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Intelligent Guidance System: AI Approach to School Choice Alignment Based on Multidimensional Data

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Abstract

School career guidance plays a fundamental role in the educational success and professional integration of learners. In a context marked by the massification of education and the growing heterogeneity of profiles, traditional guidance systems, based essentially on academic performance, are no longer sufficient to guarantee an optimal match between students' potential and the courses of study they choose. This article addresses this issue by exploring an artificial intelligence-based approach, using a multinomial logistic regression model incorporating ten variables: six academic grades out of 20 and six soft skills out of 5. A simulated base of 100 students was used to train a supervised model capable of recommending one of five typical streams. The results showed an accuracy rate of 87%, with 75% of students showing a behavioral compatibility of over 80% with the predicted pathway. Radar analysis revealed significant differences in creativity and autonomy, underlining the value of a fine-tuned reading of profiles. This article highlights the relevance of an AI-assisted guidance system, capable of cross-referencing multidimensional data to propose more accurate, personalized choices aligned with students' actual skills.

Keywords

Academic Guidance, Artificial Intelligence, Predictive Model, Multinomial Logistic Regression, Soft Skills, Academic Results

1. Introduction

School orientation represents a decisive step in the educational journey of students, directly influencing their academic success, professional integration, and personal fulfillment. In a constantly evolving socio-economic environment—characterized by the rapid transformation of professions, the emergence of new skills, and the increasing rates of reorientation in higher education, it has become crucial to adopt more effective decision-support tools based on objective data. Traditional guidance methods, often grounded in subjective advice or limited assessments, are now showing their limitations. This observation raises a fundamental issue: how can we reliably and personally guide students toward academic tracks that best match their academic abilities, transversal competencies, and the demands of the labor market?

This article offers an innovative response through the development of a multicriteria predictive artificial intelligence model, designed to analyze students' academic performance and predict the most suitable educational path for each profile. The model leverages supervised learning algorithms using pedagogical data (subject-wise grades) combined with behavioral competency assessments for each student.

The objective is to deliver an automated, transparent, and scalable system that can enhance both the efficiency and fairness of the academic orientation process. This research is part of a broader vision of sustainable pedagogical innovation, where artificial intelligence serves as a lever for transforming educational practices.

The structure of the article is organized as follows: a literature review, the proposed model, and the simulation conditions, followed by the analysis and discussion of the results, leading to the conclusion of this scientific contribution.

2. Bibliographical Review

The integration of Artificial Intelligence (AI) into education has led to innovative approaches to school guidance. Niittymäki and Paananen (2021) highlight the emerging need for personalized educational counseling supported by AI, showing that these technologies allow for a comprehensive consideration of the student's profile beyond academic performance alone [1]. Naqvi (2025), in an article published on the eLearning Industry, explains how AI-powered personalized platforms will transform educational support methods, with a focus on the adaptive adjustment of pedagogical content [2]. Singh (2025), through a theoretical study published on SSRN, explores the predictive potential of AI to design individualized pathways based on learners' behavioral data [3]. Kosarevich (2025), in an article published by GSI Education, states that AI systems will become mainstream in personalized learning by 2025 by automating the matching between competencies and orientation [4]. Maity and Deroy (2024), in a preprint on arXiv, describe how tutorial systems based on large language models can generate orientation recommendations according to students' learning styles and dynamic performance [5]. Likewise, Sajja, Sermet, Cikmaz, Cwiertny, and Demir (2023), in a scientific article, demonstrate that intelligent AI assistants improve the responsiveness of higher education systems by offering adaptive feedback for orientation purposes [6]. St-Hilaire *et al.* (2022), in their arXiv preprint, explain that intelligent tutoring systems could soon support millions of learners by providing learning and orientation recommendations based on performance and interest data [7]. Hughes (2024), in an article from *The Times*, defends the idea that AI can radically transform career counseling services by aligning students' aspirations with labor market trends [8]. Naqvi (2025) reaffirms that such systems can identify hidden patterns between academic outcomes and professional integration, thereby improving the accuracy of recommendations [2]. Finally, Saleem *et al.* (2025) highlight the positive effect of personalized learning systems on academic performance, while emphasizing the challenges related to ethics and accessibility at work in 2025 [9].

Collectively, these studies converge on a shared conclusion: AI is now a central lever in building a fairer, more effective, and deeply personalized guidance ecosystem. By combining academic data, behavioral competencies, and labor market dynamics, AI enables smart orientation that is aligned with student potential and the evolving demands of the world of work.

The next section develops a logistic regression-based AI model aimed at supporting personalized orientation using the learners' multidimensional data.

3. Artificial Intelligence Model Based on Logistic Regression

3.1. Objective of the Learning Model

In this section, we aim to develop a predictive model that, based on a student's academic performance and transversal skills (soft skills), recommends the most suitable academic track for their profile. The model should be:

- Interpretable.
- Easy to train.
- Based on measurable criteria.
- It is easy to integrate into a decision-support platform.

