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PAPER

Aligning Educational Stakeholder Perceptions of Learner Profiling with Explainable AI

Abdelkader Ouared (✉), Madeth May, Claudine Piau-Toffolon, Nicolas Dugué

University of Le Mans, Le Mans, France

abdelkader.ouared@univ-lemans.fr

ABSTRACT

The education community continuously develops learner profile (LP) models to support decision-making in learning analytics (LA). However, a gap persists in aligning abstract stakeholder requirements with complex machine learning (ML) patterns. Educational stakeholders such as decision-makers, educators, and pedagogical engineers perceive and categorize LPs (e.g., learners *in difficulty*, *active/inactive learners*, *those in progress*, and *success-oriented vs. at-risk learners*) through mental models. These latter reflect real-world perceptions and pedagogical practices grounded in common educational concepts. To bridge this gap, data scientists must ensure technical ML insights align with stakeholder needs by selecting relevant features, addressing explainability, mitigating biases, and validating patterns against domain assumptions. For example, a learner generating extensive log data through repeated solution attempts may appear engaged from a human perspective but exhibit disengagement based on unexpected ML discovery patterns, highlighting biases in data interpretation or human perception. We propose Req2XAI (From Requirements to Explainable Machine Learning Models), a framework that establishes a bidirectional mapping between stakeholder requirements for LP analysis and ML-driven learner profiles. Req2XAI externalizes stakeholders' mental model about LP via a conceptual model into requirements and goals and formalizes an end-to-end workflow, from stakeholder objectives to explainable ML models, ensuring transparency at each stage. A proof-of-concept prototype is implemented through a use case, considering the requirements of the Steering Committee of the écri+ project. This work introduces open research challenges associated with the Req2XAI framework, which merit further exploration.

KEYWORDS

learning analytics (LA), learner profile (LP), explainable AI (XAI), conceptual modeling, stakeholder requirements, machine learning (ML)

1 INTRODUCTION

Educational stakeholders' mental models and perceptual biases shape their understanding of learner profiles (LP) often abstracting complex educational

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phenomena into simplified categories (e.g., *at-risk*, *engaged*) [1–3]. These conceptualizations, however, risk introducing subjective biases when translating pedagogical intuitions into actionable requirements for defining LPs. A shared requirement vocabulary is critical to formalize stakeholders' abstract notions such as learning context, competency gaps, or behavioral indicators into machine-interpretable LPs constructs [4]. Yet, the absence of standardized conceptual frameworks for modeling LPs perpetuates misalignment between stakeholders' perceptions and the technical implementation of learning analytics (LA), limiting trust and interpretability in AI-driven educational systems [5]. As the result, determining the LP within LA is critical for educational stakeholders to support learners in achieving their educational goals [6–8].

A LP typically refers to a structured description of attributes representing the learning context, encompassing assessments, competencies, demographics, and behavioral characteristics such as motivation and engagement [9]. For example, teachers often seek to identify specific learner profiles by asking questions such as: Who struggles? How do they struggle? Who is most engaged? Why no progress? What's the trajectory? Why no advancement? The accuracy of addressing these questions depends on contextual factors such as personal information, academic records, and emotional aspects. However, a significant gap persists between educational stakeholders' hypotheses (expressed through pedagogical concepts) and the data features used in LA. Understanding implicit LPs to address stakeholders' needs remains challenging, particularly in digital environments where real-world behaviors are ambiguously reflected. Current approaches lack standardized conceptual modeling frameworks to represent LPs as machine-interpretable abstractions, hindering stakeholders' ability to interpret learners' digital behaviors and receive quick feedback as they calibrate and alter the requirement specifications without relying on empirical trial and error. This work addresses the research question: *How can we align educational stakeholders' perceptions of learner profiling with explainable AI to efficiently identify and analyze learner profiles?*

To bridge this gap, we propose a framework Req2XAI (From Requirements to Explainable Machine Learning Models) for modeling LPs using conceptual modeling languages that explicitly bridge stakeholder-centric abstractions with technical machine learning (ML) implementations to enable interpretable representations of LPs while integrating white-box AI models with annotated datasets. Req2XAI unifies the representation of the LP in a human-understandable way using conceptual modeling languages that explicitly link educational stakeholders' requirements to their corresponding LP, Explainable AI (XAI) models, and data, rather than relying on direct data manipulation. Prior studies have not explicitly bridged learner profiles, data indicators, learning context, and user requirements, which is essential for interpretability. Our conceptual modeling approach externalizes stakeholders' mental models (e.g., categorizing learners as in difficulty, active/inactive, or at-risk) and captures the end-to-end process from conceptual requirements to explainable ML models. This enables multi-level, interpretable representations of LPs while integrating explicit white-box AI models with annotated datasets. We further introduce a process model formalizing the workflow from conceptual requirements to explainable ML, enabling hypothesis validation, reuse, and bias mitigation.

We start in Section 2 by motivating example and related Work. In Section 2.1 we present a motivation scenario of a multi-view analysis levels to highlight the usefulness to bridge the models of the user profile, context and the requirements of the educational stakeholders. Section 2.2 presents the related work. Section 3 presents our framework and its theoretical foundations. Section 4 presents the proof of concept. Section 5 wraps up the conclusions.

2 BACKGROUND AND RELATED WORK

2.1 Educational stakeholders' requirements

Educational stakeholders including decision-makers, educators, pedagogical engineers, and data scientists analyze LPs at varying levels of abstraction to address diverse objectives. These objectives, such as decision support, guidance, explanation, and recommendation, collectively aim to assess, monitor, and enhance learner performance. By integrating data-driven insights with effective pedagogical strategies, this collaborative process aligns with the distinct expertise of each stakeholder group, fostering synergy among them [5].

The challenge lies in how LPs are analyzed from different perspectives, with each requiring distinct levels of abstraction, data granularity, and goals. The "Learners Profile Iceberg" metaphor illustrates this variance: the visible indicators (e.g., grades, attendance) represent the easily accessible aspects of learner performance, while the deeper, underlying factors (e.g., learning patterns, emotional engagement, and cognitive progress) require more complex and nuanced analysis [1]. In the current educational landscape, educational actors often use their preferred methods, typically natural language, to describe specific LPs (e.g., a learner struggling with a particular competency) and express their concerns using their own terminology (jargon and universe of discourse) with multi-level analysis abstraction. For instance, the disaggregation of data and the calculation of indicators tailored specifically to each actor's needs (e.g., trends, metrics, behavioral patterns, and predictive insights).

Table 1 provides a global overview of the main features of profile analysis according to stakeholder perspectives. It clarifies the relationships between different vocabularies, layered levels of abstraction, and the views of three main educational actors related to LP analysis. This illustration shows the need for a connection between LP, educational stakeholders requirements, learning context, and the required information from data sources.

