Formal Concept Analysis Applied to Characterize Longitudinal Associations Between Depressive and Anxiety Disorders and Somatization

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Abstract: This study examines somatic syndromes as a significant public health challenge, highlighting the necessity of longitudinal sampling to comprehend the evolution of physical symptoms over time. It investigates the interplay between depressive and anxious symptoms and somatic symptoms related to disease. The research characterizes these symptoms within a diverse population in Isfahan, Iran, over a three-year period, utilizing Triadic Concept Analysis (TCA) as the primary analytical method to extract insights and establish correlations across time. The findings emphasize the importance of longitudinal methodologies in exploring patterns and rules associated with the symptoms under investigation. These insights enhance the understanding of the relationship between mental and physical health, offering valuable insights for clinical decision-making and treatment strategies.

1 INTRODUCTION

Somatic syndromes pose a significant public health issue, affecting both individuals and healthcare systems. A somatic symptom is diagnosed when a person significantly focuses on experiencing physical symptoms such as pain, weakness, shortness of breath, palpitations, fatigue, and organ pain.

These abnormal sensations may be classified as somatic syndromes when they cause substantial distress or functional impairment, without being linked to a primary clinical condition.

Physical symptoms may or may not be associated with a medical diagnosis, yet an individual experiencing these symptoms believes they are unwell. Research conducted in various countries over the past few decades, primarily focusing on primary care settings, indicates that somatization occurs in 16% to 50% of patient encounters(Schreiber et al., 2007) (Spitzer et al., 2004) (WHO, 1997).

Identifying when a somatic symptom is directly linked to a medical condition is a complex and nuanced task. Studies indicate that an individual experiences an abnormal symptom approximately every seven days (Birket-Smith and Mortensen, 2010), and most often does not seek emergency care, as these symptoms tend to resolve after a few days.

It is frequently necessary to observe patients over several years to understand the abnormal symptoms associated with physical conditions, highlighting the importance of longitudinal sampling — often conducted annually — within the context in which a patient is situated.

A well-known fact is that sadness and distress, common human emotions, are always accompanied by physical components. Similarly, persistent mental disorders—such as depression and anxiety—are associated with various physical symptoms, indicating that in 50% of cases, there is a direct relationship between depression, anxiety, and somatization (Löwe et al., 2008).

Based on this principle, logistic regression analyses were employed in (Bekhuis et al., 2015), revealing results indicating that all groups of somatization were more prevalent among patients with depressive and/or anxiety disorders, as explained further in this article. Thus, it becomes feasible to investigate and analyze depressive and anxious symptoms primarily in rela-

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tion to somatization.

In this article, depressive symptoms, anxious symptoms, and somatization were characterized using Triadic Concept Analysis (TCA) based on a multidimensional and longitudinal data repository (Adibi et al., 2023) from the Isfahan region, Iran - Isfahan is the third most populous city in the country, with a population exceeding 1.8 million residents. This setting was chosen primarily due to the diversity of its population and the observable socio-cultural influences.

The data encompass various factors contributing to somatization, involving 1,930 participants, primarily adults aged between eighteen and sixty-five years, who were randomly selected and monitored from 2017 to 2020. These factors include:

(a) functional symptoms across multiple body organs,
(b) psychological assessments,
(c) lifestyle factors,
(d) demographic and socioeconomic aspects,
(e) laboratory studies,
(f) clinical analyses, and
(g) clinical history.

The aim is to primarily characterize psychological phenomena that are independently related to somatic symptoms through this longitudinal sampling.

Formal Concept Analysis (FCA) was introduced in 1982 by Rudolf Wille (Dau and Wille, 2000) as a derivation of concepts that possess hierarchies based on a set of objects and properties. One of the primary objectives of this method is to extract knowledge and characterize a database, thereby enhancing the understanding of a context and facilitating better decision-making in data analysis - the Triadic Concept Analysis (TCA) is an extension of FCA, proposed by Wille in 1995, which incorporates a third component in the data analysis process.