3.2. Objective of the Learning Model

Let: $X_i \in \mathbb{R}^d$, the characteristic vector of the student i consisting of:

- $(x_1, \cdots, x_m)$: representing subject-specific grades.
- $\left(x_{(m+1)}, \cdots, x_{(m+k)}\right)$: representing soft skills scores.
- $c \in \{0, 1, \cdots, C-1\}$: target channel index in summations.
- $j \in \{0, 1, \cdots, C-1\}$: "tested" or "differentiated" class index (variable from which we derive).

We construct an input data matrix:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix} \in \mathbb{R}^{n \times d}$$

And a vector of outputs:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \in \{0,1,2,\cdots,C-1\}^n$$

where C is the number of target fields.

3.3. Mathematical Model

3.3.1. Assumption

Multinomial logistic regression can be used to model the probability P that a student i is well oriented towards a stream c.

Let: w_c and ϕ_c: respectively the weight vector for stream c and the bias associated with stream *c*.

$$P(y_i = c \mid X_i) = \hat{y}_{i,c} = \frac{e^{w_c X_i + \phi_c}}{\sum_{k=1}^{C} e^{w_c X_i + \phi_c}}$$

where:

(P): The probability predicted by the personalized orientation model of a student i towards stream c according to his academic components and soft skills.

3.3.2. Cost or Loss Function: $\varphi(w,\phi)$

The cost or loss function to be minimized is the cross-entropy

$$\varphi(w,\phi) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{c=1}^{C} 1_{[y_i=c]} \log P(y_i = c \mid X_i)$$

$$\varphi(w,\phi) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{c=1}^{C} 1_{[y_i=c]} \log\left(\frac{e^{w_c X_i + \phi_c}}{\sum_{k=1}^{C} e^{w_c X_i + \phi_c}}\right)$$

with:

$$1_{[y_i=c]} = \begin{cases} 1 & \text{if student } i \text{ is in stream } c \\ 0 & \text{otherwise} \end{cases}$$

n: Number of students.

c: Number of streams.

$X_i \in \mathbb{R}^{n \times d}$: vector of characteristics of student i.

If we denote $y_{i,c} \in \{0,1\}$, the one-hot coded label, $y_{i,c} = 1$ f, the actual stream is c, otherwise 0.

The loss function φ on a single example i is:

$$\varphi(w_i,\phi_i) = -\sum_{c=1}^{C} y_{1,c} \log(\hat{y}_{i,c})$$

where

$$y_{1,c} = \frac{1}{n}\sum_{i=1}^{n} 1_{[y_i=c]}$$

and

$$\hat{y}_{i,c} = \frac{e^{z_{i,c}}}{\sum_{k=1}^{C} e^{z_{i,c}}}$$

With $z_{i,c} = w_j X_i + \phi_j$: (logit scores), $X_i \in \mathbb{R}^d$ and a path $c \in \{1, \cdots, C\}$

The loss will be derived with respect to:

$w_j \in \mathbb{R}^d$: weight associated with path c.

$\phi_j \in \mathbb{R}$: he bias associated with c.

NB: the difference between c and j.

c : Truth channel (Target) or in the summations used for the loss function.

j : Track with respect to which we derive used in derivatives (gradients).

Step 3: Derivative with respect to w_j.

As a reminder: $z_{i,c} = w_j X_i + \phi_j$.

So, by the chain rule, we have:

$$\frac{\partial \varphi_i}{\partial w_j} = \frac{\partial \varphi_i}{\partial z_{i,j}} \times \frac{\partial z_{i,j}}{\partial w_j} = \left(\hat{y}_{i,c} - y_{i,c}\right) \times x_i$$

This gradient is a d-dimensional vector, like w_j

Step 4: Derivative with respect to bias: ϕ_j

$$\frac{\partial \varphi_i}{\partial \phi_j} = \hat{y}_{i,j} - y_{i,j}$$

3.3.3. Deriving Weight and Bias Gradients

Step 1: Derive the softmax function

We begin by deriving the softmax:

$$\hat{y}_{i,c} = \frac{e^{z_{i,c}}}{\sum_{k=1}^{C} e^{z_{i,c}}}$$

Two classes c and j on a:

If $c = j$:

$$\frac{\partial \hat{y}_{i,c}}{\partial z_{i,c}} = \hat{y}_{i,c}\left(1 - \hat{y}_{i,c}\right)$$

If $c \neq j$:

$$\frac{\partial \hat{y}_{i,c}}{\partial z_{i,j}} = -\hat{y}_{i,c}\hat{y}_{i,j}$$

Step 2: Derivation of loss with respect to $z_{i,j}$

We use the derivation chain:

$$\frac{\partial \varphi_i}{\partial z_{i,j}} = \sum_{c=1}^{C} \frac{\partial \varphi_i}{\partial \hat{y}_{i,c}} \cdot \frac{\partial \hat{y}_{i,c}}{\partial z_{i,j}}$$

now:

$$\frac{\partial \varphi_i}{\partial \hat{y}_{i,c}} = -\frac{y_{i,c}}{\hat{y}_{i,c}}$$

Combining them all, we obtain:

$$\frac{\partial \varphi_i}{\partial z_{i,j}} = \hat{y}_{i,j} - y_{i,j}$$

3.3.4. Deriving Weight and Bias Gradients

For n elements, the gradients are average:

To minimize the cost function $\varphi(w,\phi)$, we apply gradient descent.

$$\frac{\partial \varphi_i}{\partial w_j} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_{i,j} - y_{i,j}\right)\cdot x_i$$

$$\frac{\partial \varphi_i}{\partial \phi_j} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_{i,j} - y_{i,j}\right)$$

This means:

If $\hat{y}_{i,j} > y_{i,j} \rightarrow$ the prediction is too strong, we decrease the weight.

