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LEARNING MOTIVATION: PREDICTIVE MODEL WITH MACHINE LEARNING ANALYSIS

MOTIVAZIONE ALL'APPRENDIMENTO: MODELLO PREDITTIVO CON ANALISI ATTRAVERSO IL MACHINE LEARNING

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Abstract
The direction of development undertaken by the world of research in the field of education has gradually been oriented to the identification of tools capable of collecting and implementing the considerable amount of data that can be extrapolated in this context, in order to identify improvement trajectories common to the various application scenarios. Therefore, the operationalization of the numerous theoretical paradigms linked to education plays a prominent role. In this sense, learning motivation is one of the most studied constructs in the field of educational neuroscience, due to the implications associated with it in mediating learning processes. Within this context, the project presented aims to operationalize the learning motivation through the inclusion of specific factor variables (socio-demographic, cognitive, affective and intra-individual) in a machine learning algorithm, structured on the basis of the evidence in the literature on the characteristics that allow to identify the construct at an inter-subjective level. This algorithm is part of the wide range of studies related to Educational Data Mining, with the aim of structuring a predictive model that allows to outline the various profiles of learning motivation of individual students, with the aim of creating a useful tool to identify appropriate learning paths customized on the basis of the motivational characteristics of each student.

La direzione di sviluppo intrapresa dal mondo della ricerca in ambito educativo si è progressivamente orientata all'identificazione di strumenti capaci di raccogliere e implementare la notevole mole di dati estrapolabile in tale contesto, allo scopo di identificare traiettorie di miglioramento comuni ai vari scenari di applicazione. Dunque, riveste un ruolo di primo piano l'operazionalizzazione dei numerosi paradigmi teorici legati all'educazione. In tal senso, la motivazione all'apprendimento rappresenta uno dei costrutti maggiormente studiati nell'ambito delle neuroscienze educative, a causa delle implicazioni ad essa associate nel mediare i processi di apprendimento. All'interno di questo contesto, il progetto presentato si pone l'obiettivo di operazionalizzare la motivazione all'apprendimento attraverso l'inserimento di specifiche variabili fattoriali (di natura socio-demografica, cognitiva, affettiva e intra-individuale), in un algoritmo di machine learning, strutturato sulla base delle evidenze presenti in letteratura relativamente alle caratteristiche che permettono di identificare il costrutto a livello inter-soggettivo. Tale algoritmo si inserisce all'interno del vasto filone di studi relativo all'Educational Data Mining, con l'obiettivo di strutturare un modello predittivo che consenta di delineare i vari profili di motivazione all'apprendimento dei singoli studenti, con la finalità di creare uno strumento utile

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all'identificazione di adeguate traiettorie formative personalizzate, sulla base delle caratteristiche motivazionali proprie di ciascuno studente.

Keywords

Machine Learning, Educational Data Mining, Learning Motivation

Machine Learning, Educational Data Mining, Motivazione all'apprendimento

1. Introduction

The study of the elements characterising the complexity of learning processes has undergone a significant evolution over the last decades, due to the development of increasingly accurate analytical techniques that have made it possible to change the perspective through which to observe the mechanisms underlying the learning processes (Thomas et al., 2018). The latter, in fact, have traditionally been studied by taking into account only the variables related to the student's performance, through the use of assessment tools aimed at reconstructing a framework of competences indicative of the level achieved by the learner (Kuncel et al., 2004). Such methods, although undoubtedly useful in terms of application, have the limitation of considering the student's effectiveness only on the basis of performance in specific profit tests for each teaching (Meleddu & Scalas, 2009).

The numerous evidences coming from the field of educational neuroscience have allowed to revolutionize this paradigm, shedding light on brain mechanisms related to learning that are differentially influenced by the numerous variables involved in the educational process (Thomas et al., 2018). Indeed, the study of the neural correlates of learning has highlighted the relationship existing between cognitive, affective and behavioural factors and to outline explanatory models that allow their operationalisation (Gallistel & Matzel, 2013). In this scenario, learning motivation, one of the most studied constructs in the field of educational neuroscience, plays a major role due to its fundamental role in mediating learning processes (Filgona et al., 2020).

