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Three-Way Multiblock Methods for Decision-Making in Health Services:

A COSTATIS Approach to Improving Management at a Private Clinical Laboratory

Abstract

In the last decade, the clinical laboratory sector in Portugal has witnessed an increase in competition through the integration of small private laboratories in multinational organizations. In this competition scenario, it is imperative that decisions related to management are made based on the analysis of varied and detailed information data in order to propose strategies and prioritize management. Thus, the growing need for data analysis, especially in dynamic contexts, to detect, identify and characterize the most relevant issues for a more efficient decision-making process, is essential. This research was based on data for the period 2014-2017, from a private clinical laboratory located in the Algarve. The use of two interrelated information structures, namely 14 collection points and the subsequent 10 clinical tests with the highest billing volume in 2017, led to the application of the COSTATIS method (Thioulouse et al., 2011) in order to capture a common co-structure that analyses the stability or instability of the two data structures. An exploratory three-way multiblock method highlights the relations between two data structures as a whole. Therefore, the interpretation of the influence relationships of the production of clinical tests on the performance of collection points can reveal particularly useful discrepancies and/or coincidences for the management. With this detailed information, it is possible to propose initiatives for improvement or correction and to promote functional strategies with the objective of assisting the laboratory management process and suggesting strategies that are more efficient.

Keywords

Private Laboratory of Clinical Analysis; Health Care Management; COSTATIS.

1. Introduction, Objectives and Relevance

In recent decades, the health sector has undergone many changes. Globalization, technological development, the fast pace of knowledge and development of practice have increased the complexity of a sector with limited resources. In this context, clinical tests (CT) have gained a growing relevance in disease prevention diagnosis and treatment and in health promotion. In fact, the demand for more and more sophisticated tests, new technologies and complex and costly systems with high productivity have contributed to CT being concentrated in large laboratories. In this context, globalization has also fostered international competition and pressure to reduce costs (Bossuyt et al., 2007). However, the performance of clinical laboratories (CL) continues to be assessed based on indicators relying on quality management, while laboratory management focuses exclusively on financial performance.

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In this study, we will discuss several aspects related to the internal environment of a CL that influence how the laboratory collection points (CP) work and, consequently, the laboratory's competitiveness. Our aim is to attain a set of results and recommendations that may be disseminated through knowledge transfer and become a useful tool for CL management and evidence the suitability of COSTATIS method as a support tool for management.

In any decision regarding the strategy of a CL or its CP, several factors are taken into consideration, not all of which have the same weight. Some decisions are taken based on intuition while others are made based on evidence identifying the variables leading to that decision. However, we are not always able to understand the relation between the variables. In fact, introducing information management systems in the CL and the CP allows us to gather information and to control, manipulate and measure the variables but not to identify how they correlate. None of the studies on inefficiency performance assessment of a CL from the perspective of the CP has focused on the effect that the tests have on the performance of the CP and, consequently, on the performance of the lab. Typically, the CP are indirectly included in the studies through the indicators in the pre-analytical stage. However, the competitive environment in which the CL and their CP are included in leads us to consider the relevance of using a methodology that allows us to analyse the dynamics throughout time rather than only at a specific moment. Therefore, we believe that three-way multivariate data analysis methods such as COSTATIS, because they describe the three-way interaction, generate more complex analyses and, in this context, take on special relevance by allowing for a simultaneous analysis of several data tables, leading to more robust and more real-life results, since they are able to understand the phenomena and the changes. This new tool for analysis allows us to study the differences and similarities among the CP in terms of space and time or even to study several experimental situations by providing us with the information needed to change or define strategies.

2. Methodological Framework

Since laboratories have become part of multinational corporations, management is now conducted by a professional trained in that field. Effective laboratory management requires a leader to set guidelines and a manager to put them into practice. Strategic planning, marketing, management of human resources and quality management, according to McPherson & Pincus (2016), are key elements in managing a CL.

At a CL, the management process must be in line at institutional, intermediate and operational levels to ensure that it performs efficiently and effectively. Designing and implementing strategies is part of the decision-making process and for those decisions to be viable and lasting, there is the need to firstly define the threats and opportunities involving the business (the external diagnosis) and, at a second stage, identify the strengths and the weaknesses of the business when compared to its competitors (the internal diagnosis).