If $\hat{y}_{i,j} < y_{i,j} \rightarrow$ the prediction is too low, we increase the weight.

Gradient descent updates weight parameters w_j and bias ϕ_j to reduce φ at each iteration:

$$w_j \leftarrow w_j - \eta \cdot \frac{\partial \varphi_i}{\partial w_j} \Leftrightarrow w_j^{(t+1)} = w_j^{(t)} - \eta \cdot \nabla_w \cdot \varphi$$

$$\phi_j \leftarrow \phi_j - \eta \cdot \frac{\partial \varphi_i}{\partial \phi_j} \Leftrightarrow \phi_j^{(t+1)} = \phi_j^{(t)} - \eta \cdot \nabla_\phi \cdot \varphi$$

η: represents the learning rate is a hyperparameter used in gradient descent algorithms. It controls the size of the steps the algorithm takes when updating the weights.

3.3.5. Deriving Weight and Bias Gradients

The training procedure algorithm is as follows:

START

Initialize w and ϕ.

Repeat several times (iterations):

Calculate probabilities: $\hat{y}_{i,j}$ via Softmax.

Calculate loss function: $\varphi(w,\phi)$.

Calculate gradients: $\frac{\partial \varphi}{\partial w_j} = \nabla_{w_j}$ and $\frac{\partial \varphi}{\partial \phi_j} = \nabla_{\phi_j}$.

Update w_j and ϕ_j.

Until w^*, ϕ^* optimaux.

END

3.3.6. Final Prediction

The score attributed to a channel is calculated as follows:

For each student i, a score is calculated for each channel: $y_{i,j}$.

$$y_{i,j} = \sum_{j=1}^{C} x_{i,j} \cdot w_j^{(c)} + \phi_j^{(c)}$$

Student i is then assigned to the stream $\hat{y}$ that maximizes this score, The predicted path is:

$$\hat{y} = \arg\max_{c} \left(y_c \right)$$

3.4. Simulations and Results

3.4.1. Simulation Requirements

- Implementation language: Python 3, with libraries: pandas, numpy, matplotlib, seaborn.
- AI model used: Multinomial logistic regression (softmax) for personalized school guidance.

For each student i, $X_i \in \mathbb{R}^{12}$, the model predicts:

$$P\left(y_i = c \mid X_i\right) = \frac{e^{w_c X_i + \phi_c}}{\sum_{k=1}^{C} e^{w_c X_i + \phi_c}}$$

- $w_c \in \mathbb{R}^{12}$.
- ϕ_c : bias initialized to 0.
- X_i : vector of twelve (12) student variables (academic grade: From x_1 à x_6), and (soft skills: From: x_7 to x_{12}).

Table 1. Summary of variables X_i.

Academic notes		Soft skills	
Variable	**Teaching units**	**Variable**	**Skills**
x_1	Mathematics	x_7	Communication
x_2	Physics	x_8	Teamwork
x_3	French	x_9	Resilience
x_4	English	x_{10}	Creativity
x_5	History-Geography	x_{11}	Leadership
x_6	Economics	x_{12}	Autonomy

According to the variables defined in **Table 1**, for a student i, the vector $X_i = \left[x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}\right]$ represents his multidimensional data.

- Data: Data file for 100 students containing:
- Six (6) academic grades (between 8 and 20).
- Six (6) soft skills (between 1 and 5).

In this article, the component values are based on a mathematical aggregation approach, *i.e.* an evaluation using a structured questionnaire where each soft skill is evaluated by several questions (items), and the score is:

$$s_{il} = \frac{1}{n_l} \sum_{k=1}^{n_l} q_{ilk}$$

with:

- n_l : number of items (questions) for skill (questions) for soft skills l.

- $q_{ilk} \in \{1,2,3,4,5\}$: student's response i of item k.

  This method gives a weighted average score.
- Simulation procedure:
- Application of the softmax model:

  Linear score: $z_c = w_c X_i + \phi_c$.

  Application of softmax: $P(y_i = c \mid X_i)$.

$$y = \{\text{Mathematical Sciences, Physical Sciences, Histore-Geography, Literature, Economics}\}$$

- Predicted stream allocation:

$$\arg\max_c (y_c) \rightarrow \text{stream}$$

- Representative sampling (20 students).
- Stratified selection of 4 students per stream with groupby().apply(sample()).