The remainder of the paper is organized as follows: the background is outlined in Section 2. The Related Work is described in Section 3. Section 4 presents the Methodology. Results are discussed in Section 5. The conclusion and further research are in Section 6.

2 BACKGROUND

Longitudinal study approaches aim to investigate a sample of individuals with specific characteristics over consecutive time periods, referred to as waves. This methodology is widely utilized in the field of health, as it provides flexibility in analyzing treatment periods with medications and methodologies.

Longitudinal studies in the health field can encompass various characteristics and samples, referred to as the dimensionality of the database. Databases can have longitudinal characteristics, allowing for the tracking and characterization of behaviors and patterns of the objects and attributes involved in the study. Therefore, a longitudinal study of such a database can yield valuable insights to validate the clinical procedures being adopted.

Studies may be conducted with thousands of samples and characteristics to assess, for example, how a pre-existing symptom in a patient may affect another clinical condition, representing a study based on a high-dimensionality database. Conversely, studies involving treatments that require specific characteristics of a particular population may consist of only a few hundred samples, indicating low or medium dimensionality.

Low dimensionality can lead to reduced learning rates and knowledge extraction when utilizing artificial intelligence methods, such as machine learning.

Conversely, longitudinal studies are highly effective for detecting patterns and rules associated with the study group. Overall, when longitudinal techniques are applied to the analysis of a database, it becomes possible to extract important data, such as:

1. The evolution of clinical symptoms over years of patient sampling;
2. The relationship between characteristics and symptomatic variables;
3. The direct relationship between two clinically analyzed symptoms considered in isolation.

All of this information can be of great value for clinical analysis, providing support for decision-making.

The database (Adibi et al., 2023) analyzed in this study possesses longitudinal characteristics, as it involves the observation of objects (patients) and attributes (somatic symptoms) over the periods from 2017 to 2020. This work focused on the first three years of patient sampling to maintain the highest possible dimensionality of the database, thereby avoiding excessive sparse data—specifically, patients who dropped out of the study from one year to the next. Consequently, a total of 1,616 patients were analyzed during the years 2017, 2018, and 2019, representing approximately 83% of the original sample.

This database is well-suited for the application of longitudinal studies, as it allows for the measurement of the effects of symptoms related to depression and anxiety on somatization across different periods, as well as the evolution and potential persistence of these symptoms.

2.1 Formal Concept Analysis

Formal Concept Analysis (FCA) can be used to recognize patterns with the help of association rules and their implications. FCA consists of a set of objects forming a formal context, formal concepts, and rules.

A formal context can be represented as a triple $K = (G,M,I)$: G is a set of objects, M is a set of attributes, and $I \subseteq G \times M$ an incidence relation where $(g,m) \in I$ indicating that the object g possesses the attribute m.

The association rule $A \rightarrow B$ is valid only if for every object that contains the attributes of B, it also contains the attributes of A. Given a rule r, and the parameters s and c, it can be denoted:

$s = suppr(r) = \frac{|A' \cap B'|}{|G'|}$

and

$c = conf(r) = \frac{|A' \cap B'|}{|A'|}$

S referred to as the support of the rule and **C** referred to as the confidence. When $conf(r) = 100\%$, the rule is referred to as an implication (Felde and Stumme, 2023) .

2.2 Triadic Concept Analysis

The definitions of FCA extend to a third dimension, resulting in a triadic context T, denoted by the quadruple $T = (G,M,B,Y)$, where G, M, and B are, respectively, the set of objects, attributes, and conditions, belonging to the ternary relation $Y \subseteq (G \times M \times B)$. This relation can be interpreted as: object g possesses attribute m under condition b.

From the triadic context, it is possible to extract triadic concept which is defined as (A, B, C). As in dyadic concepts, $A \subseteq K_1$ (extent) and $B \subseteq K_2$ (Intent) exist, however, there is also the addition of a third component, $C \subseteq K_3$ (modus). From this concept, it is possible to extract triadic rules, that are in the scope of this paper.