In psychology, the construct of motivation arose in response to the need to investigate all those phenomena that take part in determining behaviour and that give it unity and meaning (Froiland & Worrell, 2016). Due to its latent nature, after more than a century of studies in this field, researchers have not yet been able to identify an unambiguous definition of learning motivation. Generally speaking, a particularly effective attempt at an explanation was made by Elliot and Church (1997) and subsequently taken up by Wigfield et al. (2006), who defined the construct as "the enactment of certain behavioural patterns with the aim of achieving a goal".

This definition is useful to frame learning motivation as a dynamic and multidimensional construct. In fact, motivational mechanisms consist in the activation of a series of cognitive-behavioural patterns that allow to adhere to a goal, activate a behaviour, modulate the intensity of the action and persist in achieving it (Filgona et al., 2020; Piceci & Barbieri, 2022).

Considering the construct from this point of view means adopting a multifactorial approach across very broad domains of a cognitive, affective and socio-cultural nature. Among the strands of study dealing with the analysis of education-related variables from a predictive perspective, Educational Data Mining occupies a prominent role, as it aims to answer questions from the educational environment by combining disciplines such as statistics, probability

calculus and machine learning, providing a valuable decision support tool (Dutt et al., 2017). In this sense, the study presented aims to operationalise learning motivation through the identification of specific factorial variables and the processing of these through a computational algorithm for the construction of a predictive machine learning model, structured on the basis of evidence in the literature. The algorithm in question makes use of cluster analysis to form subgroups based on motivational profiles, since the methods of analysis based on the search for causality between variables, such as regression analysis, do not allow us to understand the trajectories of the different motivational patterns (Zhao et al., 2020).
The aim of this study is to provide teachers and trainers with a tool that can be used to design learning trajectories that are tailored to the characteristics of each student. The project in question is therefore structured according to an integrated approach, in order to identify clusters of individuals within the school population on the basis of specific domains and properties.

1.1 Neural correlates of motivational processes

The implementation of high-level behavioral patterns depends on a series of neural patterns that converge systematically at the level of the cingulate cortex (Rolls, 2019). This area of the brain is involved in the mechanisms of attribution of the emotional salience of the stimuli, through a complex phase of information processing in and out operated by the three sections into which this vast portion of the brain is divided, namely: rostral (anterior), dorsal (medial) and caudal (posterior) (Mendes & Park, 2014). The analysis mechanisms in question concern the decoding of a series of processed environmental data by assessing based on the representations in memory, that reach the anterior cingulate cortex through projections from the hippocampus (Rolls, 2019; Bryant & Barker, 2020). This process happens very quickly because the comparison between present and stored representation is made based on the recognition of the salient characteristics of the stimulus that elicited a variation of the basic arousal dependent on the decoding of the valence emotional by the amygdala (which in turn receives inputs from sensory areas such as the primary visual cortex) whose connections to the nerve centers of the brain stem responsible for neurovegetative control determine physiological reactions (e.g. alterations at the level of Hearth Rate Variability) whose cognitive processing is carried out by the medial cingulate cortex based on inputs from the mentioned subcortical structures (Cunningham & Brosch, 2012). The subsequent activation of a given behavioral response depends on the connections between the posterior cingulate cortex that deals with processing information from the medial portion to structure action patterns in the form of output directed to the premotor areas (Rolls, 2019; Salamone et al., 2015). The implementation of such schemes depends on the mediation of the orbitofrontal cortex that allows the creation of prospective representations relative to the results of the actions to be performed (Rolls, 2004).
These neurobiological mechanisms are mediated by a series of intra-individual factors (such as perceived self-efficacy and the type of locus of control) and context that determine the structuring of the macro elements that act as the arrival point of motivated behavior: the objectives. These play a fundamental function in self-regulation and directing the motivational processes, of which the objectives are both predictors and modulators (the motivation changes in relation to the variability of the objectives over time) (Froiland & Worrell, 2016). As explained above, cognitive systems that support goal-oriented behavior have mechanisms of a conscious and unconscious nature. The latter can be defined as pre-motivational factors and