Table 1. Different vocabularies, layered levels of abstraction of learner profile analysis, and views of the three main educational actors

Goals	Vocabularies	Layered Levels of Abstraction					Stakeholder Perspectives (View)
		Advanced Analytics		Indicators/ Metrics		Raw Data Sources	
		Learning Patterns	Visual Analytics	High-level	Derived		
Strategic	Concepts			X	#		Decision Maker
	Measures						Teacher
Operational	Indicators		#		X		Data Scientist
	Data Level	X	X		X	X	

Note: "X" means mandatory utilization and "#" means optional utilization.

As illustrated the Table 1, generally, *decision-makers* such as academic managers or administrators focus on high-level strategic goals by using high-level indicators (e.g., institutional performance trends, grades, attendance, dropout rates). These indicators help identify learner profiles, make informed decisions that impact policy, and guide institutional strategies and resource allocation.

On the other hand, *teachers* focus on the indicators and measures level, using derived metrics (e.g., success rates, participation frequency) to identify specific learner patterns related to a set of characteristics. Thus, teachers have operational goals related to teaching. When teachers specify a LP, they express their requirements in terms of competencies and metrics. *Data scientists* and LA researchers focus on raw data and advanced analytics (e.g., learning patterns such as correlations, cognitive progress, time-on-task metrics, and visual analytics) to analyze learner profiles and explain the hidden reasons behind a learner's success or failure. The output provided to decision-makers and teachers is well-explained and justified, detailing how the learner behaves and the reasoning path leading to the decision. In this case, data scientists need domain knowledge and ML expertise to ensure that ML-driven insights align with stakeholder needs, addressing explainability while discovering interesting and unexpected patterns. This process helps confirm or challenge stakeholders' mental models and perceptions, preventing bias and errors.

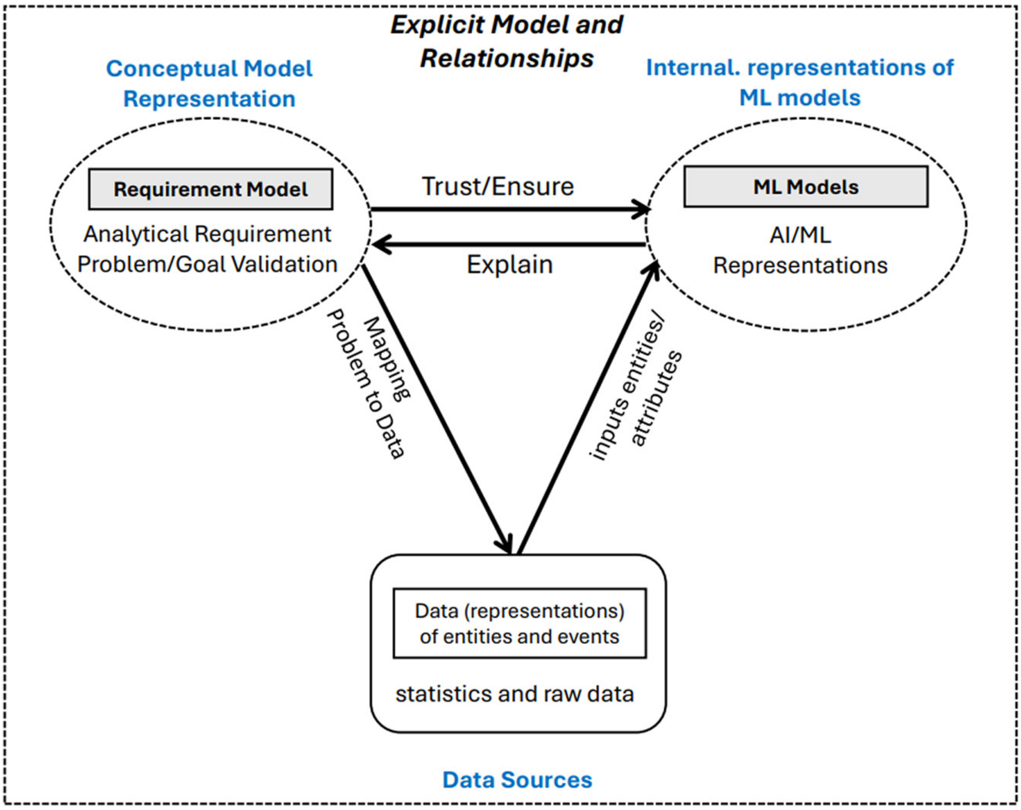

Fig. 1. Illustration of the need for a connection between the requirement model, ML models, and educational data sources involved in LP analysis

Stakeholders' mental models about LPs are constructed within a domain by educational knowledge and shape their perceptions according to their expertise and pedagogical practices. A conceptual model formally represents the externalization of stakeholder's mental model about LP into requirements and goals, serving as a bridge between domain knowledge and technical implementation. In this context, data scientists need to understand both the problem at hand and the domain it pertains to, while also considering the decision-making process. This includes identifying the pertinent data features, process enabling profile ML models, and ensuring that XAI approaches meet the expectations of stakeholders. To address this, a formalism is needed to link profile models, data indicators, learning context, and user needs, along with a process enabling profile analyze and data mapping for hypothesis validation. However, selecting the appropriate LP requires considering learners' contextual data, stakeholders' preferences, and profile awareness at different granularities.

Our vision for improving this situation is outlined in Figure 1, illustrating three connections between Requirement (RQ_{LP}) analysis of LPs, XAI models (XAI_{Model}), and required data from the Data Sources for Profile Analysis. To bridge this gap, we need to establish a bidirectional mapping between stakeholder requirements represented using conceptual models and ML-driven learner profiles.

Both components are related through two types of mapping:

$$RQ_{LP} \underset{explain/reason\,up}{\overset{trust/ensure}{\rightleftharpoons}} XAI_{Model}$$

In operations, ***trust/ensure*** from RQ_{LP} to XAI_{Model} is necessary because trust and fairness allow stakeholders to follow the rationale behind the ML model's judgment, and ensuring aligns with stakeholders' instructions and constraints. It indicates an end-to-end workflow, from conceptualizing stakeholder objectives to developing explainable ML models, ensuring transparency at each stage.

On the other hand, the operation ***explain*** from XAI_{Model} to RQ_{LP} is crucial as it reasons up through the causality of the implications and the impact of data features and patterns at the problem level. This operation synthesizes features into common educational concepts defined by domain knowledge, i.e., the requirement vocabulary.

