e-palli

JOURNAL OF NATURAL LANGUAGE AND LINGUISTICS (JNLL)

VOLUME 2 ISSUE 1 (2024)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

Journal of Natural Language and Linguistics (JNLL)

Volume 2 Issue 1, Year 2024
ISSN: 2995-9837 (Online)
DOI: https://doi.org/10.54536/jnll.v2i1.3058
https://journals.e-palli.com/home/index.php/jnll

Interaction between the Teaching/Learning of Formal Logic, Algorithms, Mathematics and French in a Multilingual and Multiethnic Context: Case of Mahajanga High School

Lwanga Albert Razafindrabehita[1*], Juvenile Christalin Ravelomanana[1], Vatosoa Tsirinala Fabiola Ravelojaona[1]
Hery Frédéric Rakotomalala[1], André Totohasina[1]

Article Information

Received: July 05, 2024

Accepted: August 07, 2024

Published: August 10, 2024

Keywords

Algorithms, French, Logic, Mathematics, Multilingual and Pluriethnic Teaching

ABSTRACT

This article aims to study the eventual links between the teaching/learning of French, formal logic, mathematics and algorithms in a plurilingual and pluriethnic context, case of the secondary school of Mahajanga. The study will be based on surveys of the languages, and dialects spoken by pupils in class and their respective scores in French, formal logic, mathematics and algorithms. The data obtained will be further analysed using Implicative Statistical Analysis (ISA) under ICHC-MGK. Among the results of the ICHC-MGK analysis: students with a very strong level in logic are generally those who have a strong level in French, an average level in French generally leads to an average level in logic, those who are very strong in mathematics often have high skills in logic as well, students who are blamed in algorithms tend to be also blamed in logic, students who are strong in mathematics are probably also strong in algorithms and students with a very strong level in algorithms are generally those who express themselves in French. These results encourage us to consider future collaboration with French teachers in order to integrate logic into the teaching of French, to improve students' levels in logic, mathematics and algorithms.

INTRODUCTION

Today, only 7% of Malagasy students aged between 7 and 14 attending school demonstrate basic skills in mathematics, while 23% show similar skills in reading . This reflects a particularly low level of mathematics and difficulty in mastering the language of instruction. To remedy this situation, the teaching of formal logic and algorithms has been integrated since 2018, providing students with a solid foundation for mathematical reasoning and an introduction to computer science. These subjects are taught in French, as are the other disciplines. Nevertheless, the language barrier persists, hindering understanding of the knowledge taught. As Yaguello (1988) points out, "I understand you, you understand me, so we speak the same language".

Some teachers of language and non-linguistic subjects have authorised the use of languages/dialects during lessons, depending on the ethnic origins of the students, with the aim of encouraging argumentation. The main aim is to create a positive classroom environment, open to linguistic and cultural diversity, enabling students to mobilise, confront and use their linguistic knowledge and skills in different languages, thus actively engaging them in the acquisition of new knowledge (Armand, 2012).

This research aims to explore the links and relationships between the teaching and learning of French, formal logic, mathematics and algorithms in a plurilingual and multi-ethnic context, as in the case of Mahajanga high school. To do this, classroom surveys on the languages/dialects spoken by students in class and their respective scores in each of the above disciplines were carried out. The data collected will be processed and interpreted using Implicative Statistical Analysis in ICHC-MGK, in order to open up discussions.

MATERIALS AND METHODS

Tools Used

Plurilingual and intercultural education concerns all the languages and cultures existing in a school, even if they are neither recognized nor taught, as well as languages that are recognized but not taught and languages that are taught (Cavalli *et al.*, 2009). Its first objective is to maintain a holistic vision of education. The second objective is that it is necessary in order to define the teaching objectives and the forms of competence to be attained in an explicit and coherent manner, as well as to make the assessment of prior learning transparent and fair.

