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Development and validation of a semantic ontology in Spanish based on a transdiagnostic model for detection of anxiety symptoms in written narratives

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ABSTRACT

This exploratory research aims to develop, validate, and implement a semantic ontology in Spanish for the detection of anxiety symptoms in written narratives by young Colombians aged 18 to 30. 430 young people responded to a questionnaire on sociodemographic data, six open-ended questions, and the DASS-21 scale, in an online form. A mixed methods design was used, implementing a text analysis study using natural language processing, a semantic ontology of anxiety symptomatology, and agile software development methodology. The procedure included six phases: 1) development and validation of open-ended questions on anxiety symptomatology to collect information from narrative texts, 2) data collection, 3) ontology construction, 4) ontology validation through interjudge analysis, 5) software development and application, and 6) Efficacy of software for automatic symptom identification. The software developed in this project proved to be effective in its intended task of accurately identifying symptoms in both clinical and non-clinical participants, with more than 80% agreement with clinical experts. The results showed that the majority of symptoms had higher percentages in clinical participants compared to non-clinical participants.

Keywords
anxiety, semantic ontology, transdiagnostic and natural language processing

RESUMEN

Esta investigación exploratoria pretende desarrollar, validar e implementar una ontología semántica en español para la detección de sintomatología ansiosa en narrativas escritas de jóvenes colombianos de 18 a 30 años. 430 jóvenes respondieron un cuestionario de datos sociodemográficos, seis preguntas abiertas y la escala DASS-21, en un formulario en línea. Se utilizó un diseño de métodos mixtos, implementando un estudio de análisis de texto mediante procesamiento del lenguaje natural, una ontología semántica de la sintomatología de la ansiedad y una metodología ágil de desarrollo de software. El procedimiento incluyó seis fases 1) desarrollo y validación de preguntas abiertas sobre sintomatología de ansiedad para recoger información de textos narrativos, 2) recogida de datos, 3) construcción de la ontología, 4) validación de la ontología mediante análisis interjueces, 5) desarrollo y aplicación del software, y 6) Eficacia del software para la identificación automática de síntomas. El software desarrollado demostró su eficacia en la tarea prevista de identificar con precisión los síntomas tanto en participantes clínicos como no clínicos, con una concordancia superior al 80% con los expertos clínicos. Los resultados mostraron que la mayoría de los síntomas presentaban porcentajes más elevados en los participantes clínicos en comparación con los no clínicos.

Palabras clave
ansiedad, ontología semántica, transdiagnóstico y procesamiento del lenguaje natural

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Desarrollo y validación de una ontología semántica en español basada en un modelo transdiagnóstico para la detección de síntomas de ansiedad en narrativas escritas

Introduction

In Colombia, anxiety disorders are among the most common mental health problems affecting the population. According to the National Mental Health Survey (Ministerio de Salud y Protección Social & Colciencias, 2015), nearly every individual aged 18 to 44 reported experiencing two or more symptoms associated with depression or anxiety. About 12.3% of individuals reported experiencing three or four symptoms indicative of anxiety. Furthermore, 3.9% of respondents presented an anxiety disorder. World Health Organization estimated that anxiety and depression disorders might have increased by 25% during the COVID-19 pandemic (WHO, 2022).

Even though anxiety is a natural response to diverse situations, when it is excessive, disproportionate, pervasive, or departs from the appropriate level of threat within a specific context, it may significantly disrupt an individual's daily functioning and overall sense of well-being (Blakey & Abramowitz, 2020). Anxiety disorders in young adulthood can further impact social functioning, academic performance, and employment opportunities, potentially leading to economic challenges or financial burdens (Jefferies & Ungar, 2020). Anxiety ranks among the top fifteen causes of global disability-adjusted life-years (DALYs) in people aged 25–49 years and is one of the top ten causes in those aged 10–24 years (Vos et al., 2020).

Most clinical perspectives in psychology rely on what the patient talks about (e.g. clinical interviews, free association, autobiographical narratives, among many others) — to understand and contextualize psychological symptomatology. Some theoretical frameworks such as “narrative psychology” (Bruner, 1990; McAdams, 2001; Polkinghorne, 1988), “narrative therapy” (White & Epston, 1990), and “narrative research methods in clinical psychology” (Riessman, 2008; Lieblich et al., 1998) place language at the core of psychological understanding and symptom treatment. These approaches highlight not only the content of a person's story but also how it is structured and emotionally framed, revealing potential signs of disorganization, distress, or maladaptive meaning-making involved in the development of symptomatology.

