

MAPPING SCHOOL DROPOUT FACTORS IN TUNISIA: REGIONAL COMPARATIVE STUDY

1***AICHA CHERIF**, 2* **ALI ELLOUMI** and 3***GILLES FERREOL**

1*Laboratory LARIDIAME, University of Sfax; Tunisia.

2*Laboratory LARIDIAME, University of Sfax; Tunisia / Laboratory TEC, University Paris Descartes, France.

3* Laboratory C3S, University Of Besançon, France.

Correspondence author: alielloumi62@gmail.com

Abstract

As the process of urbanization progresses, school dropout goes more visible and concentrated in cities. Whether in rich cities of wealthy countries or in slums of developing countries. The article aims to provide the cartography that highlights a panorama of the situation of the phenomenon (school dropout factors) in Tunisian regions. A simple fact is at the core of the paper: the more regional disparities persist, the higher school dropouts factors are specifically rural (disadvantaged regions) there. How to explain such a phenomenon? By using data analysis techniques, based on factorial methods and automatic classification, this work proposes a mapping of the multidimensional hierarchies of Tunisian regions according to geographical space. We identified significant differences in the factors of dropouts across regions. These differences are explained by regional disparities, exclusion and social inequality.

Keywords: School dropout, dropout factors, régional disparities, mapping, Tunisia

1. Introduction

The phenomenon of school dropout is not new in Tunisian society and may have even concerned a much larger number of students than today. In the 2019's about 100,000 (MEN, 2019) young people left the school system without a diploma. What has probably changed the perception of dropping out is the combination of the increase in youth unemployment and the importance of the diploma as a condition of access to the labour market. From then on, leaving the school system without anything has become an educational problem but also a political, social and economic one. The phenomenon is all the more worrying because it has an impact on the entire life of individuals. In short, this phenomenon is international. Dropout cannot therefore be associated with any particular educational policy. On the other hand, the magnitude of the phenomenon calls into question the democratic school and the dreams of equality of our societies.

Dropout factors differ across countries: in the poorest countries, dropout is linked to child labour (especially in rural areas, girls more than boys, (Blaya, 2010a). In Western countries, the causes of dropout are no longer linked to economic factors but are multifactorial (personal, family, social and educational reasons). Some argue that "dropping out" and "dropping out" are only more politically correct words for at-risk populations, which were previously stigmatized by the terms "maladjustment" or "academic failure" (Janosz and al., 2000).

Many publications link school dropouts to family and personal breakdowns, especially in families of popular origin and/or immigration. Dropouts have similarities, although each course is unique (Janosz et al., 2000). These points are identified by the institution, are of modest social origin and are characterized by precarious living conditions and difficulties in early learning (Fortin and al., 2006; Potvin and Lapointe, 2010). Yet the reality is more complex: more and younger people from privileged backgrounds drop out. There is currently a great deal of scientific work being done to define the profile of dropouts. Previously, there was a unique and stereotyped profile of school dropouts. This was most often a boy, coming from a disadvantaged background, showing problems of behaviour in class and/or problems of delinquency outside. This student was forced to leave school because of poor academic results, or because of an educational sanction (Blaya 2012). Of course, this reductive vision is of no use today, and Janosz and Le blank (1996) point out that this unique profile does not exist. In addition, current work is based on a set of risk factors related to profiles of students at increased risk of dropping out of school. The corpus of data from longitudinal samples also allows empirical knowledge of the school drop-out process. However, this work in North America or Europe is based on very different samples. As far as we are concerned, we will not quote all of this work in full.

In conclusion, some elaborated works highlight macro social factors (institutional and family) and others highlight micro social factors (individual and interpersonal). In our study, we will adopt the “multidimensional explanatory model of school dropout” developed by Potvin and al. (2005, 2010). It seems to us the most appropriate in the Tunisian context to identify the factors influencing the risk of dropping out. On the one hand, it encompasses a variety of complex risk factors. On the other hand, it states that the risk of dropping out increases more than the student runs risk factors. In other words, the complexity and multiplicity of risk factors affect the educational pathways of young people. Overall, the risk factors identified from Potvin’s perspective are associated with four dimensions (living environment/ school/ families/ student).

Our study therefore opts, for the screening of young Tunisians at risk of dropping out and the most powerful factors associated with school dropout, to develop a regional mapping of school dropout according to the different profiles of potential dropouts. For this, we will aim to detect the most powerful predictors, but in a non-exhaustive way. From then on, we will focus our investigation on the cultural and geographical factors that present the specificity of the Tunisian context and our study. Nevertheless, under no circumstances will we deny the role of other factors since all studies have revealed the complexity of the dropout phenomenon in which several factors associated with it interact, such as family, school and personal factors. (Janosz and al., 1996; Fortin and al., 1996-2000; Rumberger, 1995; Blaya, 2012).

From this perspective, the risk factors are numerous and can be divided into four components: those related to the living environment, such as poverty, geographical isolation, school-related risk factors such as lack of support for students in difficulty, class climate and problematic student-teacher relationship, family-related risk factors as

examples; poor parent education, instability of the family unit and the risk factors related to young people and learning difficulties as an illustration; association with deviant peers, ill-being at school, refusal to attend school, etc. Through this study and following the example of several Western countries, Tunisia must adopt its first Strategic Framework to Combat School Dropout, which is characterized by its regionalization through the elaboration of a Regional Strategic Framework to combat this phenomenon for each of the seven Tunisian regions (7) that count the country.

Having detailed information on school drop-out at more targeted levels than the city can contribute to better targeting of remedial programmes and actions (Deichmann, 1999; Davis, 2003; World Bank, 2003; Boudesseul and al. 2017, etc.). The cartographic approach of a social phenomenon makes it possible to reconstruct its indicators at the regional, provincial and municipal levels, based on survey data from school actors.

to a large extent on a good knowledge of the socio-economic characteristics of the most vulnerable pupils and their geographical and socio-economic targeting. The indicators of school dropout as produced so far through the various studies on this phenomenon are mainly monetary and their disaggregations are limited to the regional level. As a result, the diversity of intra-regional dropout levels and facets is not highlighted.

The mapping of school dropouts thus becomes, increasingly, for governments and non-governmental organizations an important tool for the development of effective policies to reduce social and economic inequalities, governance and local management of development. In addition, the mapping of school dropouts can prove to be a powerful means of communication and advocacy on inequalities within a country (Deichmann, 1999). Firstly, mapping at national level will enable the central government to better target regions experiencing a certain delay in development or equipment. Then, at more disaggregated levels (regions), it will enable local authorities to better guide their development programmes and actions. To carry out such an exercise, sufficient detailed and comprehensive data sources are required. The general census of dropouts is the preferred source. Indeed, the data from the Validated School Dropout Questionnaire (SDQ) Survey (Cherif and Elloumi, 2021), carried out in Tunisia on this phenomenon will allow us to establish the first school dropout mapping up to the regional level.

The hypothesis of this study is based on a simple observation: the more regional disparities persist in Tunisia, the more different and high the factors for dropping out of school that are specifically rural (disadvantaged regions). Our objective is therefore to use the quantitative data from our school dropout survey to construct the various indicators of school dropout at a regional level.

One of the promising avenues in the analysis of the mapping of school dropouts is to recognize its multidimensional character and to describe each of these dimensions separately. In fact, sticking to a single stall measurement indicator in order to define policies to reduce this phenomenon can lead to bias. Rather, it is the paralleling of different facets and/or dropout maps that will allow a better definition of policies and programs (Deichmann, 1999)

2. Methods

2.1. Participants

This study uses data collected in the fall of 2019 as part of our thesis work on student dropout and academic achievement. The students come from the colleges of the twenty-four Tunisian cities, in short one class of one college per city. All students were solicited and participated in the study, representing (35 students x 24 cities = 840 youth). Of these, some questionnaires had to be rejected because they were incomplete or invalid. Thus, the sample of this study consists of 840 students (girls and boys). These young people are between 12 and 15 years old and come from seven Tunisian regions. All The sample participated and completed our School Dropout Risk Assessment Questionnaire.