In fact, at a CL, as in any other organization, you must adapt strategies that allow the business to attain and fulfil its goals and be resistant to competitive environments, and, according to Stoner & Freeman (1995), the functional strategies are more detailed and present shorter timelines in attaining three objectives: communicate short-term goals; describe the actions needed to attain short-term goals and create an environment that fosters attaining those goals.

Slack et al. (1997) state that functional strategies should be coherent with the company's global strategy or with the competitive strategy of the business unit and should provide support to obtaining and maintaining the desired competitive advantage, as well as integrating and planning the existing interfaces among the several functional areas (financial, human resources, research & development, marketing, production, operations). Functional strategies establish actions, approaches or practices for a business function to operate. Nevertheless, decisions and actions carried out within a specific functional area of the business should be made based on detailed information that supports implementation of generic strategies and the organization's competitive strategies. This information is usually obtained through assessing the performance of the functional areas.

Performance assessment is an essential tool to manage any organization, as is the case of a CL. Assessing elements such as each CP's efficiency allows knowledge and measurement of performance of the various CP and compare their expected and actual performance. This process provides the manager with important information for decision-making and makes it easier to attain the strategic goals. However, from the

perspective of competitiveness, comparing production and resources used is not always enough. It is important to compare what was produced considering the resources available with what could have been produced with those resources (Soares Mello et al., 2005). The use of performance indicators for strategic decision-making may indicate a guideline but it is useful to associate them with other methodologies in order to have a more complex perspective (Santos, 2012).

In addition to financial performance, throughout the years the clinical laboratory sector has focused on minimizing errors occurring during the analytical process in order to ensure process efficiency and efficacy in the results of their tests. The way those errors are addressed or ignored may lead to unnecessary procedure repetitions leading to an increase in costs and to process inefficiencies (Plebani, 2010). Unlike what was initially thought, most errors in CL occur in the pre- and post-analytical phases (Plebani, 2006; Howanitz, 2005). In the pre-analytical stage, the errors are linked with the sample (insufficient, haemolyzed, incorrect, in inadequate conditions), with sample identification and transportation conditions (Hawkins, 2012; Plebani, 2010; Valenstein & Sirota, 2004; Bonini, et al., 2002). In the analytical stage, most errors have to do with the malfunctioning of equipment or with mixing or switching samples while being processed, thus causing repeating of samples (Valenstein, 2004). In the post-analytical phase, the errors reported are high turnaround time, wrongly processed data and report errors (Valenstein, 2004).

Bonini et al. (2002) emphasize that it is not enough to state that an error occurs when something took place that was not supposed to. They believe that it is crucial to define errors according to their relevance and clarify the consequences of those errors during the analytical process and create an indicator linked to the errors. On the other hand, according to Aita et al. (2017), it is important not only to define the errors but also the way they are accounted for and measured in order to be managed. Ricós et al. (2004) and Vieira et al. (2011), analyse usefulness of performance indicators from an isolated perspective for an efficacy-focused management of a CL leaving efficiency in the background.

In this context, Santos (2012) presents a lean methodology for cost reduction and productivity increase and Bulijanovic et al. (2011), refer to the use of SWOT analysis to assess CL performance. Therefore, pre-analytical, analytical and post-analytical and extra-analytical processes are approached in isolation, with no consideration for their impact on general efficiency and performance. According to Santos et al. (2012), there should be benchmarking that encompasses economic and financial indicators or efficiency indicators so that strategic decisions can be made based on evidence. Steiner et al. (2006) consider benchmarking an important tool for Laboratory Medical Directors and managers to have a general perspective of the laboratories' performance. Valenstein et al. (in Steiner et al., 2006) also state that benchmarking is an excellent tool to determine needs in laboratory human resources and trends in productivity and use.

In any case, whether using economic and financial indicators or indicators, the evidence is more and more complex and a development analysis requires a study of multidimensional structures that include multiple sets of data, as is the case of three-way data analysis. Information on the complexity of laboratory procedure, even if resorting to benchmarking, requires other measuring tools that produce more detailed information.

3. Data and Methodology

Information on the period 2014-2017, from a CL located in the Algarve (Figure 1), namely, information on the number of tests conducted per CP (Figure 2) and the information on the descriptors of the CP (Figure 3) were collected between January and June 2018 using a private clinical laboratory information management system and the registries in the quality management system. The variables used in this study were defined at a meeting with the CL's management team and the medical director. The medical director selected CT according to the top ten in the CL's invoicing. The CP were chosen according to the manager's strategic interest.