A survey of the languages and dialects spoken by students in class and their scores in mathematics, logic, algorithms and French was carried out. Five languages/dialects were spoken by the 91 students in two second-year classes at Mahajanga high school during each lesson in these

Table 1: Languages and dialects present in two classes at Mahajanga high school, with a total of 91 students

Languages and dialects spoken during classes	Number of students out of 91 surveyed
Official Malagasy	91
Merina	40
Sakalava from Boeny	43
French	33
Tsimihety	34

[1] Mathematics and Computer Science Laboratory, University of Antsiranana, Madagascar
[*] Corresponding author's e-mail: lwanga.razafindrabehita@gmail.com

subjects. The distribution of these languages and dialects according to pupil numbers is shown in Table 1. It should be noted that the teachers of these subjects speak French, but also official Malagasy and Boeny Sakalava.

We've categorised students based on their scores in each subject targeted by our study: those who scored from 0 to 5 are classified as ' Blame', those who scored more than 5 but less than 10 are considered 'Weak', those who scored between 10 and 12 are classified as 'Average', those who scored more than 12 to 15 are considered 'Strong', and those who scored more than 15 are classified as 'Very Strong'.

The data collected on students' languages, dialects and scores were transformed into binary data using Excel software. Table 3 above shows the meaning of the data variables in Table 3, which will be further, processed using ICHC-MGK softwar

Table 2: Signification of Variables

Variables	**Signification**
Bla_mat	Blame in mathematics
Bla_alg	Algorithmic blame
Bla_log	Blame in logic
Bl_frs	Blame in French
Fbl_mat	Weak in mathematics
Fbl_alg	Weak in algorithmic
Fbl_log	Weak in logic
Fbl_frs	Weak in French
Moy_mat	Average in mathematics
Moy_alg	Average in algorithmic
Moy_log	Average in logic
Moy_frs	Average in French
For_mat	Strong in mathematics
For_alg	Strong in algorithms
For_log	Strong in logic
For_frs	Strong in French
TFor_mat	Very strong in mathematics
TFor_alg	Very strong in algorithms
TFor_log	Very strong in logic
TFor_frs	Very strong in French
Mal_of	Expresses in official Malagasy
Mer	Expresses in Merina dialect
Sak_b	Expresses in Sakalava from Boeny
Frs	Expresses in French
Tsim	Expresses in tsimihety dialect
El	Students

Table 3: Extract of binary table

	Bla_log	Fbl_log	Moy_log	For_log	TFor_log	Bla_alg	Fbl_alg	Moy_alg	For_alg	TFor_alg	Bl_frs	Fbl_frs	Moy_frs	For_frs	TFor_frs	Bla_mat	Fbl_mat	Moy_mat	For_mat	TFor_mat	Mal_of	Mer	Sak_b	Frs	Tsim
El_1	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0
El_2	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	1	0	1
El_3	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	1	1	0	1	0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
El_{90}	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	1	1	1	1	1
El_{91}	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	1	0	1	0	0

METHODOLOGY

The data collected is processed and studied using the theory of Implicative Statistical Analysis (ISA) (Gras 1979), which is a non-symmetrical method of analysing data that crosses subjects or objects with variables of different types (in our case Boolean). The technique of extending Implicative and Cohesive Hierarchical Classification - ICHC (Ratsimba-Rajohn & Gras, 1992) called Implicative and Cohesive Hierarchical Classification based on MGK (ICHC-MGK) (Rakotomalala, 2019) is applied to the analysis of these data collected to deal with the numerical and graphical problems required by the use of ISA. This application is also used to classify MGK-valid rules according to the cohesion index based to MGK (Rakotomalala & Totohasina, 2018) in order to obtain meta-rules to facilitate interpretations of the analysis results.

Let (K,E,T) be a binary context (Table 3). Consider the set of students E= {El_1, El_2,...,El_{91} } and the set of items T = {Bla_log, Fbl_log, Moy_log, For_log, TFor_log, Bla_alg, Fbl_alg, Moy_alg, For_alg, TFor_alg, Bl_frs, Fbl_frs, Moy_frs, For_frs, TFor_frs,Bla_mat, Fbl_mat, Moy_mat, For_mat, TFor_mat, Mal_of, Mer, Sak_b, Frs, Tsim} (Table 3). The association rules between two Boolean variables are defined by analysing the contingency table obtained by crossing them (Table 4).

Table 4: Table of contingence and the conjoint probability associate.