The introduction of a third dimension allows for a better characterization and representation of data. Bi-dimensional data may receive the dimension time to monitor the evolution of objects in relation to attributes and discovery of hidden patterns in the database, and this is exactly the shape of longitudinal studies, such as the database used in this study.

Two types of triadic association rules can be described for a context $K := (G,M,B,Y)$ (Biedermann, 1997a): the Bierdermann Conditional Attribute Association Rule (BCAAR) and the Bierdermann Attributional Condition Association Rule (BACAR).

The BCAAR rule is represented by: $(R \rightarrow S)C(sup.,conf.)$, where $R,S \subseteq M$ and $C \subseteq B$. This means that for every object possessing all attributes of R, it also possesses all attributes of S under condition C, with a support (sup) and a confidence (conf).

The BACAR rule is represented by: $(P \rightarrow Q)N(sup,conf)$, where $P,Q \subseteq B$ and $N \subseteq M$. This means that for every object under the condition in P, it will also be under the conditions in Q in attribute N, with a support (sup) and a confidence (conf).

The support corresponds to the proportion of objects in the subset $g \subseteq G$ that satisfy the implication $P \rightarrow Q$, relative to the total number of objects $|G|$ in the formal context K:

$$Sup(P \rightarrow Q) = \frac{|(P \cup \{Q\})|}{|G|}$$

Confidence corresponds to the ratio of objects$g \subseteq G$ that contain P and also contain Q, compared to the total number of objects $|G|$:

$$Conf(P \rightarrow Q) = \frac{|P \cup \{Q\}|}{|P'|} = \frac{Sup(P \rightarrow Q)}{Sup(P)}$$

2.3 Somatic Syndromes

The phenomenon known as "somatization" can be better defined by (Lipowski, 1988) as follows: "Somatization is defined here as a tendency to experience and communicate somatic discomfort and symptoms that cannot be explained by pathological findings, attributing them to physical illnesses and seeking medical help for them."

Analyzing somatic physical symptoms in a patient is always a significant challenge for healthcare professionals, as many times a somatic symptom does not directly reflect a clinical condition but rather an emotional state of the patient.

One subfield of study on somatic symptoms is psychosomatic disorders, where psychological distress can, in some way, cause or exacerbate a physical symptom. This psychic suffering is often involuntary and unconscious. On the other hand, (Bekhuis et al., 2015) shows that somatization is greatly influenced by other psychological clinical conditions, with significant connections to depressive and anxious symptoms.

The characterization of these symptoms and clinical conditions, combined with a professional analysis of a patient's history, can help identify a cause for a somatic condition. Thus, from a longitudinal sample of patients, it is possible to characterize, through TCA, a database containing relevant information on depressive symptoms, anxious symptoms, and somatization.

This can be obtained from implication rules of the form $(P \rightarrow Q)N(sup, conf)$, meaning, for example, that an anxious/depressive condition p implies a somatic condition q over a specific period n with a support (sup) and a confidence (conf), contributing to the analysis of a clinical condition.

3 RELATED WORK

This work utilizes Formal Concept Analysis, with the approach justified through a relationship between theoretical and practical knowledge of the subject. Related Work on this topic are presented below.

(Wei et al., 2018) analyzes the triadic approach of formal concept analysis in four aspects: (i) the basic approach of triadic concept analysis, (ii) triadic implications and rules, (iii) the triadic factor of analysis, and (iv) the analysis of fuzzy triadic concepts.

(Biedermann, 1997b) systematically Illustrates the application of triadic formal concept analysis in databases to represent complex concepts that are difficult to visualize. It also explains the generation of rules and implications from an analyzed dataset. In (Blevente Lorand Kis and Troanca, 2017), a tool is presented that enables the visualization of these concepts and rules, facilitating navigation and understanding of triadic structures .

The work presented in (Ganter and Obiedkov, 2004) shows several possible biases that can be generated from triadic formal concept analysis and various implications in multiple scenarios.

