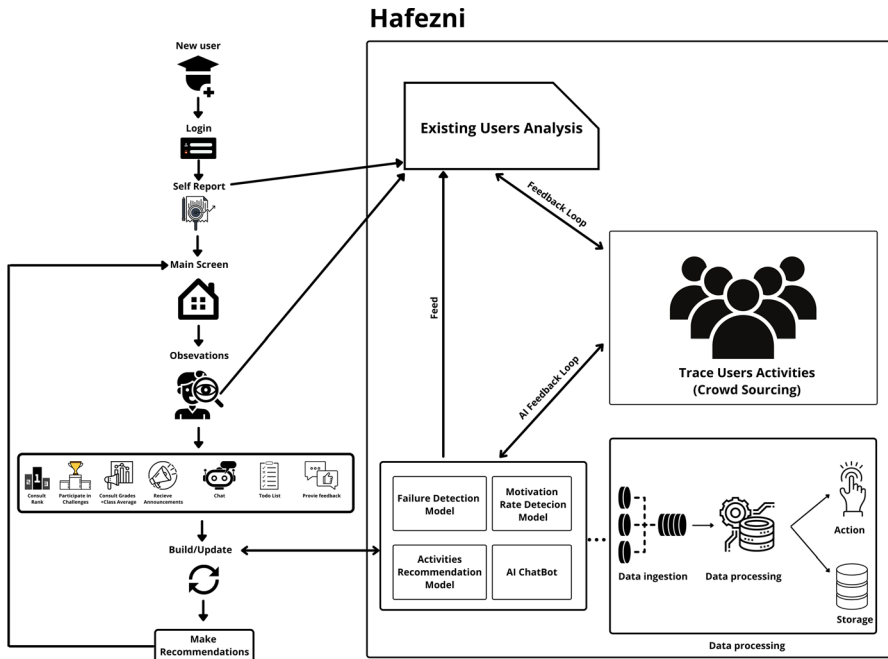
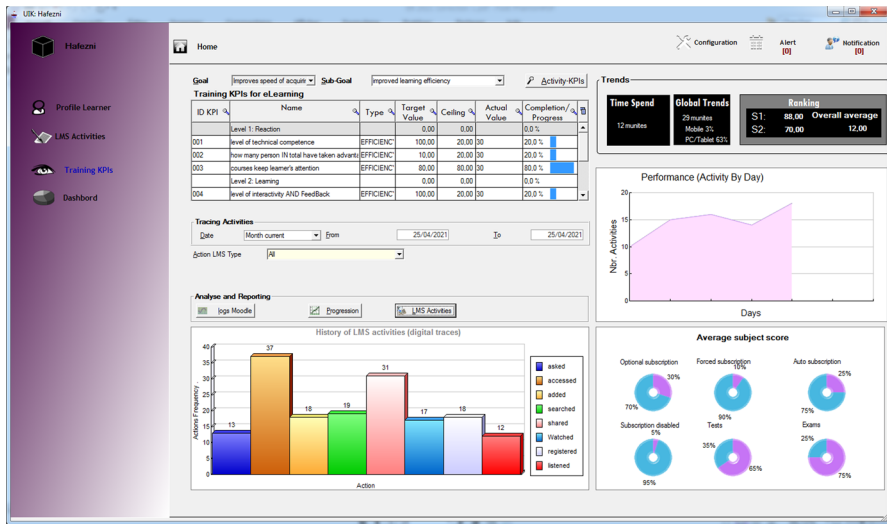


Fig. 12 Architecture of our system *Hafezni*

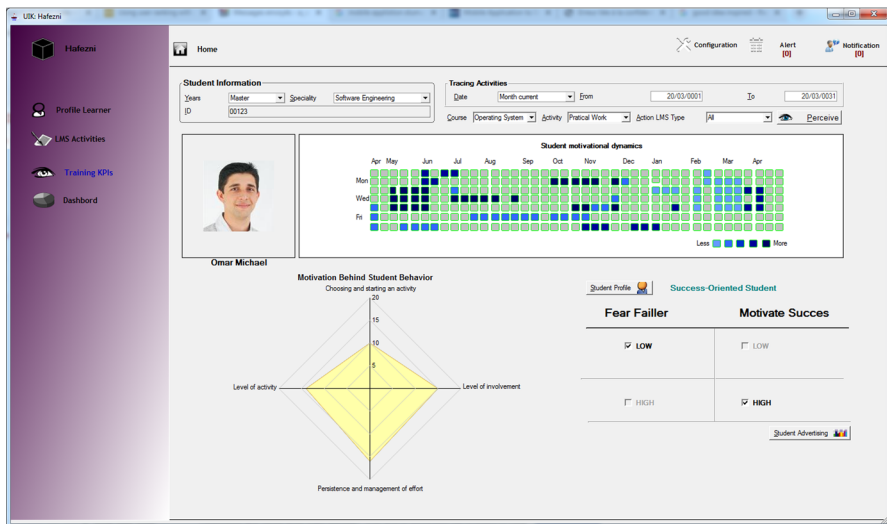
representations of student behavioral interaction that are synchronised with the motivation aspects. In this section, we present its capabilities.

