Unveiling social media considerations in ADHD treatment: Machine Learning study using X´s posts over 15 years.

Alba Gomez-Prieto, Alejandra Mercado-Rodriguez, Juan Pablo Chart-Pascual, Cesar I Fernandez-Lazaro, Francisco Lara, Maria Montero Torres, Claudia Aymerich, Javier Quintero, Melchor Alvarez-Mon, Ana Gonzalez-Pinto, Cesar A Soutullo, Miguel Ángel Alvarez-Mon

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Alba Gomez-Prieto[1*]; Alejandra Mercado-Rodriguez[1*]; Juan Pablo Chart-Pascual[1, 2, 3, 4]; Cesar I Fernandez-Lazaro[5]; Franciso Lara[6]; Maria Montero Torres[7]; Claudia Aymerich[8]; Javier Quintero[9, 10, 11]; Melchor Alvarez-Mon[11, 12, 13]; Ana Gonzalez-Pinto[1, 2, 3, 4]; Cesar A Soutullo[14]; Miguel Ángel Alvarez-Mon[9, 10, 11]

[1]Departamento de Psiquiatría Hospital Universitario Araba Vitoria ES
[2]BIOARABA Research Institute vitoria ES
[3]Universidad del Pais Vasco vitoria ES
[4]Centro de Investigación Biomédica en Red Salud Mental CIBERSAM madrid ES
[5]Department of Preventive Medicine and Public Health, School of Medicine University of Navarra, 31008 Pamplona, Spain Pamplona ES
[6]Department of Signal Theory and Communications and Telematic Systems and Computing, School of Telecommunications Engineering, Rey Juan Carlos University madrid ES
[7]5. Department of Medicine and Medical Specialties, University of Alcala, Alcalá de Henares, Spain. madrid ES
[8]Biobizkaia Health Research Institute, University of the Basque Country UPV/EHU, Basurto University Hospital, OSI Bilbao-Basurto, Centro de Investigación en Red de Salud Mental (CIBERSAM), Instituto de Salud Carlos III, 48903 Barakaldo, Spain Bilbao ES
[9]Department of Medicine and Medical Specialties, University of Alcala, Alcalá de Henares, Spain madrid ES
[10]Department of Psychiatry and Mental Health. Hospital Universitario Infanta Leonor. Madrid. Spain madrid ES
[11]Ramón y Cajal Institute of Sanitary Research (IRYCIS), 28034 Madrid, Spain. madrid ES
[12]Department of Medicine and Medical Specialties, University of Alcala, Alcalá de Henares, Spain. madrid ES
[13]Immune System Diseases-Rheumatology and Internal Medicine Service, Centro de Investigación Biomédica en Red Enfermedades Hepaticas y Digestivas, University Hospital Príncipe de Asturias, Alcala de Henares, Spain madrid ES
[14]Louis A. Faillace Department of Psychiatry and Behavioral Sciences, The University of Texas Health Science Center at Houston, Texas, USA. Houston US
[*]these authors contributed equally

Corresponding Author:
Juan Pablo Chart-Pascual
Departamento de Psiquiatría
Hospital Universitario Araba
Calle Olaguibel 24
Vitoria
ES

Abstract

Background: This study investigates social media content related to Attention-Deficit/Hyperactivity Disorder (ADHD) treatment by analysing public discourse on X (formerly Twitter) over the past 15 years. It differentiates between user types and focuses on medical and non-medical content related to ADHD medications.

Objective: The study aims to analyze social media content on X (formerly Twitter) related to ADHD medications from 2006 to 2022, classifying the tweets based on user types and the nature of medical and non-medical discussions. It seeks to provide insights into public perceptions of ADHD medications, particularly stimulant and non-stimulant treatments, and their use, misuse, and side effects. Ultimately, the study aims to help healthcare professionals better understand these online discussions and improve their communication with patients, facilitating more informed treatment decisions.

Methods: An observational study was conducted analysing 254,952 tweets in Spanish and English about ADHD medications from January 2006 to December 2022. Content analysis combined inductive and deductive approaches to develop a categorisation codebook. BERTWEET and BETO models were used for machine learning classification of English and Spanish tweets, respectively. Descriptive statistical analysis was performed.

Results: Overall, stimulant medications were posted more frequently and received higher engagement than non-stimulant medications. Methylphenidate, dextroamphetamine, and atomoxetine were the most frequently mentioned medications, especially by patients, who emerged as the most active users among the English tweets. Regarding medical content, tweets in

English contained more than twice the number of mentions of inappropriate use compared to those in Spanish. There was a high content of online medication requests and offers in both languages.

