Triadic Rules for Analysis of Productive and Well-Being Social in Activity-Based Working Environments

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Abstract: A longitudinal database records data and its variations over a period of time. The objective of this article is to use this resource, together with the Triadic Concept Analysis theory, to analyze and characterize how employees adapted and felt before, during and after the implementation of an activity-based work environment which is defined as a flexible work setting where employees have the autonomy to choose where they perform their tasks, seeking locations that offer optimal solutions in terms of social interaction, communication, and collaboration. The results seek to support the implementation of this concept, verifying how, and under what conditions, key points of employee experiences vary over time.

1 INTRODUCTION

Longitudinal studies involve the collection and analysis of data from the same sample of objects or individuals over consecutive time periods referred to as waves. These studies can be applied to various areas of interest, such as health, social studies, ecology, among others. For example, in the social work context, these studies allow for the analysis of an individual's behavior before, during, and after a specific organizational change, whether related to the individuals themselves or influenced by the environment in which they interact. Playing an essential role in verifying and identifying temporal behavioral patterns, longitudinal studies become a valuable source for validating and describing appropriate procedures to ensure the well-being of individuals in work environments.

An Activity-Based Working Environment (ABW) is characterized by being a flexible work environment where employees have autonomy to choose where to perform their tasks, seeking locations that offer the best solutions related to social, communication, collaborative, and well-being aspects.

With the constant advancement of information technology and the increasing connectivity of work environments, the ABW concept has stood out, aiming to optimize usable spaces, increase productivity, foster information exchange, and enhance the well-being and mental health of employees.

This study considers a longitudinal study regarding the implementation of an activity-based working environment (ABW) (Halldorsson et al., 2022) to extract information related to the fluctuation of satisfaction and productivity metrics: a) before the implementation of ABW, b) during the implementation of ABW; and c) after the implementation of ABW; and establish the relationship between these changes considering the temporal aspect. The goal is to assist decision-making regarding the adoption or not of this type of work environment in a business office. The longitudinal study considered in this work contains 11 variables tracking 100 employees before, during, and after the application of the Activity-Based Working Environment concept in their workplace.

For the description of employee behavior patterns subjected to the ABW concept, this work is based on Formal Concept Analysis (FCA), which is a branch of applied mathematics related to the theory of conceptual lattices, constructed from a dataset composed of objects, attributes, and their incidence relationships (Ganter et al., 1999). Through Triadic Concept Analysis (TCA), an extension of FCA that allows introducing a third condition, such as time, it is possible

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to identify temporal relationships for changes in variables of interest over time, such as aspects of satisfaction, stress, psychological factors, etc. These relationships can also be characterized using association rules for specific contexts, such as the relationship between variables before and during the implementation of ABW, the relationship between variables during and after its implementation, and the relationship between variables before and after the implementation of ABW.

In this study, triadic rules are extracted to characterize and evaluate the efficiency and satisfaction of the work office over time. The results obtained highlight the potential of Triadic Concept Analysis (Konecny and Osicka, 2010) in investigating longitudinal databases. Overall, observing the implementation of an Activity-Based Working Environment (ABW) through a longitudinal study enables an understanding of the impacts of this transition both on the work environment itself and on the employees involved.

This article is organized as follows: in Section 2, the theoretical framework covering Formal Concept Analysis and Longitudinal Data Analysis is presented. In Section 3, related works are discussed. Section 4 describes the adopted methodology, including the materials and methods used. Section 5 presents the results and discussions based on the evaluation metrics. Finally, Section 6 provides the concluding remarks, including potential future work.

2 BACKGROUND

2.1 Formal Concept Analysis

Formal Concept Analysis (FCA) is a branch of applied mathematics related to the formal conceptual hierarchization, based on a set of objects, attributes, and incidence relations between them (Ganter et al., 1999), with the aim of identifying properties and extracting relevant knowledge from data.

In FCA, a formal dyadic context corresponds to a tuple of the form $K := (G, M, I)$, where G corresponds to a set of objects (extension), M to a set of attributes (intension), and I corresponds to the incidence relation ($I \subseteq G \times M$) between objects and their properties (attributes). From this formal context, it is possible to extract formal concepts, from which association rules can be derived. Table 1 shows an example of a dyadic context.