are manifested through rapid and automatic reactions attributable to approach and avoidance behaviors (Elliot, 2006). The purpose of the project presented is precisely to analyze these factors to identify the mechanisms common to all individuals (excluding the presence of any pathologies) that allow the subject to "adhere" whether or not to a target and according to which trajectories of action (approach or avoidance) (Phaf et al., 2014). In this case, the objective is referred to as a specific target that acts as a trigger of motivational processes and that represents only one element of the macro objective towards which the behavior is directed (Froiland & Worrell, 2016; Phaf & Rotteveel, 2012). In the case of learning motivation, it is possible to explain this principle by identifying a hypothetical main objective in the examination promotion and a micro objective in learning the contents of a given course module. In this case, the pre-motivational processes can be detected when the subject has to approach the study of the teaching material.

1.2 Learning motivation

Several shreds of evidence in the literature show that high levels of learning motivation are associated with better school performance and a more functional classroom climate for effective training (Filgona et al, 2020). Motivation is a well-studied construct in the field of educational neuroscience and represents an important moderating variable of the behavior of the individual, since it determines the amount of personal resources to be employed in a task, attributes a target to cognitive and affective processes and supports the persistence to act in order to achieve a specific goal (Froiland & Worrell, 2016). The line of research that over the years has been concerned with enhancing the construct in question has shown that the motivation to learn is not associated exclusively with academic and academic performance but also with creativity (Gibbens, 2019) productivity (Kuncel et al., 2004) and resilience (Bakar, 2014). Seifert and Sutton (2009) noted that motivated behavior is modulated by the type of objectives to be met that can be grouped into three main macro-categories: mastery, failure-avoidance and social contact. This classification, although not exhaustive, allows highlighting the differential weight of subjective intra-individual factors unrelated to the subject to be learned. In this sense, the typology of locus of control plays a fundamental role, which concerns the way of attributing the causes of success and failure, therefore the subjective perception of the degree of correlation of a given event with factors such as personal skills, task difficulties and luck (Schipor & Schipor, 2014). It is therefore important that teachers are trained in the recognition of the basic mechanisms of learning processes and that they are able to set up training courses that encourage all students of the course but also allow a certain degree of customization. This aim can be pursued through the study of the general cognitive and affective processes underlying the acquisition of new knowledge, based on which it is possible to identify models of functioning of psychic activity that allow eliciting common patterns of learning motivation and that take into account individual differences. It is therefore necessary to implement the characteristics of the teacher that allow him to transcend the role traditionally assigned to him as a mere dispenser of knowledge and enhance his task as a facilitator of learning paths. The existence of a large number of definitions of motivation indicates the difficulty in describing the construct in relation to education (Filgona et al., 2020). Motivation has been defined as the behavioral process that allows the implementation of self-regulation mechanisms concerning the body’s internal and external environment (Salamone, 2010) involving factors of a sensory, motor, cognitive and emotional nature. The complexity inherent in the study of motivation requires the overcoming of rigid explanatory paradigms, intending to seek the elements common to the models proposed by scholars over time. In this sense, it is necessary to use research strategies that enhance the connecting points of the various constructs related to learning motivation in order to structure theoretical models generalizable to the various areas in which it is possible to meet the domains in the object. This conceptualization places in the foreground the possibility of identifying motivational profiles, based on which lead back to the changing characteristics that motivated behavior assumes at the inter-objective level (Bråten & Olaussen, 2005). The creation of these profiles requires careful analysis of cognitive, affective and behavioral manifestations related to learning motivation in the general population.