2.2. Geographical distribution of Tunisian regions to be compared

Currently, the Tunisian territory is organized according to two approaches (Figure 1 & 2): (a) administrative decentralization (composed of 24 governorates (wilayat) subdivided into 264 delegations (mutamadiyat) and 2073 sectors (imadat), all directly determined by the central government; and (b) political decentralization (350 municipalities (baladyiat) directly chosen by the citizens and 24 municipal councils, which correspond to the 24 cities). All divided into seven regions (Greater Tunis, North East, North West, Central East, Central West, South East, South West).

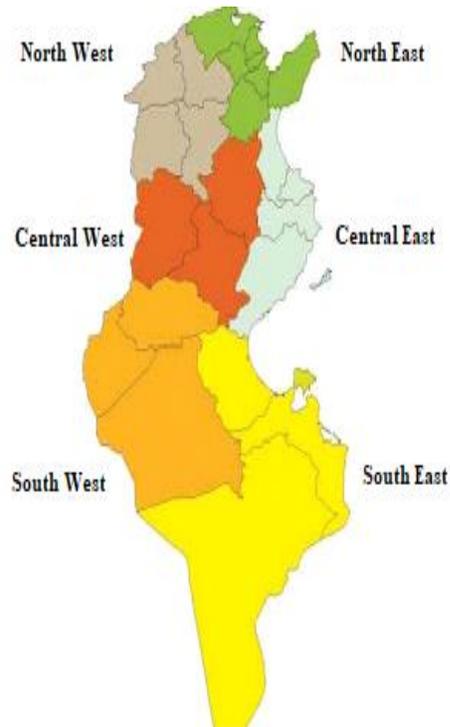
In sociology, before any other stage, it is necessary to determine the territory on which the sociologist works. At the national level, "economic territory" means: The area (geographical territory) under effective economic administration and control of a single public administration. In Tunisia, the choice was made to divide the territory into seven major regions (tab.1- fig 1-2)

Cities Regions	Table 1 : Geographical distribution of Tunisian regions			
Greater Tunis	Tunis	Ariana	Ben Arous	Mannouba
Northeast	Nabeul	Bizerte	Zaghuan	
North West	Beja	Jendouba	Kef	Siliana
Central East	Sousse	Monastir	Mahdia	Sfax
Central West	Kairouan	Kasserine	Sidi bouzid	
South East	Gabes	Medenine	Tataouine	
South West	Gafsa	Tozeur	Kébili	

Figure 1: Geographical distribution of the 24 Tunisian governorates Source : INS Tunisia, 2015)



Figure 2 ; Geographical distribution of the 7 Tunisian regions (Source : INS Tunisia, 2015)



2.3. Screening questionnaire for students at risk of dropping out of school:

Our validated School Dropout Questionnaire (SDQ) (Cherif and Elloumi, 2021), this questionnaire is based on data from Potvin and al. (2009) allows to identify students who are at risk of dropping out of school. It consists of seven sub-scales: parental commitment, attitudes towards school, perception of school achievement, parental supervision, educational aspirations, for a total of thirty-three questions. These questions are used to achieve two objectives: on the one hand, to identify the most powerful factors in the careers of dropouts and on the other, to identify a typology of Tunisian students at risk of dropping out. Seven variables are considered: social factors, school factors, economic factors, personal factors, cultural factors and geographic factors. The first variable (social factors) is divided into six items: 1/Poverty and precariousness, 2/Social inequality of opportunity, 3/Peer groups, 4/Environmental impact, 5/ Social networks and 6/ Health problems. For the second variable, school factors, it consists of ten items that are : 1/Negative classroom climate, 2/ Negative

interactions with the teacher, 3/Negative interactions with colleagues, 4/Damaged infrastructure, 5/Traditional school, 6/Devaluation of vocational training courses, 7/ Over-staffing of classes, 8/Low-value and low-differentiation pedagogical practices, 9/Massification of programmes and 10/System of evaluation and sanctions. The third variable of economic factors contains the following seven items: 1/Low economic and professional level of parents, 2/Regional disparity (Lack of development in internal regions), 3/Local labour market in jobs not attractive, 4/Parallel trade, 5/Illegal migration, 6/Illegal child labour and 7/Displacement of families for seasonal agricultural work. While the fourth variable that corresponds to family factors consists of five items related to family relationships (1/ Low intellectual level of parents, 2/ Family disintegration (Divorce/ Death/ domestic violence), 3/ Strained relationships with parents (generation conflicts/ adolescent crisis), 4/Individual confrontation with the school (lack of parental supervision) and 5/Belonging to a poor environment). In addition, the Personal Factors variable contains six items: 1/ Psychological Factors (Low Self-esteem Demobilization and Impairment), 2/Low Academic Achievement, 3/Behavioural Disorder, 4/Early Learning Difficulties and 5/Disintegration 6/Repetition. The last two variables that we consider very appropriate for the Tunisian context are cultural factors and geographical factors. On the one hand, The former (cultural factors) are divided into four items : 1/Negative vision of the school, 2/ Girls in rural areas drop out more than boys, 3/The culture of the environment prevails over the culture of the school and 4/Refusal of gender diversity within the school. On the other hand, the last (geographical factors) are divided into three items: 1/Social, residential and regional differences, 2/Distance/ Home-School and 3/Harsh Climatic Conditions (Rains, rivers, and mountains wild animals).

The higher the score, the more at risk the student is. The questionnaire has a very good internal consistency (Cronbach alpha coefficient of 0.89) and an acceptable to very good consistency for the subscales (0.72 to 0.84). A test-retest also showed that the questionnaire is stable over time.

2.4. Mapping of school dropouts

The mapping of school dropouts was inspired by the geographer's work (Davis, 2003; Andrei and al. 2012). It refers to a set of techniques whose objective is to disaggregate a dropout indicator at finer administrative or geographic levels (Davis, 2003; Andrei and al. 2012). Stall mapping can take many forms, each with specific requirements for data availability or collection, but also specific pros and cons. The stall map follows this logic and is a preferred instrument for assessing stall status at finer levels of disaggregation and allows to some extent to provide objective criteria for budget allocation to the various regions. There are several methodological approaches to the implementation of stall mapping (Davis, 2003. Andrei and al. 2012). These methodologies all share the concern to represent at much disaggregated geographical levels the usual indices of dropout. The degree of accuracy of stall charts therefore depends on the geographic level at which data are available. Davis (2003) distinguishes several groups of methods in mapping : methods combining surveys and censuses (which Davis calls "small-area

estimation"), multiple indicators weighted from basic needs, methods combining qualitative information and secondary data sources, methods for extrapolating participatory approaches, direct measurements from regional surveys and direct measurements from censuses.

2.5. Direct measurements from surveys

When survey staff are sufficiently large and at a fairly detailed geographical level, it is often possible to construct maps directly from survey data (Davis, 2003; Andrei and al. 2012).

Multiple Indicators

Various factors of school dropout have been developed in recent years. They differ from each other in terms of the choice of variables but also in terms of weighting schemes. With regard to the identifier (the variables used to construct the indicators), most of the work takes into account the school, family, personal and economic characteristics of dropouts (Epicum and Murray, 1975; Charest 1980; Kronick and Hargis, 1990; Watherhouse Price, 1990; Violette, 1991; Janos et al, 2000, Blaya, 2009, Potvin and al ., 2003, Fortin and al., 2006). As for the methods of aggregation of the school achievement proxy, they range from simple methods of summing scores previously assigned to the different modalities of the study variables to methods of factor analysis, through intermediate methods of standardisation. In terms of factor methods, we can mention the Analysis in Main Components (CPA) and the Analysis of Multiple Correspondence (ACM) (Kobiané, 2004). Several authors have used the CPA to determine the weights of variables characteristic of student socio-economic conditions. The CPA's active variables are all dichotomous variables.

As a result, the school dropout index is determined by the coordinates of the factors and after types on the first factor axis of the Analysis of Multiple Matches whose active variables are the variable K of the factors and types considered. The demographic components of school drop-outs are conceptually well known and are generally provided by surveys conducted by some of the authors we have already cited.

In this study, the approach consists of direct measurement from survey data from Tunisia.

2.6. Geographic Tools

It is important to note that as a research group we do not claim to be experts in this area. The literature on the subject of indicators or mapping is abundant.