Considering the formal dyadic context $K := (G, M, I)$, it is possible to obtain formal concepts defined by a pair *(A, B)* where $A \subseteq G$, and $B \subseteq M$. The formation of the pair *(A, B)* follows the following condition: $A = B'$ and $B = A'$, where the derivation operator ($'$) is defined by Equations 1 and 2:

Table 1: Dyadic Context.

G/M	a_1	a_2	a_3
o_1	×	×	
o_2		×	×
o_3	×		

$$A' = \{m \in M | (g, m) \subseteq I \forall g \in A\} \tag{1}$$

$$B' = \{g \in G | (g, m) \subseteq I \forall m \in B\} \tag{2}$$

From the formal context, it is possible to extract implication rules of the form $P \rightarrow Q$, where P and Q are subsets of attributes with $P' \subseteq Q'$. This means that a given object that has attributes in P also has attributes in Q. An implication rule $P \rightarrow Q$ is valid if and only if every object that possesses the attributes in P also possesses the attributes in Q. These implications are dependencies between elements of sets obtained from a formal context.

For each rule, evaluation metrics can be associated, such as $Support$ and $Confidence$. Formally, $Support$ corresponds to the proportion of objects in the subset $g \in G$ that satisfy the implication $P \rightarrow Q$, relative to the total number of objects $|G|$ in the formal context K (Equation 3) where ($'$) corresponds to the derivation operator.

$$Suporte(P \rightarrow Q) = \frac{|(P \cup \{Q\})'|}{|G|} \tag{3}$$

Confidence corresponds to the proportion of objects $g \in G$ that contain P and also contain Q, relative to the total number of objects $|G|$ (Equation 4).

$$Conf(P \rightarrow Q) = \frac{|(P \cup \{Q\})'|}{|P'|} = \frac{Suporte(P \rightarrow Q)}{Suporte(P)} \tag{4}$$

2.2 Triadic Concept Analysis (TCA)

In some applications, it becomes essential to associate a condition related to the temporal aspect. TCA extends the classical FCA theory by introducing a new dimension. In this case, the formal context is defined by a quadruple $K = (K1, K2, K3, Y)$, where $K1$, $K2$, and $K3$ are sets of objects, attributes, and conditions, respectively, and Y corresponds to a ternary relation among them ($I \subseteq K1 \times K2 \times K3$). Table 2 shows an example of a triadic context.

Although originating from FCA, the triadic approach has more complex definitions of concepts, implication rules, and derivation than the dyadic approach. For example, a triadic formal concept is now defined by a triple (A_1, A_2, A_3), such that $A_1 \subseteq K_1$, $A_2 \subseteq K_2$, and $A_3 \subseteq K_3$, and $A_1 \times A_2 \times A_3 \subseteq Y$. The sets A_1, A_2, A_3 are called objects, attributes, and mode, respectively. The set of all concepts in a partially ordered triadic context forms a complete lattice, also called a conceptual lattice.

From triadic contexts, it is possible to obtain association rules of the *Biedermann Conditional Attribute Association Rule* (BCAAR) and *Biedermann Attributional Condition Association Rule* (BACAR) types (Biedermann, 1999):

1. BCAAR: $(A1 \rightarrow A2)B(sup, conf)$, where $A1$ and $A2$ are subsets of attributes, $(A1, A2 \subseteq K2)$, and B is a condition, $(B \subseteq K3)$. If the subset of attributes $A1$ occurs with the condition B, then $A2$ will also occur, with support (sup) and confidence $(conf)$.
2. BACAR: $(B1 \rightarrow B2)A(sup, conf)$. Here, $B1$ and $B2$ are conditions, $(B1, B2 \subseteq K3)$, and A is a subset of attributes, $(A \subseteq K2)$. If $B1$ occurs for the attributes A, then the condition $B2$ will also occur, with support (sup) and confidence $(conf)$.