2. Educational Data Mining

The analysis of motivational profiles and patterns has the advantage of first providing the researcher, and then the educational institution, with a greater understanding of how various motivational structures are organised (Linnenbrink & Pintrich, 2003).
The aim of the project, in line with the literature, is to use each student's own characteristics and domains to extrapolate subgroups of individuals (Oyelade, Oladipupo & Obagbuwa, 2010) on the basis of motivational behaviour, then make available a tool capable of placing each new individual within the reference cluster and thus guide interventions on the basis of the characteristics that determine membership of one subgroup rather than another (Jamesmanoharan, et al., 2014).
The studies carried out in this area, in most cases, have been conducted with basic methods such as simple comparisons between averages, percentages and calculations of correlation coefficients that are ineffective for the problem posed and above all unsuitable for processing the amount of data necessary for cluster analysis (Meleddu & Scalas, 2009). For this reason, the tool proposed in this research is part of the vast strand of Educational Data Mining. Integrating artificial intelligence and machine learning techniques, represents at this point in history no longer a valid alternative but the natural evolution of statistical analysis (Paul et al., 2021).
Educational Data Mining plays a key role, through the design of models and algorithms, in advancing the academic environment by providing accurate predictions of student and teacher behaviour and performance (Peña-Ayala, 2014). Moreover, it represents a valuable decision support tool because it aims to identify data patterns, organise information about hidden relationships, structure association rules and estimate the values of unknown elements to classify objects. In the course of student-teacher-academic interaction, it acquires input and interprets its meaning by suggesting adaptive recommendations (Albreiki et al., 2021).
The outputs of Educational Data Mining are designed to respond to two fundamental tasks: description and prediction (Aleem & Gore, 2020). Descriptive models seek to extract useful information in order to explain and process the intrinsic structure of the distribution, correlations and various interconnections formed by the attributes and features of the data; unsupervised learning or deep learning is used to accomplish these tasks (Carbonell, Michalski, & Mitchell, 1983).
Predictive models, on the other hand, use supervised learning to estimate unknown values or possible dependent variables based on the features of the independent variables (Kotsiantis et al., 2007). The model is trained on a training dataset where the inputs (independent variables) and outputs (dependent variables) are known (Jiang et al., 2020) and all it has to do is calculate,

and adjust from time to time, the Weight and Bias of the function in order to best intercept the data it has available and provide accurate predictions on subsequent information (Yin et al., 2019).

Clustering techniques, used in this study, fall under the descriptive analysis of unsupervised learning. Clustering in machine learning can be defined as the identification of similar classes of objects (Romero & Ventura, 2007). The aim of the model is to identify distribution and correlation rules between data attributes and to be able to highlight dense regions in the object space to identify groups and anomalies.

Educational Data Mining follows precise steps to be able to extract information useful for the production of new knowledge: data collection and storage, selection, transformation, actual data mining, evaluation of the accuracy of the results and communication of these results (Baradwaj & Pal, 2012).

Descriptive analyses of the student population and the detection of behavioural anomalies, at the beginning and throughout the learning phase, helps universities to develop effective intervention plans for the benefit of students, teachers and the management that has to manage and allocate available resources (Kuncel et al., 2004).

Machine learning, as a branch of artificial intelligence, allows computers to learn from their environment by augmenting patterns that can guide machine decisions (El Naqa & Murphy, 2015). Consequently, in a field such as academia, it allows us to shed light on all those factors capable of linking learning, academic success and the specific characteristics of each student that remain unknown to this day, after centuries of research.

The model implemented in this study is the DBSCAN (Ester et al., 1996). As a clustering method, it provides for the grouping of data on the basis of density, because it connects regions of points with sufficiently high concentration of information (Khan et al., 2014).

It requires only two parameters: epsilon (ε) and minPoints (Rahmah, & Sitanggang, 2016). Epsilon provides the radius of the circle to be created around each point in the database to check the density (Ozkok, & Celik, 2017). MinPoints correspond to the minimum number of data points required within that radius in order to define clusters (Kumar & Reddy, 2016). Points can be: core points, if located in the centre of ε; border points, if they are at the end of ε and have a core point nearby; noise points if they do not fall within any cluster (Kryszkiewicz & Lasek, 2010). The main advantage of the DBSCAN is summarised in its ability to identify the number of actual clusters within the database, without having to establish this a priori (as in other models, e.g. K-means) (Sinaga & Yang, 2020).