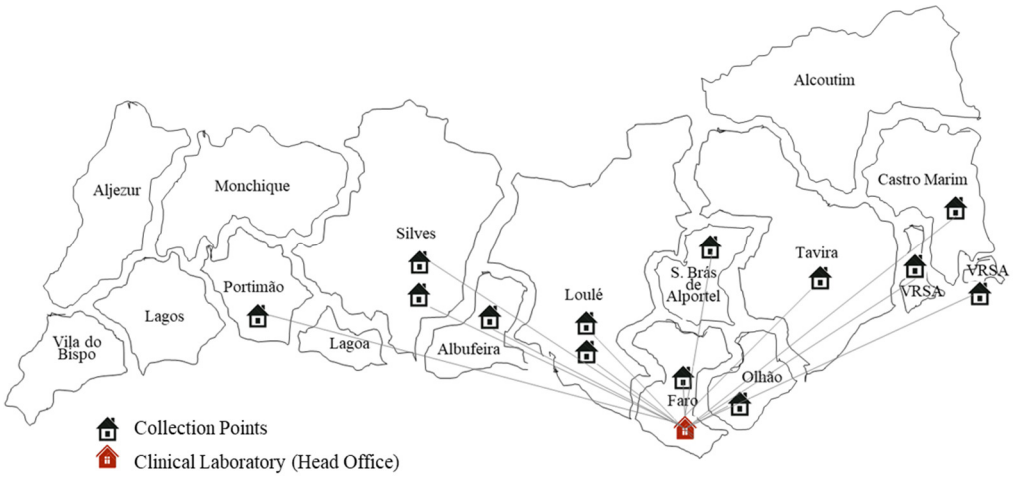

Figure 1. Distribution of collection points in the Algarve region (2014-2017).

Code	Location	Population PORTIDATA (2016)	Number of Workers	Production Level (Number of Tests) 2014-2017
PC1_IRC	Faro	61.046	4 to 5	29524
PC2_IC	Loulé	69.399	4 to 5	14845
PC3_IRC	São Brás de Alportel	10.556	1 to 3	9975
PC4_IRC	Silves	36.512	1 to 3	10329
PC5_RC	Portimão	55.446	1 to 3	1932
PC6_RC	Silves	36.512	1 to 3	2294
PC7_IRC	Albufeira	40.495	1 to 3	3094
PC8_IC	Faro	61.046	1 to 3	3452
PC9_IRC	Olhão	45.198	1 to 3	18563
PC10	Vila Real de Santo António	19.060	1 to 3	2825
PC11_IC	Castro Marim	6.426	1 to 3	6346
PC12_I	Vila Real de Santo António	19.060	1 to 3	2552
PC13_C	Tavira	6.426	1 to 3	5530
PC14_IC	Loulé	69.399	1 to 3	5294

C = Phlebotomist
I = IT (Information Management System)
R = Lab-bound Receptionist

Figure 2. Description of the collection points.

Code	Variables	Designation	Descriptive
V1	Number of Samples (Frequency)	Production Descriptor	Number of samples
V2	Registration errors (Changed Registrations)	Performance Descriptor (Pre-Analytical Phase)	Errors regarding patient identification, requesting physician, order of the test, which leads to a modification of the initial registration.
V3	Recollected samples	Performance Descriptor (Pre-Analytical Phase)	Number of recollected samples
V4	National Health Service	Paying Entity	National Health Service pays for the tests
V5	Private	Paying Entity	Private patients
V6	Insurance	Paying Entity	Tests payed by private insurance companies
V7	Repeated samples	Performance Descriptor (Analytical Phase)	Number of samples repeated

Figure 3. Descriptors of the collection points.