2.2 Related work

The user profile has demonstrated its relevance across various domains, such as the banking sector, universities, and telecommunications [10, 11]. In this section, we explore research that has developed LP models to enhance support services in the education field. Designing LPs has become increasingly important to support for decision-making at different levels such as learning, orientation, and recommendation. [6–8]. In [12], the authors present an analytical and statistical study on LP modeling to provide a comprehensive description of learner profiles derived from various techniques across different educational contexts. The goal is to identify and categorize learner features that can be used individually or in combination to support decision-making in various domains. Recently, in [13], the authors proposed a taxonomy of systematic literature reviews on learner profile characteristics, identifying the factors affecting learner academic performance and engagement prediction. Similar efforts have been carried out by the educational community using learner profile modeling with ML techniques (please refer to the survey [9]). At the same time, several studies (e.g., [14]) propose solutions to enhance learning, analyzing the relationship between online learners' behavior and cognitive load using multi-level data mining on the Canvas Network. In [15], user profiling in online learning is explored through behavioral analysis, identifying three learning patterns via ML on Shanghai Open University data. In [16], the study presents the MMSy-Orientation project, a meta-model of E-orientation platforms that uses WSDL to compare these platforms for improved learner guidance. Similarly, with their work, several works have explored learner models in adaptive learning systems [17]. In [18], the authors propose a user-centered approach to personalize e-learning platforms using Bayesian Networks to predict preferences. The study also highlights the role of user profile modeling in web-based learning management systems to tailor the learning experience. Aligned with our work, others work leverage to conceptual modeling and ontological engineering to provide a granular and comprehensive representation of learner knowledge. [19–24]. In [25], the authors propose recommendations for content and services tailored to tourist profiles and their immediate context to assist visitors during their exploration of cultural sites. In another line of research, the authors of [2, 4, 26] addressed the research consider using XAI to explain AI for analyzing learner profiles. Similarly, [27–29] a study conducted to address the issue of bias in the field of education transparency, and Ethics in AI and higher education. In a similar trend, other work considering the constraints in perception and mental models suggests that anchoring bias affects mental model formation and user reliance in XAI systems [3, 30]. Recent work explores the opportunity for interaction between generative AI and human expertise using different techniques such as chatbots and voice explanations [31–33]. There has been a significant amount of work on LPs in educational fields [8]. However, previous studies have not focused on explicitly defining a LP for educational stakeholders. Bridging the models of learner profile, data indicators, learning context, and user requirements is essential. Such an explicit connection is crucial for simplifying and unifying LP representations in a human-understandable way with greater control. Furthermore, aligning these models with the cognitive and contextual priorities of stakeholders is vital for the accuracy and relevance of the LP. This requires not only a deep understanding of the pedagogical needs but also a strong integration of ML techniques to tailor the profiles to the dynamic needs of learners. Aligning educational stakeholder perceptions of learner profiling with XAI is also key to fostering trust and ensuring transparency in decision making, as it enables stakeholders to understand and interpret how LPs are derived and applied.

3 OUR FRAMEWORK AND ITS THEORETICAL FOUNDATIONS

We propose a framework Req2XAI designed to transition from stakeholders' educational requirements to explainable ML models that enable LP analysis while maintaining an interactive workflow. Figure 2 provides an overview of our framework. The user requirement model, a conceptual artifact, captures educational stakeholders' mental models and perceptions related to LP analysis (cf. 1). These requirements, once refined to be translated into testable factors (cf. 2), improving controllability and precision in selecting data entities and attributes from explicitly defined data sources as input features in the dataset (cf. 3). The data scientist conducts the execution of the ML pipeline (cf. 4) to ensure ML-driven insights align with stakeholder needs, addressing explainability and validating if patterns confirm or challenge stakeholder assumptions. Subsequent components define internal ML model representations, which generate explanations using XAI models to foster stakeholder trust (cf. 5), and XAI-enabled dialogue-based interface of LP explanation, dedicated to checking bias and fairness (cf. 6).