"DBSCAN uses a definition of clusters based on the notion of density-reachability. A point X is directly reachable from a point Y if their distance is less than an assigned ε (i.e., it is part of its ε-neighbourhood) and if Y is surrounded by a sufficient number of points, then Y and X can be considered parts of a cluster" (Tran et al., 2013).

It allows, therefore, to identify arbitrary data distributions and to be able to highlight values in dense areas, not limiting its effectiveness only to distinct datasets (Chakraborty & Nagwani, 2014).

3. Integrated model of learning motivation: structure and paradigm

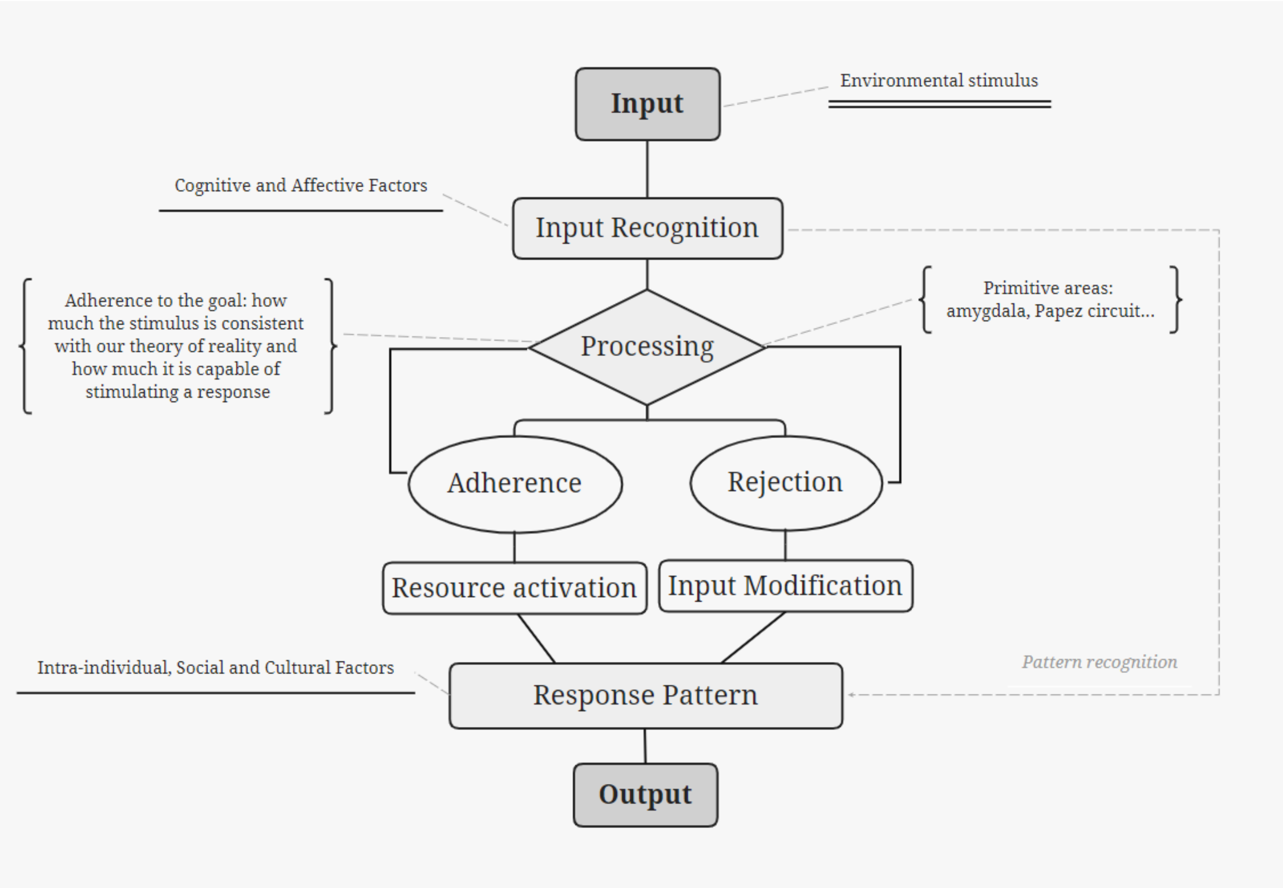

Fig. 1: Research paradigm flow chart

4. Materials and methods

The identification of motivational clusters to be attributed to each student goes through a systematic process of analysis through which it is possible to attribute a differential weight to the variables considered from a predictive point of view. Each model, however, requires a dataset on which to be trained and, in the case of the study in question, this is built on the basis of indicators of a cognitive and affective nature of the pre-motivational processes at the basis of the behavioral patterns implemented in order to obtain a result. Figure 1 shows an explanatory flowchart of the sequence of processes that, starting from a preliminary step of stimulus recognition, allows the subject to define patterns of action-oriented toward the achievement of the goal. The sequence described begins with a phase of sensory decoding of an environmental stimulus, followed by identification mechanisms monitored at a cortical level by the dorsolateral prefrontal cortex, directly involved in the processes of approach and avoidance (Spielberg et al., 2012). That is, respectively, the set of emotional, cognitive and behavioral factors elicited by the desire to achieve a goal or avoid an adverse situation (Van Dessel et al., 2018; Elliot, 2006). The dual behavioral direction is undertaken on the basis of the integration of sensory information operated by the basal ganglia and the mediating action of the amygdala, which determines the motivational salience of the stimulus (Cunningham & Brosch, 2012; Phaf et al., 2014). These elaboration processes occur outside of consciousness and allow the structuring of basic cognitive schemas with positive or negative affective valence, on the basis of which the subject in question is led to adhere or not to the learning objectives (Phaf & Rotteveel, 2012; Bryant & Barker, 2020). In this sense, the impact of executive and attentional functionality plays a major role, which, through the synergistic action of the dorsolateral prefrontal cortex and the orbitofrontal cortex (Rolls, 2004; Mendes & Park, 2014), allows the activation of filtering and environmental control mechanisms aimed at obtaining the information needed by the anterior cingulate cortex for the implementation of behavioral strategies whose purpose is the achievement of the learning goal (Van Dessel et al., 2018; Rolls, 2019). The final output, however, will not be the result of pre-motivational processes alone but will also be influenced by other factors of an intra-individual and socio-demographic nature.