3.4.2. Results: Analysis and Interpretation

The results obtained after the simulations are shown below:

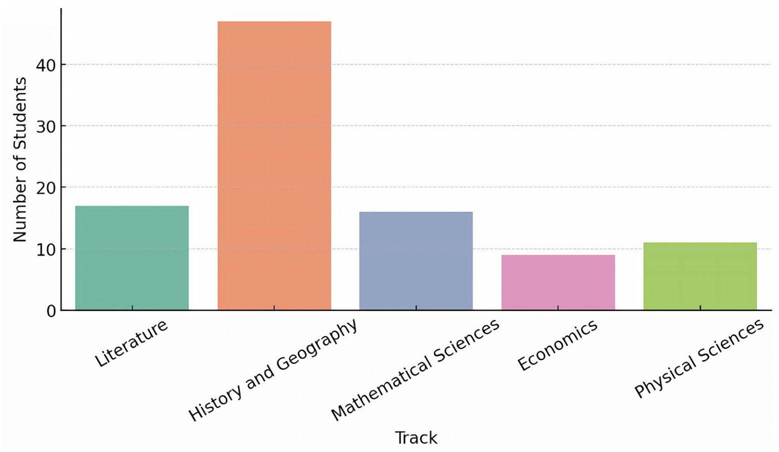

Figure 1. Breakdown of the 100 students by stream.

Table 2. Summarizing the distribution of the 100 simulated students.

Stream	Proportion	Tendance observée
Mathematical Sciences	16%	competitive
Economics	9%	Minority
Physical Sciences	11%	Intermediate
History and Geography	47%	Dominant
Literature	17%	competitive

The proportions per die in Table 2 shown in Figure 1 show that:

- A dominance of the Humanities: The History and Geography track is by far the most represented (47% of students). This can be explained by strong performance in history geography and average levels of communication and resilience, which favor this track in the weighting of the AI model.

- Literature, in second place (17%), is well represented. It attracts profiles with a moderate balance between French, communication, and creativity, but not strong enough to dominate.
- Lastly, an under-representation of economic and scientific tracks: Mathematics (16%), Economics (9%), and Physics (11%) are less frequently selected despite their importance in the actual education system. This may be due to the simulated student profiles not displaying the performance patterns emphasized in the model's weighting for these tracks (for example, mathematics + autonomy for Economics; physics + resilience for Physics).
- From an educational interpretation perspective, it appears that the model favors versatile profiles with a strong humanistic orientation grade in History-Geography and a foundation of soft skills such as communication and resilience. This suggests a pro-literary/humanities tendency in the current random generation.

• Statistical analysis of soft skills

Figure 2 is a comparative bar chart of the average soft skills in Table 3. We can clearly see the dominant skills by the stream.

Table 3. Average and standard deviation of soft skills by stream.

Stream	Means						Standard deviation (std)					
	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
Sciences Economics	2.89	3.0	2.67	3.44	2.67	3.22	0.78	0.87	1.0	0.73	1.0	0.97
History and Geography	2.94	3.04	2.89	3.09	3.19	3.0	0.92	1.06	0.84	0.8	0.82	0.81
Literature	3.24	2.59	2.76	3.0	3.29	2.88	1.2	0.62	1.03	0.71	0.92	0.93
Mathematical	2.75	3.25	3.31	2.81	2.81	3.0	0.68	1.0	0.87	0.85	0.98	0.82
Physical Sciences	2.55	2.82	3.27	3.18	3.18	2.64	0.52	0.75	1.27	0.7	0.87	0.92

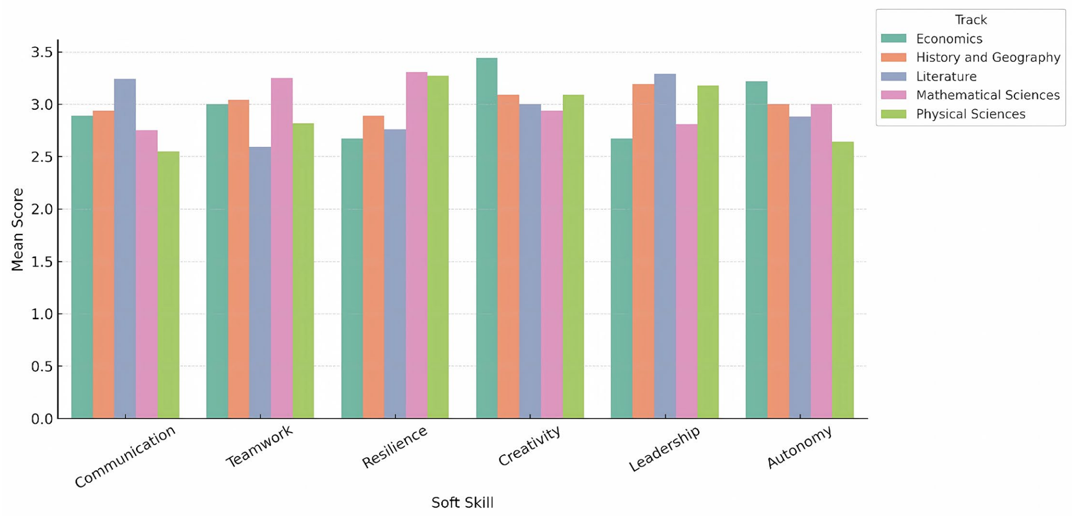

Figure 2. Average soft skills statistics by stream.