	V	$\bar{V}$	Σ
U	n_{UV}	$n_{U\bar{V}}$	n_U
$\bar{U}$	$n_{\bar{U}V}$	$n_{\bar{U}\bar{V}}$	$n_{\bar{U}}$
Σ	n_V	$n_{\bar{V}}$	n

$\Longrightarrow$

	V'	$\bar{V}'$	Σ
U'	$P(U'\cap V')$	$P(U'\cap \bar{V}')$	$P(U')$
$\bar{U}'$	$P(\bar{U}'\cap V')$	$P(\bar{U}'\cap \bar{V}')$	$P(\bar{U}')$
Σ	$P(V)$	$P(\bar{V}')$	$\frac{card(E)}{n} = 1$

Mathematical Modelling

Consider a discrete finite probability space (E,T(E),P) such that for any event X in T(E), P(X)=(card(X))/(card(E)). Let us note the set of n sequences, over which we have measured m Bernoulli random variables, and let I be the set of items $I = \{i_1, i_2, i_3,..., i_n\}$. For all X ∈ P(I) \ {∅; I}, for all x_i ∈ X, x_i is an application from E to {0 ; 1} and $P(x_i=1)=((card(x_i^{-1} (1))))/n$, where n = card(E). Any non-empty part of I will be called a motif of I. So for the motif U,U'=U^{-1} (1) and n_U= card(U'). For the motifs U and V, n_{UV}=card(U' ∩ V') the number of transactions that use both U and V. Agree to $\bar{U}$= I-V be the logical negation of a motif U. The real number P(U') will be called the support of the motif U noted supp(U)= (card(U'))/n (Agrawal, *et al.*, 1993).

A probabilistic interest measure is a real function μ of T(I) × T(I) such that for any association rule U→V , with U∩V = ∅, the value of μ (U→V) is computed from the four quantities n = card(E), P (U'), P (V') and P(U'∩V') = supp(U ∪ V). Finally, for two motifs (or items) U and V in a binary context, the measure of interest MGK is defined by

$$M_{GK} = \begin{cases} M^f_{MGK}(U \to V) = \dfrac{P(V'/U') - P(V')}{1 - P(V')} & \text{, if } U \text{ favours } V\text{ ;} \\ 0 & \text{, cases of independence;} \\ M^d_{MGK}(U \to V) = \dfrac{P(V'/U') - P(V')}{P(V')} & \text{, if } U \text{ disfavours } V. \end{cases}$$

Theoretical research in Rakotomalala, *et al.*, (2017), Rakotomalala, *et al.*, (2018) allowed us to develop an M_{GK}-valid association rule extraction algorithm (Rakotomalala & Totohasina, 2018).

- The extraction of association rules is based on the M_{GK} measure of interest, which detects a possible non-symmetrical relationship between two of the variables, the validation of the extracted rules is done with respect to the favourable component M^f_{GK} which is implicative and the critical value $M^f_{GK}(\alpha)$ having a relationship with the χ2 statistic of independence or dependence of degree of freedom 1 at the risk threshold α chosen by ourselves such that $M^f_{GK} > M^f_{GK}(\alpha)$ with

$$M^f_{GK}(\alpha) = \sqrt{\frac{1}{n}\frac{n-n_U}{n_V}\frac{n_V}{n-n_V}\chi^2_{Theorical(\alpha)}}$$

In our case, α=10%, which gives the critical value of χ2 equal to 2. ;

- The value of the support according to M^f_{GK} such that $supp^f_{MGK}(U\to V)= supp(U)[(1-supp(V)) M^f_{GK}(U\to V)+supp(V)]$ is generally small (Rakotomalala *et al.*, 2017). It is therefore essential to normalise this value (Rakotomalala & Totohasina, 2018), and we denote it by $supp^f_{(n)M\_GK}$, with

$$supp^f_{(n)M_{GK}}(U \to V) = \frac{supp^f_{M_{GK}}(U \to V) - P(U')P(V')}{P(U')(1 - P(V'))}$$