4.1 Research project

The experimental procedure is divided into three phases within a training course, during which a series of assessment instruments will be administered to obtain data useful for structuring a dataset, based on which the machine learning algorithm will be trained. In this sense, the information obtained will be systematized within specific clusters that will allow the elaboration of motivational profiles for each student (Bråten & Olaussen, 2005).

The first step of the project takes place at the beginning of the course through the assessment of students in the key domains that determine the construct of motivation to learn. In this sense, a questionnaire is administered to collect socio-demographic, intra-individual (self-efficacy and locus of control) and cultural data. Next, a Stroop Test in digital version will be administered for the assessment of selective attention and executive functions (Scarpina & Tagini, 2017; MacLeod, 1997; Normah & Edbert, 2019), followed by a 2-back for the analysis of working memory (Meule, 2017). The information obtained through this last testing phase is useful for the identification of cognitive profiles underlying the pre-motivational processes under study. The latter are the result of the synergistic and complementary action of factors of a cognitive and affective nature, the analysis of which is affected by the short time interval in which they occur (Spielberg et al., 2012). The assessment of affective states is carried out through the analysis of approach/avoidance behaviors using a VAAST (Visual Approach/Avoidance by Self Task), i.e. the set of emotional, cognitive and behavioral factors elicited by the desire to achieve a goal or avoid an adverse situation (Aubé et al., 2019). The stimuli presented through this modality are related to the educational content that students encounter during the study and are of textual and iconic types. The first type of these is also used for the stimuli of an alternative version of the Stroop Test, in order to use the paradigm underlying the instrument in an analysis protocol aimed at investigating the mechanisms of inhibition, concerning the motivational salience intrinsic to the educational content (Lamers et al., 2010; Parris, 2014). Instead, a series of stimuli in the form of images is presented within a modified 3-back, aimed at analyzing the updating capacity of working memory related to the motivational elicitation of the topics covered (Gajewski et al., 2018).