4.1.1 Interface for reporting activities students

Our tool shows an overview of a given student activity on his/her profile. We can enable the activity overview section on student profile to give viewers more context about the types of actions he/she makes. When we enable the activity overview section of student profile, viewers can see more information about the types of actions he/she makes and we can filter actions and activity timeline for a specific student (see Fig. 13a). In Fig. 11a, the LBI are loaded and ready to be queried. Our tool providing users with a tool that offers a wide possibility of analysis and collect all information necessary for decision-making and allow users to have reports of their activity in a timely manner. The LBI are used by users to monitor the performance of students relative to their behavior (i.e. actual values of LBI and its limited value, and threshold values are a way to measure motivational students). LBI indicate a status in different aspects of the student's behavior thereby providing a global overview of the student. To monitor these indicators, our dashboard reporting presenting one or more LBI together with contextual information and activities related to a given course to help decision-makers identify deviations and their root causes.



(a) screenshot of reporting activities students.



(b) screenshot of motivation state perceive.

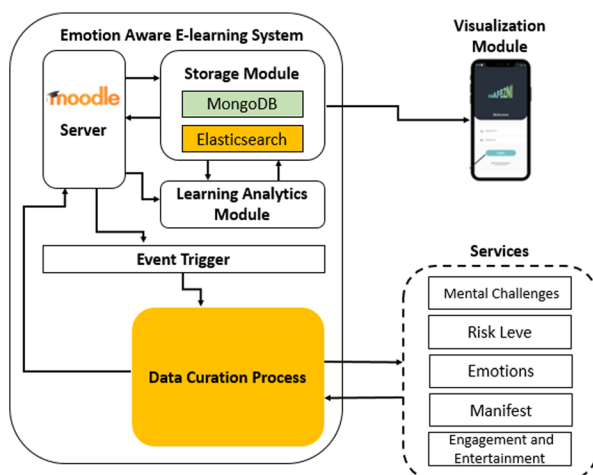
Fig. 13 Proof-of-concept prototype (Screenshots)

4.1.2 Interface for motivation state perceive

On a student's profile we can see the actions graph inspiring by Github contribution graph. In this graph blue squares actions activity count as levels from less to more advanced. But some of the squares and darker (if *actualValue*(indicator) tends to *limitedValue*(indicator)) and some are lighter. When we look at an active, established student's profile, they seem to have a

4.2 Mobile application for stimulate student behavioral motivation (RQ2)

Fig. 14 Integration of *Hafezni* Mobile App with LMS Moodle



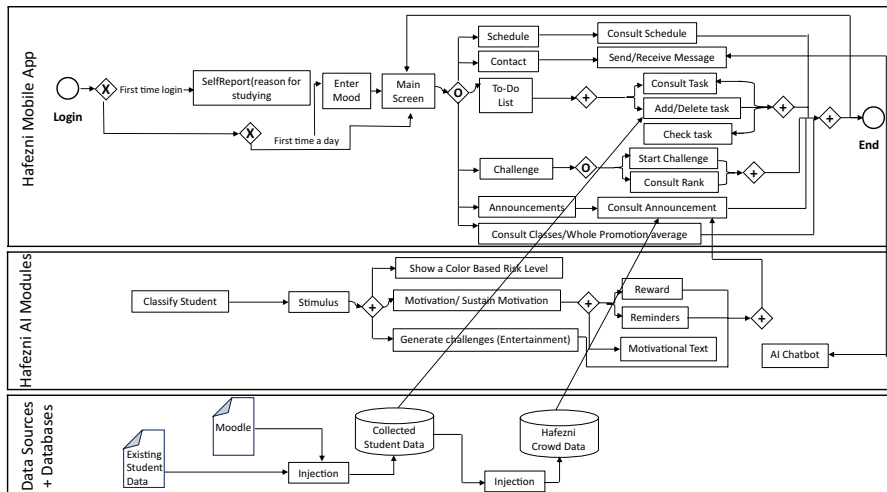


Fig. 15 The usage scenario of *Hafezni*

4.2.1 Demonstration scenario

To stress our approach and to proof how it is useful and helpful, this section is devoted to present a global usage scenario of the system *Hafezni*. In parallel, technical implementations are highlighted. The usage scenario is organized as it is shown in Fig. 15.