From a contextual behavioral perspective, such as Relational Frame Theory (RFT; Hayes et al., 2001; McAuliffe et al., 2014; Törneke et al., 2008), language is a form of operant behavior which is learned and then generalized through social interactions which often involve physical and/or verbal reinforcement (Hayes et al., 2001; Hughes & Barnes-Holmes, 2016; Luciano et al., 2007). Said behavior is called “arbitrary applicable relational responding” or “relational responding” and it’s considered a unique ability that only human beings have. Relational responding consists of relating stimuli based not only on their physical properties but also based on arbitrary and socially determined rules (Hayes et al., 2001; Healy et al., 2000). This ability to form abstract, bidirectional links is the foundation of language. Considering the latter, verbal expressions are seen as shaped by the person's learning history, contextual contingencies, and rule following behaviors (Hayes et al., 2001; Healy et al., 2000; Kissi et al., 2017; Zettle & Hayes, 1982). The resulting behavioral patterns such as experiential avoidance, cognitive fusion, lack of contact with the present moment, attachment to the self as content (or narrative), lack of clarity on values and omission of valued actions are included as part of the In-Hexaflex model that theoretically explains emotional suffering according to the Acceptance and Commitment Therapy (ACT; Hayes et al., 2012; Wilson & Luciano, 2002), which is strongly rooted on behavioral and RFT principles.

However, stigma often discourages young adults from seeking healthcare services, hindering the detection and treatment of anxiety symptoms (Gronholm et al., 2017; Sheikhan et al., 2023). Early prevention and intervention of anxiety symptoms can significantly mitigate their harmful effects (Colizzi et al., 2020). In this regard, there is a growing emphasis on leveraging data-driven methods as an innovative approach for the early detection and prevention of mental health disorders (Naslund et al., 2019; Russ et al., 2019). Given that language can offer valuable insights into an individual's psychological state (Pennebaker et al., 2003), researchers are utilizing machine learning (ML) and natural language processing (NLP) methods to recognize emotional symptomatology in textual narratives, particularly within social networks (Chen & Genc, 2022; Cummins et al., 2020; Le Glaz et al., 2021; Wongkoblap et al., 2017; Zhang et al., 2022).

One method to make free text phrases machine-processable is mapping text phrases to ontology concepts that express the phrases' meaning (Kersloot et al., 2020). An ontology is a structured framework that formally defines concepts within a specific field of knowledge. It comprises classes (also known as concepts), properties associated with these classes (referred to as slots), and rules or constraints governing these properties (commonly referred to as facets) (Noy & McGuinness, 2020). Ontologies support NLP tasks by formally representing concepts, relationships, and properties, enabling better understanding and interpretation of text (Sonbol et al., 2022).

Ontologies have been used to detect and monitor various mental health conditions. For instance, Tajuddin et al. (2020) devised a Stress Detection Framework strategy utilizing ontologies to identify stress among users of microblogs. They employed a hybrid ontology domain extraction process, which involved filtering messages and extracting and comparing words against a formal and terminological ontology. Similarly, Chang et al. (2015) utilized ontologies and Bayesian networks to estimate the probability of depression. Similarly, in previous studies, Ortiz et al. (2024) designed an ontology using machine learning to detect depressive symptoms in narratives written in Spanish. Dias et al. (2020) integrated an ontology into developing a model designed for the continuous care of individuals with depression, anxiety, and stress disorders (DASD). Additionally, Benfares et al. (2019) used ontologies and ML techniques to monitor emotional symptoms in cancer patients. El Bolock et al. (2021a) employed ontologies for evaluating sleep and promoting healthy eating habits and even monitored students' psychological well-being during the pandemic (2021b).

Regarding anxiety, Elaraby et al. (2021) employed ontology techniques to develop a Java-based application to detect anxiety during the COVID-19 pandemic. The study involved 221 participants, of whom 50% were female. The researchers administered a battery of psychometric tests, including the Big Five Inventory (BFI-10), Self-Assessment Manikins (SAM), State-Trait Anxiety Inventory (STAI), Toronto Alexithymia Scale (TAS), and Patient Health Questionnaire (PHQ). By analyzing the collected data, the researchers discerned pertinent indicators for state anxiety, trait anxiety, and depression. Additionally, ontologies have been employed to systematize information on anxiety-related disorders, such as post-traumatic stress disorder (PTSD, Gamble et al. (2014), and obsessive-compulsive disorder (OCD, Nachiya et al. (2018).

Nevertheless, the existing research predominantly concentrates on detecting depression symptoms, with anxiety receiving limited attention (Di Cara et al., 2023; Zhang et al., 2022). Also, to our knowledge, no software exists for detecting emotional symptomatology in Spanish. Therefore, this study aims to develop, validate and implement a semantic ontology in Spanish for the detection of anxiety symptoms in written narratives of Colombian young adults. For that, natural language processing and ontology techniques were implemented. A semantic ontology was constructed from a transdiagnostic perspective, considering that clinical psychology has begun questioning the disorder-centric perspective of mental health proposed by psychopathology (Harvey et al., 2004). This transdiagnostic view is fundamented on the understanding and consensus that mental disorders development, course and prognosis is related to a few underlying processes (Sandín et al., 2012). Thus, the ontology proposed by the present study does not focus on a specific set of symptoms but rather understanding anxiety-related symptomatology across all their potential physiological, cognitive, and behavioral manifestations.

Method

Design

This study followed a mixed methods design that integrated text analysis techniques derived from natural language processing and agile methodology in software development to build a semantic ontology for anxious symptomatology. According to Hernández-Sampieri and Mendoza (2018), mixed methods represent a set of systematic, empirical and critical research processes that involve the collection and analysis of quantitative and qualitative data, as well as their integration and joint discussion, to make meta-inferences that arise from all of the information collected and contribute to a greater understanding of the phenomenon under study.