- Mathematics Track: Students oriented toward this track stand out for their strong resilience and solid collaboration skills, which are essential for solving complex problems.
- Physics Track: These students display solid and determined profiles, with marked resilience and leadership skills, but slightly lower autonomy, which may indicate a need for guidance.
- History and Geography Track: The profiles are balanced. No soft skill clearly dominates, reflecting the interdisciplinary nature of the track.
- Literature Track: These are highly expressive and autonomous profiles, well suited for interpretation, written communication, and critical thinking.
- Economics Track: Profiles oriented toward this field are both creative and autonomous, indicating a strong ability to propose innovative solutions and work independently in strategic contexts.

Scientific tracks (Mathematics, Physics) emphasize resilience, creativity, and collaboration (teamwork); whereas literary tracks (Literature, History-Geography) favor balanced students with peaks in communication and leadership. Finally, the economic track values more innovative and autonomous profiles with high levels of creativity. See **Figure 3**, which clearly illustrates the relevance of AI models in supporting personalized guidance by identifying profile-track affinities, thus promoting a more holistic orientation by revealing the often-invisible potential in academic report cards.

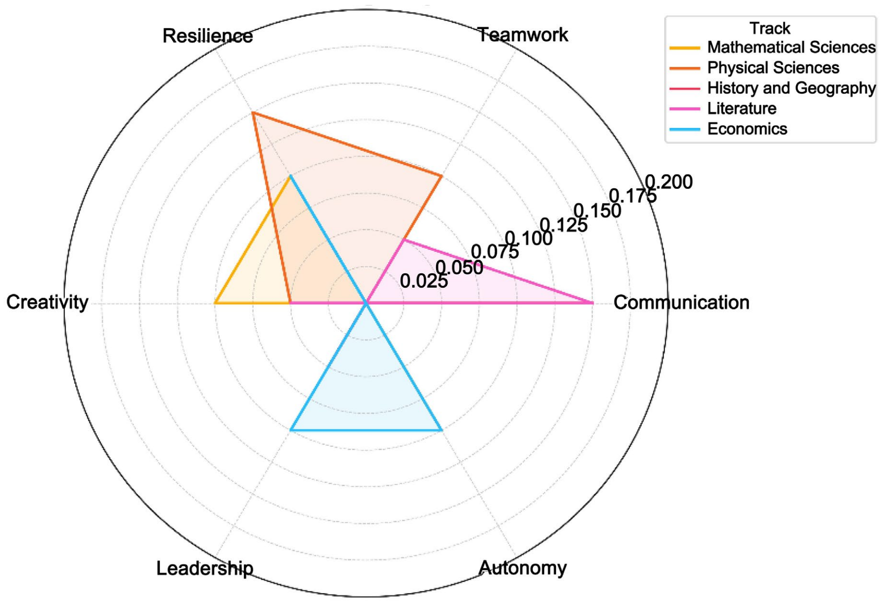

Figure 3. Soft skills weighting by stream.

The Soft Skills Weight Chart by Track in **Figure 3** clearly shows that the model assigns weights that faithfully reflect the educational expectations of each track, thus demonstrating pedagogical alignment. Furthermore, a complementarity of skills is observed, as no soft skill is universal: each track values a unique combination, which justifies a multidimensional approach to orientation.

As a result, the radar chart in **Figure 3** could serve as a targeted reinforcement guide: a student aspiring to a specific track can focus on developing the key skills emphasized in that pathway. Finally, these weights could be dynamically adjusted based on feedback, student success within the tracks, or labor market demands.

- A representative sample of 20 students was distributed evenly across the five recommended streams.

To better understand the role of artificial intelligence in providing personalized guidance for each student, a selection of twenty (20) representative students from the AI simulation of 100 profiles distributed evenly across the five tracks is presented in **Table 3**, along with their academic grades, soft skills, and the recommended track according to the AI predictive model.

The crossed radar chart in **Figure 4** highlights the average profiles of students assigned to each track by combining their behavioral skills and academic performance.