Wireframe-based UX Design Based on the analysis, we will create a wireframe for your app to give a rough idea of the look and feel of our application. It will let you know how your final product will look like. Figure 16 shows the wireframe of our tool support. This wireframe represents the initial stage of design that plays a key role in reduce user churn with better UX Design. In our design, we have considered several aspects: emotional effects, psychophysical reaction and including a dark mode option performed by Google and Apple (Cao et al., 2018).

Technical Implementation Our approach has been implemented and made available as an open-source code on Github⁵. Our deployment architecture including the main components of our system. The system is deployed in the Cloud, on a Windows Server 2012 virtual machine as follows: (i) Talend, R, Tableau server are deployed on the virtual machine, (ii) Data is stored in a database MongoDB and (iii) The main application is accessible via android. To ease the understanding, we provide

⁵ <https://github.com/OUARED-A/Hafezni-2021>

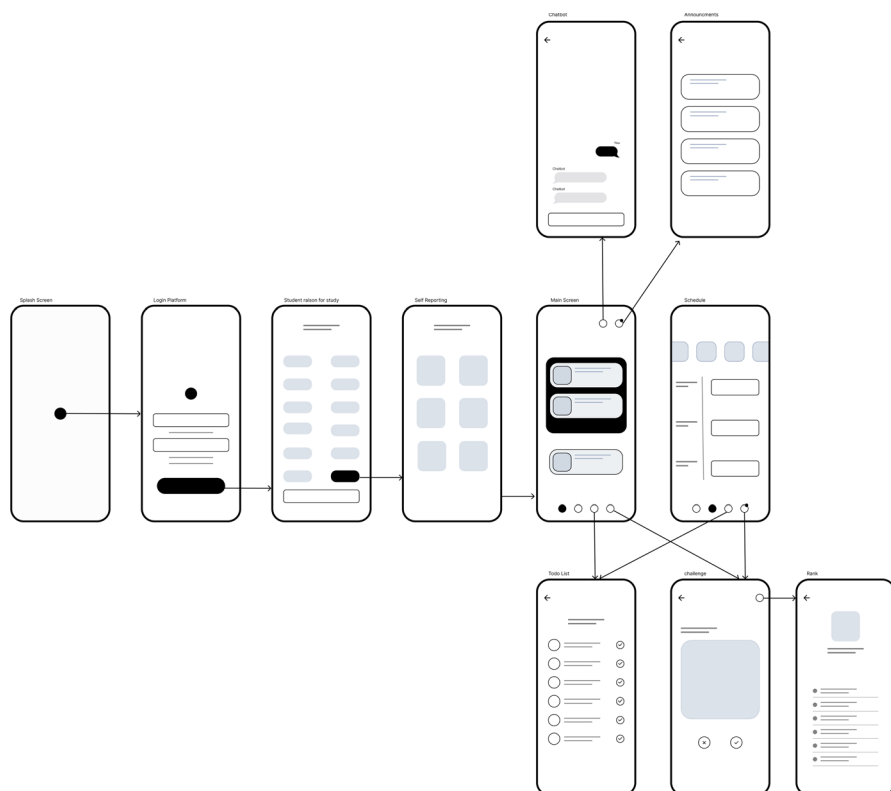


Fig. 16 Wireframe-based UX Design of *Hafezni*

the URL of a demonstration video of the project. The demonstration video of our tool is available at: <https://youtu.be/PkrGcjUTji0>.

Application Scenario Let us consider the application scenario of our system to help students in HE and motivate them to enjoy the LMS course. We take for instance a student who is highly unmotivated, to study or to learn to program and we will try to push them to do their best to be motivated and learn a programming language. The application scenario is shown in Fig. 17. The student will log in (c.f. Fig. 17 ②)) into the mobile application *Hafezni* and will be asked about their reason for studying if they have not submitted it in more than six months (c.f. Fig. 17 ③)), they also will enter their mood once a day (c.f. Figure 17 ④)) this information will help our system to predict and decide how to treat each case separately. When connected the student then will be redirected to the Main Screen (c.f. Fig. 15 ⑦)) where their grades are shown with the average of their whole class so they can compare themselves to the Mass. Our system then detects that the student is unmotivated and sends them personal notifications saying motivating quotes such as “*Cheer up Buddy, everything will be okay*” and asking about their feelings.



Fig. 17 Snapshot of *Hafezni* smartphone application GUI

The student can contact(c.f. Fig. 17 ③)) a Smart Motivating chat-bot saying for instance “I don’t feel so good about today’s class” and the chat-bot will reply by some comforting phrases such as “Its Okay, Our Database shows that most of your class feel frustrated about today’s class” or “Don’t you worry about that, our Database shows that 90% of last year’s succeeding students had the same problem”.