2.3 Longitudinal Database

Longitudinal studies in health typically record observations related to clinical, symptomatic, psychological, emotional, environmental, among other data. Depending on the type of study, the database may include the addition of new individuals from the study population and even add new variables of interest to the study. Longitudinal databases are sets of records where the time period (wave) is a parameter of analysis. In these databases, one can observe the variation of attributes and characteristics, monitoring their updates during the waves. This opens up possibilities to explore cause-and-effect relationships, making this area of study relevant.

Table 3 shows part of the database considered in this work. It presents the variation of attributes (P1, P2, and P3) for an employee (Object) over two waves (t1 and t2), making it possible to observe how the data behaves between these time periods. For example, attribute P1 changed from a satisfaction level of 6 (high) to 3 (intermediate) between the first and second waves. In this work, we extract association rules that allow evaluating changes in satisfaction and well-being relationships among employees in a company after the implementation of the ABW approach.

3 RELATED WORKS

The articles (Lana et al., 2022) and (Noronha et al., 2022) are likely the first works to explore triadic analysis in describing longitudinal studies in the field of health. The first article focuses on analyzing the effectiveness of prevention methods against COVID-19 infection, while the second work delves into pattern discovery related to human aging by observing the clinical and environmental evolution of individuals over time.

In the realm of TCA-related work, there is the study by (Zhuk et al., 2014), where a series of experiments compared the results and performance of algorithms for triadic context analysis. Additionally, one can mention the work by (Missaoui and Emamirad, 2017), where the Lattice Miner tool is proposed to generate triadic association rules, including implications.

In the context of ABW, numerous studies propose various methodologies to assess its impact. The majority of these studies benefit from longitudinal research, utilizing the variation of performance metrics over time as an analytical tool. The works by (Rolfö et al., 2018) and (Blok et al., 2012), both longitudinal in nature, provide a good introductory understanding of the theme and detail case studies of implementing this type of approach in work environments, as well as the adoption of more flexible practices. In these studies, employees are subjected to questionnaires, and the responses are used to define comparison metrics. The obtained results offer values and references for comparison and composition of the triadic context presented in this article.

The present work differs from previous studies such as (Arundell et al., 2018) and (Haapakangas et al., 2019), which utilized Linear Mixed Models (LMM), and (Haapakangas et al., 2018) and (Bäcklander and Richter, 2022), which used Linear Regression models, by addressing Formal Concept Theory. Although all of them are longitudinal studies and share similar data collection methods (questionnaires), the study proposed in this article differs in its utilization of FCA (Formal Concept Analysis) as the foundation of the methodology.

4 METHODOLOGY

The methodology proposed in this work aims to describe temporal associations between questionnaire variables concerning the level of satisfaction with the implementation of ABW and the new type of workplace organization.

Table 2: Triadic Context.

K_1/K_2-K_3	c_1			c_2			c_3		
	a_1	a_2	a_3	a_1	a_2	a_3	a_1	a_2	a_3
o_1	×	×			×		×		
o_2			×			×	×		×
o_3	×			×				×	

Table 3: An example of a longitudinal database.

Object	P1-t1	P2-t1	P3-t1	P1-t2	P2-t2	P3-t2
1	6	6	6	3	4	3

4.1 Materials

The longitudinal database used for this study is available in (Halldorsson et al., 2022). The database contains records of 100 employees working for a state-owned company implementing ABW. This database comprises 43 questionnaire variables, including responses from different perspectives of interest. Table 4 shows the attributes that make up the database, segmented according to the area related to each questionnaire item. The longitudinal study spans 3 waves: the first wave representing 2 months before the ABW implementation, the second for 4 months after implementation, and the last for 9 months after adopting this approach. However, upon exploring the database, it is evident that not all employees responded to the entire questionnaire, resulting in response rates of 87%, 75%, and 69%, respectively, across the waves.

4.2 Methods

4.2.1 Preprocessing

Before effectively starting the extraction of triadic rules from the database, a preprocessing stage was applied. Firstly, as discussed earlier, the database does not have 100% adherence in responses during the 3 waves. Therefore, employees with many missing data in more than one wave were disregarded, reducing the database size from 100 to 83 records.