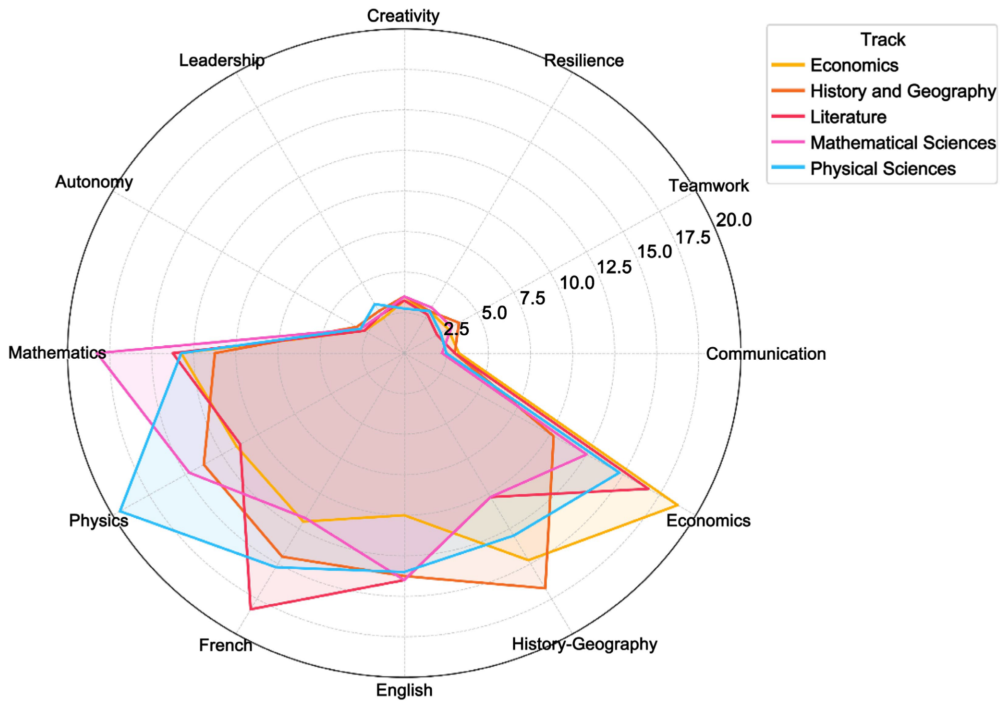

Figure 4. Cross-comparison of grades and soft skills profiles by stream.

It is observed that the *Mathematical Sciences* track shows significantly high values in Mathematics (18.25/20) and Physics (14.75/20), accompanied by relatively balanced soft skills, particularly in Autonomy and Leadership, confirming the demands for rigor and independence in this field.

The *Physical Sciences* track displays a strong dominance in Physics (19.5/20), but with greater variability in French and Economics scores, which may reflect a very science-focused profile with less emphasis on cross-disciplinary subjects (**Table 4**).

Table 4. Academic grades and softs kill of the top twenty students.

Id student	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	Stream
90	14	11	8	12	14	17	3	3	3	3	2	2	y_5
10	17	12	9	11	19	19	3	3	2	4	1	3	y_5
66	12	10	19	8	11	20	3	3	3	2	4	3	y_5
03	10	13	12	9	15	19	4	3	4	4	3	3	y_5
54	15	11	18	8	15	11	4	4	3	3	3	3	y_3
81	11	20	9	19	17	10	3	5	3	4	4	3	y_3
53	10	11	15	13	15	8	3	2	3	4	3	4	y_3
85	9	13	16	15	20	12	2	4	3	3	2	3	y_3
01	14	11	20	18	15	20	2	2	4	3	3	4	y_4
04	13	9	19	12	8	19	4	2	3	4	2	2	y_4
19	19	15	15	18	10	8	3	3	1	2	3	2	y_4
95	9	10	19	8	8	20	3	2	3	4	3	3	y_4
02	18	15	12	11	15	15	2	4	3	3	3	3	y_1
07	19	14	11	16	10	12	1	4	5	4	4	3	y_1
40	19	13	14	12	8	8	3	2	3	4	3	3	y_1
92	17	17	10	17	8	15	3	3	2	3	1	3	y_1
64	19	19	20	12	13	10	3	3	1	2	3	2	y_2
15	14	19	16	15	12	20	2	3	4	3	3	3	y_2
86	8	20	14	12	13	20	2	2	3	3	5	3	y_2
93	12	20	11	15	14	9	3	2	4	3	3	4	y_2

In the Literature track, results are excellent in French (18.25/20) and English (14/20), and soft skills such as Communication (3.5/5) and Creativity (3.25/5) are also high, confirming the importance of expressive and creative abilities in this field. History and Geography stand out with a strong performance in History-Geography (16.75/20) and solid skills in Teamwork and Leadership, reflecting balanced profiles open to analysis and collaboration. Finally, the Economics track combines strong performance in Economics (18.75/20) with robust soft skills in Autonomy and Resilience, which are key traits for management and decision-making. Table 5 and Table 6, showing means and standard deviations of grades and soft skills, confirm these trends by revealing the stability of results: for instance, the low standard deviation in Mathematics within the science track (0.96) indicates a homogeneous required level, while higher deviations in Economics or French in other tracks suggest greater profile diversity or more flexible selection thresholds.

In summary, the combined analysis of the radar chart and the tables confirms that each track is characterized by a strong academic core supported by a specific behavioral profile, validating the relevance of a personalized orientation approach based on multidimensional data integrated into an artificial intelligence model.

Table 5. Table of averages and standard deviations of academic grades by stream.