Table 1 Questionnaire answers with the percentage of each answer

Hafezni Mobile Application	Experiment
1. Easy to use.	(A-50%), (D-50%)
2. Impacts the motivational perception of users like Value.	(SA-27%), (A-50%), (U-12%), (D-11%)
3. Readable and understandable notifications and motivation texts.	(SA-32%), (A-27%), (D-29%), (U-12%)
4. Clearness and understandability of the visual elements' representation.	(SA-29%), (A-36%), (U-25%), (D-14%)
5. Clarity on how different aspects of motivation are presented to users, textually and visually.	(SA-25%), (A-38%), (U-25%), (D-12%)
6. Usefulness of the user manual of the application.	(SA-40%), (A-35%), (D-25%)
7. Usefulness as helps students to maintain or address their motivation issue.	(SA-25%), (A-38%), (U-25%), (D-12%)
8. Help students to adopt an approach to success than being afraid of failure.	(SA-38%), (A-37%), (U-25%)
9. I do not have problems in adopting the solution.	(SA 20%), (A-48%), (U-16%), (D-16%)
10. Useful educational tool for students.	(SA-19%), (A-37%), (U-23%), (D-21%)

An announcement (c.f. Fig. 17 ④)) can be generated by our system to the student challenging them to play a quiz where they can win prizes and compare themselves to all other students who played the quiz. For urgent issues, the student can access the *Hafezni* participants, which will be available at need. They can expect a reply in a few minutes depending on the manifest expressed by a user. Please note that messages posted in this *Hafezni* are public and shared with all other participants. As a result, the student will feel included and that he/she counts, comparing himself to other students will make them feel motivated.

4.2.2 Perceived Usefulness of our mobile application (RQ2)

Satisfaction is measured via a questionnaire, containing questions on ease of task, time on task, tool satisfaction and group agreement, to be answered. Learners and educational stakeholders are asked to provide positive and negative feedback. The survey included 10 questions on usefulness and usability of our approach to be rated on a Likert scale with options ranging: Strongly agree (SA), Agree (A), Undecided (U), Disagree (D), Strongly disagree (SD). The questions aimed at collecting some background information from participants. Full results are available in Table 1. It shows that most of the participants agree or fully agree that the proposed model is easy to learn, useful in using our

mobile application *Hafezni*, clear in the system process, and understanding the meaning of the elements, among other aspects. The results from reflection questionnaire would benefit. Most of the comments provided by students indicated that they enjoyed working with our assistant tool. However, participants claimed that they would use our approach in an educational environment, because the lack of tooling support. Participants also reported that it took time and effort to carry out the planning and execution of prioritization.

4.3 Does motivation state model make sense on the causality of failure/success ? (RQ3)

We believe that to get an explicit model on the perceptions that the student attaches to his/her success or failure helps the educational staff to address motivation issues unlike a black box system limited to provide a binary result. In this section, we detail the experiment design and procedure according to answer the RQ3.

4.3.1 Our dataset

With the aim to check if Motivation State Models makes sense on the students academic results (failure/success), we have used dataset of the computer science department of Ibn Khaldoun University of Algeria⁶ that has been used in previous work (for more details refer to Talbi et al. (2021)). This dataset set the profile student with information about demographic, available modules, assessments, available materials in LMS, results of student's assessments, etc. We have enriched our dataset by two types of indicators that reflecting the students learning motivation into the LMS, that we presented in the Section 1, namely: (i) CPI (e.g. Completed course activities, Submitted discussion prompts, Current course grade), and (ii) LBI (e.g. Engagement in discussions, Timing of starting activities, Timing of completing activities).

4.3.2 ML algorithm

In order to identify if the Motivation State Model makes sense on the causality of failure/success, we needed to build and test explicit models to help educational stakeholders.

This by using ML algorithms like Decision Tree (DT) and Random Forest (RF) that provide explicit model describing the reason of for fail/success.

The RF and DT models, implemented in Python, are optimized to use the optimal number of trees, oversampling ratio of the minority class and the number of samples at leaf nodes. We evaluate the DT model and RF model on the collected data and compare them along several dimensions: (a) classification accuracy (ACC), (b) generalization through rule extraction.

⁶ <https://www.univ-tiaret.dz/fr/>

4.3.3 Experiment design

This setup includes the different scenarios considered in our experiment procedure. The experiments we conducted aimed at evaluating the validity of the following main features: **(i)** Evaluation of the classification results obtained from models RF and DT using metrics: *F-Measure*, *Precision*, *Accuracy*, and *Recall*. **(ii)** Rule Extraction from Students Results to show how much models predicting success/fail are related to motivation aspects by exploring learning behavior and CPI. **(iii)** Explication of the motivation state synthesis from combination of fundamental learning indicators: LBI and CPI to show in which this representation is a human understandable way of one or many aspects of the students' motivation states.