Code	Nomenclature	Description
A1	Complete blood count	A complete blood count test measures several components and features of blood.
A2	Urine culture	Test to check for germs or bacteria in the urine that can be responsible for a urinary tract infection.
A3	TSH	A thyroid-stimulating hormone (TSH) levels test is used to help diagnose thyroid disorders and to monitor treatment of hypothyroidism and hyperthyroidism.
A4	PSA	Prostate-specific antigen test is used to measure blood PSA levels and help detect prostate cancer or other prostate abnormalities.
A5	Hemoglobin A1c	The glycosylated haemoglobin test determines the average level of blood sugar.
A6	T4 (Thyroxine)	Evaluation of suspected thyroid function disorders using free thyroxine measured together with thyroid-stimulating hormone
A7	HIV 1/2 + AgP24	Human immunodeficiency virus
A8	Triglycerides	Determination of triglyceride levels.
A9	Cholesterol HDL	Determination of cholesterol high-density lipoprotein (HDL) levels.
A10	C-Reactive Protein	A c-reactive protein test measures the level of c-reactive protein (CRP) in the blood. Detecting systemic inflammatory processes.

Figure 4. Clinical tests.

Two “data cubes” were created for the period 2014-2017. A multiblock structure with the information from the laboratory CP – the 14 CP characterized through the 6 descriptors studied and a second multiblock structure with information from the CP that included the number of tests conducted, per type of test, collected in each CP being studied – the top ten of the CT with highest invoice volume. Simultaneous analyses of these structures

are the basis for applying COSTATIS in order to analyse the relations between the structures in the two data matrices as a whole (Vale, 2019). It uses data coupling processes, like those used in canonical correspondence analysis (see Braak, 1986), in redundancy analysis (Van Den Wollenberg, 1977) or in co-inertia analysis (Dolédec & Chessel, 1994; Dray et al., 2003).

This was followed by partial triadic analysis (PTA) (Thioulouse & Chessel, 1987; Kroonenberg, 1989; Thioulouse et al., 2011), to explore the relations between the information in a series of data matrices, such as assessing the stability or diversity of the structures in all other matrices (Interstructure analysis).

Finally, we conducted the co-inertia analysis (COIA) (Dolédec & Chessel, 1994; Dray et al., 2003) to analyse the influence of CT on the performance of the collection points. The COIA, just like canonical correspondence analysis and redundancy analysis, is a statistical procedure that couples information between two data matrices.

Moreover, it is a multivariate statistical methodology that aims to explore the relations between two data tables, such as measuring the discrepancies and the coincidences between two sources of information. The methodological procedure in represented in Figure 5.