Participants

Participants for this study were selected through non-probability convenience sampling. Invitations were extended via popular social media platforms, including Facebook and Instagram, as well as through institutional channels (i.e. e-mail, webpage, etc). The inclusion criteria were: being between 18 and 30 years old, Colombian, willing to provide informed consent and thus granting permission to use of their data for research purposes. Participation was voluntary and involved completing an online form hosted on Google Forms. People who did not meet these criteria were excluded from the study.

The sample consisted of 430 young people, 276 women (64.2%) and 154 men (35.8%) from 39 municipalities of Colombia with ages ranging from 18 and 30 years old (M=22.04; SD=3.3). Most of the participants were studying: 79.5% an undergraduate course, 4.0% a technician-technologist course and 4.9% a postgraduate course. 11.6% were not studying at that moment. 21% reported a previous diagnosis of a mental health or psychological condition while 79% did not. Regarding marital status, the participants were: 1.2% married, 92.8% single and 6% in a common law union. 56% did not work, 30% had a formal job and 14% had informal gigs (rebusques). According to the Colombian socioeconomic classification of the residential properties where the participants live, 3% were at tier 1- very low, 29.0% tier 2 - low, 52.5% tier 3- medium-low, 14.4% tier 4 medium and 1.1% tier 5- medium high.

Based on the scores obtained on the anxiety subscale of the DASS-21, participants were categorized into two groups: clinical and non-clinical symptomatology. A cutoff score of 7 was used to establish group membership. Participants scoring 7 or above were classified as exhibiting clinical levels of anxiety, whereas those with scores below 7 were considered non-clinical.

Instruments

Sociodemographic questionnaire

A socio-demographic questionnaire was designed to collect information on sex, age, socioeconomic classification, marital status and educational level of the participants.

Open-ended questions

Six open-ended questions were developed and validated in order to collect enough narrative textual data to allow the assessment of anxious symptomatology within the participants' answers.

Depression Anxiety and Stress Scale (DASS-21; Original: Antony et al., 1998; Colombian Version: Ruiz, García-Martín, et al., 2017)

DASS-21 is a psychometric instrument with three subscales that evaluates the presence and severity of depression, anxiety and stress symptoms during the last week. It has 21 items with a four-point Likert-type scale (0 = It has not happened to me; 3 = It has happened to me a lot, or most of the time. However, the present study focused on the anxiety scores and considered the following categories for the subscale: <4 mild anxiety, 5-7 moderate anxiety, 8-9 severe anxiety, >10 extremely severe anxiety. The present study, used a score of 7 as cut-off point for the classification of clinical and non-clinical cases. Reliability analyses from the original study (Antony et al., 1998) reported Cronbach's α= .97 for depression, α= .92 for anxiety and α= .95 for stress. Ruiz et al., (2017a) found Cronbach's α= .93 for the total DASS-21 score and α= .87 for depression, α= .80 for anxiety and α= .83 for stress. For the sample of the present study said properties were also confirmed (α = .95; ω = .95; CFI= .99, TLI= .99, NNFI= .99, PNFI= .88, RMSEA=.03 and GFI= .99).

Procedure

Phase 1

Development and validation of open-ended questions on anxious symptomatology. To gather narrative data on anxiety symptoms, two professional psychologists developed six open-ended questions grounded in the transdiagnostic model. These were validated through the Delphi method with five clinical psychologists specializing in anxiety and transdiagnostic approaches. In the first round, experts independently rated each question on clarity (clear and understandable wording), coherence (ability to elicit relevant symptom-related information), and relevance (alignment with the transdiagnostic framework), using a 4-point Likert-type scale (0 = “Does not comply”, 4 = “Excellent”). Questions scoring below 3 on any criterion were revised based on group discussion and re-evaluated in a second round. This iterative process ensured the content validity and conceptual adequacy of the final set of questions.

Phase 2

Data Collection. All data was collected online via Google Forms. The form started with an “Informed Consent and Habeas Data" section, where detailed information regarding the study was provided, and explicit participant consent was obtained, ensuring compliance with ethical and data protection standards. Then, provided their sociodemographic data and responded to six open-ended questions previously designed and validated to elicit detailed and nuanced descriptions of anxiety experiences. Finally, participants completed the Depression, Anxiety, and Stress Scale-21 (DASS-21). Participants were categorized according to their scores on the anxiety subscale of the DASS-21 into two groups: those exhibiting clinical symptoms of anxiety and those without clinical symptoms. A cutoff score of 7 was used for this classification; participants scoring 7 or higher were assigned to the clinical group, while those scoring below 7 were placed in the non-clinical group.