- An implicative graph, denoted G, consists of a finite set of variables representing the vertices of the graph, and edges associated with the normalised support value of valid rules. For ease of interpretation and to highlight meaningful relationships, only implications with a support value $supp^f_{(n)M\_GK}$ (U→V)≥0.5 are retained; alternatively, the implicative tendency of U over V is preferred to neutrality (Gras, *et al.*, 2001).
- The value of $supp^f_{(n)M\_GK}$ ∈]0.5;1] is used to establish the value of cohesion between two items, denoted $coh_{supp(n)M\_GK}$ (Rakotomalala & Totohasina, 2018) with:

$$coh_{\mathrm{supp}_{(n)M_{GK}}}(U,V) = \begin{cases} \sqrt{1-(supp^{f}_{(n)M_{GK}}(U \to V))^2}, & \text{if } supp^{f}_{(n)M_{GK}}(U \to V) > 0.5 \\ 0 & \text{, if } supp^{f}_{(n)M_{GK}}(U \to V) \leq 0.5 \\ 1 & \text{, if } supp^{f}_{(n)M_{GK}}(U \to V) = 1 \end{cases}$$

• The implicative and cohesive hierarchical classification method according to the M_{GK}(ICHC-MGK) measure of interest is based on the cohesion $coh_{supp(n)M\_GK}$ (Rakotomalala, *et al.*, 2018).

RESULTS AND DISCUSSION

Characteristics of the Variables

The data in Table 5 reveal significant variability in student performance in different academic areas. In logic, less than a quarter of students, 20.88%, are classified as strong (For_log), while almost 40% have an average level (Moy_log). However, it is worrying that only a small fraction, 4.40%, are rated as very strong in logic (TFor_log), perhaps indicating a need for particular attention in this area to encourage more students to excel.

In algorithms, the results appear to be slightly better, with almost a quarter of the students classified as strong (For_alg), i.e. 24.18%. However, the percentage of very strong students (TFor_alg) is quite low (3.30%), which suggests potential for improvement in acquiring more advanced skills in this area.

Performance in mathematics appears to be the area of greatest concern, with only a small fraction of students classified as very strong (TFor_mat) and strong (For_mat), at 1.10% and 2.20% respectively. More than half the students (50.54%) are considered weak in mathematics (Fbl_mat), requiring immediate intervention to strengthen basic mathematical skills.

With regard to languages and dialects, it is encouraging to note that all students are able to express themselves in Malagasy (Merina, Sakalava du boeny and Tsimihety), the official language (Mal_of). However, the predominance of expression solely in French during lessons raises questions about the accessibility and use of other dialects, which could be explored further to encourage linguistic and cultural diversity.

Finally, as far as French is concerned, it is worrying to note that a significant proportion of students are classified as weak (Fbl_frs), 38.46%, or blamed (Blm_frs), 13.19%, indicating an urgent need for efforts to improve French language skills among students.

Table 5: Characteristics of the variables

Variables	Moyenne(%)	Occurrence
Bla_log	8.80	8
Fbl_log	28.57	26
Moy_log	37.36	34
For_log	20.88	19
TFor_log	4.40	4
Bla_alg	2.20	2
Fbl_alg	23.07	21
Moy_alg	47.25	43
For_alg	24.18	22
TFor_alg	3.30	3
Bl_frs	13.19	12
Fbl_frs	38.46	35
Moy_frs	17.58	16
For_frs	20.07	21
TFor_frs	12.08	11
Bla_mat	34.06	31
Fbl_mat	50.54	46
Moy_mat	12.08	11
For_mat	2.20	2
TFor_mat	1.10	1
Mal_of	100	91
Mer	43.96	40
Sak_b	47.25	43

Frs	36.26	33
Tsim	37.36	34

Results Obtained by ICHC-M_{GK}

After processing the binary data (Table 3), with the ICHC-M_{GK} tool, concerning the languages and dialects spoken by the students in class and their respective scores for each dicipline of mathematics, algorithmics, logic and French, we had two hundred and ninety six (296) valid rules, with a 10% risk threshold set by ourselves, of which one hundred and twelve (112) are positive rules and one hundred and ninety four (184) are negative with $0.1 \leq supp^{f}_{(n)M\_GK}(U \rightarrow V) \leq 1$ and formed seventeen (17) pairs of oriented variables i.e. $Card(coh_{supp(n)M\_GK\ (U \rightarrow V)}))=17$ with $0.03 \leq coh_{supp(n)M\_GK\ (U \rightarrow V)} \leq 1$. Thus, we had six (6) meta-rules (Table 8).