Conclusions: Our study underscores the potential of social media, particularly X, in exploring perceptions of ADHD medications. These insights highlight the need for healthcare professionals to stay informed about these conversations on platforms like X. By understanding patient-led discussions, physicians could more effectively address concerns and misconceptions during consultations, leading to better-informed treatment decisions

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Alba Gómez-Prieto[1#], Alejandra Mercado-Rodríguez[1#], Juan Pablo Chart-Pascual[1,2*], Cesar I Fernandez-Lazaro[3], Francisco Lara[4], María Montero Torres[5], Claudia Aymerich[7], Javier Quintero[5,6,8], Melchor Alvarez-Mon[5,8,9], Ana Gonzalez-Pinto[1,2], Cesar A. Soutullo[10], Miguel Angel Alvarez-Mon[5,6,8]

1. Psychiatry Department, Osakidetza Basque Health Service, Araba University Hospital, Vitoria-Gasteiz, Spain
2. Bioaraba Research Institute. University of the Basque Country UPV/EHU. Centro de Investigación en Red de Salud Mental (CIBERSAM).
3. Department of Preventive Medicine and Public Health, School of Medicine, University of Navarra, 31008 Pamplona, Spain; ORCID 0000-0003-2366-2528. IdiSNA, Navarra Institute for Health Research, 31008 Pamplona, Spain
4. Department of Signal Theory and Communications and Telematic Systems and Computing, School of Telecommunications Engineering, Rey Juan Carlos University, Madrid, Spain.
5. Department of Medicine and Medical Specialties, University of Alcala, Alcalá de Henares, Spain.
6. Department of Psychiatry and Mental Health. Hospital Universitario Infanta Leonor. Madrid. Spain
7. Biobizkaia Health Research Institute, University of the Basque Country UPV/EHU, Basurto University Hospital, OSI Bilbao-Basurto, Centro de Investigación en Red de Salud Mental (CIBERSAM), Instituto de Salud Carlos III, 48903 Barakaldo, Spain.
8. Ramón y Cajal Institute of Sanitary Research (IRYCIS), 28034 Madrid, Spain.
9. Immune System Diseases-Rheumatology and Internal Medicine Service, Centro de Investigación Biomédica en Red Enfermedades Hepaticas y Digestivas, University Hospital Príncipe de Asturias, Alcala de Henares, Spain
10. Cesar A. Soutullo MD, PhD. Louis A. Faillace Department of Psychiatry and Behavioral Sciences, The University of Texas Health Science Center at Houston, Texas, USA.

[#] Alba Gomez-Prieto and Alejandra Mercado-Rodríguez contributed equally.

[*] Corresponding author:
Juan Pablo Chart Pascual
Psychiatrist at Hospital Universitario Araba
C/ Olaguibel 29 01009 Vitoria, Spain
johnnychart@gmail.com

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Keywords: ADHD; Social Media; Twitter; Natural Language Processing

Introduction:

Attention-deficit/hyperactivity disorder (ADHD) is a childhood-onset neurodevelopmental disorder marked by excessive and impairing inattention, hyperactivity, and impulsivity inappropriate for the child's age [1]. ADHD is highly genetic, with some environmental causes that interact in a complex way [2]. Up to 60% of children with ADHD experience comorbid conditions throughout their lives, such as mood disorders, anxiety, substance use disorder and an increased risk of suicide. Due to the comorbid conditions, diagnosis is difficult, and treatment is delayed. Early treatment is crucial to improving prognosis [3,4].

ADHD treatment involves psychoeducation and behavioural treatment, academic accommodations and pharmacotherapy with stimulants or non-stimulants [5]. Currently, stimulant medications continue to be the first-line therapy for ADHD across all ages due to their safety and efficacy in managing ADHD [6]. Conversely, non-stimulant medications are typically considered a second-line treatment, prescribed when stimulants are ineffective, not tolerated or contraindicated [7,8]. The effectiveness of the ADHD stimulant treatment in treating the primary symptoms of ADHD has been well-determined [9], providing also an improvement in the quality of life [8,10]. It also significantly increases academic achievement and workplace productivity [11,12]. Hence, ADHD may be associated with a potential risk of overdiagnosis [13]. Some studies indicate inconsistencies in prescription practices, which may stem from a lack of consensus on diagnostic criteria, highlighting the need for clearer clinical guidelines [14].