Phase 3

Ontology Construction. Drawing upon an extensive literature review, three broad categories (physiological, cognitive, behavioral) including manifestations of anxiety were identified from a transdiagnostic perspective. Variables common across various anxiety disorders were pinpointed and classified as distinct types of symptoms. Natural language expressions denoting anxiety symptoms used for the construction of the ontology were extracted from blogs about anxiety and psychometric tests assessing anxiety. These expressions were then associated with the subcategories identified within the broad categories as anxiety symptoms (e.g., hypervigilance, digestive discomfort, uncertainty intolerance, repetitive negative thinking and experiential avoidance).

Phase 4

Ontology Validation Through Interjudge Analysis. The constructed semantic ontology underwent rigorous validation by three expert judges with masters and/or doctoral degrees in clinical psychology. The Delphi Method was used, involving a first round of individual scoring of each subcategory by each expert judge using a 4-point likert type scale (0="Does not comply", 4="Excellent"). Subcategories scored below 3 were discussed and adjusted between the judges and then these categories were reassessed by each judge. This phase allowed consensus-building to ensure the clarity (how adequate, correct and adjusted to a transdiagnostic model was the definition of the symptoms), coherence (how accurately the natural language expressions reflected the definition of the symptoms) and relevance (how comprehensively the natural language expressions represented the complexity and variability of the symptoms) of the subcategories within the ontology to capture the diverse nuances of anxiety symptomatology.

Phase 5

Software development and application. This phase was developed by the project's computer science team, based on the formalization of the functional and non-functional requirements. The software was developed using Python programming language. First, the long texts or written narratives provided by the participants were converted into analyzable elements using natural language processing techniques. Second, the software automatically identifies each of the physiological, cognitive, and behavioral symptoms, based on the combinations of words and connectors on the semantic ontology. This identification assigns one (1) if the symptom is present in the evaluated text of each participant or zero (0) if it's absent. Finally, it allows the export of the classified data set.

Phase 6

To evaluate the efficacy of software for automatic symptom identification, a cross-validation procedure was implemented. Initially, a random sample of 30 participants (15 clinical and 15 non-clinical) was selected, including their responses to the six open-ended questions. The classification of the symptoms was carried out in two ways: the psychology team conducted a manual classification, while the software carried out the automatic classification. From both classifications, a confusion matrix was developed and the corresponding performance metrics were calculated.

Ethical considerations

No psychological intervention was conducted whatsoever, the participants only responded to the instruments hosted on Google Forms once and that was the extent of their participation. Every possible measure to ensure the security, privacy and protection of the participants' personal, clinical and contact data were taken into account. Informed consent fully complied with national (Law 1090 of 2006, Statutory Law 1266 of 2008, Statutory Law 1581 of 2012) and international (APA, 2023; WMA, 2013) ethical standards. The document explained the goal, procedures and scope of the study, as well as the participation terms and conditions, inclusion/exclusion criteria and the possibility of withdrawing at any time, without any repercussions and warranting the protection of their personal data. On the other hand, the virtual platform Google Forms adheres to all applicable norms in Colombian territory (Law 1090 of 2006, Statutory Law 1266 of 2008, Statutory Law 1581 of 2012) and has an SSL certificate that warrants the informatic security of the users through a 128-bit encrypted connection that prevents the attack of hackers and viruses. The procedures in this study were approved by the Bioethics Committee of the sponsoring institution.

Data Analysis

Interjudge Analysis

The scores obtained from the two content validation processes—one for the open-ended questions and the other for the terms included in the semantic ontology—were analyzed separately using descriptive statistics and Aiken's V (Aiken, 1980, 1985), with 95% confidence intervals (CIs). This analysis was applied to expert judges' ratings of clarity, coherence, and relevance for each item or term. Aiken´s V may range between 0 and 1, with 1 indicating a perfect agreement. Computation was conducted with the Microsoft Excel calculator provided by Cordón (2017), based on Merino-Soto and Livia-Segovia (2009). According to Charter (2003) V values beyond .70 should be statistically significant and that significance can be tested assessing whether or not 95% CI includes values below .70. This guideline was adopted to consider judges' consensus.

Software development and application

The present study used Python programming language in "Colaboratory-Google" where the response dataset was then imported into a dataframe from the Pandas library. For natural language processing, the Natural Language Toolkit (NLTK) library was used; initially all texts were normalized: all uppercase letters were converted to lowercase, accent marks were removed from vowels, special characters were removed, and the space between characters were standardized so that only single spaces are present between each word.

A "stop_word_español" ("spanish_stop_word") list of words that do not contribute to the understanding of the texts was searched and adapted. The NLKT list in Spanish was not used because it eliminates words such as "I am", "I have", "I have not", among others which are important for the present research. The process resulted in 292 words in Spanish, a lambda expression function with a conditional was used for depuration. The texts were also tokenized (which consists of dividing a text into smaller entities called tokens) for each participant using the Pandas library.

To develop the software used for automatic identification based on the semantic ontology of anxiety, only the 10 symptoms associated with the Emotional/physiological channel were selected. As the ontology built and validated in the project was proposed with words and logical operators between them, it was decided to directly use logical functions that test whether a condition is true or not. With these words and relationships, matches were sought in the tokens of the texts from each participant. Once the code was adjusted in Python, they were identified by assigning one (1) if the symptom is present in the evaluated text, or zero (0) if it was absent. The software allowed the export of a classified dataset.