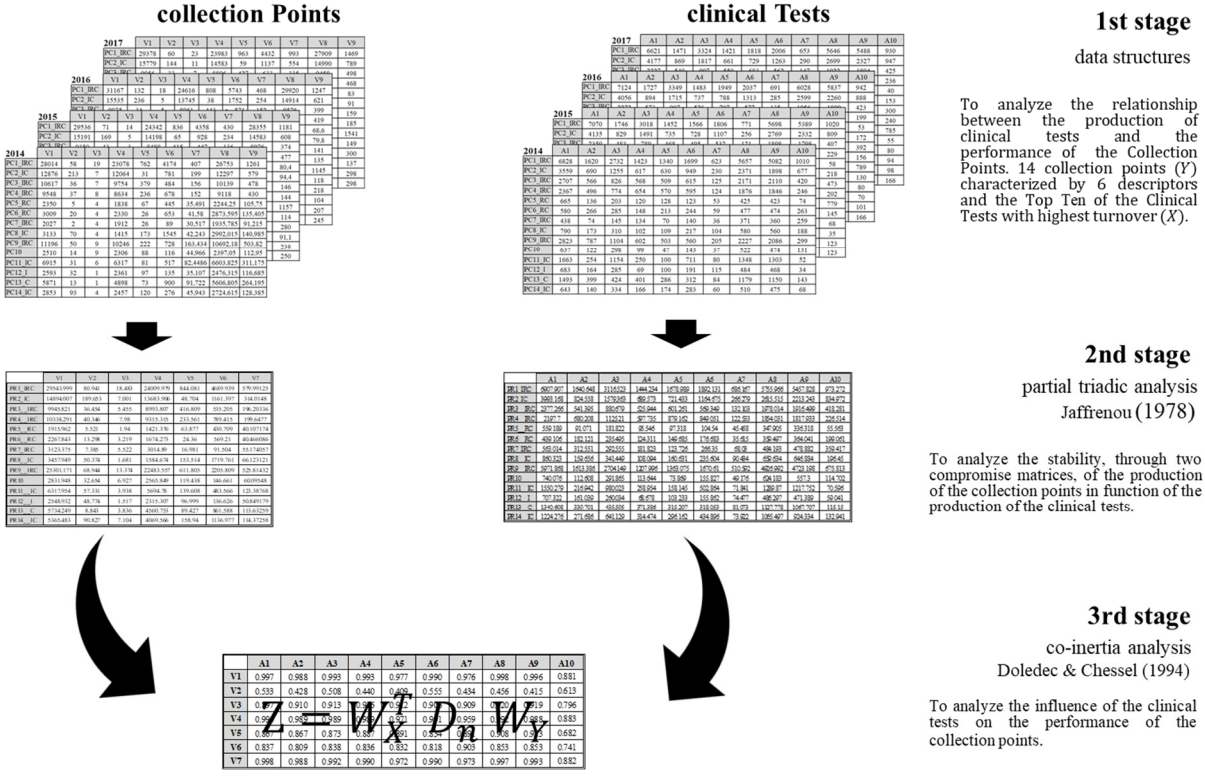

Figure 5. The stages of the COSTATIS method.

4. Results and Discussion

4.1. Results

When we analysed the Interstructure of each of the data structures for the 2014-2017 period, we noted that they were similar. Both in terms of the descriptors of the CP and of the CT, their correlation matrices were positive, which means there is stability in the period analysed. Nevertheless, in 2014-2016, we could also see two realities in the two structures: in Figure 6, in regards to CP (a) and under the axis of lowest inertia, with 91% interpretability, in the 4th quadrant, a less stable reality associated with 2014; and another, in the 1st quadrant, equally stable and related to the 2015, 2016 and 2017 periods (highly correlated). In regard to the CT (b) and under the axis of highest inertia, also with 91% interpretability, in the 4th quadrant, a stable reality associated with 2014, and another, in the 1st quadrant, equally stable and related to the period of 2015, 2016 and 2017 (highly correlated).

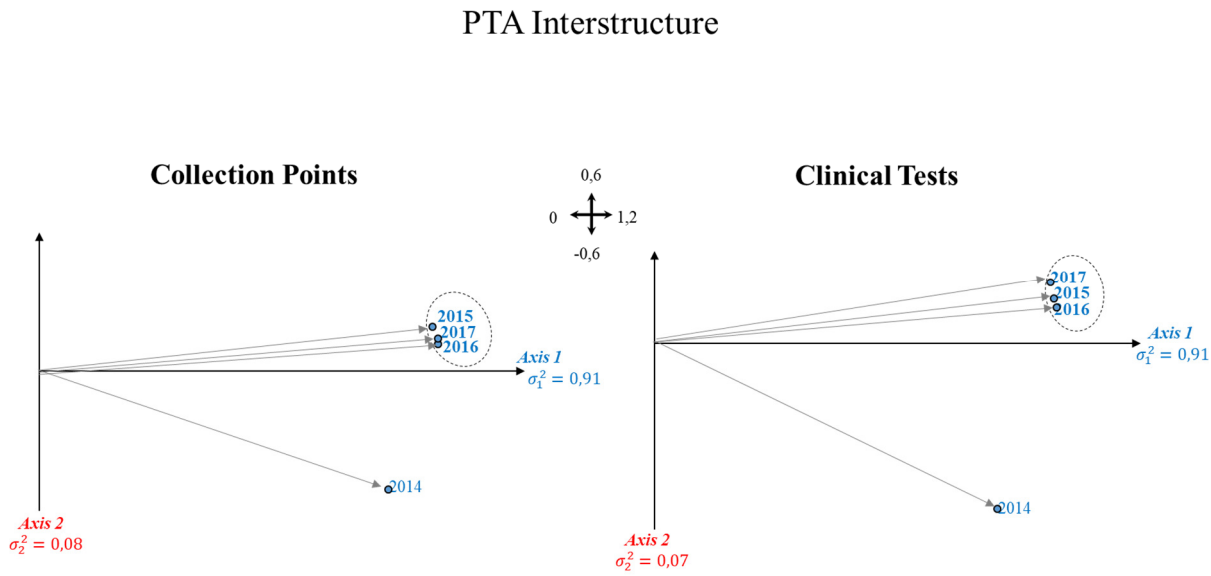

Figure 6. Representation of the interstructure (Adapted from outputs of Software ADE4 Program R).