Mapping is a graphical technique for the production of maps. Although a multitude of fields of activity (sociology, psychology, biology) can use the map to treat their object of study, it is a technique that is mainly used by geography. As part of this research, we will treat cartography as an instrument for mapping spatial information. In short, mapping is: 1) a graphical conceptualization exercise that requires a census and a processing of specialized information; 2) a reduced and synthesized visual model of our

complex world; and 3), an information and communication tool for knowledge dissemination.

2.7. The Geographic Information System (GIS).

Mapping is the technique or process to arrive at a final product that is the map, plan or other related instrument (geographic information system).

The thematic maps (adopted by our study) deal with more specific themes and are constructed by assigning values to polygons (neighbourhood, city, etc.), lines or geographical points. Values can be qualitative (insecure zone for neighbourhood x) or quantitative (proportion of low-income people) depending on the objectives of the communication. Thematic maps can deal with variables such as unemployment rate, population density, family income, etc. The last level is the development of a geographic information system (GIS).

2. 8. Linkages between Indicators of Early School Leaving and Mapping

In the first part of this research, we addressed the question of indicators and in the second part we focused on mapping. Here we will briefly try to explain the links between these two instruments.

Indicators of school drop-out and mapping can include social, economic, person, cultural, territory, etc. For its part, mapping is limited to geographical space. From the moment when actors have an interest in analysing the situation of school dropout in one or more territories, they can set up a system of indicators (factors, and types, etc.) and use mapping as a means of communication. In this logic, the location of the territory can partly explain the social conditions of the population living there.

2.9. Factor analysis

The Typological Analysis of Multidimensional School Dropout is a methodology that offers new perspectives in the context of this multifactorial phenomenon (Boidin and Lardé, 2008; Bentler, 2004). It is carried out in two stages:

First, a factor analysis is carried out to construct indicators of school dropout based on many dimensions. Primary variables are combined within a few common factors that each contain a stall facet.

Second, classification methods are used to construct homogeneous groups based on the factorial scores obtained. Among the most widely used techniques is the Hierarchical Automatic Classification (HAC), which aims to create homogeneous classes of different factors and types of school dropout (Boidin and Lardé, 2008). The nature of the data processed by factor analysis lends itself to classifications according to the dynamic cloud method (NDT), a method that proceeds by partitions by optimising an inertia-type criterion (Boidin and Lardé, 2008). Moreover, once the typology is made, the interpretation of the profiles of the classes constituted is determined by the supervised classification approaches based on a qualitative variable, in this case logistic regression or discriminating factor analysis. However, in the case where the analysis is

performed on a small number of axes derived from factor methods, it is preferable to use the discriminating factor analysis (Sautory and Vong, 1992). This approach, not yet used at the national level, offers new perspectives for understanding the multiple aspects of stall. All the more so since the statistical system offers a wide range of regional indicators giving information on all dimensions and types of school dropout. Using data analysis techniques based on factorial and automatic classification methods, this work proposes a multidimensional hierarchy of Tunisian cities and regions according to geographical and cultural territory. Using data analysis techniques, based on factorial and automatic classification methods, this work proposes a multidimensional hierarchy of Tunisian regions and governorates according to geographical space

The multi-dimensional stall analysis approach in the regions is based on data analysis techniques in three stages:

Step 1: Factor analysis

Because the variables are quantitative, it was natural to use Principal Component Analysis (PCA), a very useful tool for spatial comparisons (Husson and al, 2017).). Factor analysis reduces the number of starting variables by eliminating redundant information and focusing the information on a small number of new variables called “factors or dimensions”.

Step 2: Clustering method

Cluster analysis is an unsupervised classification technique that consists of searching for proximities of observations in a multidimensional space; the nearest cities and regions are grouped into classes. The technique used is the Hierarchical Automatic Classification (HAC), which uses an algorithmic partition approach to propose a typology of cities in the region in terms of drop-out.

Step 3: Discriminating factor analysis

Discriminating Factor Analysis (DFA) is a supervised classification technique designed to classify (i.e., assign to pre-existing classes) individuals characterized by a number of numerical variables. DFA has a descriptive power since it can identify the most discriminating indicators to characterize each class, and a predictive power because it can predict the assignment class of a new individual (city/region) described by the same quantitative variables.

2.10. Development of a combined statistical model

To meet the objectives of the study, analyses were first carried out to highlight the means and percentages to better understand the meaning of the data for each of the dependent variables. Subsequently, tests of the difference between the means, logistic regression and variance analyses were performed. This is done to see if students who drop out of school differ from each other with respect to certain variables (urban, rural). Logistic regression analyses were also conducted to assess whether geographic and cultural variables are adequate to classify students at risk and not at risk by city and region. Other ANOVA-type variance analyses were conducted to assess the presence

of a link between regional disparities and the typology of students at risk of dropping out of school in Potvin and al. (2003) and Fortin and al. (2006) of the training and school program.

2.11. Data Sources and Variable Definitions

The screening questionnaire for students at risk of dropping out of school (Cherif and Elloumi, 2021) is the main source of data for the definition of variables. The K variables characteristic of school dropout factors and types are characterized as shown in Table.2. These 11 variables (7 factors and 4 types) were all used to generate the composite stall indicator.

Table 2: Nature and definition of school dropout factors

Variables	Items	Components
Description of the seven dropout factors		
1) School factors	10 items	Stated according to the factor Items related to school
2) Social factors	6 items	Items related to the social environment
3) Economic factors	7 items	Items related to the economic aspect of the family
4) Family factors	5 items	Items related to family relationships
5) Personal factors	6 items	Items related to the psychological aspect of the student
6) Cultural factors	4 items	Items related to the impact of culture on student behavior
7) Geographic factors	3 items	Items related to the socio-geographical environment of the student

2.12. Summary of geographical methods

2.13. Mapping of regions in response to different school drop-out situations

This study proposes to assess the different factors and types of school drop-out based on several geographic variables jointly examined. These are the objective dimensions developed from data from a regional survey (the screening questionnaire for students at risk of dropping out, (Cherif, A and Elloumi, 2021) providing information on the different school dropout situations in Tunisian regions. It is the main source of data for the definition of variables.

1. Creation of variables related to the phenomenon studied: use of data at the group level from sociological surveys to create variables specific to the factors and types of dropout on aspects such as school causes, socio-economic, geographical etc.
2. Mapping of school dropouts at different levels of geographic synthesis (7 regions) and development of assumptions based on visual inspection.

- Analysis of the influences of different dimensions (socio-economic, geographic, etc.) separately to observe the influence of these factors, respectively.

We believe that this article will help to inform the use of these analyses, in particular because it deals with a niche not addressed in the French-language writings and in a language accessible to non-specialists.

3. Results

3.1. School dropout by region

Table3: Average scores of the seven factors by Tunisian regions

Facteurs Regions	Economic	Social	Schools	Cultural	Personal	Family	Geographical	Overall average
Greater Tunis	2,79	2,68	2,16	3,42	3,09	2,14	2,47	2,68
North East	2,28	2,05	1,54	2,35	2,11	2,28	2,51	2,16
North West	3,04	3,27	3,06	3,68	3,01	3,65	4,06	3,40
Central West	3,92	3,36	3,41	3,93	3,53	3,36	4,20	3,67
Central East	2,35	1,93	1,78	2,56	1,8	1,8	2,6	2,12
South West	3,36	2,96	3,19	3,73	2,96	3,26	3,70	3,31
South East	3,20	3,21	3,03	3,57	3,3	3,35	3,56	3,28
Overall average	2,99	2,78	2,60	3,32	2,79	2,84	3,30	2,95

This table reflects the average scores of school dropout factors for each region and includes the following variables: economic, social, academic, cultural, personal, family and geographic. As shown in the table opposite, the distribution of average scores is indicative of significant disparities between regions with a coefficient of variation of 19.6% (i.e. regions generally differ by 19.6% from the national average value of 2.95). These disparities reveal, however, a systematic opposition between coastal and inland regions. Indeed, the interior regions have an average dropout score of (3.40) well above the national average (2.95), or 0.46 points above the national average.