Table 6 below records the value of the normalised supports of the favourable valid rules according to the M_{GK} quality measure.

Table 6: Normalised support for pairs of variables

	Bla_log	Fbl_log	Moy_log	For_log	TFor_log	Bla_alg	Fbl_alg	For_alg	TFor_alg	Bl_frs	Fbl_frs	Moy_frs	For_frs	TFor_frs	Bla_mat	Fbl_mat	For_mat	TFor_mat	Sak_b	Frs	Tsim
Bla_ log						0.23	0.51				0.59				0.62						
Fbl_ log										0.11	0.44				0.36				0.27		
Moy_ log								0.15				0.22									
For_ log													0.25	0.22				0.04		0.42	
TFor_ log								0.67					0.68							0.61	
Bla_ alg	1.00																				
Fbl_ alg	0.17														0.28			0.04			
For_ alg			0.27		0.10												0.07				
TFor_ alg													0.57							1.00	
Bl_ frs		0.30													0.37						
Fbl_ frs	0.09	0.28													0.35						
Moy_ frs			0.60															0.05			
For_ frs				0.22	0.10				0.06							0.33				0.55	
TFor_ frs				0.43													0.07			0.86	0.42
Bla_ mat	0.12	0.28					0.16			0.11	0.42										
Fbl_ mat													0.10							0.15	

Tsim	Frs	Sak_b	TFor_mat	For_mat
		0.12		
	0.20		1.00	
	0.05			
			1.00	
				1.00
	0.06			
			1.00	
	0.29			
0.10	0.21			0.43
	0.27			
	0.04			
				1.00

The implicative graph shown in Figure 1 below is generated from valid rules that have a support value (Table 6) greater than or equal to 0.5. It reveals complex relationships between different attributes of the students, such as their skills in mathematics, logic, French and algorithms. The vertex 'Frs' (student expressing in French) is strongly connected to several other vertices, including 'For_mat' (strong in mathematics), 'TFor_log' (very strong in logic), 'TFor_frs' (very strong in French), 'TFor_alg' (very strong in algorithmic) and 'TFor_frs' (strong in French), suggesting that "students who excel in these areas tend to also express themselves well in French". This underlines the importance of an integrated approach to teaching, where language skills are strengthened alongside academic skills.

On the other hand, the connection between 'For_alg' (strong in algorithms) and 'TFor_log' (very strong in logic) highlights the association between these two skills, indicating that "students who master logic often have good algorithmic skills". This observation can guide teachers in designing teaching activities that reinforce these skills in a synergistic way.

In addition, the connections between the peaks "TFor_mat" (very strong in mathematics) and "Moy_frs" (average in French), "For_log" (strong in logic) and "Fbl_alg" (weak in algorithms) highlight the impact of mathematical skills on other academic areas. These results highlight "the need to support students in developing strong mathematical skills, as this can have a positive effect on their performance in other subjects".

Finally, connections involving the vertex 'Bla_log' (blame in logic) highlight the challenges that some students face in acquiring specific skills. For example, the connection with 'Fbl_frs' (weak in French) suggests that "students who have difficulties in logic may also face obstacles in learning French".

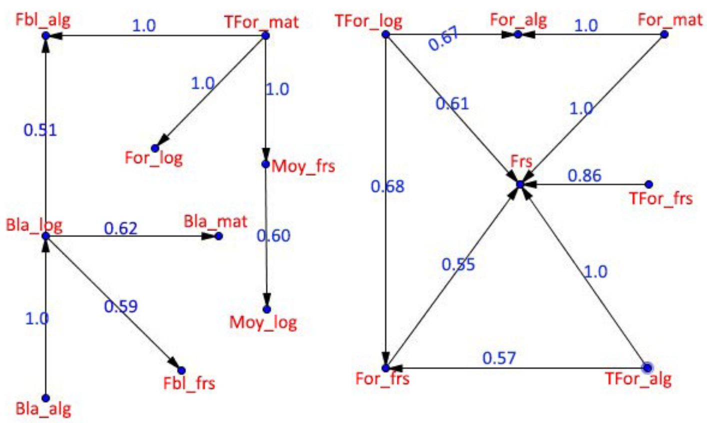

Figure 1: Implicative graph G generated from normalised support greater than or equal to 0.5

Table 7 reveals a variety of associations between different pairs of variables. Pairs of variables with a cohesion of 100% indicate a total relationship, which means that they are strongly related in the context of our study. For example, students who are blamed for both algorithmic and logical problems show total cohesion, as do those who are very strong in mathematics and strong in logic, or those who are very strong in mathematics and weak in algorithmic problems. These results suggest fundamental relationships between these attributes, underlining the importance of considering them together when analysing student performance.