Finally, the resulting classified dataset for a sub-sample of 30 participants (15 clinicians and 15 non-clinicians) was reviewed considering: the original text in everyday language, the tokenized text, the classification of 0 and 1 provided by the software and the semantic ontology for the emotional/physiological channel. The efficiency of the software was also reviewed using the automatic method for performing this classification.

Results

Development and validation of open-ended questions

Initially, two professionals in psychology formulated 6 open-ended questions corresponding to the transdiagnostic model (Table.1), which were subsequently subjected to a content validation process using the Delphi methodology (León y Montero, 2003) in which five expert reviewers in clinical psychology and the transdiagnostic model participated. In the second round, following the initial adjustments, an inter-observer agreement rate of 100% was found.

Table 1

Open-ended question applied

Question	Open-ended question	Translation for the open-ended question
1	Por favor explícanos si en el último mes has tenido algún síntoma físico asociado a malestar emocional. Por ejemplo: dolor de cabeza, molestias digestivas, palpitaciones, dificultad para respirar, sudoración, tensión muscular, escalofríos, fatiga, bruxismo u otras similares. Describe en detalle lo que has sentido en tu cuerpo.	Please explain if in the last month you have had any physical symptoms associated with emotional discomfort. For example: headache, digestive discomfort, palpitations, difficulty breathing, sweating, muscle tension, chills, fatigue, bruxism or other similar symptoms. Describe in detail what you have felt in your body.
2	Descríbenos si en el último mes te has sentido preocupado de forma excesiva o presentas ideas repetitivas (pensar lo mismo todo el tiempo) sobre un tema, situación o problemática. Cuéntanos un poco más en detalle las situaciones que te preocupan y el contenido de las ideas que te vienen a tu cabeza.	Describe if in the last month you have felt excessively worried or have had repetitive ideas (thinking the same thing all the time) about a topic, situation or problem. Tell us a little more in detail about the situations that concern you and the content of the ideas that come to your head.
3	¿Durante el último mes has tenido algún temor o te has agobiado con situaciones en las que no tienes el control o es imposible saber con seguridad qué va a ocurrir? ¿Qué te agobia exactamente? Explica tu respuesta.	During the last month have you had any fear or have you been overwhelmed by situations in which you have no control or it is impossible to know for sure what is going to happen? What exactly is overwhelming you? Explain your answer.
4	¿Durante el último mes has notado que te agobias cuando las cosas no salen a tu manera? Si es el caso, cuéntanos qué pensamientos has tenido y en qué situaciones te ha ocurrido.	Over the last month have you noticed that you get overwhelmed when things don't go your way? If this is the case, tell us what thoughts you have had and in what situations it has happened to you.
5	En el último mes ¿Has tenido dificultades para concentrarte en tus actividades cotidianas o para recordar sucesos o tareas que hayas realizado durante el día? Describe con lujo de detalles en qué consisten tales dificultades.	In the last month, have you had difficulties concentrating on your daily activities or remembering events or tasks you have completed during the day? Describe in great detail what these difficulties consist of.
6	En el último mes, ¿Te has estado esforzando conscientemente por evitar, posponer o escapar ante determinadas situaciones, pensamientos, emociones, sentimientos, recuerdos, lugares, personas o actividades que te producen algún grado de malestar emocional? Describe con detalle qué es exactamente aquello que estás intentando evitar y qué haces puntualmente para minimizar, sobrellevar o eliminar el malestar.	In the last month, have you been consciously making an effort to avoid, postpone or escape from certain situations, thoughts, emotions, feelings, memories, places, people or activities that cause you some degree of emotional discomfort? Describe in detail what exactly you are trying to avoid and what you specifically do to minimize, cope with or eliminate the discomfort.

Descriptive statistics

The sample included 430 participants. 69 of them were disqualified for not answering the open-ended questions (e.g. leaving them blank, placing only one letter, or answering "no" to all of them), thus obtaining a final dataset of 361 records. Participants were classified using a cut-off point of 7 on the DASS-21 anxiety subscale, said classification revealed that 69.5% (n = 251) of the participants presented clinical symptomatology (M= 12.32; SD= 4.22); while 30.5% (n = 110) of the participants showed non-clinical symptoms (M= 2.28; SD= 1.8). For the total sample, the average symptomatology score was 9.18, with a standard deviation of 5.91.

Ontological Structure and Content

The ontology consists of three hierarchical levels. The lowest level contains 226 combinations of words or boolean expressions that reflect the ways people refer to anxiety symptoms in natural language. Whereas, the intermediate level groups these expressions into 16 specific anxiety symptoms. Finally, the highest level classifies these symptoms according to the channel of manifestation in three broad categories: physiological, cognitive or behavioral. Ten symptoms correspond to the physiological category, including hypervigilance, muscle tension, chest pain, headache, digestive discomfort, respiratory symptoms, palpitations, sweating, irritability, and insomnia. Five fall within the cognitive category: uncertainty intolerance, repetitive negative thinking, perfectionism, anxiety sensitivity, and cognitive discomfort. The behavioral category comprehends only experiential avoidance as a symptom. Table 2 shows the symptoms grouped into the three broader categories and the number of combinations or Boolean expressions included for each one.