The ranking of regions according to the School Dropout Factor Index shows a wide disparity between coastal regions on the one hand and inland regions on the other.

The ranking of regions according to the School Dropout Factor Index shows a wide disparity between coastal regions on the one hand and inland regions on the other.

Table 4: Ranking of Regions by Dropout Rate

Ranking	Regions	General means of the factors
1	Central East	2,12
2	North East	2,16
3	Greater Tunis	2,68
4	South East	3,28
5	South West	3,31
6	North West	3,40
7	Central West	3,67
National Means		2,95

}

Low dropout mean

}

Medium dropout mean

}

High dropout

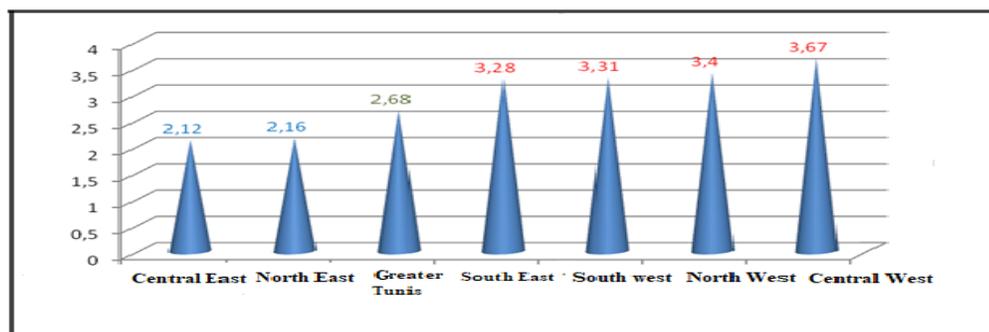
Greater Tunis: (Tunis, Ariana, Ben Arous and Manouba), **North East:** (Nabeul, Bizerte and Zaghouan), **North West:** (Béja, Jendouba, Le Kef and Siliana), **Central West:** (Kairouan, Kasserine and Sidi Bouzid). **Central East:** (Sousse, Monastir, Mahdia and Sfax), **South West:** (Tozeur, Kébili and Gafsa). **South East:** (Gabès, Médenine and Tataouine).

At the regional level, the dropout rate is becoming increasingly apparent. Of the 7 Tunisian regions ranked by their stall factor averages, there are seven (7) groups, (See Table 2 and Figure 1):

- 1-The group with an average of less than 2.50 has two regions (Central-East and North-East);
- 2-The group whose average is between 2.50 and 3, has 1 region (Greater Tunis);
- 3-The group whose average is between 3 and 3.70, has 4 regions (Central-West, South-East, South-West, North-West);

This result shows that the dropout rate in deep regions far exceeds the national average of 2.95.

Figure 3: Dropout Rates by Region



3.2. Analysis in Main Components

The following results relate to the ACP dataset

This dataset contains 7 regions and 7 variables (dropout factors).

3.3. Observation of extreme regions

Analysis of the graphs reveals no singular regions.

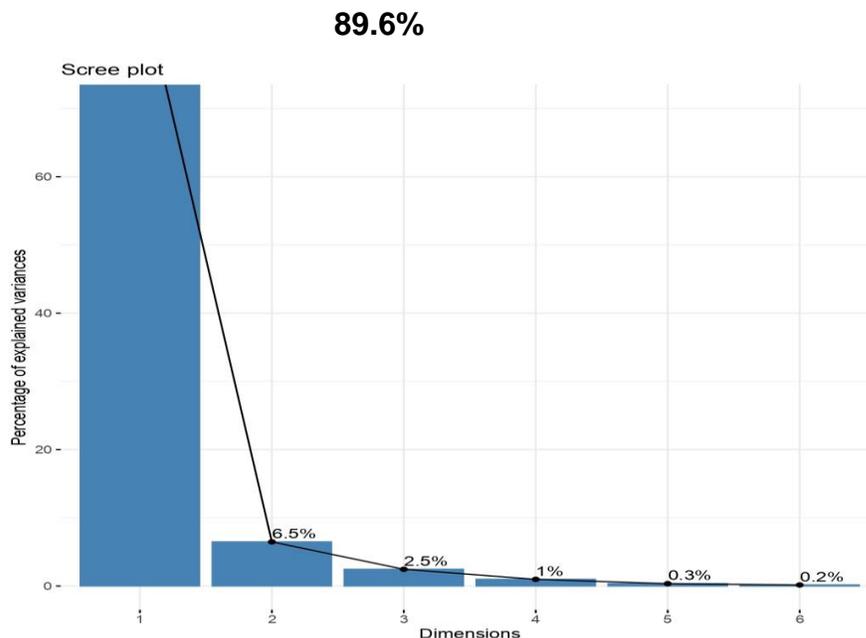
3.4. Distribution of inertia

The inertia of the factorial axes indicates on the one hand whether the variables are structured and on the other hand suggests the judicious number of main components to be studied.

The first 2 axes of the analysis express **96.07%** of the total inertia of the dataset; this means that 96.07% of the total cloud variability of the regions (or variables) is represented in this plane. That's an extremely high percentage, so the foreground is a very good representation of the variability in the whole active dataset. This value is higher than the reference value of **78.03%**, so the variability explained by this design is significant. (This reference inertia is the 0.95-quantile quantile of the distribution of the inertia percentages obtained by simulating 3169 sets of random data of comparable dimensions on the basis of a normal distribution).

As a result of these observations, it is probably not necessary for the analysis to interpret the following dimensions.

Figure 4: Decomposition of total inertia (Axis 1: 89.6%)

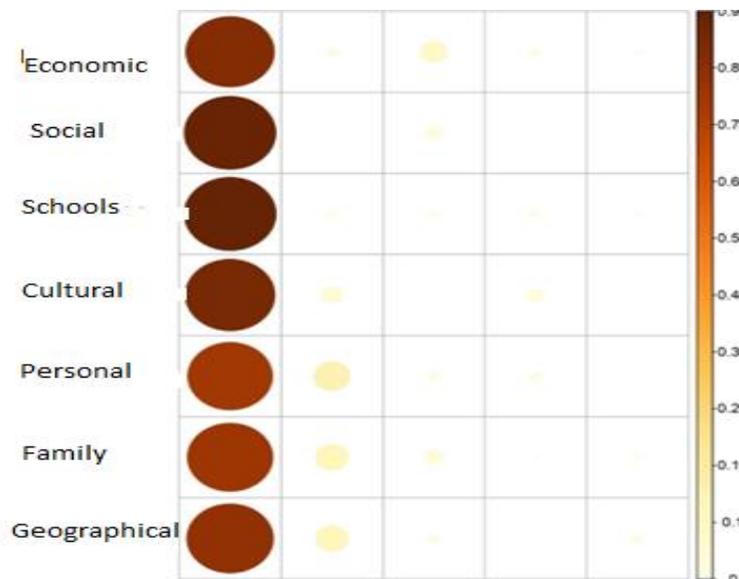


The first factor is largely dominant: it alone explains 89.6% of the total variability of the data. It should be noted that in such a case, the variability related to the other components may be meaningless, despite a high percentage.

An estimate of the relevant number of axes to be interpreted suggests limiting the analysis to the description of the first axes. These components reveal a higher inertia rate than the 0.95-quantile quantile of random distributions (89.6% versus 6.47%).

This observation suggests that only this axis carries real information. Consequently, the description of the analysis will be restricted to these areas alone.