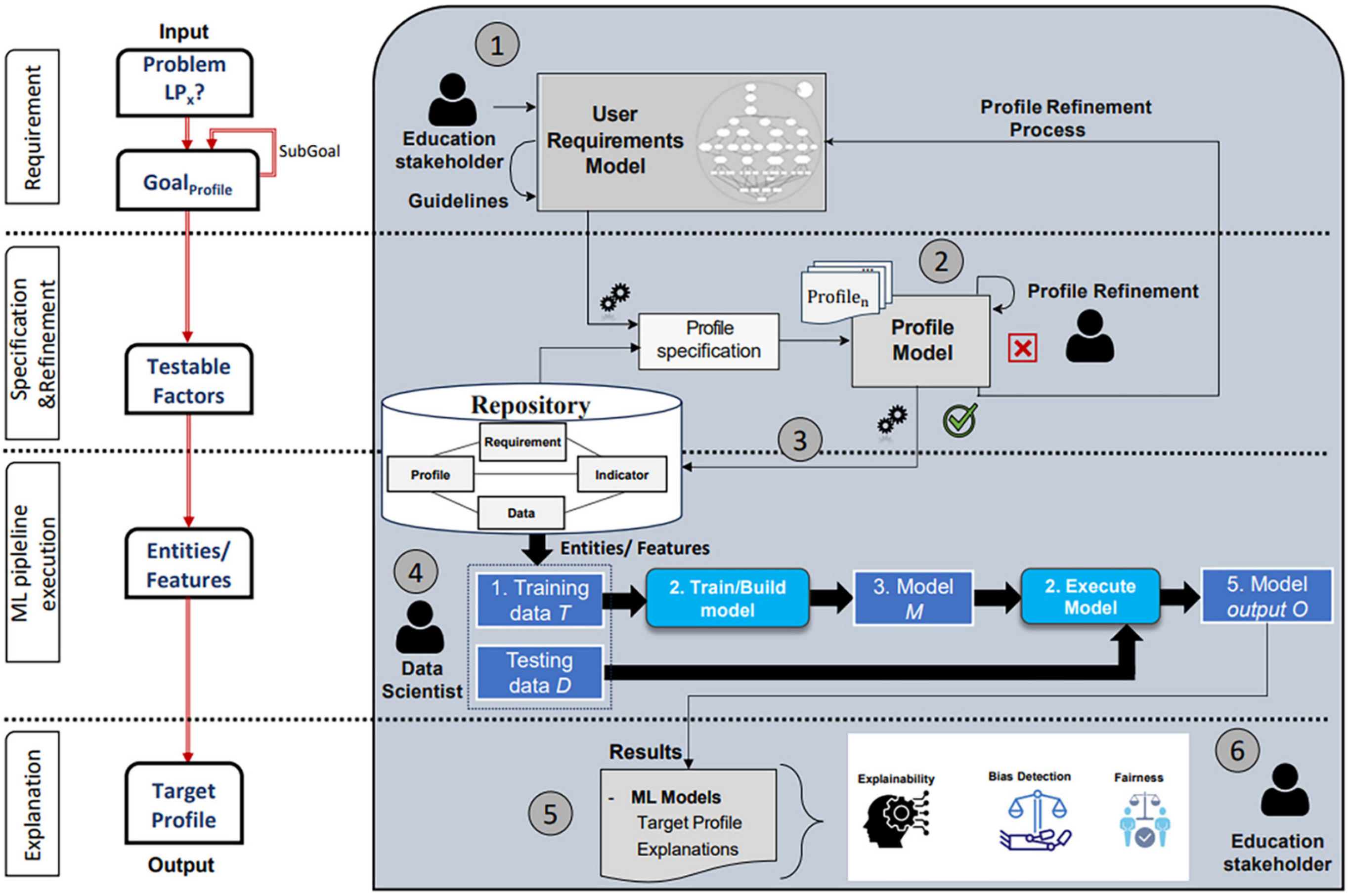

Fig. 2. Overview of our framework Req2XAI

3.1 Learner profile expression and storage

The process for expressing and storing learners profiles consists of five stages (see Figure 3): Expressing the LP (cf. 1), detecting relationships between learners' profile requirements (cf. 2), conducting a manual review of consistent profiles and indicators [cross-reader] (cf. 3), and ensuring profile persistency (cf. 4). We detail these steps in the following:

1. **Learner profile expression:** In order to define a learner profile in a structured way and to enable comparisons, each profile must be expressed using our design language that is a learner profile description language. Every profile is an instance that conforms to our formalism dedicated to enabling the creation and management of LP, including analysis, storage, and reuse, while maintaining an interactive process.
2. **Traceable and consistent:** Our framework ensures traceability and consistency through: (1) Automatic identification of direct and indirect requirement relationships. (2) Automatic consistency checking of inferred links. A requirement's domain is the union of its tasks and criteria. For instance, an Equal relationship between Req1 and Req2 is identified if their subjects, actions, objects, and criteria are equivalent.

3. **Manual review of consistent profiles:** As teaching needs evolve, learner profiles are revised by experts using predefined enumeration actions selected from RelevanceScore and ConfidenceScore lists. Revisions rely on two indicators: (1) Profile relevance (NOT, RELEVANT, VERY), where VERY indicates high-quality insights. (2) Reviewer confidence (NOT, CONFIDENT), where NOT triggers further review by experts, potentially leading to discussions for classification.

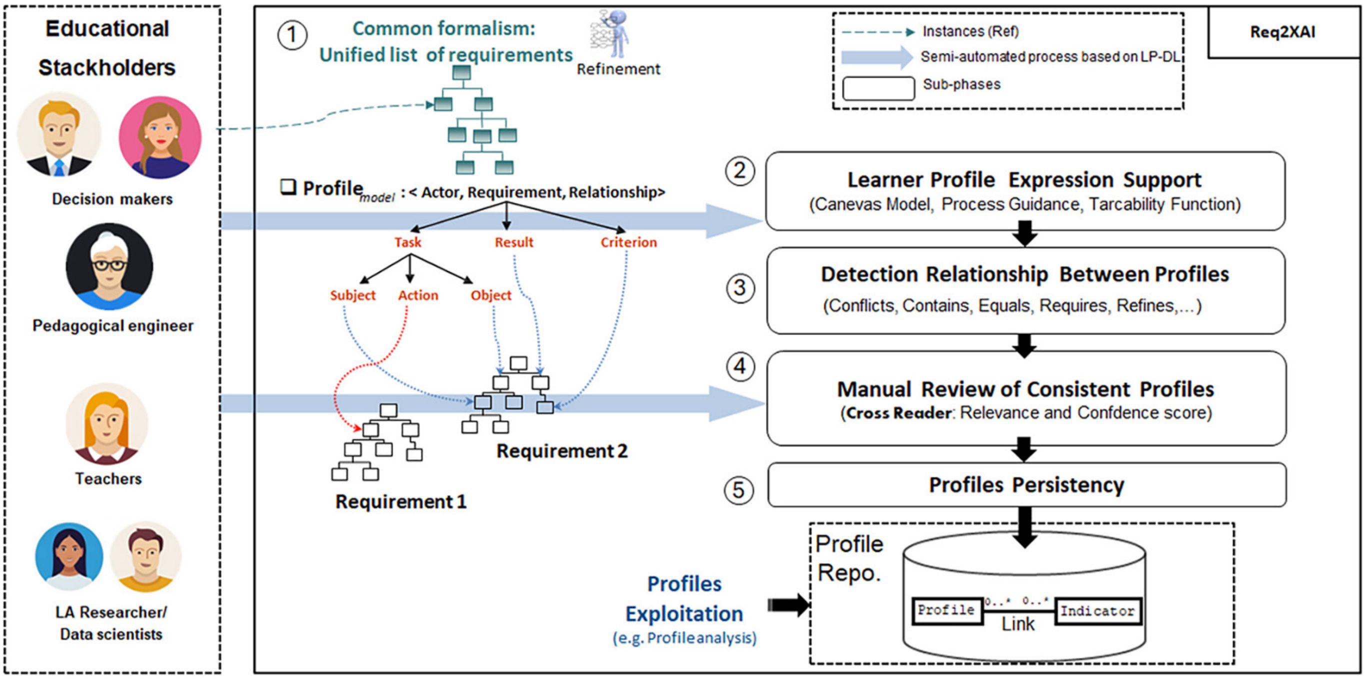

Fig. 3. Process of expressing and storing the learner profile

4. **Persisting of the consistent profile requirements:** In the requirements engineering (RE) life cycle, the final step focuses on capitalizing on profile requirements to track their current status (such as proposed, realized, analyzed, accepted, rejected, or replaced). In our approach, we introduce a process for capitalizing on LP requirements in a model based repository (see Figure 3). This method aims to maintain the relevance of LP, ensuring they continue to provide value to end-users across different contexts and over time as CRUD entities (*create, read, update, and delete*).

3.2 Linking LP requirements and ML models

The levels of nesting in the LP expression are designed according to the goals of educational stakeholders. The suitability of the detail level in profile analysis depends on the educational actor's background and requirements. However, validating educational stakeholders' goals could be achieved through high-level descriptions provided by our Goal Model (GM), which is refined through AND or OR splits. The GM is linked to vocabulary and common educational concepts, and its generator maps these concepts to the target LP and its metrics. This is achieved through the *LearnerProfileGoalMappingRelation* class, which provides a multi-level mapping of the target LP through type in-heritance at the profile level, learning objective level, and indicator level. This solution facilitates the understanding of different vocabularies, layered levels of abstraction in learner profile analysis, and the perspectives of the three main educational actors. We integrate ML models such as DT and RF to analyze learner profiles, extract patterns, and predict trajectories. Explainable techniques ensure transparency, aligning outcomes with stakeholders' needs. This approach bridges automated analysis with human understanding across vocabularies and abstraction levels.