In summary, we can state that, in the scope of a stable Interstructure for the 2014-2016 period, 2014 was less stable in terms of performance of the CP and in the production of the CT.

Compromise analysis aims to study the main similarities and differences in the collections conducted in the CP and the following CT for 2014-2017. Reproduction using factor plans of the Compromise matrices allowed us to assess the possibility of defining common structures throughout the stability detected in the period 2014-2017. The Euclidean representation of the Compromise in the CP regarding to the top ten of CT is shown in Figure 7. Three patterns were detected in both structures; in both cases, pattern 2 was the one that most contributed to the description. In Figure 7, we can see that patterns 2 and 3 are those that most contribute to Axis 2 of Compromise, which presents a gradient that increases right to left. In fact, this dimension of the analysis links the occurrence of Repeated samples (V7), Nº of Samples and Recollected samples (V3) with the samples associated with the paying entities. The most predominant relation is with the National Health Service (V4), followed by Insurance and the least relevant is with Private (V5). The variable Registration errors (V2) is the least contributing variable. Thus, in view of Figure 7 (a), Axis 1 was named PRODUCTION PER PAYING ENTITY.

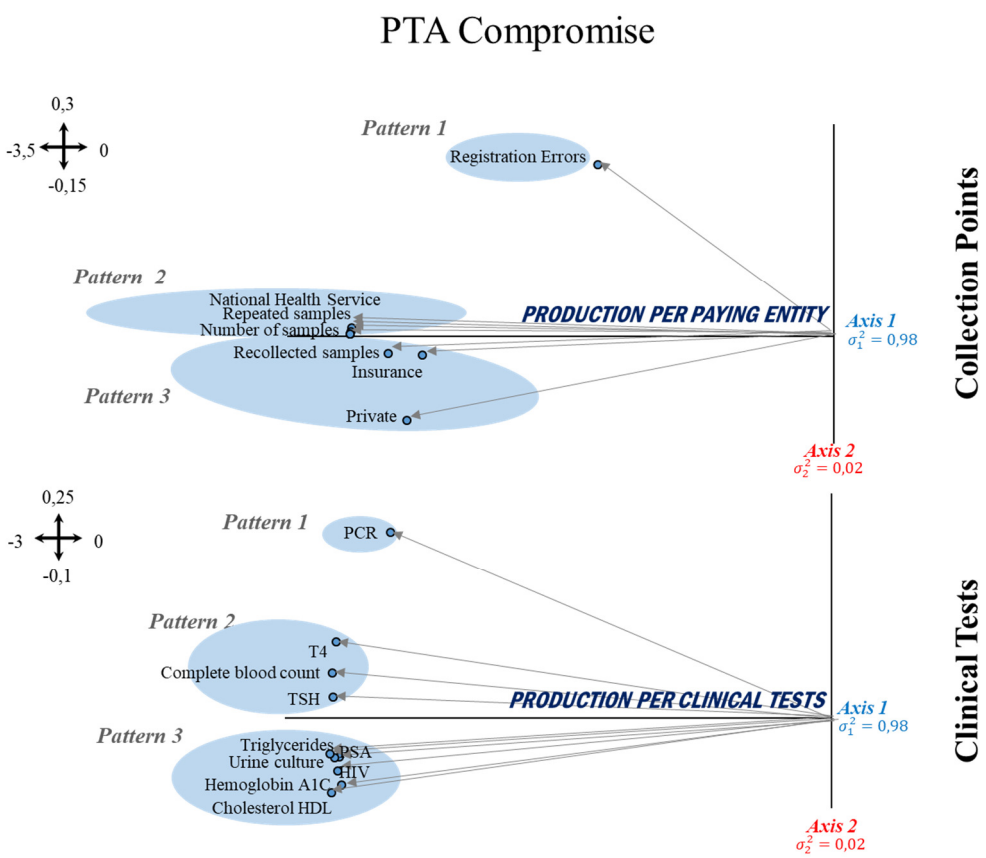

Figure 7. Representation of the Compromise (Adapted from outputs of Software ADE4 Program R).