Figure 5: Factorial Correspondence Analysis (FCA): Explained variance of the factor variable

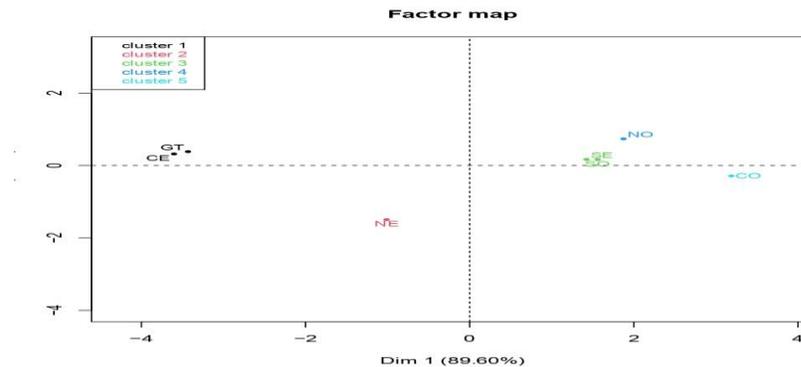


3.5. Description of Dimensions (1-2)

In this regard, we recall that the first factorial plane explains more than 89.6% of the total variance. The graphical projection of the variables on this plane is visualized on the following factor map:

The combination of the selected variables makes it possible to define two main axes capturing 96.07% of the total variability. The first Dim1 axis (89.6% of total variability) essentially combines basic infrastructure endowment. The second axis Dim 2 (6.47% 51.38% of the total variability) groups the stall variables of each region. The distribution of regions along the two axes gives the following typology:

**Figure 6: Distribution of regions on the two factor axes, Dim1 and Dim2 (PCA)
 (The regions with the largest contribution to the construction of the plan)**

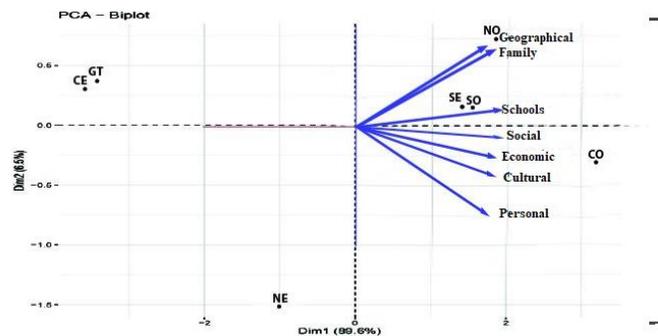


The reading of this map clearly shows that the axes regions North-West, South-East, South-West and Centre-West, are oriented in the opposite direction of the variable axes Grand-Tunis and Centre-East. This indicates that there is a negative correlation between these two groups of variables and a positive correlation between the variables within each group. We then find the same conclusion drawn from the matrix of correlations. In the same graph, we see that the North-East region is oriented in the negative direction of the Dim.2 dimension, indicating that there is a negative correlation between this variable and the axis in question.

In relation to the first axis (Dim1), three groups can be identified. The first is the Northwest, Central-West, South-East, and South-West regions. They have a positive score. The second group formed by the regions, Greater Tunis and Central East, has a negative score. A Third group concerns the Northeast region, also has a negative score.

Indeed, the projection of regions on the F2 axis (Figure 6) raises three groups. The first group represents positive trends while the other two have negative trends.

**Figure7: Graphical representation of variables in the factorial plane (Dim.1, Dim.2)
 (The variables denominated are those best represented on the plan)**



This figure shows three groups of regions. The position of the North-West, Central-West South-East and South-West regions in relation to the first axis (Sun.1) indicates that this group has a very high dropout rate characterized mainly by the following factors: Geographical, Social, Economic, cultural and personal. Their position in relation to the second axis has no significance since the dropout index only concerns the other regions. The second group of regions concerns Greater Tunis and Central East, which represent a relatively high dropout rate (all factors combined). Finally, the third group in the Northeast region with low dropout rates (all factors combined), In addition, the representation of all regions (Greater Tunis and Central East) on the factorial level, the majority of the points are concentrated around the centre, which means that the corresponding regions have an average dropout rate.

Dimension (1) (map 1-2) contrasts regions such as Northwest, Central-West Southeast and Southwest (to the right of the graph, characterized by a strongly positive coordinate on the axis) with the Northeast region (to the left of the graph, characterized by a strongly negative coordinate on the axis).

The group to which the North-West, South-East and South-West regions belong (characterized by positive co-ordination on the axis) shares:

- Strong values for school and geographic variables

The group to which the regions of Greater Tunis and Central-West belong (characterized by positive coordination on the axis) shares:

- Strong values for social, economic, cultural and personal variables (from the most extreme to the least extreme).

The group to which the Northeast region belongs (characterized by a negative coordinate on the axis) shares:

- Low values for all variables (from the most extreme to the least extreme).

In order to clarify the results achieved by the PCA, we are proceeding with a hierarchical upward classification of governorates (CAH) according to their weights on both axes. The results of this classification are shown in the figure below.

3.6. Hierarchical Upward Classification of Governorates (HCA)

Classification technique use an iterative algorithmic approach that seeks to group the nearest statistical individuals in a multi-dimensional space. The principle of the algorithm consists in creating, at each step, a score obtained by aggregating two to two the closest elements. To perform the classification, we use:

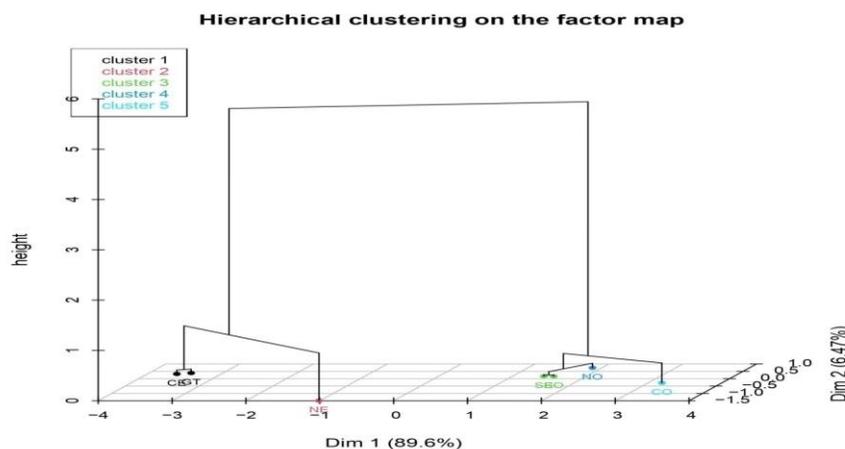
- Euclidean metric to measure similarities between individuals since the variables are quantitative;
- Ward's criterion for measuring similarities between groups of individuals. Ward's method of aggregation is based on the decomposition of variance such that the inter-group variance remains the largest and intra-group variance the smallest (homogeneous classes).

The HCA technique makes it possible to build classes that group homogeneous regions in terms of multidimensional stall. The ACP performed on the 7 variables of the file allows to extract 2 factors with an explained variance percentage equal to 96.0%. It is useful, therefore, to apply the HCA on the factor foreground (Dim.1, Dim.2).

3.7. Dendrogram

The automatic hierarchical classification based on the Euclidean distance and the Ward method leads to the classification tree or dendrogram which highlights the proximities between regions and between groups of regions with similar profiles. The classification tree can also be used to select the number of classes.

Figure 8: Regions Hierarchical Upward Classification Tree



Moreover, the quality of the partition can be determined from the tree, the coefficients of aggregation, the number of individuals, the variability of individuals or even according to the interpretation and the description of classes.

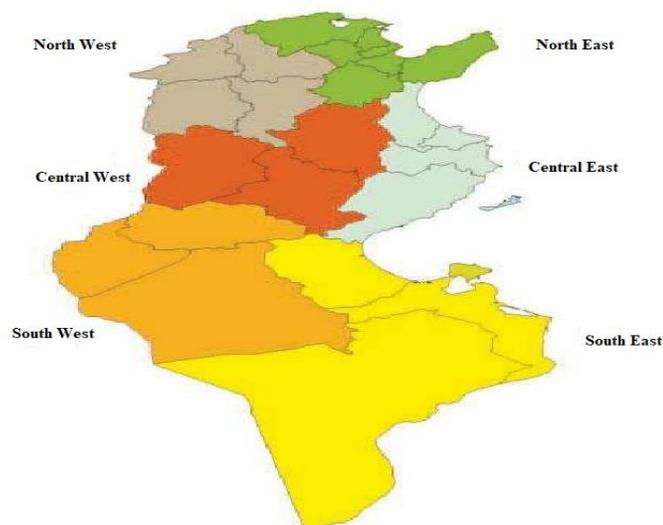
3.8. Classes of regions obtained

The dendrogram obtained from the (HCA) allows to rank all the Tunisian regions in five homogeneous classes. The following table presents the elements of each of these five classes

Table 5: Classes of regions by HCA

Class 1	Class 2	Class 3	Class 4	Class 5
Greater Tunis Tunis, Ariana, Ben Arous Manouba	North East Nabeul, Bizerte Zaghouan	South East Gabès, Médenine and Tataouine	North West Béja, Jendouba, Le Kef and Siliana	Central West Kairouan, Kasserine and Sidi Bouzid
Central East Sousse, Monastir, Mahdia and Sfax		South West Tozeur, Kébili and Gafsa		

Figure 9: Mapping of Multidimensional Absolute Dropout Variation by Region



The multidimensional mapping of school dropouts for Tunisian regions presented in Figure 10, highlights the result of the typology carried out. The analysis of the map

makes it possible to raise some annotations on the distribution of multidimensional dropouts in the regions: North-East, Greater Tunis and Central-East, are slightly spared from dropping out of school. The magnitude of this phenomenon increases differently as it moves from the south (east and west) to the northwest and becomes more severe in the west-central region with an average of (3.67) compared to the national average of (2.95).