4.3.4 Machine learning testing

The RF and DT models, implemented in Python, is optimized to use the optimal number of trees, oversampling ratio of the minority class and the number of samples at leaf nodes. For both datasets, we randomly sample 80% for training and the rest of 20% for testing and validation. We report precision and F1-score values for the minority class, as well as the balanced accuracy across both classes. We compared the classification results obtained from models RF and DT. The classification parameters consist of correctly classified several examples of our dataset, incorrectly classified examples, *F-Measure*, *Precision*, *Accuracy*, and *Recall*. The classification results show that Random Forest gives better results for the same number of attributes and large data sets i.e. with greater number of instances, while DT is handy with small data sets (less number of instances). The results show that the percentage of correctly classified instances increased from 69.23% to 96.13% for Random Forest i.e. for dataset with the same number of attributes but having more instances, the Random Forest accuracy increased (Fig. 18).

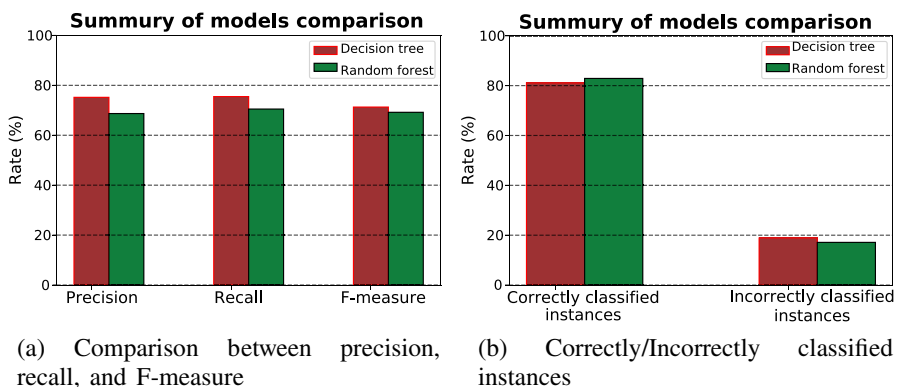


Fig. 18 Summary of models comparison

To ensure the robustness of our model, we repeat these experiments using the 2nd years of computer science department to Detect Student Fails. This benchmark has a Master student of software engineering, an opportunity for the evaluation of DT and RF. Our results show that RF estimates provide good recommendations with higher accuracy than the DT model. For instance, the difference in the overall accuracy and the accuracy in prediction between RF and DT is $ACC = 37\%$, because RF can trace the dependency between features, which DT is unable to take control of its.

4.3.5 Rule extraction from students results

Rule Extraction from Students Results brings benefits of explaining knowledge encoded as rules to explain how Student Fails/success. With the use of our ML model, the support staff has efficiently solution to predict Student Fails and compare the goodness of the hypothetical of educational success/failure. Table 2 shows examples the derived rules ($Rule = R_{1j} \bowtie R_{2j} \dots \bowtie R_{kj}$) by our ML Models to explain how to predict a academics result (i.e. Success, Fail). Our result suggested is encoded as rules, the support staff can understand if the indicator behavior is correlated with CPI and how can impact the academics result. From these outcomes, the support staff can see the rules generated by our ML algorithm and checks the logic behind the result academic prediction to trust without regret on the alternative consideration. For instance the rule 4, the two learning behaviour indicators, *Timing of starting activities* and *Timing of completing activities* show the delay of initiation or timely completion of activities that denote the student' procrastination within the meaning of You (2015), which affect negatively their success. Also, the lack of participation in the forum as evidenced by the *Effort in discussion* indicator will also negatively impact these two indicators.

We present an example that generates a set of rules to predict a Student Fails for a given instances of Computer Science, specialization of Software Engineering (SE), with $PR_j^{C_i}$: Course Prerequisites in which a particular Course C_i is involved, $C(1..n)_i$: Number of Course Prerequisites of a particular Course C_i , $\mathcal{F}$ is Fundamental Unit, $\mathcal{M}$ is Methodological Unit and $\mathcal{D}$ is Discovery Unit. TSC_i is Timing of Completing activities indicator and TCC_i is Timing of Completing activities indicator. The indicators $TC(C_i)$ and $TS(C_i)$ are related to the threshold values that is specific to a given learning activity. For example, a student is enrolled in course with a theoretical working time of 10 hours that represent the required threshold of presence.