Table 2

Boolean expressions and hierarchic structure for the three categories

Category	Subcategory name	Subcategory name translation	Number of Boolean Expressions
Physiological	Hypervigilance	Hipervigilancia	16
	Muscle tension	Tensión muscular	13
	Chest pain	Dolor torácico	1
	Headache	Dolor de cabeza	7
	Digestive discomfort	Molestias digestivas	34
	Respiratory symptoms	Síntomas respiratorios	7
	Palpitations	Palpitaciones	10
	Sweating	Sudoración	11
	Irritability	Irritabilidad	21
	Insomnia	Insomnio	12
Cognitive	Uncertainty intolerance	Intolerancia a la incertidumbre	12
	Repetitive negative thinking	Pensamiento negativo repetitivo	23
	Perfectionism	Perfeccionismo	9
	Anxiety sensitivity	Sensitividad ansiosa	8
	Cognitive discomfort	Dificultades cognitivas	8
Behavioral	Experiential avoidance	Evitación experiencial	20

Interjudge Analysis for the Semantic Ontology

On their first scoring expert judges already had significant consensus among them (i.e. every Aiken V score was above.70) for every subcategory regarding clarity, coherence and relevance with mean scores ranging from 3 to 4 out of 4. However, qualitatively said consensus was harder to consolidate and adjustments were made to some of the subcategories (e.g. hypervigilance, muscle tension, thoracic pain, headache, intolerance to uncertainty, repetitive negative thinking, perfectionism, anxious sensitivity, cognitive difficulties and avoidance) names, definitions and natural language expressions included on the ontology were based on the expert's feedback.

The specific changes were: changing the name of the "rumination" subcategory and redefining it as "repetitive negative thinking to include worry as another aspect of the same behavioral pattern; merging the "behavioral" and "cognitive avoidance" subcategories in a single "avoidance" subcategory that is superordinated to the "Behavioral" broad category of symptoms. Including more natural language expressions and change others in order to improve coherence and relevance for "hypervigilance", "muscle tension", "thoracic pain", "headache", "intolerance to uncertainty", "repetitive negative thinking", "perfectionism", "anxious sensitivity" and "cognitive difficulties" subcategories.

The second scoring after the aforementioned changes lead to a total agreement among all experts (i.e. every Aiken V score was above 1) for all subcategories as per their clarity, coherence and relevance with mean scores still ranging from 3 to 4 (Detailed information is provided on the calculator files provided). Experts were not consulted any further after this point.

Dataset, software development and application

There were 430 participants who answered the DASS-21 questionnaire and the six (6) open-ended questions that evaluate anxiety that were developed and validated within this research. The 6 responses were concatenated to obtain a single long text or written narrative. When analyzing the final text of each participant, it was found that some preferred not to answer the open-ended questions or only included the word "NO", so these records were removed, leaving 361 valid response texts in the dataset. Considering the anxiety subscale scores of DASS-21 (with a cut-off point of 7), 251 participants were classified as having clinical levels and 110 as having non-clinical levels of anxious symptomatology.

According to the descriptive analysis for the long texts or written narratives: for the clinical participants the average number of words used was 127, with a standard deviation of 98.5, a minimum of 1 and a maximum of 544; for the non-clinical participants the average number of words used was 74 words, with a standard deviation of 78.9, minimum of 1 and maximum of 465.

Regarding the identification of each symptom for the physiological channel as seen in table 3, the software reported a total of 700 symptoms for the 361 participants. Finding that headache corresponds to 24.1% (clinical=52%, non-clinical=35%), digestive discomfort to 21.3% (clinical=46%, non-clinical=30%) and muscle tension to 17.6% (clinical=41%, non-clinical=19%) of said total. The other symptoms were identified in lower percentages (insomnia 3.9%, irritability 3.1% and chest pain 3.4%).

Table 3

Descriptive analysis for pshysiological channel symptoms

Physiological channel						
Symptom	**Clinical (n=251)**		**Non-clinical (n=110)**		**total (n=361)**	
Hypervigilance	35	14%	8	7%	43	6,1%
Muscular tensions	102	41%	21	19%	123	17,6%
Chest pain	22	9%	2	2%	24	3,4%
Headache	131	52%	38	35%	169	24,1%
Digestive discomfort	116	46%	33	30%	149	21,3%
Respiratory symptoms	48	19%	3	3%	51	7,3%
Palpitations	31	12%	5	5%	36	5,1%
Sweating	53	21%	3	3%	56	8,0%
Irritability	18	7%	4	4%	22	3,1%
Insomnia	24	10%	3	3%	27	3,9%
Total symptoms identified	580		120		700	

Regarding the identification of each symptom for the cognitive channel as seen in table 4, the software reported 487 total symptoms for the 361 participants. Finding that anxiety sensitivity corresponds to 35% (clinical=17%, non-clinical=12%), cognitive discomfort to 31% (clinical=10%, non-clinical=7%), uncertainty intolerance to 28% (clinical=30%, non-clinical=24%), repetitive negative thinking to 25% (clinical=42%, non-clinical=57%), and perfectionism symptoms which were identified in a lower percentage (5%).