Poverty and territorial disparities between Tunisian regions are the main factors that differentiate between them, from the most precarious to the most favoured. Coastal regions have more or less homogeneous characteristics with regard to these factors. (See figure.10)

This confirms our hypothesis that the more sociogeographical disparities persist, the more the phenomenon of school dropout increases.

However, this classification does not allow to describe the classes obtained, nor to distinguish between classes. The question then arises about the variables that best characterize the score. To do this, we will analyze the characteristics of the most discriminating indicators between classes by applying the Discriminating Factor Analysis.

3.9. Discriminating factor analysis (DFA)

The Discriminating Factor Analysis technique not only validates results but also identifies the performance indicators that discriminate the most between classes of regions while providing the characteristics of each class. AFD has a descriptive objective which consists in the search for linear combinations of variables, which allow to separate at best the 5 classes of individuals defined beforehand. It also has a decision objective in that it provides for the assignment class of a new individual (regions) described by the same quantitative variables.

3.10. Selection of the most discriminating indicators

The values of non-standardized coefficients of the linear discriminant function make it possible to directly use the values of explanatory variables to calculate the factor coordinate or discriminating score of the discriminant function (D. Desbois, 2003). By analysing the partitions obtained by (CAH) and based on the study variables, the application of AFD makes it possible to obtain: - The coefficients of the four discriminating lines (number of classes -1)

Table 6: Discriminating function coefficients

Dimensions Variables	1	2	3	4
Economic	1,513	-1,650	0,428	0,131
Social	-0,364	0,526	0,413	0,409
Schools	-0,362	-0,075	0,494	0,174
Cultural	-7,501	14,824	0,599	10,575
Personal	8,539	2,539	-1,168	1,011
Family	0,018	0,040	0,006	-0,021
Geographical	0,008	0,064	0,063	-0,017
(Constante)	11,920	-9,951	-26,033	-18,499

The structure matrix that provides information on the most discriminating indicators1

Table 7: Structure Matrix

Dimensions Variables	1	2	3	4
Social	-0,286	-0,018	0,275	0,147
Economic	0,098	-0,791	0,043	-0,125
Schools	0,223	-0,809	0,182	-0,002
Family	0,272	-0,102	0,594	-0,417
Cultural	0,280	-0,714	0,286	0,104
Personal	0,429	-0,498	0,401	0,242
Geographical	0,279	0,189	0,552	-0,423

Reading the structure matrix shows that school, family, personal and geographical variables are the most discriminating variables for the four discriminating functions respectively. As for the test of equality of means of classes, the results displayed in the following table, reveal that there is a significant difference ($\alpha=5\%$) between the means of the five classes for all variables. Thus, the seven variables allow to give a definition to each class in terms of the magnitude of multidimensional school dropout. In addition, Fisher's statistics show that the geographical variable contributes the most to the constitution of classes. Another statistic leads to the same result, the Lambda de Wilks which is constituted by the ratio of the intra-class variance to the total variance. All things being equal, the most discriminating indicators have the lowest Wilks Lambda values. (See Table8)

Table 8: Equality tests of group averages

	Wilks Lambda	F	Meaning
Geographical	0,236	90,613	0,000
Schools	0,240	88,747	0,000
Personal	0,292	75,492	0,000
Family	0,319	69,847	0,000
Cultural	0,419	59,899	0,000
Social	0,305	38,888	0,000
Economic	0,396	39,415	0,000

3.11. Class Interpretation

In order to propose a definition for each of the five classes in terms of school drop-out variables, it is based on the averages and standard deviations of the seven indicators, all of which contribute to class composition.

Table 9: Means and standard deviations of variables within the five classes

Class	Class 1		Class 2		Class 3		Class 4		Class 5	
	Means	Sd	Means	Sd	Means	Sd	Means	Sd	Means	Sd
Geographical	2,54	2,8909	2,51	2,4331	3,63	2,524	4,06	3,2885	4,20	5,3126
Schools	1,97	2,9664	1,54	2,2172	3,11	1,2157	3,06	1,493	3,41	0,6884
Personal	2,45	0,4225	2,11	0,2765	3,13	0,3717	3,01	0,4947	3,53	1,0239
Family	1,97	1,7281	2,28	1,5023	3,31	1,9015	3,65	1,1557	3,36	1,0551
Cultural	2,99	0,0371	2,35	0,0382	3,65	0,0348	3,68	0,0395	3,93	0,02
Social	2,31	3,0713	2,05	0,1438	3,09	0,0967	3,27	0,1196	3,36	0,0781
Economic	2,57	5,8128	2,28	4,6064	3,28	3,5887	3,04	4,5825	3,92	5,24

Looking at the data in the table, it can be seen that Class 1 and Class 2 groups the regions with the lowest dropout rates. This result seems very logical because these classes are made up of all the urban governorates of the regions represented (See Table 8 of the classes: Greater Tunis, Central-East and North-East). This confirms the spatial disparities between urban and rural areas in terms of multi-dimensional dropouts. Class 3 groups the regions of the South (East and West) with intermediate values at the level of all the variables and therefore an average level above the national average (2.95) in terms of multidimensional stall. Finally, classes 4 and 5 bring together the regions of Nord-Oouest and Centre-Oouest with the highest rates of indicators of school dropout compared to the national average (2.95). This implies that classes 3, 4 and 5 bring together the most disadvantaged governorates in terms of economic development and consequently of dropout in its multidimensional aspect.

3.12. Validation of Classification Results

Regardless of the classification method used, the estimation of the misclassification error is interesting since it makes it possible to assess the quality of the discrimination. In practice, the data are subdivided into two disjointed subsets: the learning set used to construct the prediction model and the test set used to measure performance. The ranking error can then be estimated without bias on the test sample. This procedure, called a test sample, has the advantage of providing unbiased estimates of a percentage of well-classified and misclassified (Desbois 2003). In other words, the test error is an unbiased estimator of the model built on the learning part. The application of this partition technique on the data (7 regions) made it possible to divide the whole into a learning sample (24 governorates) and a test or independent sample (7 regions). The table below summarizes the results of AFD's ranking.

Table 10: AFD ranking results

Scheduled Assignment Classes		Class 1	Class 2	Class 3	Class 4	Class 5	Sum
/	Class 1	8	0	0	0	0	8
	Class 2	0	3	0	0	0	3
	Class 3	0	0	6	0	0	6
	Class 4	0	0	0	4	0	4
	Class 5	0	0	0	0	3	3
	Sum	8	3	6	4	3	24
Observations not selected	Class 1	2	3	6	4	3	2
	Class 2	0	1	0	0	0	1
	Class 3	0	0	2	0	0	2
	Class 4	0	0	0	1	0	1
	Class 5	0	0	0	0	1	1
	Sum	2	1	2	1	1	7

In comparison to the classification obtained by the (CAH), 100% of the original observations selected (dependent sample) are correctly classified. Similarly, the independent sample with the rest of the non-selected individuals shows a real well-classified rate of 100%.