Table 7: Cohesion of the pairs of variables

	Bla_log	Fbl_log	Moy_log	For_log	TFor_log	Bla_alg	Fbl_alg	For_alg	TFor_alg	Bl_frs	Fbl_frs	Moy_frs	For_frs	TFor_frs	Bla_mat	Fbl_mat	For_mat	TFor_mat	Sak_b	Frs	Tsim
Bla_log						1.00	0				0				0						
Fbl_log										0	0				0				0		
Moy_log								0				0.24									
For_log													0	0				1.00		0	
TFor_log								0					0							0	
Bla_alg	0																				
Fbl_alg	0.03														0			1.00			
For_alg			0		0.40												1.00				
TFor_alg													0							0	
Bl_frs		0													0						
Fbl_frs	0.23	0													0						
Moy_frs			0															1.00			
For_frs				0	0.42				0.16							0				0	
TFor_frs				0													0			0	0
Bla_mat	0.29	0					0			0	0										
Fbl_mat													0							0	
For_mat								0						0						0	
TFor_mat				0			0					0									
Sak_b		0																			
Frs				0	0.26				1.00				0.13	0.81		0	1.00				
Tsim														0							

On the other hand, the pairs of variables with a cohesion of around 80% or 40% also indicate significant correlations, although slightly less strong than those with a cohesion of 100%. For example, the strong cohesion between students who are very strong in French and those who express themselves in French highlights the impact of linguistic competence on the effective use of the language in the context of the study. Similarly, the cohesion between students who are very strong in logic and those who are strong in French or in algorithms highlights subtle but important relationships between these domains.

On the other hand, pairs of variables with lower cohesion, around 20% or less, indicate weaker or less regular links between the corresponding attributes. This may suggest a certain independence between these variables or less direct influences on each other. For example, the weak cohesion between students who are reprimanded in logic and those who are weak in French or algorithms suggests that these attributes may be influenced by other factors or intermediate variables.

Analysis of the cohesion of pairs of variables provides crucial information on the relationships and interactions between different student attributes. These results can be used to better understand the dynamics underlying student performance and guide the development of educational strategies and targeted interventions to support their academic success.

According to the hierarchical classification under ICHC-MGK, six rules were identified and classified hierarchically, as described in Table 8 and illustrated in the dendrogram (Figure 2). The interpretation of each rule is as follows:

R(1): (Bla_alg⇒Bla_log)

This rule indicates that students who are blamed in algorithms tend to also be blamed in logic. This suggests a dependency between skills in algorithms and logic, where difficulties in one of these areas can often be reflected in the other.

R(2): (TFor_mat⇒For_log)

According to this rule, those who are very strong in mathematics often have high skills in logic as well. This observation highlights a positive association between performance in mathematics and logic, perhaps underlining a strong logical foundation for those who excel in mathematics.

R(3): (For_mat⇒For_alg)

This rule suggests that students who are strong in mathematics are also likely to be strong in algorithms. This indicates a dependency between mathematical and algorithmic skills.

R(4): (TFor_alg⇒Frs)

According to this rule, students with a very strong level in algorithms are generally those who express themselves in French in class. This could indicate that students who excel in algorithms are also more comfortable expressing themselves in the language of instruction.

R(5): (TFor_log⇒For_frs)

This rule suggests that students with a very strong level in logic are generally those with a strong level in French. This may reflect a general aptitude for logical and linguistic problem solving in these students.