From this explanation, the motivation aspect significantly impacts which configuration parameters correlate with success and failure of student. This is expected since the motivation aspects related to students behaviors are intrinsically linked.

4.3.6 Motivation state synthesis from learning behavior indicators

The last test consists in verifying if the academic results is synchronized with the motivational state derived by our DSL and accordingly with the viewpoint of educational stakeholders.

Table 2 Examples of rules extracted from the dataset

Line	Model	Rule	Outcome	Outcome
1	DT	If C_i is $\mathcal{F}$: 'Data Science' and $F(1..n)_i \geq 2$ and all $M(1..n)_i$ is achieved and $TS(C_i) \geq \text{threshold}$	Success	87%
2	DT	If C_i is $\mathcal{F}$: 'Data Science' and C_i Type is $\mathcal{M}$ and C_i Type is $\mathcal{M}$ and contain 'Algebra/Prob' and C_i not contains <i>Stat</i> and $F(1..n)_i \leq 1$ and $M(1..n)_i \leq 1$	Failure	86%
3	DT	If C_i is $\mathcal{F}$: 'Data Science' and not all $F(1..n)_i$ are achieved and C_i Type is $\mathcal{M}$ (C_i is a Methodological Unit Type)	Success	80%
4	DT	If C_i is $\mathcal{F}$: 'Data Science' and number of $F(1..n)_i \leq 1$ and $TC(C_i) < \text{threshold}$	Failure	97%
5	RF	If not all $F(1..n)_i$ are achieved and <i>Baccalaureate-Category</i> = "Scientific" OR "Science Exact" and $F(1..n)_i \geq 2$ (Fundamental Unit) and contain Methodological Unit ($F(1..n)_i \geq 1$)	success	90%
6	RF	If Mathematics Grade (Score > 12) and Probability and Statistic Grades (Scores ≤ 10) or Statistical Grade ≤ 10 and Grade Linguistic is Low Level (Score ≥ 8) and <i>BaccalaureateCategory</i> is not "Sciences" OR "Exact Sciences"	Failure	92%
7	RF	If Not all $\mathcal{PR}_i^{C_i}$ is achieved (Score > 10) and <i>BaccalaureateCategory</i> = "Sciences" OR "Exact Sciences" and 'Algebra/Prob' are achieved (Score ≥ 10) and Student has not a Good Background on Statistic	Success	78%
8	RF	If <i>BaccalaureateStudent</i> = "Sciences" OR "Exact Sciences" $\geq \text{threshold}$ (Result Score <i>Baccalaureate(IB)</i> > 14) and $TS(C_i)$	Success	97%

$\mathcal{PR}_i^{C_i}$: Course Prerequisites in which a particular Course C_i is involved, $C(1..n)_i$: Number of Course Prerequisites of a particular Course C_i , $\mathcal{F}$ is Fundamental Unit, $\mathcal{M}$ is Methodological Unit and $\mathcal{D}$ is Discovery Unit. TSC_i is Timing of Completing activities indicator and TCC_i is Timing of Completing activities indicator

To get the viewpoint of educational stakeholders, we give a motivation state that is expressed in high level of abstraction simplifies and in a human understandable way the representation of one or many aspects of the motivation's state and provides a visual mental image that facilitates understanding.

By analyzing instances of students motivation states obtained by instantiating our DSL and we synthesis the motivation's states from combination of LBI and CPI as spider chart of students engagements to be interpreted by educational stakeholders. We compare the behavior generated by our DSL with the appreciation of the educational stakeholders and we see if this motivation state is synchronized with the academic result obtained from the CPI (e.g. Completed course activities, Completed graded assignments) (Fig. 19).

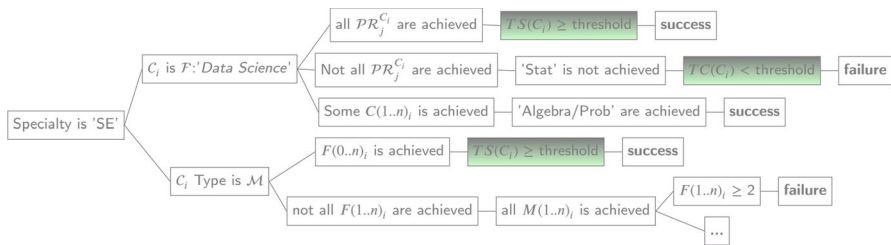


Fig. 19 Excerpt of Decision Tree Instance

Our result illustrate the correlation between the LBI and CPI into the LMS and the aspects of motivation through two spider charts see Fig. 20, the first corresponding to an instantiation of an unmotivated student (Fig. 20a) and the second to that of a motivated student (Fig. 20b).