Table 4

Descriptive analysis for cognitive channel symptoms

	Cognitive channel					
Symptom	**Clinical (n=251)**		**Non- clinical (n=110)**		**Total (n=361)**	
Uncertainty intolerance	114	30%	24	24%	138	28%
Repetitive negative thinking	161	42%	58	57%	123	25%
Perfectionism	6	2%	0	0%	24	5%
Anxiety sensitivity	65	17%	12	12%	169	35%
Cognitive discomfort	40	10%	7	7%	149	31%
Total symptoms identified	386		101		487	

Regarding the identification of the only symptom for the behavioral channel as seen in table 5, the software reported 223 total symptoms for the 361 participants. Finding that experiential avoidance corresponds to 46% (clinical=44%, non-clinical=53%).

Table 5

Descriptive analysis for behavioral channel symptoms

Behavioral channel						
	Clinical (n=251)		Non-clinical (n=110)		Total (n=361)	
Symptoms						
Experiential avoidance	169	44%	54	53%	223	46%
Total symptoms identified	169		54		223	

Efficacy of software for automatic symptom identification

To evaluate the efficacy of the software for automatic symptom identification, a sample of 30 random responses to the open-ended question was selected. Then these responses were organized in clusters of clinical and non-clinical participants considering their DASS-21 anxiety scores and assigning 15 to each cluster. The clinical psychology team blindly (i.e. without knowing what the software identified) evaluated the clusters using a new database containing only the original narrative text responses, the names of the symptoms classified on the three channels: physiological/emotional (10), cognitive (5) and behavioral (1) and the semantic ontology definitions for anxiety. The authors from the clinical psychology team evaluated the presence (coded as 1) or absence (coded as 0) of each symptom within the 30 narrative text responses.

The classification made by the authors reading and interpreting the texts was assessed for agreement, finding complete agreement in 84% of the cases and differences between their scores for 16% of the cases. Their degree of agreement with the results of the automatic method was also reviewed as shown in Table 6. Finding that the classification made manually by each member of the psychology team was beyond 80% agreement with the automatic classification made by the software.

Table 6

Percentage of agreement between the manual and automatic classification

Evaluators	Agreement to Automatic method	Error
1	83.1% (399)	16.9% (81)
2	85.2% (409)	14.8% (71)
3	81.8% (393)	18.2% (87)

Finally, the classification errors of the automatic method were calculated according to the manual evaluation conducted by the three psychologists on the team, view results in Table 6. A total 5% (24) of errors were found distributed by category as follows: hypervigilance (1), headache (1), digestive discomfort (5), irritability (4), insomnia (3), intolerance to uncertainty (1), negative thinking (3), anxious sensitivity (4), avoidance (2).

The software developed in this project, which incorporates an automatic method for the classification of anxiety symptoms, has an average efficiency level of 83.3%. This means that, out of every 100 narratives written, approximately 83 are correctly classified, while in 16.7% of cases there are classification errors. These errors may be due: first, to the fact that the ontology, although designed with a broad set of terms for each category in order to facilitate machine learning, does not reach the variety of expressions typical of human natural language, which includes more synonyms and linguistic variants. Secondly, in this project, words were tokenized and unigrams and bigrams were used; however, natural language presents more complex combinations not taken into account.

Discussion

The primary goal of this study was to create, validate, and implement a semantic ontology in Spanish designed for identifying anxiety symptoms in written narratives of Colombian young adults. The resulting three-level hierarchical semantic ontology encompasses 10 physiological, 5 cognitive, and 1 behavioral symptoms, providing a comprehensive framework for understanding anxiety manifestations. The significance of this model lies in its ability to identify symptoms in both clinical and non-clinical samples, which could be useful for the local Colombian context and the broader regional context including Latin America and the Carribean.

This achievement is promising, given that "mental health" extends beyond the mere absence of mental disorders; it encompasses a broader state of physical, emotional, and social well-being, as acknowledged by the World Health Organization (2022). As seen in numerous studies (Naslund et al., 2019; Russ et al., 2019; Colizzi et al., 2020), detecting emotional symptoms in non-clinical subjects offers the opportunity to implement preventive interventions at an early stage. This proactive approach has the potential to alleviate the social and individual burden of mental health issues (Singh et al., 2022; Waechter et al., 2023).

Moreover, by adopting a transdiagnostic view, our ontology facilitates the detection of symptoms across various mental health conditions. This approach uncovers underlying processes common to these disorders, enabling more effective treatment through the implementation of intervention techniques targeted at these shared processes (Harvey et al., 2004). This represents a significant advancement in understanding and addressing mental health concerns, emphasizing the importance of early detection and intervention in a comprehensive and transdiagnostic manner.