R(6): (Moy_frs⇒Moy_log)

According to this rule, an average level in French generally leads to an average level in logic. This indicates

Table 8: Hierarchical rules with cross-class cohesion, cross-class implication and significative value

Level	Rule	Inter-class cohesion	Inter-class implication	Significant value
1	(Bla_alg⇒Bla_log)	1.0	1.0	0.0028867593647241415
2	(TFor_mat⇒For_log)	1.0	1.0	4.819311202535566E-6
3	(For_mat⇒For_alg)	1.0	1.0	-9.526037267877335E-4
4	(TFor_alg⇒Frs)	1.0	1.0	-0.0014337208244764657
5	(TFor_log⇒For_frs)	0.415	0.675	-0.001720450361018653
6	(Moy_frs⇒Moy_log)	0.242	0.6008771929824561	-0.0019132124586164678

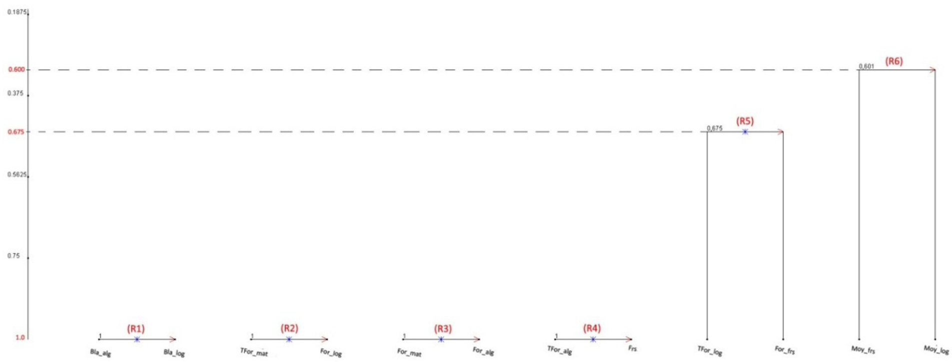

Figure 2: Dendrogram representing the metarules

a relationship between linguistic skills and logical skills, where an average level in one skill can indirectly influence the level in the other skill.

DISCUSSION

The results presented provide significant insight into students' competencies in different subject areas, as well as their interactions in the context of teaching French. The observed dependencies between disciplines, such as mathematics, logic, algorithms and French, underline the importance of an integrated approach to teaching that recognises the interconnections between these areas. For example, students who are strong in mathematics also tend to excel in logic and algorithms (R(2) and R(3)), suggesting that these skills are interdependent and mutually reinforcing. Similarly, the relationship between French language skills and achievement in other subjects (Figure 1) highlights the impact of the language of instruction on learning. These results also highlight the challenges that some students may face, particularly with regard to understanding logical concepts in a specific linguistic context. In response to these findings, it is imperative to adopt differentiated teaching approaches that take account of students' individual needs and value linguistic and cultural diversity. By integrating concepts and examples from different disciplines into French lessons and providing additional support where needed, teachers can create an inclusive and stimulating learning environment where all students have the opportunity to succeed.

Following rules R(5) and R(6), discussion about improving the teaching of logic in the context of teaching in French is crucial to ensuring a thorough understanding and effective mastery of this fundamental discipline. Here are some points to consider in this discussion, as well as suggestions for improving the teaching of logic within the French language framework.

Integrating Logical Concepts into the Language Curriculum

It is essential to integrate logical concepts organically into the French language curriculum. This can be done by selecting texts and exercises that highlight logical structures, encouraging students to analyse and argue logically in their French writing and discussion.

Teacher Training

Teachers need to be trained to integrate logic teaching techniques into their French classes. This may involve professional development focusing on familiarisation with the principles of formal logic and pedagogical strategies for teaching these concepts in a way that is accessible to French-speaking students.

Use of Adapted Teaching Resources

It is important to provide teachers with adapted teaching resources that incorporate examples and exercises in logic in the context of the French language. This can include textbooks, interactive activities and educational games that reinforce the understanding of logic concepts while encouraging the practice of French.

Multidisciplinary Approach

The teaching of logic can be strengthened by adopting a multidisciplinary approach that links logic to other areas of study, such as mathematics, science and philosophy. This allows students to see the practical application of logical concepts in different contexts and strengthens their overall understanding.

Encouraging Critical Thinking

The teaching of logic should emphasise the development of critical thinking and problem solving skills. Teachers can encourage students to analyse arguments, recognise errors in reasoning and formulate counter-arguments clearly and logically in French.