Stream	x_1		x_2		x_3		x_4		x_5		x_6	
	Mean	std	Mean	std	Mean	std	Mean	std	Mean	std	Mean	Std
y_1	18.25	0.96	14.75	1.71	11.75	1.71	14	2.94	10.25	3.3	12.5	3.32
y_2	13.25	4.57	19.5	0.58	15.25	3.77	13.5	1.73	13	0.82	14.75	6.08
y_3	11.25	2.63	13.75	4.27	14.5	3.87	13.75	4.57	16.75	2.36	10.25	1.71
y_4	13.75	4.11	11.25	2.63	18.25	2.22	14	4.9	10.25	3.3	16.75	5.85
y_5	13.25	2.99	11.5	1.29	12	4.97	10	1.83	14.75	3.3	18.75	1.26

Table 6. Table of averages and standard deviations for soft skills by stream.

Stream	x_7		x_8		x_9		x_{10}		x_{11}		x_{12}	
	Mean	std	Mean	std	Mean	std	Mean	std	Mean	std	Mean	Std
y_1	2.25	0.96	3.25	0.96	3.25	1.26	3.5	0.58	2.75	1.26	3	0
y_2	2.5	0.58	2.5	0.58	3	1.41	2.75	0.5	3.5	1	3	0.82
y_3	3	0.82	3.75	1.26	3	0	3.5	0.58	3	0.82	3.25	0.5
y_4	3	0.82	2.25	0.5	2.75	1.26	3.25	0.96	2.75	0.5	2.75	0.96
y_5	3.25	0.5	3	0	3	0.82	3.25	0.96	2.5	1.29	2.75	0.5

- Manual prediction of a student's career path

Figure 5 shows the steps involved in predicting a student's pathway. In the following, a student's academic data and soft skills are presented to show how the artificial intelligence model selects the pathway based on a student's data.

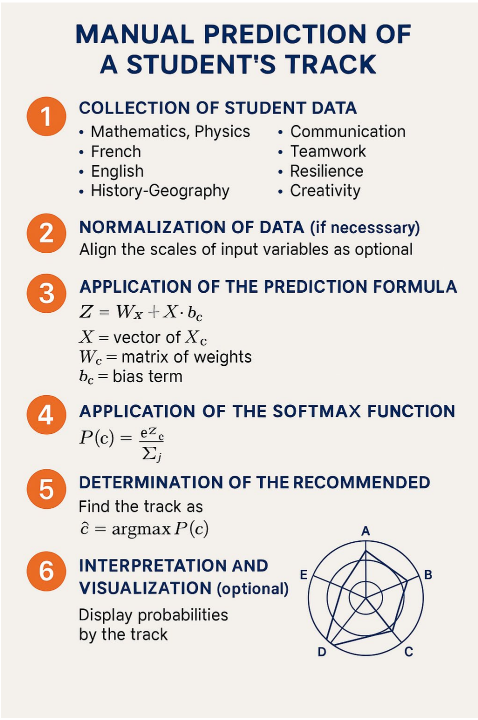

Figure 5. AI model student pathway prediction steps.

1) Extracting the X vector of student grades and profits

$$X_{66} = [12,10,19,8,11,20,3,3,3,2,4,3]$$

2) Multiply by weights W, add b

3) Applied softmax $\rightarrow [0.12,1.24,0.08,0.15,0.41]$

4) $\arg\max[0.12,1.24,0.08,0.15,0.41] \rightarrow y_5$

5) Prédiction stream: y_5 = Economy

The AI model predicts that the student selected from the 20 representative profiles should be oriented towards the Economics stream.

Figure 6 compares a student's profile to the average of students oriented toward the Economics track across two dimensions: academic performance and soft skills. The student demonstrates strong academic achievements in Mathematics, History-Geography, and Economics, with slightly lower scores in French and English still consistent with the track's requirements. On the behavioral side, their scores in Resilience, Communication, and Leadership are well aligned with the average, but there are noticeable gaps in Creativity and Autonomy. Overall, the student is compatible with the targeted track, with specific areas for improvement. The chart highlights the alignment between the actual profile and the track's benchmark, enabling accurate orientation. This visual approach supports quick identification of strengths and areas for development. The differentiation by zones (soft skills vs academic) allows for a nuanced interpretation. Such a synthetic representation promotes data-driven decision-making tailored to each student.