Given the different interests that can be addressed from a triadic context, the authors provide extensive and compact descriptions through implication-generating algorithms in the triadic context.

Examples of these interests, which can span different areas yet still be resolved in a triadic context, are found in (Kent and Neuss, 1997), where the focus is on hypertext analysis, and in (Carullo et al., 2015), which presents an application of this method in online recommendation systems.

(Hu et al., 2004) presents modeling techniques based on a logical description language applied to a cancer database. Results generated from the intentions and extensions of entities present in these databases are provided, obtained through formal concept analysis.

In (Santos et al., 2022), an analysis of infant mortality in two regions of Minas Gerais is conducted. The process utilized the triadic formal concept analysis approach to extract rules and implications from a database. The study generated a series of rules with certain hierarchies that characterized this database.

In (Ferreira et al., 2021), an application is made to extract knowledge from a database generated by a survey conducted with women undergoing chemotherapy for breast cancer. The application of Formal Concept Analysis theory allowed for the extraction of a set of hierarchically organized concepts, and from these, rules that relate them were derived, thus describing the results of the antiemetic treatments in this database.

(Lana et al., 2022) conducts a longitudinal analysis of a database on COVID-19 using the processes of triadic formal concept analysis. The results of this work present implication rules that longitudinally describe the evolution of the COVID-19 pandemic at different points in time. The literature shows that FCA can be applied in many different contexts ((Ananias et al., 2021), (Alves et al., 2023)).

4 METHODOLOGY

The database discussed in this article (Adibi et al., 2023) consists of a multidisciplinary longitudinal sampling of somatic symptoms, primarily represented by adults aged eighteen to sixty-five from Isfahan, Iran, who were randomly selected and monitored over four consecutive years. In this study, seven databases were collected:

(a) assessment of functional symptoms in various organs,
(b) psychological assessment,
(c) lifestyle variables,
(d) demographic and socioeconomic variables,
(e) laboratory measurements,
(f) clinical examination, and
(g) historical information.

Psychological details, including depression, anxiety, post-traumatic stress, and other attributes related to psychosomatic symptoms, were also included in this database. Additionally, this study addressed the issue of post-traumatic stress focused on COVID-19 through questionnaires. The questionnaires offered a choice between 1 and 4, where 1 indicated the presence of a symptom and 4 indicated its absence.

The study was initially conducted with 1,943 patients in 2017, and by 2020, it was completed with 1,176 patients who remained. This particular article analyzes the periods from 2017 to 2019, which had the highest patient participation rate, with 1,697 participants and a response rate of 88%, comprising an average age of 40.03 years, with 756 being male.

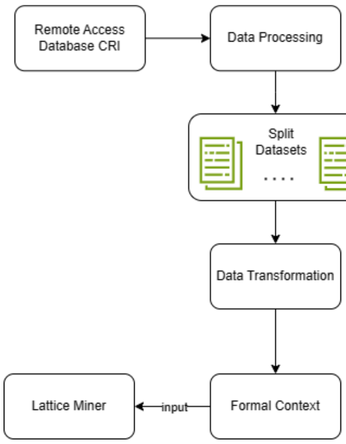

Figure 1: Methodology.

There are many articles that address formal concept analysis applied to the field of health and human behavior. This particular article seeks to characterize depressive symptoms, anxious symptoms, and somatization based on a multidimensional and longitudinal data repository using: data collection, exploration, attribute selection and transformation, and the extraction of contexts and rules (Figure 1).

In the first stage, it was necessary to collect the required data and its description. For this, access to the objects and attributes to be worked on was requested. Due to legal restrictions, the data cannot be processed outside the servers of the Isfahan Cardiovascular Research Center. Therefore, as shown in Figure 1, it became necessary to install systems and analyze the data through a remote connection to the servers.

After the installation of the necessary systems, data preprocessing is required in the second stage. For this, the selection of attributes to be the focus of this article was made. The choice was primarily based on the aim of conducting a direct analysis of the effects of anxiety and depression on somatization.