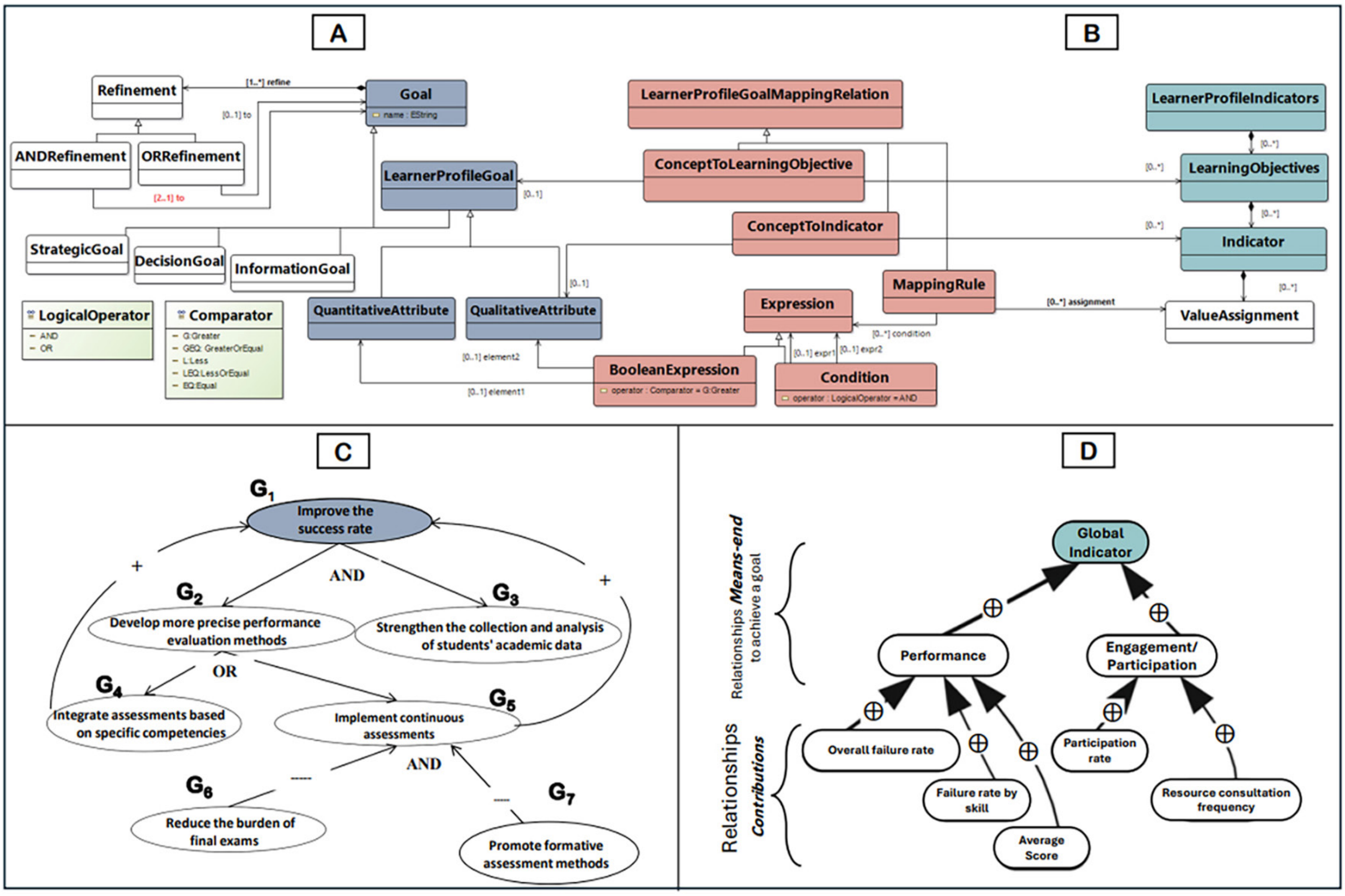

Fig. 4. **A:** Excerpt of Requirements model based on ***i**** goal-oriented modeling, **B:** Excerpt of the Indicator Calculation – Disaggregation Level using the mapping relation, depicted in pink, **C:** Analyze decision-makers' needs using a goal graph, **D:** A Goal achieved based on atomic and derived indicators

Figure 4 shows an example of validating educational stakeholders' hypotheses (goal or problem hypothesis G1) into sub goals (G1–G7) based on AND or OR refinement with their metric counterparts that involves breaking down complex metrics into basic ones, which are progressively combined into a comprehensive set of data indicators for stakeholders. Our framework keeps the user actively involved in the LP expression process thanks to our GM. The main intentional elements of GM represent goals with no clear criteria for their satisfaction. Additionally these intentional elements can be interrelated by using relationships such as Means-end (e.g. a task can be a mean to achieve a goal), Contributions (e.g., some resource could contribute to reach a quality concern or *softgoal*) and Decompositions (e.g., a task can be divided into subtasks). The data indicators and patterns generated by XAI models that impact the goal are modeled as *softgoals* and evaluated using contribution links in the global indicator. The evaluation can be qualitative, with the both values include (+), or exclude (–) as show in Figure 4. A *softgoal* is satisfied if there is more positive than negative.

3.3 XAI-driven dialogue interface for LP analysis

A novel process guidance framework assists users through this workflow, combining interactive visualizations with dialogue-based interactions. We propose an XAI-enabled dialogue-based interface for editing explanations, addressing bias and fairness, and validating stakeholder goals using interpretable ML (Decision Trees and Random Forests) with human collaboration. The interaction between the user and Req2XAI encompassing the essential interaction mechanisms between the user and Req2XAI to identify and locate interpretations for ML models, browse, locate them, and make edits. Our framework structures trust formation through a cyclical workflow: administrators adjust parameters (e.g., confidence thresholds), observe effects via visualizations, and document trust decisions using ordinal scales (e.g., "certain" to "doubtful"). Machine-readable formalisms encode decision rules and iterative feedback, ensuring reproducibility. Through the evaluation of our approach across three distinct use cases, we demonstrate the effectiveness of integrating the educational stakeholder's expertise with explainable machine learning.

4 PROOF OF CONCEPT

To demonstrate our approach's effectiveness, this section presents a global usage scenario and highlights technical implementations.