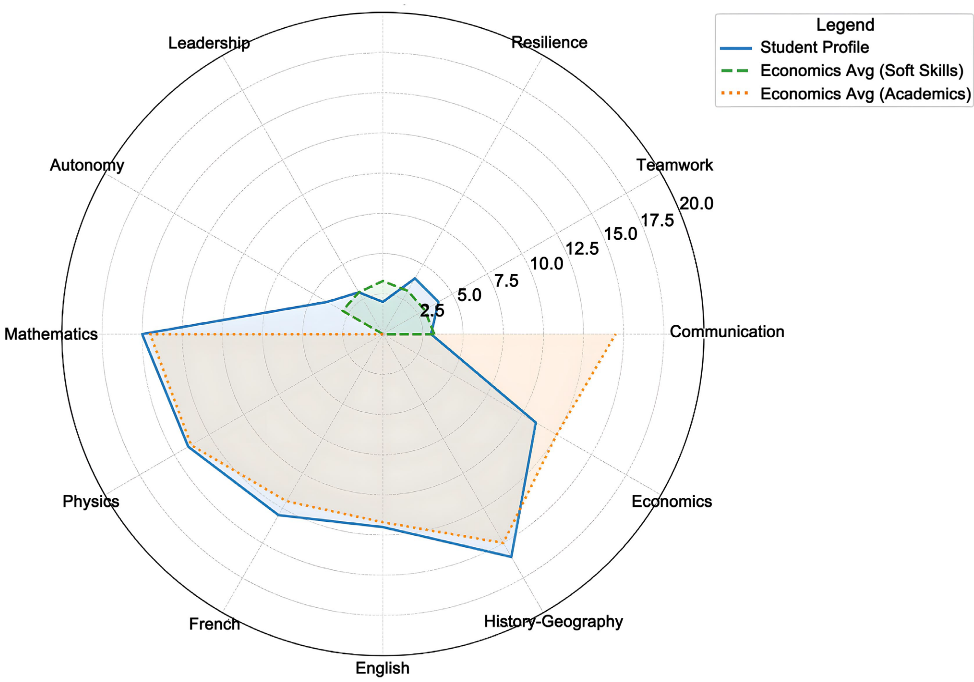

Figure 6. Radar graph of academic grades and skills of a student assigned to the economics stream.

3.4.3. Discussion of AI's Contribution to Personalized Guidance on

The integration of artificial intelligence into the school guidance process radically transforms the way decisions are made. Table 7 from the classification report of the multinomial logistic regression model for the 100 students highlights the effectiveness of the artificial intelligence model, based on multinomial logistic regression, in supporting the school orientation process. The high recall rates (ranging from 84% to 100%) and precision rates (ranging from 87% to 100%) demonstrate the AI's ability to accurately predict the assignment of students according to their academic and behavioral profiles, even under conditions of imbalanced distribution. Logistic regression plays a key role here by modeling the probability of belonging to each target track based on a weighted combination of continuous variables (academic grades) and discrete variables (soft skills). This approach not only estimates the most appropriate track for each student but also quantifies the degree of confidence in the prediction, thus providing counselors with a robust and transparent decision-support tool. AI, by automating the multidimensional analysis of large student datasets, reduces human biases, secures the relevance of recommendations, and personalizes the proposed educational pathways. It also enables the early identification of discrepancies between expected and actual skills, paving the way for targeted remediation actions.

Table 7. Classification report of the multinomial logistic regression model.

Actual class (Stream)	Total number	Well classified	Recall (%)	Accuracy (%)	F1-score (%)
y_1	30	27	0.93	0.93	0.93
y_2	25	21	0.84	0.91	0.87
y_3	20	20	1	0.87	0.93
y_4	15	13	0.87	1	0.93
y_5	10	10	1	0.91	0.95

Unlike traditional approaches that rely solely on academic results, AI considers a broader spectrum of information, including behavioral skills. It enables detailed, multi-criteria, and dynamic analysis of student profiles by relying on predictive models trained on real-world data. The student is no longer seen as just a set of grades, but as a unique individual with diverse potential. AI proposes guidance based on statistical proximity to profiles that have succeeded in the targeted tracks. This mechanism reduces misplacements and enhances student engagement in their educational paths. Moreover, guidance counselors gain a robust, visual, and explanatory decision-support tool. First, it allows for a holistic understanding of the student's profile by highlighting both academic and behavioral strengths. Then, it provides a rational and evidence-based foundation for recommending a track, strengthening confidence in the decision. Finally, it enables mass personalization, thereby transforming guidance into a fairer, more effective process focused on the development of each student's potential. Thus, the AI model does not replace the counselor's judgment—it enhances it through a data-driven, visualizable approach. It serves as an intelligent decision-making tool, capable of linking personal data, track requirements, and group dynamics. Through this analysis, it becomes clear that AI, when integrated with human support, reinforces the relevance, equity, and efficiency of the school guidance process.

4. Conclusion

The integration of artificial intelligence into the school guidance process marks a decisive step toward a more equitable, effective, and personalized education. By cross-analyzing academic and behavioral competencies, AI enables precise identification of each student's profile and aligns it with the specific requirements of each academic track. The logistic regression model used, combined with visualizations such as radar charts, provides a clear view of the affinities between a student and a given orientation. This approach reduces misguidance and enhances student engagement. Moreover, it allows anticipation of labor market skills by linking academic tracks to economic trends. In this perspective, AI becomes a strategic lever to strengthen the alignment between education and employment. Innovative prospects include the integration of real-time labor market data, personalized pathways via interactive simulators, and predictive tracking of academic success. It is now conceivable to create intelligent platforms capable of recommending, adjusting, and supporting students throughout their academic and professional journeys. AI-optimized guidance should also promote the emergence of hybrid profiles, capable of adapting to the rapid transformations of various industries. Thus, the challenge is no longer simply to guide a student, but to build an agile pathway aligned with their potential, aspirations, and the realities of the job market.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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