3.13. Multidimensional Stall Factor Mapping in Regions

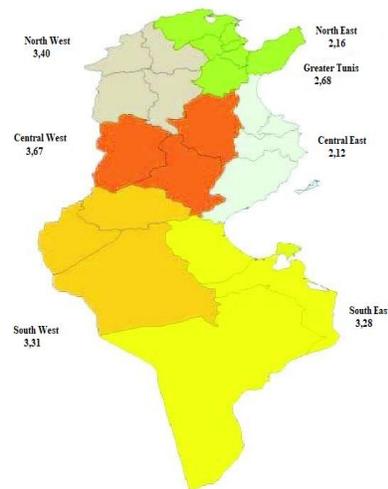
The results of the classification are displayed on the map below, which highlights the multidimensional map stall distribution of the regions. Similarly, the examination of this board makes it possible to identify the following main remarks:

- The majority of governorates in coastal regions have a high dropout rate than inland regions;

-Multi-dimensional stalls occur with greater breadth and severity as they move south, northwest and west-central. This applies to all the governorates of the regions mentioned.

- Two large multi-stall areas stand out in Tunisia: the North-West and the West Centre (See Figure 10)

Figure 10: Map Typology of Multi-dimensional Stall Factors by Region



3.14. Summary of factor analyses

Thus, the application of factor and automatic classification methods on the matrix (provinces, variables) made it possible to create 4 homogeneous classes from the point of view of multidimensional stall analysis. The characterization of the clusters of the regions reveals the following description: Classes 1 and 2: regroup the regions with a profile of light multidimensional school dropout (Greater Tunis, Central-East and North-East: coastal cities) Class 2: is made up of the regions (South-East and South-West) with an average multidimensional stall level. Class 4 and 5 are regions (Northwest and West Central) characterized by an acute multidimensional dropout rate.

4. Discussion

The results of the factorial analyses of this study for causes of school dropout at the regional level show a positive sign when measuring the correlation between the dropout rates of coastal governorates. Going west, its sign becomes negative. The spatial distribution of this index shows the absence of a horizontal spatial correlation between coastal and deep regions. The spread of wealth from large urban centres to the rest of the territory is gradual and covers only a thin strip bordering areas of economic concentration. This result proves that socio-economic development (Alaya and al. 2018; Belhedi, 2019) affected only coastal governorates at the expense of deep governorates.

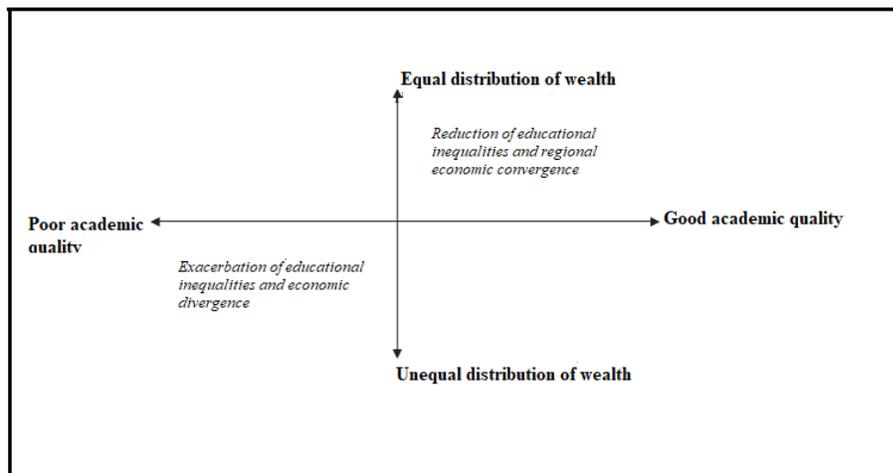
In general, the use of composite variables shows that there is no direct relationship between the quality of educational institutions on the one hand and geographical disparities on the other. This result poses different scenarios:

The first scenario: we accept the result obtained and we consider that the institutional factor did not contribute to the exacerbation of geographical disparities in Tunisia (Boughzela and al. 2020, Medinilla Alfonso and El Fassi Sahra, 2016). This scenario takes us back to the debate on the liberal foundations of development policies conveyed by international institutions (Ref). Indeed, accusing the institutional factor hides the shortcomings inherent in these development models. This assumption is based on the fact that even countries with good institutional quality have not been able to reduce school dropout to the bare minimum. Worse still, school failure in the USA and Europe follow an upward trend (Boughzela and al. 2020, Gleyse, J. 2020, Lahire, 2021, UNESCO, 2014, Romeo, 2014, Medinilla Alfonso and El Fassi Sahra, 2016, BIRD, 2014).

An analysis of regional inequalities also shows that disparities in school dropout rates within regions are not ready to disappear. In the deep regions, the governorates of Kasserine, Sidi-Bouzyd and Kairouan lag behind other governorates. Throughout the coastal strip, the Tunis agglomeration, Sousse and Sfax are well ahead of other governorates. This result proves the exacerbation of educational inequalities between coastal bands and deep regions on one side and within each region on the other (See summary figure).

It must be said that this reversal finds its explanation in the repeated social tensions deliberately provoked by regional disparities. Moreover, through the rural exodus that they are driving, regional disparities are increasingly becoming a real obstacle to economic growth, since it is social cohesion in Tunisia that has been hit hard. For sociologist Bernard Lahire (2021), "the root cause of school failure is the existence of social classes and an unequal distribution of wealth."

Figure 11 (Summary): Quality of educational institutions in Tunisia, distribution and inequality (source: author of study)



5. Conclusion

The purpose of this study is to examine the method of territorial targeting adopted by the Ministry of National Education, which has given rise to criticism and questions from the actors, decision-makers and researchers on the list of governorates affected by school dropout. In fact, the primarily percentage-based targeting approach does not address the multi-sectoral aspect or the multiple aspect of school achievement deficits. To eliminate selection bias and optimize spatial targeting, a multi-dimensional stall measurement would have been more appropriate. Since the 2000s and following some Western research, the multidimensionality of school dropouts has been universally recognized. Especially since the national statistical system of Tunisia does not offer the various indicators of school dropout. In this study, we developed maps, based on in-depth statistical analysis that will be used to target governorates and regions, and a drop-out approach based on multidimensional indicators. It is in this vision, that our research has proposed a new approach of typological analysis of multidimensional dropout (Cluster analysis of multidimensional dropout). The approach adopted is based on factorial (ACP) and automatic classification (CAH) methods, thus making it possible to go beyond the restricted framework of the one-dimensional analysis of the stall or the correlations taken two to two. The discriminant analysis made it possible to characterise each of the classes obtained from the point of view of socio-educational level and to predict the classification of a new individual (city or region).

By way of conclusion, in our approach, the emphasis is on a multidimensional approach to school dropout which: (i) Takes into account the different variables, of this phenomenon, observed by censuses, other statistical surveys and regional studies; (ii) Optimizes the informational gain of available quantitative indicators at the finest geographical level; (iii) Meets the need for remedial programs for multivariate territorial

targeting. Such targeting allows decision-makers to optimise resources and means to combat dropout, by going beyond the fixed administrative boundaries and focusing on the areas affected by the various forms of school failure in Tunisia. The typology of school dropout factors in the Tunisian regions thus proposed, represent a new multivariate mapping of school dropout and thus a tool for multidimensional territorial targeting and decision support. Its acuity is such that it can serve as Baseline Information for public policy impact assessments in education, including the national initiative to combat school dropout.

The Charter of the World Conference of Jomtien (1990), proclaims a universal right to education, thus the educational provision should cover anyone born on the national territory without discrimination according to gender or region, the main aim should be to break down the barriers between the two systems so as to prevent pupils in certain regions from leaving school prematurely. Positive discrimination laws should therefore be considered and activated to ensure greater equality of opportunity and to reduce the difference in the Tunisian education system. Finally, I conclude with Stiglitz's quote:

« *Inequality has a price, it is the cause and consequence of the failure of the political system, and it fuels instability and inefficiency in our economic system, which in turn aggravate it. It is this vicious circle that plunges us into the abyss* ». Stiglitz, Joseph E 2012

References

Alaya. N; Ben Jelili. R & Markhout. A. (2018) Déséquilibres régionaux et inégalités sociales en Tunisie. Axes et actions prioritaires. Publié en 2018 par Friedrich-Ebert-Stiftung Projet Régional « Vers UN Développement Socialement Juste dans la Région MENA » Friedrich Ebert Stiftung Tunis, Tunisie.