Formative and Ongoing Assessment

Regular assessment of logic skills, integrated into formative and ongoing assessments in French, enables teachers to monitor students' progress and identify areas where further support is needed.

By implementing these suggestions, teachers can help to improve the teaching of logic in the context of French, helping students to develop the critical thinking and logical analysis skills that are essential for success in their studies and daily lives.

CONCLUSION

The analysis carried out on the links between the teaching and learning of French, formal logic, mathematics and algorithms in a multilingual and multi-ethnic context, such as that of the Mahajanga high school, reveals several significant results. Firstly, the linguistic and ethnic diversity present in the classes provides an environment conducive to interaction and the mobilisation of students' linguistic knowledge. However, despite this diversity, French remains the dominant language used during lessons, which raises questions about the accessibility and use of other dialects. It would therefore be interesting to explore ways of encouraging greater linguistic and cultural diversity in teaching. Secondly, the results show variable performance by students in different subjects, with particular challenges in acquiring skills in mathematics and French. These results highlight the need for targeted interventions to strengthen students' fundamental skills in these areas. Thirdly, analysis of the associations between skills in mathematics, logic, French and algorithms highlights complex and interdependent relationships between these areas. For example, students with a very strong level in logic are generally those with a strong level in French; an average level in French generally leads to an average level in logic. Those who are very strong in mathematics often have high skills in logic too. Students who are blamed in algorithms tend to be blamed in logic as well. Students who are strong in mathematics are probably also strong in algorithms. Students with a very high level in algorithms are generally those who express themselves in French in class. These results would encourage us to consider future collaboration with French teachers in order to integrate logic into the teaching of French, with the aim of improving the level of students in logic, mathematics and algorithms.

REFERENCES

Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. In *Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data* (pp. 207–216). Association for Computing Machinery. https://doi.org/10.1145/170035.170072

Armand, F. (2012). Enseigner en milieu pluriethnique et plurilingue : Place aux pratiques innovantes. *Québec français, 167,* 48–50.

Cavalli, M., Coste, D., Crisan, A., & Van de Ven, P. H. (2009). *L'éducation plurilingue et interculturelle comme projet.* Langues dans l'éducation.

Gras, R. (1979). *Contribution à l'étude expérimentale et à l'analyse de certaines acquisitions cognitives et de certains objectifs didactiques en mathématiques* (Doctoral dissertation). University of Rennes I.

Gras, R., Kuntz, P., & Briand, H. (2001). Les fondements de l'analyse statistique implicative et quelques prolongements pour la fouille de données. *Mathématiques et sciences humaines, 154.*

Gras, R., & Totohasina, A. (1995). Conceptions d'élèves sur la notion de probabilité conditionnelle révélées par une méthode d'analyse des données : Implication-similarité-corrélation. *Educational Studies in Mathematics, 28*(4), 337–363.

Rakotomalala, H. F. (2019). *Classification hiérarchique implicative et cohésitive selon la mesure MGK: Application en didactique de l'informatique* (Doctoral dissertation). University of Antananarivo.

Rakotomalala, H. F., Ralahady, B. B., & Totohasina, A. (2018). A novel cohesitive implicative classification and its application in diagnosing informatics literacy among higher education students in Madagascar. In *Proceedings of the Third International Congress on Information and Communication Technology: ICICT 2018* (pp. 161–174).

Rakotomalala, H. F., & Totohasina, A. (2018). An efficient new cohesion index based on the quality measure of association rules MGK. In *Proceedings of the Second World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4)* (pp. 28–35).

Rakotomalala, H. F., Totohasina, A., & Diatta, J. (2017). Extraction des règles d'associations MGK valides avec contribution de support. In *Actes des 24ème Rencontres de la Société Francophone de Classification (SFC)* (pp. 29–32).

Ratsimba-Rajohn, H. (1992). *Contribution à l'étude de la hiérarchie implicative : Application à l'analyse de la gestion didactique des phénomènes d'ostension et de contradictions* (Doctoral dissertation). University of Rennes I.

Yaguello, M. (1988). *Catalogue des idées reçues sur la langue.* Éditions du Seuil.