4.1 Learner profile as machine-interpretable entities

We have developed a design tool allowing creating and visualizing LP conform to our design language. The structure of the developed design tool is based on Java EMF (Eclipse Modeling Framework) API and has been integrated as a plugin in Eclipse which is an integrated development environment (IDE). Figure 5 sketches this structure where the abstract syntax of the formalism has been implemented using Ecore2 meta-modeling language and the implementation of concrete syntax is based on Sirius framework. Thanks to Sirius and *Ecore plugins*[1], users can instantiate their LPs in a user-friendly manner by using the Eclipse tree editor and a suitable properties tab. Figure shows an example of the instance that corresponds to the LP discussed in the motivating example (refer to Section 2). This instance indicates the goal, the different data indicators and the parameters related to the learning context. It also shows properties of some parameters. Through to the design tool, every LP instance is saved as an XMI format, hence every LP become a machine-interpretable entity which can be consumed easily by the front-end via several usages. At the end of the design, one can check the conformity of the LP instance. A set of structural rules, expressed as OCL invariants, has been added to the formalism.

[1] https://projects.eclipse.org/projects/modeling.ecoretools.

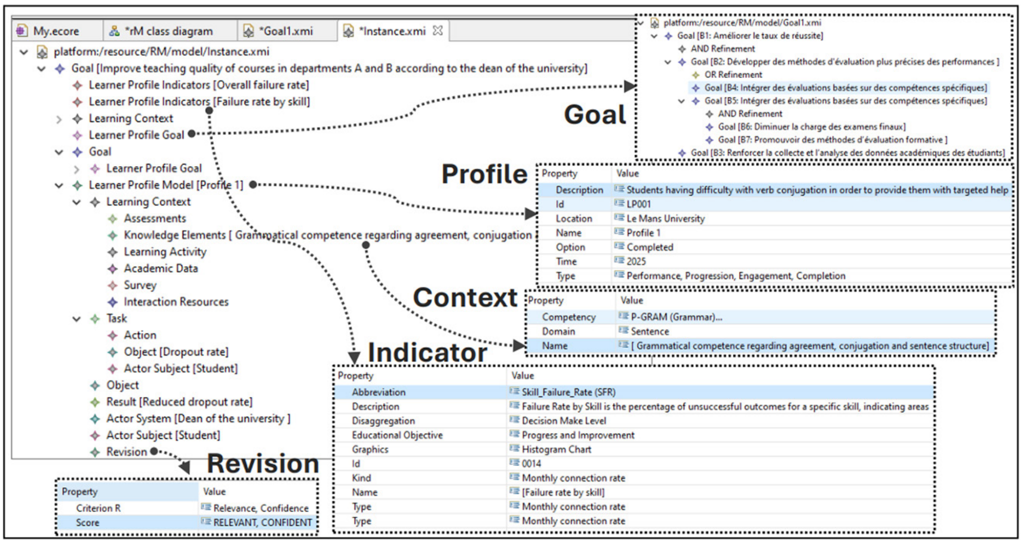

Fig. 5. Excerpt of the profile generated from user requirements

A combination of manually defined requirements and those elicited through collaboration with educational stakeholders was used to capture the target profile category. After identifying complex relationships, the global designer validates consistency and removes redundancies to ensure a structured set of requirements, particularly in educational contexts. Using our design tool's notation, we formalized these requirements to express semantic relationships such as *Equal*, *ConflictWith*, *Contain*, *Refine*, and *Require*. Table 2 shows relationships detected between learners' profile requirements. This formalization revealed 121 semantic relationships across four learner profile categories: Difficulty, Active/Inactive, Progress, and Engagement (refer to Table 2). The most frequent relationships were *Equal* (49), *Refine* (28), and *ConflictWith* (25), reflecting consensus, refinement, and contradictions among stakeholders. By analyzing these relationships, our tool inferred complex learner profiles from fragmented inputs, enabling refined interpretations such as "in difficulty and disengaged." This experiment confirms the tool's ability to formalize expectations and enable automated reasoning for adaptive learning.

Table 2. Relations detected in each profile category

Category	*Equal*	*ConflictWith*	*Contain*	*PartiallyRefine*	*Refine*	*Require*
In Difficulty	10 (71%)	2 (14%)	0 (0%)	0 (0%)	6 (43%)	2 (14%)
Active/Inactive	12 (67%)	8 (44%)	2 (11%)	0 (0%)	4 (22%)	3 (17%)
Progress	13 (72%)	10 (56%)	1 (6%)	0 (0%)	5 (28%)	5 (28%)
Engagement	14 (74%)	5 (26%)	1 (5%)	1 (5%)	13 (68%)	4 (21%)
Overall	49	25	4	1	28	14

4.2 Prototype implementation

We have developed a prototyping tool to support end users in higher education (see Figure 6). Our tool consists of two main components: (i) An interface for defining and storing LPs, (ii) An interface for searching LPs. Our tool allows users to browse, edit, and select existing LP. Moreover, it enables the automatic generation of target LP structures through an AND-OR split mechanism linked to the goal model and its generator. Each instance of LP is expressed in our design language and can be uploaded as an XMI file. Users can also download these files to store them in the repository, where they can be further edited and analyzed by other users. To search for a specific profile along with its related data indicators, the user's requirement is expressed via an interface based on our GM (see Figure 6). This interface captures the profile vocabulary requirements at a high level of abstraction, allowing for the definition of optional constraints or mandatory features. This approach enables designers to focus on user requirements and goals rather than low-level specification details. By analyzing the user's requirements as expressed through our GM, our prototyping tool recommends the relevant components of the target LP (e.g., a set of profiles, data indicators, learning context parameters, and additional explanations) based on the enabled goals. Moreover, users can review the generated LP and manually refine it according to their needs. Our tool facilitates the selection of LP in a transparent manner by providing identification rules and properties, ensuring an efficient and structured approach to LP modeling. These rules provide explanations for the arguments that logically lead to decisions and form the path leading to decisions from the target learner profile.

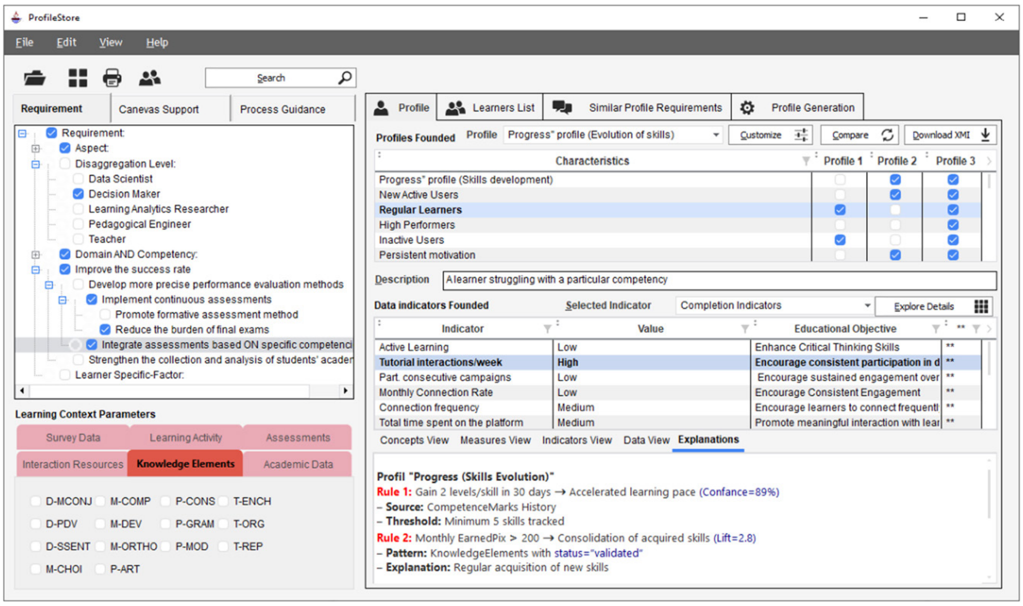

Fig. 6. Proof-of-concept prototype (Screenshots)