The attributes related to depression, anxiety, and somatic symptoms — described in Table 1 — were selected according to their relevance to the study. In Table 1, it is possible to observe the division into groups that separates depressive and anxious symptoms (H) from somatic symptoms (S).

Additionally, the data was cleaned to ensure the maximum number of participating patients. Due to limitations in the computational resources of the server and the computational cost of the algorithms used in TCA, it became necessary to divide the original database in the third stage into several subsets.

This division was based on the product of an attribute related to depression and anxiety with all the attributes characterizing a somatic symptom. This approach would allow for a longitudinal characterization of the relationship between depression and anxiety attributes and those of somatization.

Table 1: Symptoms of Depression and Anxiet (H), Somatic (S).

Group	Sub Group	Description
H	A	Sleep problems
H	B	Panic symptoms
H	C	Sadness symptoms
H	D	Anxiety symptoms
H	E	Sudden palpitations
H	F	Existential problems
H	G	Sudden restlessness
H	H	Irritation
H	I	Constant worry
Group	**Sub Group**	**Description**
S	A	Headaches
S	B	Stomach aches
S	C	Back pain
S	D	Joint pain
S	E	Chest pain
S	F	Swelling
S	G	Restlessness
S	H	Heart palpitations
S	I	Pressure in the heart

In the fourth stage, a transformation of the data was performed using discretization techniques. This discretization considered the range of the questions, initially defining $[1..2] \rightarrow no$ and $[3..4] \rightarrow yes$. This discretization was necessary for the algorithm to work correctly.

In the fifth stage, the creation of the triadic formal context was carried out, as shown in Tables 2 and 3, along with the input data for the Lattice Miner software mentioned throughout the work.

For the creation of the triadic context, each object is described by three waves: 2017 *(w1)*, 2018 *(w2)* and 2019 *(w3)*. The example of the formal context also illustrates the division of the database according to the mathematical relationship $a \times S = \{(a,b)\,|a \in H, b \in S\}$.

The tool used for the FCA algorithms is Lattice Miner 2.0. This is a data mining prototype developed under the supervision of Professor Rokia Missaoui at the University of Quebec.

It is a public access Java platform whose main functions include all low-level operations that allow for the manipulation of input data, structures, and rule associations.

Table 2: Triadic Context of the Base Sleep Problems (HA).

	w1					w2					w3				
Obj	**HA**	**SA**	**SB**	**...**	**SI**	**HA**	**SA**	**SB**	**...**	**SI**	**HA**	**SA**	**SB**	**...**	**SI**
1	x	x				x		x		x		x			x
2	x	x	x		x		x	x			x	x	x		
3		x				x					x		x		

Table 3: Triadic Context of the Base Panic Symptoms (HB).

	w1					w2					w3				
Obj	**HB**	**SA**	**SB**	**...**	**SI**	**HB**	**SA**	**SB**	**...**	**SI**	**HB**	**SA**	**SB**	**...**	**SI**
1		x	x		x	x	x			x	x		x		x
2	x	x			x		x			x		x	x		x
3		x	x		x		x	x				x	x		

The platform enables the generation of groups, called formal concepts, which include logical implications, thus showing binary relationships between collections of objects and their sets of attributes or properties.

5 RESULTS

Based on a triadic analysis conducted on the database in question, it was possible to relate how aspects of depression and anxiety interfere with somatic symptoms in the population of Isfahan, Iran.

Considering:

- w1: Data from the first wave (1) conducted in 2017;
- w2: Data from the second wave (2) conducted in 2018;
- w3: Data from the third wave (3) conducted in 2019.

The following rules were obtained:

BACAR Implications.