Despite being generally well-tolerated and safe, misuse and trivialisation of stimulant medications is common, especially among adolescents and young adults, with studies reporting misuse prevalence ranging from 2.1% to 58.7%, depending on the definition [15]. There is also evidence of very low rates of medication adherence, as low as 23% after 12 months [16]. Among the multiple causes that can explain this inappropriate use, a very common and current one nowadays, is the use of stimulant medications to enhance academic performance, often referred to as "study drugs", as indicated in several reports [17]. This potential for abuse is significant and concerning, making it necessary to improve regulation measures for the dispensation of these medications. So we have, on the one hand, low adherence to medication that is prescribed by a physician, and on the other hand, frequent misuse, either with recreational or cognitive enhancing purposes. This is where education and bias can have an important role.

Analysing social media content has become a valuable research tool, providing immediate and unfiltered insights into the experiences and perceptions of different types of users, such as patients or healthcare professionals [18,19]. Platforms like X (formerly Twitter) host real-time, spontaneous discussions, offering a closer view of attitudes towards different diseases or treatments. Specifically, numerous studies have been conducted on X, exploring mental health topics such as perceptions of pharmacological treatments for severe mental disorders, psychotherapies or electroconvulsive therapy [20–22].

This study aimed to identify and analyse tweets that mentioned medications approved for treating ADHD between 2006 and 2022, classifying them according to the type of user, medical content, and non-medical content. Furthermore, the conclusions of this study aim to bring healthcare professionals closer to the reality of the general population, involving and allowing them to be more in tune with their patients.

Methods

X data collection strategy:

We performed a combined quantitative and qualitative study, targeting the collection of tweets that mentioned any pharmacological medications approved by the Food and Drug Administration (FDA) and European Medicines Agency (EMA) for ADHD treatment. We used the Twitter Binder research engine to source these tweets, which allows access to 100% of publicly available tweets. To ensure comprehensive data collection, we first developed a list of keywords that would capture all relevant tweets. This list included the generic and authorised brand names of the medications used to treat ADHD in English and Spanish (keywords can be found in *Section 1* of the *Supplementary Material*). By incorporating these specific keywords, we aimed to cover all possible variations in how these medications might be mentioned on X. We then systematically gathered all tweets containing any of these selected keywords, ensuring that our dataset was as complete and relevant as possible. The inclusion criteria for the tweets were: Tweets publicly available that contained the specific keywords relevant to the study, published between January 1, 2006, and December 31, 2022, in English or Spanish.

Content analysis process:

Exploration of data and identification of categories:

We utilised deductive and inductive reasoning to develop a categorisation codebook for classifying tweet content into distinct codes based on key thematic categories. We integrated categories identified in our previous research on X for the deductive component [19,23,24]. We used an inductive approach by initially analysing a sample of 500 tweets from a smaller subset chosen for manual classification. This allowed us to identify potential new themes and refine the categorisation codebook. Three researchers (AG, AMR, and JCP) independently coded this subset of tweets to ensure accuracy. They then discussed any discrepancies, reaching a consensus with the mediation of a fourth researcher (MAAM). After finalising the categorisation codebook, two study members (AG and AMR) each coded 3,000 tweets in English and Spanish from the databases.

The manual analysis used a detailed codebook method involving several steps and specific criteria for evaluating each tweet. Initially, tweets were divided into two categories: *classifiable* and *unclassifiable*. On the one hand, *the classifiable* category included comprehensible Spanish or English tweets containing meaningful content and discussed neuropsychiatric information. On the other hand, tweets that fell under the *unclassifiable* category were those posted in Spanish or English, vague or lacking sufficient detail, or discussed medical topics unrelated to neuropsychiatry. Once a tweet was assessed as *classifiable,* the tweets were categorised into two main groups: *Type of user* (patient, healthcare professionals, healthcare institutions/academic entity, or undetermined) and *Content (medical content* or *other types of content*).

The tweets in the *medical content* category were further categorised based on their topics in *drug efficacy* (mentioned and not mentioned), *drug adherence* (mentioned or not mentioned), *inappropriate use* (mentioned and not mentioned), understanding inappropriate use if they mentioned the use of the drug in a recreational way, mixed with other substances, or clearly showed a different use rather than therapeutic, *Side effects* (mentioned and not mentioned) and *Psychiatric diagnosis* (mentioned the term ADHD or not).

The *other types of content* category classified tweets based on whether they addressed the following topics: *economic and legal activities*, which contained information about financial or legal aspects concerning the mentioned drug. *Advocacy* included tweets, the content of which was clearly of a scientific dissemination nature. *Trivialisation of treatment* that contained tweets whose content was rude, mocking, satirical, or absurd regarding the drug mentioned. *Requests and offers* contained tweets about the online purchase or sale of the studied medications. Finally, an *undetermined* category was established in case the tweet did not contain any of the types of content mentioned above. In *Section 2 of the Supplemental Material*, we have included various examples of tweets classified.