4.3 Validating educational stakeholders' hypotheses

Subsequently, we briefly present the validation of educational stakeholders' hypotheses using data and indicators. To support them in achieving their goals, it is essential to bridge the achievement gap between common educational concepts and a target LP. We conduct experiments to validate the Steering Committee's goals from the perspectives of two actors: decision-maker, and the pedagogical engineer, using a structured toolbox "Requirement", "Profile", "Indicator", and "Data" stored in our repository extracted from écri+ database. The Steering Committee of the écri+

project conducted two surveys: an early assessment to identify learners' needs and another to evaluate requirement satisfaction. The aim of the Steering Committee of the écri+ project is to validate two goals as shown in Figure 9: G1 (improving the success rate, associated with two hypotheses, (H1 and H2) and G2 (requirement not satisfied by learners, associated with two hypotheses (H3 and H4)). The effectiveness of the integration process largely depends on the quality of the matching phase. To assess this, we evaluated precision, recall, and F-measure widely used metrics for assessing alignment accuracy. These metrics compare the generated correspondences against reference alignments to measure reliability. For conceptual data integration, we relied on a predefined reference alignment ensuring consistency in entity and attribute matching. Similarly, the evaluation of linguistic data integration was based on an established lexical resource. The results, illustrated in Figure 7, highlight the performance of the matching process across different categories.

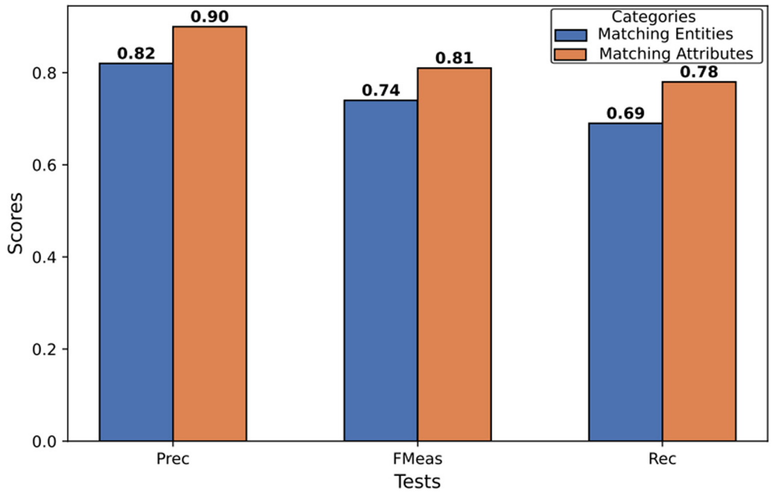

Fig. 7. Matching results

Figure 8 presents the top important features identified by XGBoost in the survey analysis for the pre-processed datasets, based on their positively/negatively impact on the students' scores in écri+. "Resources Consulted" is the most influential feature, followed by "Language (Native/Schooling)" with moderate importance. Other factors, such as "Field of Study," "Age," and "Type of Baccalaureate," have minimal impact.

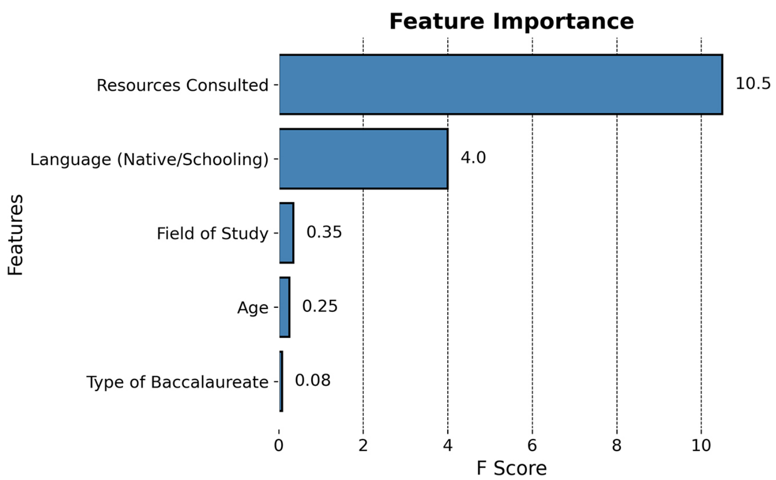

Fig. 8. Important features in the surveys for the datasets

Table 3 displays the generated rules from the dataset, showcasing how XAI-based models use these rules to assess and explain learner behavior. The rules help to build trust in the AI by providing transparent criteria for decision-making, allowing users to browse and understand the outcomes of the model.

Table 3. Generated rules based on our dataset

Line	Model	Rule	Score	Outcome
1	DT	**If** All knowledge elements of Word = "Yes" **and** All knowledge elements of Phrase = "Yes" **and** Login frequency > 20 **and** Improvement observed = "Yes"	High	85%
2	DT	**If** Some knowledge elements of Text = "Yes" **and** Not all knowledge elements of Discourse = "Yes" and Saved tutorials = "Yes" **and** Number of saved tutorials > 5	Medium	78%
3	DT	**If** Not all knowledge elements of Word = "Yes" **and** Unchecked resources = "Yes" and Abandonment Exists = "Yes"	Low	80%
4	DT	**If** French as Second/Native Language = "Yes" **and** Last Challenge ID = "Discourse" **and** All knowledge elements of Discourse = "No"	Medium	75%
5	RF	**If** (All knowledge elements of Text = "Yes" **OR** All knowledge elements of Discourse = "Yes") **and** Login frequency > 25 **and** Saved tutorials = "Yes"	High	85%
6	RF	**If** Some knowledge elements of Word = "Yes" **and** Some knowledge elements of Phrase = "Yes" **and** Number of saved tutorials > 5 **and** Unchecked resources = "Yes"	Low	88%
7	RF	**If** Last Challenge ID = "Discourse" **and** All knowledge elements of Discourse = "No" **and** If Abandoned < 10 = "Yes"	Low	82%
8	RF	**If** Number of saved tutorials > 5 **and** Unchecked resources = "No" **and** Improvement observed = "Yes"	High	87%

The overall accuracy of the ML models is depicted in Table 4. As before, RF has the highest accuracy (Precision = 81.13%, Recall = 0.708, and F-measure = 0.694 to DT, with (Precision = 70.40%, Recall = 0.743, F-measure = 0.725).