1. $(HA \rightarrow SG)\,\text{w1}\,[\text{sup} = 62,7\%, \text{conf} = 93,3\%]$
2. $(HA \rightarrow SG)\,\text{w2}\,[\text{sup} = 64,3\%, \text{conf} = 92,3\%]$
3. $(HA \rightarrow SG)\,\text{w3}\,[\text{sup} = 62,7\%, \text{conf} = 93,5\%]$
4. $(HB \rightarrow SE)\,\text{w1}\,[\text{sup} = 70,8\%, \text{conf} = 90,4\%]$
5. $(HB \rightarrow SG)\,\text{w3}\,[\text{sup} = 68,2\%, \text{conf} = 92,9\%]$
6. $(HC \rightarrow SG)\,\text{w3}\,[\text{sup} = 70,5\%, \text{conf} = 93,7\%]$
7. $(HC \rightarrow SG)\,\text{w2}\,[\text{sup} = 67,9\%, \text{conf} = 91,3\%]$
8. $(HD \rightarrow SG)\,\text{w2}\,[\text{sup} = 81,4\%, \text{conf} = 91,1\%]$
9. $(HD \rightarrow SG)\,\text{w3}\,[\text{sup} = 73,5\%, \text{conf} = 91,4\%]$
10. $(HE \rightarrow SF)\,\text{w2}\,[\text{sup} = 70,5\%, \text{conf} = 90,3\%]$
11. $(HF \rightarrow SG)\,\text{w2}\,[\text{sup} = 71,0\%, \text{conf} = 91,0\%]$
12. $(HF \rightarrow SF)\,\text{w2}\,[\text{sup} = 71,7\%, \text{conf} = 91,8\%]$

The attributes in the presented rules follow the definitions from Table 1, as well as the indicated waves. A support threshold of 60% was used for generating the rules. Several results were generated; for the interpretation of the rules in this article, only the main rules with a confidence level above 90% were considered.

For rules 1, 2, and 3, an interesting relationship can be found between the symptom of sleep problems (HA) and the somatic symptom of restlessness (SG).

In the three indicated waves for the periods of 2017, 2018, and 2019 (w1, w2, and w3), this relationship remained consistent with a support close to 63% and a confidence of 93%. This means that a portion of the database characterized by symptoms of sleep problems also exhibits symptoms of headaches.

On the other hand, rules 6 and 7 illustrate a clinical condition that emerged during the periods of 2018 and 2019 (w2 and w3).

These rules indicate that symptoms related to sadness and loss of motivation (HC) may be associated with somatic symptoms of restlessness (SG) and sudden loss of attention. This characteristic of the database also supports the context in which patients may have found themselves, such as during a global crisis or a pandemic.

It can also be inferred that the characteristics of the database lead us to understand that the somatic symptoms most directly related to depressive and anxious symptoms are the clinical conditions of restlessness (SG), sudden sensations of swelling (SF), and chest pain (SE), particularly during the periods of 2018 (w2) and 2019 (w3).

Conversely, other depressive and anxious symptoms did not appear in the analysis when considering the established support and confidence thresholds; for example, regarding the symptom of constant and sudden worry (HI), no rules were found that characterize the database according to the set parameters.

BCAAR Implications

1. $(w2 \rightarrow w3)\,\mathrm{SE}\,[\mathrm{sup} = 72,6\%,\ \mathrm{conf} = 92,5\%]$
2. $(w3 \rightarrow w2)\,\mathrm{SG}\,[\mathrm{sup} = 75\%,\ \mathrm{conf} = 92,8\%]$
3. $(w1 \rightarrow w3)\,\mathrm{HB}\,[\mathrm{sup} = 62,9\%,\ \mathrm{conf} = 90,3\%]$
4. $(w1 \rightarrow w3)\,\mathrm{SE}\,[\mathrm{sup} = 72,9\%,\ \mathrm{conf} = 91,8\%]$
5. $(w1 \rightarrow w3)\,\mathrm{SI}\,[\mathrm{sup} = 70,6\%,\ \mathrm{conf} = 94,2\%]$
6. $(w2w1 \rightarrow w1)\,\mathrm{SG}\,[\mathrm{sup} = 71,6\%,\ \mathrm{conf} = 95,7\%]$
7. $(w1w2 \rightarrow w3)\,\mathrm{SI}\,[\mathrm{sup} = 68,6\%,\ \mathrm{conf} = 94,0\%]$
8. $(w1w2 \rightarrow w3)\,\mathrm{HC}\,[\mathrm{sup} = 63,0\%,\ \mathrm{conf} = 90,9\%]$
9. $(w1w3 \rightarrow w2)\,\mathrm{HC}\,[\mathrm{sup} = 73,5\%,\ \mathrm{conf} = 93,6\%]$
10. $(w2 \rightarrow w1)\,\mathrm{HD}\,[\mathrm{sup} = 81,4\%,\ \mathrm{conf} = 91,1\%]$
11. $(w2 \rightarrow w1)\,\mathrm{SG}\,[\mathrm{sup} = 83,5\%,\ \mathrm{conf} = 93,6\%]$
12. $(w2w3 \rightarrow w1)\,\mathrm{SH}\,[\mathrm{sup} = 60,5\%,\ \mathrm{conf} = 90,1\%]$