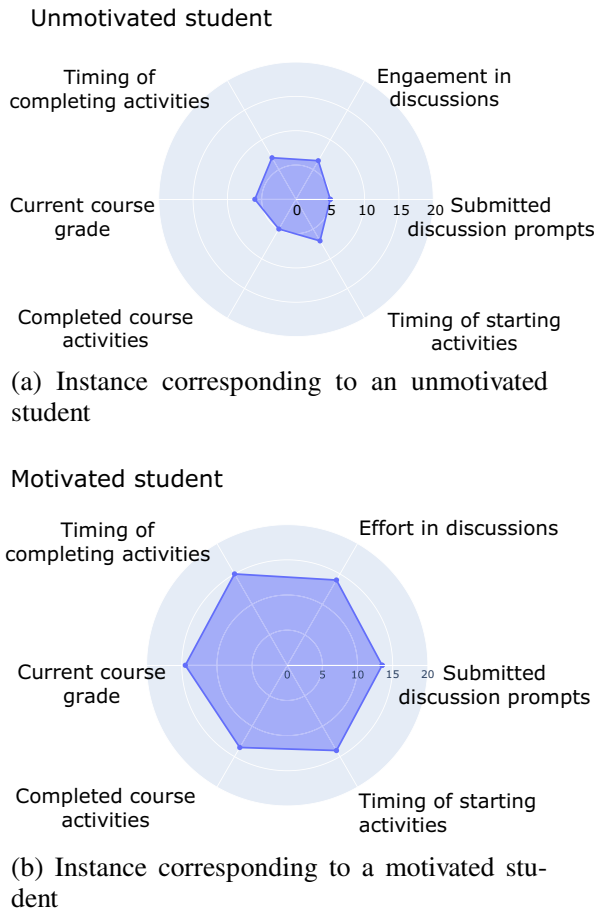
As shown in Fig. 20a, the two learning behaviour indicators, *Timing of starting activities* and *Timing of completing activities* show the delay of initiation or timely completion of activities that denote the student' procrastination within the meaning of You (2015), which affect negatively *Completed course activity* indicator and so the *Current course grade* indicator. Also, the lack of participation in the forum as evidenced by the *Effort in discussion* indicator will also negatively impact these two later indicators.

However this motivation state its dynamic. We see clearly in Fig. 21, the change of motivation state that can be indicated by the variation of six dimensions of spider chart, i.e. Content revision, Engagement in discussions, Productivity, Online presence, Timing of starting activities, Timing of completing activities.

For instance as shown in Fig. 21a that illustrate the Transition from (Low-low $L - L$) to (Low-High $L - H$), after boosting student, we can see the increase the values of Current course grade and completed course grade indicators correlated with engagement in discussions and Productivity indicators.

In opposite with the state illustrated in Fig. 21b that show the Transition from (High-Low $L - H$) to (Low-Low $L - L$). In this case, the issue of student's motivation is addressed by making a mechanism that stimulates students. From these results we can conclude that the change in motivational aspects appears in LBI variation, that means that a behavior outcome modification of a student is consistent if it yields an interrelated behavior with motivational affordances and the digital interaction of learning activity obtained from xAPI, this latter means that this motivation student state can be generated automatically or can be obtained as a projection.

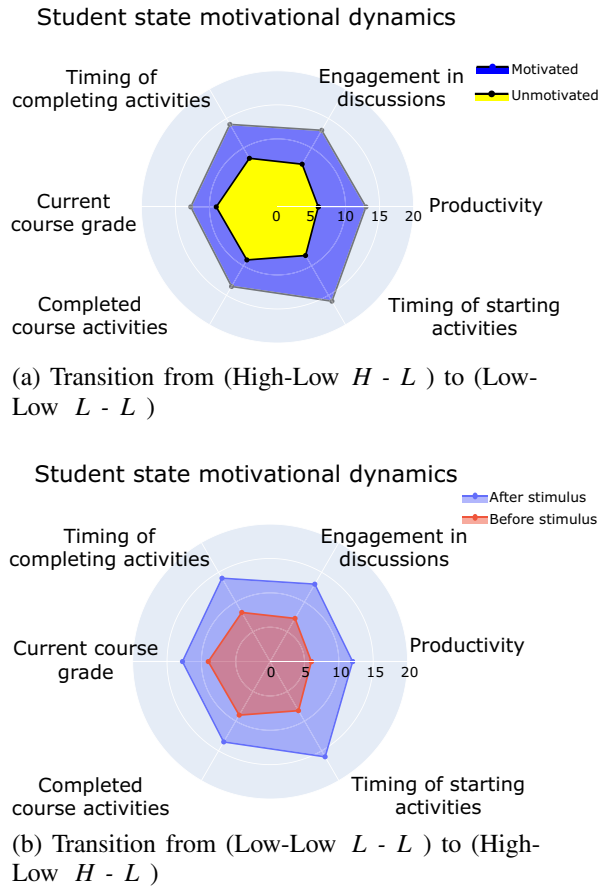
From our testing of several instances, in with each instance represent a state of students derived from LMS, and evaluate by educational stockholder, the majority of instances, the state of motivation generated by our DSL is synchronized by success/fail of students and the expert viewpoint. In some cases, the results provided by our DSL, success/fail of students and the expert opinion are not similar, that means maybe a scenario of hidden factors that impact the success/failure and is not considered in our DSL or this consolidates (Anderman and Wolters, 2006) who say "it is quite possible