Furthermore, since the database still contains empty values in some attributes, an imputation strategy was applied, filling these fields with the mean value of the responses for the same attribute within the same wave. For example, if an employee did not answer a question in the first wave (t1), this data was filled with the average of this attribute for the t1 wave. This is a common procedure in Machine Learning, although other strategies can be applied. In general, any sort of data imputation creates a distortion in reality.

Due to the large amount of information available in the dataset, it was decided to segment the database limited to the relationships between the following selected topics: ”Productivity,” ”Job Satisfaction,” and ”Workload”. This segmentation resulted in a dataset with 83 samples and 7 attributes.

4.2.2 Discretization

After the preprocessing stage, reference values, such as thresholds, were defined to determine when the total value of the questionnaire would correspond to a negative or positive satisfaction. For this purpose, the mean value of the scale was used as the threshold, i.e., on a scale from 1 to 7, the threshold defined for positivity is any value above 4. Table 5 shows an example of the triadic context, representing positive satisfactions with an X.

After obtaining the triadic context, it was converted into a suitable format for input into the Lattice Miner software ((Missaoui and Emamirad, 2017)) for the extraction of triadic rules. To do this, a JSON file was created containing the relationships between objects, attributes, and conditions in the specific format described in the tool's documentation, specifying the minimum support and confidence values for generating BCAAR and BACAR rules.

For the analysis of satisfaction levels in the ABW implementation, the following cases were considered relevant, taking into account A and B as subsets of questionnaire variables, and the waves of the longitudinal study *a - before*, *b - during*, and *c - after*:

Case 1: Relationship Between Attributes Before and During the ABW Implementation.

1. (A → B) ab
2. (a → b) A
3. (b → a) A

Case 2: Relationship Between Attributes During and After the ABW Implementation.

1. (A → B) bc

Table 4: Variables available in the database.

Questionnaire variables	
Productivity	Three items related to the impact on productivity.
Privacy	Six items related to the impact on privacy, whether focused on the task or on communication.
Feeling of Psychological Ownership	Four items related to the feeling of ownership in the workplace.
Satisfaction	Two items related to job satisfaction.
ABW	A single item related to liking or not ABW.
Workload	Four items related to workload.
Stress	Four items related to stress caused by work.
Change of environment	A single item that questions the frequency of changing the work environment.
Effects on performance	Personal estimation of the effect of the work environment on performance.
Gender	The employee's gender.
Conditions	
t1	Wave before ABW implantation - 2 months before.
t2	Wave after ABW implantation - 4 months later.
t3	Wave after ABW implementation - 9 months later.

Table 5: Example of table after processing.

ID	P1-t1	P3-t1	P1-t2	P3-t2	P1-t3	P3-t4
1	X	X			X	
2	X	X	X	X	X	X

2. (b → c) A
3. (c → b) A

Case 3: Relationship Between Attributes Before and After the ABW Implementation.

1. (A → B) ac
2. (a → c) A
3. (c → a) A

Considering, for example, rule (1) in case 1, we have: "Employees who positively assessed the variable(s) in set *A* of the questionnaire in the first wave also did so in the second wave." This rule allows evaluating the initial impact of ABW implementation and can later serve as a way to assess employee adaptation to the new concept over the longitudinal study. Another example is rule (1) in case 3, where we understand: "Employees who positively assessed the ABW implementation in *A* also did so for *B* before and after ABW implementation."

5 EXPERIMENTS AND ANALYSIS OF RESULTS

After applying LatticeMiner, it was possible to extract BACARs and BCAARs for the cases described in the previous section, enabling the analysis of the impact of ABW implementation in the company.