This type of survey is followed by a second evaluation phase at mid-course through the administration of a self-report questionnaire for the analysis of the impact of the teacher's teaching strategies on learning motivation (Student Outcomes Survey; Author: Peter Fieger).

At the end of the training, a phase of evaluation of the knowledge learned in class takes place. During this third step, a Convolutional Neural Network model is used for facial expression recognition using DeepFace, Retina Face and the FER library (Parkhi et al., 2015). This tool allows to process the fluctuations of the emotional state experienced during a monitoring time interval and to derive from this information the elements that determine the occurrence of approach and avoidance behaviors, indicative of the different types of pre-motivational processes (Phaf & Rotteveel, 2012; Phaf et al., 2014).

5. Discussions

The project presented here is part of a series of studies investigating the use of Machine Learning models in the implementation of training programs (in this case, university courses). Recent innovations in the methods of analyzing learning processes have highlighted the importance of using increasingly accurate tools for evaluating training outcomes not only in terms of performance. In this context, Educational Data Mining has made it possible to deepen the study of contextual factors that intervene in mediating effective learning. These factors constitute the fabric of the educational environment, involving all the actors involved in the educational process in an integrated and complementary way. The study of single pedagogical variables has shown all its limits as regards the possibility of isolating specific learning domains from the educational context of reference. It is, therefore, necessary to use systems of analysis that allow the study of a multiplicity of data of different nature and the integration of these in explanatory models that offer an overall view that is exhaustive in the presentation of the principles under study but also sufficiently ductile towards the innovations that follow one another in educational research. This desired fluidity can be obtained through the structuring of constructs correlated to multidimensional learning processes that allow the establishment of precise trajectories of investigation and that provide operational indications that are applicable in training courses. The study in question is part of this direction, going to analyze learning motivation in the variables that define it at an individual and contextual level from a predictive point of view. In this sense, the creation of a machine learning algorithm represents the final phase of an analysis process that has made it possible to identify the operating mechanisms of motivational processes, emphasizing the role of cognitive and affective components before the implementation of goal-directed behavior, which are configured as pre-motivational factors differentially influenced by socio-demographic and intra-individual variables.

6. Conclusions

The database that emerges from this study contains data of a multifactorial nature obtained through a research method characterised by an integrated approach, which has made it possible to adopt a holistic and vertical view of the individual.
The results reported by this research, in short, have important application implications in terms of:

- Creation of personalized educational paths, calibrated on the motivational profiles of the students;
- Possibility of a targeted orientation on the characteristics of each individual;
- Logistical and functional reorganization of classes, based on the subgroups that emerge.

Furthermore, focusing the studies on predictive algorithms allows to work on two levels of intervention: at individual level, the presented model helps educators to recognize drop-out risk factors and intervene promptly. At the population level, it is possible to identify endangered, underperforming or particularly gifted groups to be reported to the management, which thus obtains a crucial support in the decision-making process for the mobilization of resources.
Like any study, this research is not without its limitations. Firstly, due to the characteristics mentioned above, the model presented requires a rather large experimental sample (over 500 cases); secondly, the construct under examination, as presented, needs to be further developed (currently in the experimental phase) because its dynamic nature makes its tracking complex; finally, the chosen model needs to be tested on the features that make up the database to verify its levels of accuracy, since the distribution of the data is unknown and until it is known, it is not possible to say with certainty which clustering model is more effective.
We reserve for future developments the possibility of overcoming these limitations and building a tool that can evolve and progress over time.

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