Table 4. Comparison of classification models for learner profiling

Model	Precision	Recall	F-measure	True/False Classified Instances
DT	70.40	0.743	0.725	(78.08%, 21.92%)
RF	81.13	0.708	0.694	(83.80%, 6.20%)

Assumption validation is color-coded from green (fully valid) to red (fully wrong). For example, LP3 in red is irrelevant to the goals, evaluated with exclude values (i.e. in Figure 9's legend, "*Full wrong assumption*" is shown in red.). We calculate the *SuccessRate* for each goal based on the contribution of the indicators from the learner profile.

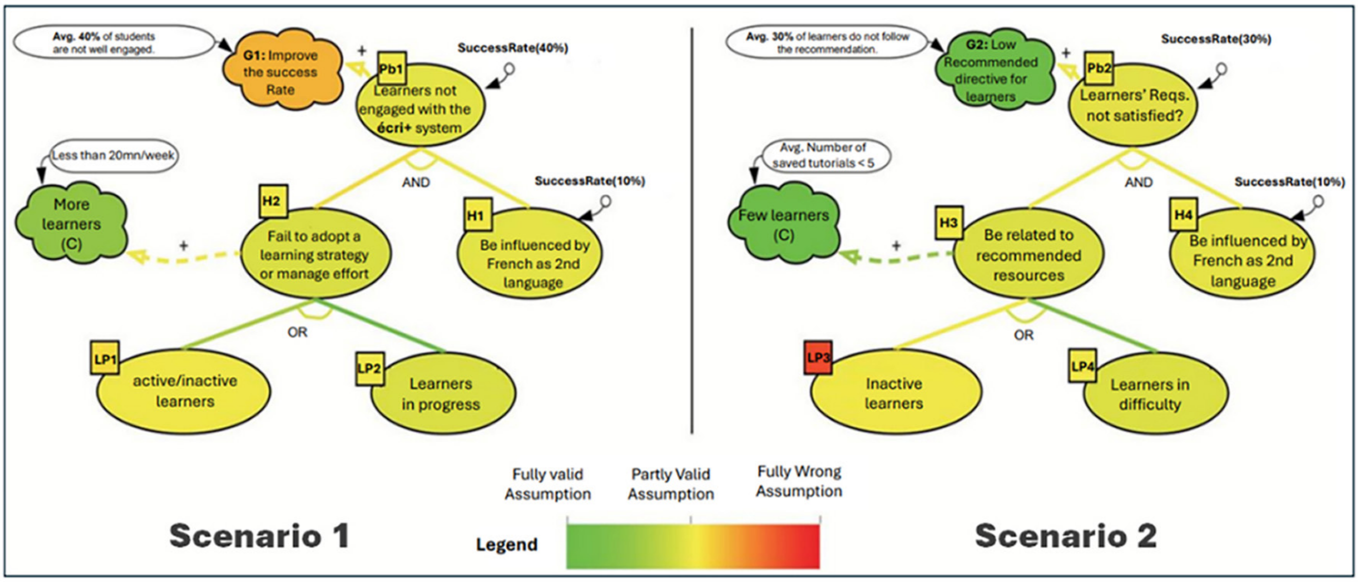

Fig. 9. Validating educational stakeholders' goals/problems corresponding to the motivation example

Table 5. Hypothesis validation with machine explanations

Stakeholders' Hypotheses	Decision Tree (%)	Random Forest (%)	Overall (%)
H_1	23.5%	21.2%	22.4%
H_2	76.5%	78.8%	77.6%
H_3	70.0%	71.5%	70.8%
H_4	30.0%	28.5%	29.2%

Table 5 illustrates two scenarios of validating educational stakeholders' hypotheses (goal or problem hypotheses) (G1, G2) through the automated validation of the generated XMI format. Each problem is mapped to its corresponding hypothesis (H1, H2), which, in turn, is linked to the relevant LPs through semi-automatic or manual mapping. The target LPs (LP1–LP4) are computed based on respective indicators and data, thanks to our formalism. In the first scenario, validation is achieved with a *SuccessRate* of 40%, relying entirely on assumptions based on average data indicator calculations. In contrast, the second scenario is only partially validated, with 30% of learners contributing to goal validation. We believe that offering diverse alternatives for LP specification, tailored to educational stakeholders, improves learner profile identification and addresses all requirements. Req2XAI bridges the gap between educational stakeholders' perceptions and learner profiling by employing conceptual models that explicitly connect stakeholder requirements with XAI models and underlying data, thus eliminating reliance on direct data manipulation. In addition, Req2XAI unifies multiple requirements by considering diverse knowledge and experiences, and helps stakeholders evaluate alternatives, relax constraints, and resolve conflicts to achieve optimal trade-offs.

5 CONCLUSIONS

Understanding LPs is crucial for educational stakeholders to support learners and track competency trajectories, but their multidimensional nature can obscure comprehension. This study proposes a framework that aligns abstract domain knowledge with ML insights, addressing the gap between stakeholders' mental models and ML outcomes. Stakeholders' categorizations, such as at-risk or success-oriented behaviors, often differ from ML patterns due to biases and interpretability challenges. Our framework establishes a bidirectional mapping to enhance explainability, mitigate biases, and reconcile contradictions in data interpretation, such as misinterpreting frequent interaction as engagement. This work contributes to responsible LA by prioritizing human-centered explainability. Future research includes formalizing bias in our model, developing a bias manipulation framework, and experimenting with bias mitigation strategies in educational ML pipelines. This will foster discussions on ensuring fairness in educational ML systems.

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8 AUTHORS

Abdelkader Ouared is with the LIUM Computer Science Laboratory, University of Le Mans, Le Mans, France (E-mail: abdelkader.ouared@univ-lemans.fr).

Madeth May is with the LIUM Computer Science Laboratory, University of Le Mans, Le Mans, France (E-mail: madeth.may@univ-lemans.fr).

Claudine Piau-Toffolon is with the LIUM Computer Science Laboratory, University of Le Mans, Le Mans, France (E-mail: claudine.piau-toffolon@univ-lemans.fr).

Nicolas Dugué is with the LIUM Computer Science Laboratory, University of Le Mans, Le Mans, France (E-mail: nicolas.dugue@univ-lemans.fr).