Case 1 (Before and During):

1. BACARs
   (a) (t1 → t2) Productivity2 [support = 96,4% confidence = 98,8%]
   (b) (t1 → t2) Productivity1 [support = 92,8% confidence = 95,1%]
   (c) (t1 → t2) Satisfaction2 [support = 68,7% confidence = 78,1%]
2. BCAARs
   (a) (Productivity2 → Satisfaction1) t1 [support = 89,2% confidence = 90,2%]
   (b) (Productivity2 → Satisfaction1) t2 [support = 85,5% confidence = 87,7%]
   (c) (Productivity1, Productivity3 → Satisfaction1) t1 [support = 86,7% confidence = 90,0%]
   (d) (Productivity1, Productivity3 → Satisfaction1) t2 [support = 78,3% confidence = 90,3%]

(e) (Satisfaction2 → Satisfaction1) t1 [support = 85,5% confidence = 97,3%]

(f) (Satisfaction2 → Satisfaction1) t2 [support = 67,5% confidence = 77,8%]

Case 2 (During and After):

1. BACARs
   (a) (t2 → t3) Productivity1 [support = 92,8% confidence = 95,1%]
   (b) (t2 → t3) Productivity1 [support = 92,8% confidence = 97,5%]
2. BCAARs
   (a) (Productivity1 → Satisfaction2) t2 [support = 72,3% confidence = 75,9%]
   (b) (Satisfaction2→ Productivity1) t3 [support = 62,7% confidence = 98,1%]
   (c) (Satisfaction1 → Satisfaction2) t2 [support = 67,5% confidence = 77,8%]
   (d) (Satisfaction1 → Satisfaction2) t3 [support = 60,2% confidence = 96,2%]

Case 3 (Before and After):

1. BACARs
   (a) (t1 → t3) Productivity1 [support = 95,2% confidence = 97,5%]
   (b) (t3 → t1) Satisfaction2 [support = 62,7% confidence = 98,1%]
2. BCAARs
   (a) (Satisfaction2 → Satisfaction1) t1 [support = 85,5% confidence = 97,3%]
   (b) (Satisfaction1 → Satisfaction2) t3 [support = 60,2% confidence = 96,2%]

With these rules, it is possible to describe and obtain information about the ABW implementation process from the longitudinal study. For example, analyzing the BACARs (c) rules from Case 1 and the (b) rule from Case 3, it can be observed that job satisfaction decreased, as employees who responded positively to Satisfaction2 ("I am satisfied with my job") did so less frequently between the waves (before → during) and (before → after), with the support dropping from 68.7

BCAARs rules (a) and (b) from Case 3 also indicates a drop in general satisfaction, pointing that the support of Satisfaction 1 ("My department/agency is a good place to work") and Satisfaction 2 ("I am satisfied with my job") decreased from 85.5% to 60.2% between the first and third wave.

Another interesting example would be BACAR rule (b) from Case 1 in conjunction with BACAR rule (a) from Case 3. In this context, it can be inferred that overall efficiency decreased, as evidenced by the support between the first and third wave, where the support dropped to 95.2%. This indicates that employees who felt efficient no longer do so. However, this support grows compared to the result in the second wave, at 92.8%, showing that some efficiency was recovered by the end of the study, highlighting a possible adaptation of employees to the new way of working.

BACAR rule (a) from Case 1, together with BACAR rule (a) from Case 2, indicates that efficiency decreased for collaborations, as employees who responded positively to Productivity2 ("I feel efficient when collaborating with my colleagues") did so less frequently between the waves (before → during) and (during → after), with the support dropping from 96.4% to 92.8

6 CONCLUSIONS AND FUTURE WORK

In this work, we showed the potential of applying triadic rules to describe longitudinal study databases in social contexts, where changes in the way of working, as described in this article, result in various implications. In this context, rules were generated that enable a better understanding of employee behavior before, during, and after the implementation of ABW.

It is important to highlight that Triadic Concept Analysis can become relevant in decision-making and the overall analysis of longitudinal databases. Its application to higher-dimensional databases will provide greater precision and description of the data, leading to even more meaningful conclusions.

As future work, it would be interesting to conduct studies involving time intervals that allow for a greater number of waves to observe whether employees become accustomed to and adapt to the new way of working. This could mitigate the negative effects on performance and job satisfaction caused by the shock of the work change.

Furthermore, the analysis could be extended to various companies, making it possible to evaluate the contribution of the internal culture of each company and its employees to the negative or positive impact of ABW implementation, given that the nature of the topic has gaps due to the possibility of personal interpretation of the changes by the participants.

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