Thus, in view of Figure 7 (a), Axis 1 was named PRODUCTION PER CLINICAL TESTS.
In Figure 7 (b) we can find the Euclidean representation of the Compromise regarding the top ten in CT.
Analysis of the intrastructure, since it is the last stage of COSTATIS, aims to investigate the existence (or not) of associations between the performance of the CP and the requested CT for the period 2014-2017. According to the definition of Compromise, the Euclidean representation of the positions in the lines of the matrices (in this case, representing the 14 CP) will vary. Therefore, the associations between the original variables and the CP will allow interpretation of the similarities/differences and trajectories to be drawn that describe the evolutionary behaviour of the CP or of each original variable. In this study, and to meet our goals, the evolutionary behaviour and descriptors of the 14 CP or those of the CT are not relevant. Therefore, the intrastructure analysis required for a traditional PTA application was not considered here.
In the context of this research, the matrix of crossed covariants will inform on the relation detected between the two Compromise matrices: one that describes a diagnosis on the performance of the 14 CP for the period 2014-2017, and another that describes a diagnosis of the top ten for the CT for the same period. Thus, and from a CL management perspective on the production of the 10 main CT with highest invoice volume in 2014-2017, the COIA allowed us to analyse the differences or similarities detected in the management of the 14 CP, both from the CT perspective and from that of the performance regarding the collection of samples.
In this context, Figure 8 evidences the relation detected between the CT and the performance of the CP in the period 2014-2017. In other words, we aim to evidence whether there were discrepancies in the running of the CP caused by the CT. In Figure 8 the long vectors describe relations with lower influence (higher discrepancy) of CT in the performance of the CP and shorter vectors evidence relation with higher influence (higher synchronism) of the CT. On the other hand, Figure 8 shows 3 outliers in the performance of 3 CP.

1. PC2_IC, whose production decreased (the direction of the vector goes against the gradient). This decrease originates in the influence that PCR (A10) had on the Registration errors (V2) (this association is explained by the relative position in the 2nd quadrant which A10 and V2 have in their respective Compromises).

2. PC3_IRC, whose production remained the same (vector perpendicular to the gradient). This situation was caused by the influence that T4 (A6); Complete blood count (A1) and TSH (A3) had on Recollected samples (V3), Insurance (V6) and Private (V5) (this association is explained by the relative position in the 3rd quadrant that the variables have in their respective Compromises);
3. PC13_C, whose production decreased (the direction of the vector goes against the gradient). This small decrease was caused by the influence that Triglyceride (A8); Urine culture (A2), Haemoglobin A1c (A5) and Cholesterol HDL (A9) had on Recollected samples (V3), Insurance (V6) and Private (V5) (this association is explained by the relative position in the 3rd quadrant that the variables have in their respective Compromises).

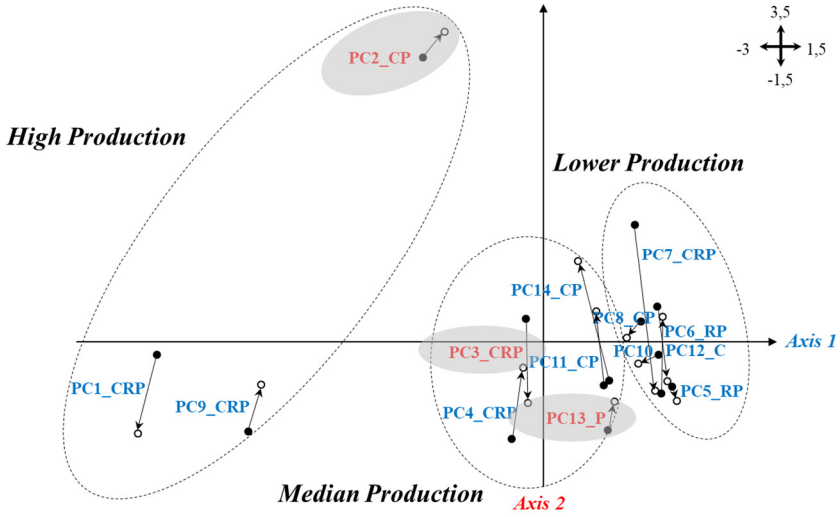

Figure 8. Outliers in the influence of clinical analyses in the collection points (2014-2017) (Adapted from outputs of Software ADE4 Program R).