Fig. 20 Example of instance motivation students

for some students to achieve at high levels yet not be highly motivated” and reciprocally.

All the results obtained show that there is a correlation between the set of beliefs and perceptions related to the importance that the student attaches to his/her success or failure and his/her motivated behaviors which will help educational stakeholder to address motivation issues in a more accomplished way. To the best of our knowledge, there is no work has been dealing with the students’ motivation issue from the conceptual models and Learning Analytics view. We introduce a Goal-Oriented Modeling language for modeling to be able to review students’ motivations and changes. We also present a software prototype that supports the approach and proposed language. At the end, the main objective of the reported research work is to contribute to the field of Learning Analytics and personalized teaching. We believe that our research reported in this paper is timely and highly interesting and the role of conceptual modeling is used to leverage Learning Analytics tasks. The

Fig. 21 Student State Motivational Dynamics before/after stimulation: The change in motivational aspects appears in learning behavior indicators variation



main contribution of the paper is supported by a mobile application called “*Hafezmi*” to provide a reader a good overview of the topic.

We hope to entice both the Learning Analytics, Artificial Intelligence, and Modeling communities to deal with the identified challenges as personality, motivation, etc. related to the smart educational decision support systems.

5 Conclusion

This article addressed the problem of modeling and perceiving motivation in educational learning.

Our work is motivated by the large number of students in higher education, student monitoring is a difficult task therefore, we need to assist the educational stakeholders with computer science solutions in order to perceive the motivation state.

We have investigated how Model-Driven Engineering paradigms captures the essence of a motivation domain, and provides deep automation in stimulating students' tasks.

In this paper, we have presented a conceptual approach that provides a unified environment in which all dimensions of students' motivation are explicitly defined. Our approach is based on three different models: (i) Goal-Oriented Requirements Models, (ii) Activities Learning Model and, (iii) Learning Motivation State Model. Our solution showed that it is possible to perceive the behavior aspect of student motivation. A Prototype implementation demonstrates the feasibility and practical utility of the approach.

The main objective of this demonstration paper is oriented Motivation Learning by mobile application system to push students to achieve success.

Our mobile application called *Hafezni* that means in English "*Motivate Me*" based on our requirement model approach. *Hafezni* is based on five pillars ((i) Emotions, (ii) Mental Challenges, (iii) Engagement and Entertainment, (iv) Risk Level and (vi) Manifest) where educational stakeholders can analyze and identify failing students early and analyze a cause of failure. This system enables teachers/support staff at the same time to orient students and receive the most suitable motivation. We have presented a case study to instantiate our system in real scenarios and provide prototype tool for the proposed solution. In addition, we have testing if the Motivation State Model makes sense on the causality of failure/success by evaluating the validity of the following three main features: (i) Evaluation of the classification results obtained from ML models RF and DT, (ii) Rule Extraction from Students Results to show if models predicting success/fail are related to motivation aspects and Explication of the motivation state synthesis is a human understandable way.

This work opens several directions of further research. *From theoretical point of view*, We plan to explore other avenues to capture the intrinsic aspects of student motivation by leveraging the model-based approach and we believe that such work can push the learning analytics community to reflect on identifying the challenges and opportunities in modeling aspects of intrinsic motivation. *From practical perspective*, we plan to add support to enable more analyze a text using NLP techniques. This includes the possibility of analyzing and aggregating the feedback of students to better influence their perception. Furthermore, *Hafezni* can be envisioned as a starting point for providing Chatbots to encourage and motivate students.

From methodological point of view, we are also planning to conduct experimental evaluations where the user feedback validates the effectiveness and efficiency of our proposal regarding the benefits in educational context. Currently, we are testing our tool by educational stakeholders to get their feedback for possible improvements. Another ongoing work pursues adapting our approach to cover aspects of the motivation dimension, more precisely the intrinsic motivation. It also opens opportunities, for instance, in online teaching (MOOCs, etc.) by students following online courses to receive a customized boost of motivation.

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