Applying the BACAR rules similarly, no rules were generated with support lower than 60%. Likewise, the interpreted rules must have support greater than 50% and confidence of 90%.

Rule 1 shows that 72.6% of the patients who participated in the study had chest pain (SE) in 2018 (w2), and 92.5% continued to have chest pain in 2019 (w3).

It can also be observed for Rule 3 that 62.9% of the patients who had panic symptoms in 2017 (w1) continued to have this symptom in 2019 (w3), maintaining the same behavior for the somatic symptoms in Rules 4 and 5, with support around 70% and confidence around 92%.

Rule 7 shows that for every patient who participated in the study during the observation period between 2017 and 2018 (w1, w2), 94% continued to exhibit a somatic symptom of heart pressure (SI) in the following year (w3).

Similarly, Rule 8 shows the same behavior for a depressive and anxious symptom. Between 2017 and 2018 (w1, w2), 73.5% of the patients had the symptom of sudden sadness, and in 2019 (w3), 93.6% of the individuals continued to exhibit the same symptom.

Another interpretation we can derive is that BACAR rules 6, 7, 8, 9, and 10 allow us to identify a certain prevalence of both depressive and anxious symptoms as well as somatic symptoms during the three waves (w1, w2, and w3). This may indicate certain characteristics that remain persistent over a long observation period, potentially supporting clinical decisions during the analysis of these patients.

Thus, by analyzing these implications, it is possible to generate practical results, especially as assistance in decision-making during the evaluation of a medical condition.

6 CONCLUSIONS

The objective of this article, following the analysis and selection of results, is to understand and primarily characterize the relationship between somatic syndromes and symptoms of depression and anxiety.

Additionally, the research seeks to highlight the contrasts in the results obtained within the context of the population of Isfahan, Iran, using a database maintained and provided by the *Isfahan Cardiovascular Research Institute (ICRI)*.

This database provided information on a study conducted with patients who experienced clinical conditions between 2017 and 2020, also considering the developments of the COVID-19 pandemic during this period.

The information was collected and validated by professionals through questionnaires and made available in the *Data in Brief* repository. Furthermore, it is important to emphasize that the database contains information on various variables that may influence a somatic symptom, making it a non-linear analysis rather than a simple one.

Conversely, the objective of this work was to enhance the applicability of Triadic Concept Analysis. This analysis has proven to be an effective approach for identifying aspects in certain variables that are not easily discernible in a primary analysis, related to various contexts across fields of knowledge.

With this result, it is possible to support a professional's analysis and be useful in the foundation and justification of decision-making. However, the study has the limitation of not considering all aspects and contexts that may correspond and relate to a somatic condition.

Therefore, by conducting a complex analysis of indirectly related data, the study reveals a correspondence and a relationship between these elements, providing an alternative perspective on the database

Thus, it is expected that various fields of study and scenarios will benefit from the methodology used in this work during the investigation and analysis stages, utilizing Triadic Concept Analysis (TCA).

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