Andrei L. I. (2012). Putting Geography Education into Place: What Geography Educators Can Learn from Place-Based Education, and Vice Versa. March 2012, *Journal of Geography* vol.111, n°2, pp.76-81 DOI: 10.1080/00221341.2011.583264

Belhedi, A. (2019). Les disparités spatiales en Tunisie, état des lieux et enjeux. *Revue Méditerranée*, vol. 91. n°1. pp. 63-72. Éditeur Persée-Portail des revues scientifiques en SHS

BIRD (2014). Tunisie : Surmonter les obstacles à l'Inclusion des jeunes. Washington: Groupe de la Banque mondiale.

Blaya, C. (2009), L'absentéisme des collégiens : prévalence et caractéristiques, *Les Sciences de l'éducation-Pour l'Ère nouvelle*, vol. 42, n°4, pp.39-58.

Blaya, C. (2010a). *Décrochages scolaires : l'école en difficulté*. Bruxelles : de Boeck.

Blaya, C. (2012). Le décrochage scolaire dans les pays de l'OCDE. *Regards croisés sur l'économie*, vol n°2, pp.69-80

Boidin B, Lardé P. (2008). Comparaisons internationales des niveaux de santé: cadre théorique et éléments d'application aux pays africains. Trentièmes Journées des économistes de la santé français », Colloque, *Calenda*, Publié le lundi 06 octobre 2008, <https://calenda.org/195649>

Boudesseul, G. (2013). Du décrochage à la réussite scolaire : Expériences française et internationales. Paris: L'Harmattan,

Boughzala M, El Lagha Abdel Rahmen, & Bouassida, Ines., (2020) « Les inégalités en Tunisie », Paris Agence française de développement, « Papiers de recherche », pp. 1-79. DOI: 10.3917/afd.bough.2020.01.0001. URL: <https://www.cairn.info/--1000000148925-page-1.htm>

Charest D, (1980). Prévention de l'abandon prématuré. Milieux économiquement faibles. Soutien aux adolescents, Québec: Ministère de l'Éducation. Direction générale des réseaux, 1980, 183 pages.

Chérif, A & Elloumi, A (2021), Construction and Validation of an Arabic Questionnaire on the School Dropout Factors (QSD), *Advances in Social Sciences Research Journal*, vol. 8, n° 1. DOI: <https://doi.org/10.14738/assrj.81.9458>

Davis, He. A. (2003). Conceptualizing the role and influence of student-teacher relationships on children's social and cognitive development. *Educational Psychologist*, vol. 38, n°4, p. 207-234.

Deichmann, U. (1999). Geographic Aspects of Inequality and Poverty." Washington, D.C.: World Bank. A text for World Bank's website on inequality, poverty and socio-economic performance. Retrieved 10/02/13 from <http://www.worldbank.org/poverty/inequal/index.htm>.

Desbois, Dominique. 2003. Une introduction à l'analyse discriminante avec SPSS pour Windows. In MODULAD 2003, vol. Modulad 30, pp.19-49.

Erpicum, D. & Murray, Y. (1975), « Le Problème du drop-out scolaire dans le monde moderne », Orientation Professionnelle, vol. 11, n° 1, pp. 9-24.

Fortin, L., Marcotte, D., Potvin, P., Royer, E & Joly, J. (2006). Typology of Students at Risk of Dropping Out of School: Description by Personal, Family and School Factors. *European Journal of Psychology of Education*, vol.n°21, n°4, pp.363-383.

Fortin, L., Toupin, J., Pauzé, R., Mercier, H., & Déry, M. (1996-2000). Les facteurs associés aux difficultés d'apprentissage des élèves en trouble du comportement de niveau primaire. Dans L. Barbeiro & R. Vieira (Éds.)? *Précursores de aprendizagem praticas educativas* (pp. 204-224). Leiria, Portugal: Escola Superior de Educaçæe de Leiria.

Gleyse, J. (2020), *Le genre de l'école en France: de la mixité à l'inégalité occultée. Expérimentations et propositions de transformation*, L'Harmattan. Collection: Genres Ecoles et Sociétés. ISBN: 978-2-343-18944-4. 298 pages

Husson, F, Sebastien Le, and Jérôme P.(2017). *Exploratory Multivariate Analysis by Example Using R*. 2nd ed. Boca Raton, Florida: Chapman; Hall/CRC. <http://factominer.free.fr/bookV2/index.html>.

Janosz, M & LeBlanc, M. (1996). Pour une vision intégrative des facteurs reliés à l'abandon scolaire. *Revue canadienne de psycho-éducation*, vol. n°25, n°1, pp.61-88.

Janosz, M. (2000). L'abandon scolaire chez les adolescents: perspective nord-américaine. *VEI enjeux*, n°122, pp.105-127.

Janosz, Mi., Leblanc, M., Boulerice, B & Tremblay, R E. (1997). Disentangling the weight of school dropout predictors: A test on two longitudinal samples. *Journal of Youth and Adolescence*, vol 26, n°6, pp. 733–762. <https://doi.org/10.1023/A:1022300826371>

Kobiané, J.-François. (2004). Habitat et Biens d'équipement comme Indicateurs de Niveau de Vie des Ménages: Bilan Méthodologique et Application à l'Analyse de la Relation Pauvreté-Scolarisation. *African Population Studies/Etude de la Population Africaine*, vol.19, pp.265-283.

Kronik, R. K., & Hargis, C H. (1990). *Drop-outs: Who drops out and why- The recommended action*. Springler, III : Charles C Thomas, 153 pages

Lahire B (2021), *Culture écrite et inégalités scolaires. Sociologie de l'échec scolaire à l'école primaire*, Lyon, Presses universitaires de Lyon, 308 p.

Medinilla A ; El Fassi S (2016). Réduire les inégalités régionales en Tunisie. ECDPM: European Center for Development Policy Mangment . No. 84 – avril 2016

Potvin, P., & Lapointe, J.-R. (2010). *Guide de prévention pour les élèves à risque au primaire : y'a une place pour toi!* Québec, QC: CTREQ.

Potvin, P., Fortin, L., & Lessard, A. (2005). Le décrochage solaire. Dans L. Massé, N. Desbiens & C. Lanaris (Eds.), *and Troubles du comportement à l'école: prévention, évaluation et intervention* (pp. 67-78). Montréal, QC: Gaétan Morin.

Potvin, P., Fortin, L., Marcotte, D., Royer, É., & Deslandes, R. (2004). *Guide de prévention du décrochage scolaire*. Québec, QC: CTREQ.

Romeo, L.G. (2014). The Territorial Approach to Local Development (TALD). Bruxelles : IBF International Consulting. http://capacity4dev.ec.europa.eu/sites/default/files/file/22/09/2014_-_1214/2013330793_tald_paper_draft_1_1.docx

Rumberger, R. (1995). Dropping out middle school: a multilevel analysis of students and school. *American Educational Research Journal*, vol.32; n°3, pp.583-625.

Sautory. Olivier et Von. Sébastien. (1992). Une étude comparative des méthodes de discrimination et de régression logistique. *In Journée de méthodologie statistique INSEE 1992*

Stiglitz, Joseph E. (2012). The Price of Inequality: How Today's Divided Society Endangers Our Future. eds., IEA Conference Volume No. 150-III, Houndmills, UK and New York: Palgrave, pp. 61-97 (originally Columbia University Working paper)

UNESCO Institute for Statistics and Education for All Global Monitoring Report (2014) 'Progress in getting all children to school stalls, but some countries show the way forward', *GMR Policy Paper*, no. 14, *UIS Fact Sheet*, no. 28 (Paris : UNESCO).

Violette, Michèle, (1991). *L'école... facile d'en sortir, mais difficile d'y revenir : enquête auprès des décrocheurs et décrocheuses*. Québec: Gouvernement du Québec. Ministère de l'éducation, direction de la recherche

Watherhouse Price (Firme), (1990). Recherche qualitative sur les décrocheurs. Rapport définitif sommaire. Ottawa: Gouvernement du Canada, Ministère d'État à la jeunesse. 1990. 16 pages.