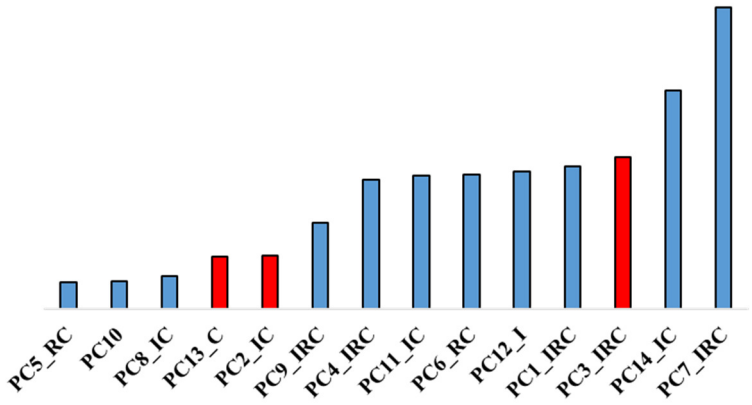

Figure 9. Degree of influence of clinical Tests in the collection points (2014-2017).

In fact, there are more consistent Compromises in the CP; for example, in Figure 9, you can see the degree of those influences in an ordered and increasing manner. There is a decrease in the influence of the type of tests on the behaviour of the descriptors in PRODUCTION PER PAYING ENTITY in the CPs PC5_RC up to PC7_IRC. This indicates that other factors rather than PRODUCTION PER CLINICAL TEST have an increasing influence on PRODUCTION PER PAYING ENTITY up to PC7_IRC.

4.2. Discussion

In the scope of a stable Interstructure for the 2014-2017 period, 2014 was less stable in terms of performance of the CP and in the production of CT. In the context of the Compromise Analysis, we could see that: a) there is a link between the PCR (A10) and Registration errors (V2) detected in the CPs; b) there is a link between the T4 (A6), Complete blood count (A1) and TSH (A3) tests and the 3 descriptors detected in the CPs: National Health System (V4), Repeated samples (V7), and Nº of Samples (V1); and c) there is a link between the T4 (A6), CBC (A1) and TSH (A3) tests and the 3 descriptors detected in the CP: Recollected samples (V3), Insurance (V6) and Private (V5).

In the table on co-inertia analysis in the period 2014-2017, we can see a relation between production of CT and the production of samples by the CP. Other items are evidenced based on the production, 3 groups of CPs (3 CPs with high production; 5 CPs with median production and 6 CPs with low production). 3 outliers were identified in terms of performance PC2_IC, PC3_IRC and PC13_C.

On the other hand, the decrease in the influence of the type of test on the behaviour of descriptors in PRODUCTION PER PAYING ENTITY, from the position of the CPs PC5_RC to PC7_IRC, suggests that factors other than PRODUCTION PER CLINICAL TEST are increasingly influencing PRODUCTION PER PAYING ENTITY up to PC7_IRC.

5. Conclusions and Transfer of Knowledge

The results and conclusions evidence a transfer of knowledge for a specific business situation as a useful tool for management – the COSTATIS method proved suitable to address the issue under analysis, representing the situation of the CP and the CT and evidencing the influences/discrepancies between them. We can see that the sample production at the CP showed less stability when compared to the production of the CT that follow, which evidences some difference in performance levels.

We identified and described the relations among the variables associated with PRODUCTION PER PAYING ENTITY and the relations among the variables associated with PRODUCTION PER CLINICAL TEST and we described the influence of the type of test on the behaviour of the descriptors in PRODUCTION PER PAYING ENTITY.

Consequently, we were able to produce a diagnosis for the CL, emphasizing the intervention areas to prioritize results, as well as the recommended actions and approaches.

The transfer of knowledge arising from this research may contribute to an effective enhancement of the business, since we were able to make the following recommendations on functional strategies aiming to enhance operational efficiency: a) Functional strategy on operations: improve operational efficiency associated with laboratory procedures and adaptation to new instructions and equipment to reduce the number of repeated samples in order to reduce the number of repetitions associated predominantly with the National Health System; b) Functional strategy on production: improve logistics and sample transportation to decrease the need to recollect samples and consequently the number of recollected samples, predominantly for private/insurance; c) Functional strategy on resources: allocation of employees with extra training in registration, identification and coding of PCR tests aiming to decrease the registration errors regarding all the paying entities.

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