The software developed in this project has proven to be effective in its designated task, accurately detecting symptoms of anxiety among both clinical and non-clinical participants, with an agreement exceeding 80% with professional experts in the clinical field. As revealed by the results, the majority of symptoms showed higher percentages in clinical participants compared to non-clinical participants. However, exceptions were noted in the subcategories of repetitive negative thinking and experiential avoidance, where a higher percentage was observed among non-clinical sample participants To improve software's performance, several strategies could be implemented: (1) enriching the vocabulary of semantic ontology, (2) expanding the model to work with longer n-grams, and (3) exploring the use of deep learning algorithms or the direct application of large language models, whose reasoning capacity could contribute significantly to improving the efficiency of classification methods.

Repetitive negative thinking and avoidance were found in larger proportions in the language used by the non-clinical participants in contrast with the clinical ones. Current transdiagnostic perspectives consider them both as functional units/processes that significantly predict mental-health outcomes (Bardeen & Fergus, 2014; Cookson et al., 2019; Faustino, 2020; Faustino et al., 2021; Hayes et al., 2012; Kashdan & Rottenberg, 2010; Levin et al., 2014; Sierra & Ortiz, 2022) and both variables are also regarded as equivalent to cognitive fusion and experiential avoidance respectively (Rolfs et al., 2016; Landi et al., 2021). The present study's findings might seem counter intuitive but actually make some sense considering that cognitive fusion and experiential avoidance are not necessarily seen as symptoms or carry a pathologizing meaning in and of themselves. As a matter of fact, the ACT model would assume that due to sociocultural processes most people in the world tend to exhibit some degree of psychological inflexibility, especially when it comes to avoiding their feelings and ruminating on their experiences (Hayes et al., 2012; Wilson & Luciano, 2002).

Transdiagnostic variables, such as those considered in the present study, demonstrate a significant correlation with anxiety and other emotional disorders. Toro et al. (2018) found that intolerance of uncertainty and cognitive rumination have a high predictive ability in explaining the development of generalized anxiety disorder and major depression. Meanwhile, experiential avoidance is considered a functional unit across various mental health conditions (Berghoff et al., 2017). The tendency to frequently experience intense emotions, label these experiences as aversive, and engage in avoidant coping strategies (experiential avoidance) constitutes a transdiagnostic factor that predicts and maintains anxiety disorders (Spinhoven et al., 2017; Abkari & Khanipour, 2018). Results Akbari et al., 2022) support the hypothesized role of experiential avoidance as a transdiagnostic and transcultural process relevant to depression, anxiety, OCRDs, and PTSD.

Notably, this is the first Anxiety Ontology based on a Transdiagnostic model of psychopathology. Previous ontologies of anxiety symptoms have primarily been based on the syndromic model, alluding to symptoms corresponding to a specific disorder, such as obsessive-compulsive disorder (Nachiya et al., 2018) and post-traumatic stress disorders (Gamble et al., 2014). Additionally, it provides necessary attention to the detection of anxiety, often overshadowed in comparison to the attention given to the detection of symptoms of depression (Di Cara et al., 2023; Ortiz et al., 2024; Zhang et al., 2022).

For the present study, the findings imply that the subcategories might be appropriately identifying the inflexible behavioral patterns within the people's language. However, it is possible that those are identified more frequently within the non-clinical participants' language due to the wider nature of those behavioral patterns that are related to a broad range of clinical mental health conditions and not necessarily to anxiety in a specific way. Future research might take a totally transdiagnostic approach and attempt to build a semantic ontology and evaluation for the identification of evidence supporting functional units, processes or behavioral patterns that are deemed transdiagnostic. Said study should include discriminative analyses that allow to accurately discern what transdiagnostic subcategories are the most present on the clinical and non-clinical participants for the main diagnostic entities they report as having been diagnosed with.

Conclusions

The software developed proved to be effective in accurately identifying anxiety symptoms across its three response channels, both in clinical and non-clinical participants, with more than 80% agreement with clinical experts. The results showed that most symptoms had higher percentages in clinical participants compared to non-clinical participants. In the physiological channel, the most commonly reported symptoms in the participants' written narratives were headache [24.1% (clinical=52%, non-clinical=35%)] and digestive discomfort [21.3% (clinical=46%, non-clinical=30%)]. In the cognitive channel, three main symptoms were reported: anxiety sensitivity [35% (clinical=17%, non-clinical=12%)], cognitive discomfort [31% (clinical=10%, non-clinical=7%)], intolerance to uncertainty [28% (clinical=30%, non-clinical=24%)], while repetitive negative thinking was higher in the non-clinical sample [25% (clinical=42%, non-clinical=57%)], as was experiential avoidance corresponding to the behavioral channel [46% (clinical=44%, non-clinical=53%)].

The study addresses an innovative topic, such as the intersection of clinical psychology and natural language processing (NLP). It is also the first study to propose a semantic ontology in Spanish to detect symptoms of anxiety from a trans-diagnostic approach. By incorporating computational tools that can contribute to the evaluation of emotional symptoms, which can be used in multiple environments where written narratives are reported, such as texts published on social media or narrative writing, it becomes a valuable contribution to the field of mental health.

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