Machine Learning Classifier:

Machine learning plays a pivotal role in analysing large datasets that are too extensive to evaluate manually. As a subset of artificial intelligence, machine learning includes three primary types: supervised, unsupervised, and semi-supervised learning [25]. This research employs semi-supervised learning, which integrates aspects of supervised and unsupervised methods by utilising labelled and unlabelled data. This approach extends traditional manual analysis, aiming to create a model replicating expert evaluations for classifying millions of tweets.

First, the tweets underwent a pre-processing step, which involved normalising them by removing special characters, splitting negative contractions, removing repetitions and transforming emojis into words. Then, the two manually classified databases (Spanish and English) composed of 3.000 tweets each were randomly divided into an 80% training subset (2.400 tweets) and a 20% testing subset (600 tweets). The training subset trained one Machine Learning model for each classification category. On the other hand, the testing subset was used to validate the performance of the models. Despite the availability of various pre-trained models for text classification in the literature, we used a transformer-based model known as BERTweet [26] for the English dataset and a model called BETO for the Spanish dataset [27]. BERTWEET is a model based on BERT trained with 80GB of text containing over 860 million English tweets. The choice of these models is based on their widespread use in the literature [28,29] and their specific training using English tweets similar to the ones we will evaluate. For the Spanish dataset, we used BETO, which is a BERT model trained on a Spanish corpus and has also been extensively use in the literature, too [30,31].

The BETO and BERTweet models required fine-tuning for each category to ensure they accurately replicated expert analyses. This process involved adjusting the parameters of a pre-trained model using specific data from the new task [32]. The goal was to leverage the general knowledge acquired by the model during its pre-training on large, unlabeled datasets and adapt it to more specific tasks. In this context, the English version of the manually labelled dataset was employed to fine-tune the BERTweet model. In contrast, the Spanish version of the manually classified tweets was used to fine-tune the BETO model. One challenge during fine-tuning was the imbalance of options within each category. To address this, we used the Easy Data Augmentation (EDA) pipeline to create new tweets, ensuring an equal number of each option within the same category [33]. EDA creates new tweets by replacing words with their synonyms, removing some random words, and switching the positions of words.

Finally, we used the test datasets to check the performance of the fine-tuned models. We used the F1 score to analyse the performance of each model across all the categories. The model performed well in the test set, achieving a mean F1 Score higher than 0.72 in all categories. The categories with a mean F1 score lower than 0.75 were *type of user* (0.72) and *other type of content* (0.72). Conversely, the categories with a mean F1 score higher than 0.85 were *inappropriate use* (0.85) and *drug adherence* (0.89). After verifying the models' strong performance, they were deployed to classify the remaining tweets.

Statistical Analysis

The statistical methods used in the analysis were descriptive. Data on tweets were summarised using frequencies and proportions stratified by drug for the Spanish and English datasets and for both (Spanish + English combined) datasets. For each dataset, we graphically represented the frequencies of tweets by user type stratified by drug-using bubble plots, the proportion of tweets according to the content topic of the study using a bar chart, and the proportions of tweets by type of content stratified by drug using a heat map. Time trends were additionally represented to describe the number of tweets posted by user type during the study period. All analyses were performed with STATA version 15 (StataCorp LP).

Ethical Considerations

The present study was reviewed and approved by the Research Ethics Committee of the University of Alcalá, and it strictly adheres to the ethical principles of research outlined in the Declaration of Helsinki [34]. As the study utilised publicly available tweets and did not directly involve human subjects or interventions, there was no direct risk to the privacy or safety of individuals. Nonetheless, we took great care to protect the confidentiality of all users by ensuring that no personal identifying information was collected or disclosed in the analysis. Additionally, we were vigilant in avoiding the inclusion of any tweets that may have inadvertently revealed the users' identities.

Results

Tweets: frequency, engagement, and temporal evolution

A total of 245,467 tweets were included in the study, with 90.3% (221,695/245,467) in English and 9.7% (23,772/245,467) in Spanish. Overall, stimulants were mentioned more frequently posted than non-stimulants. Specifically, 75.2% of English and 70.9% of Spanish tweets focused on stimulants **(Table 1).** Regarding the English-posted tweets, the most discussed drug was methylphenidate (45.9%), followed by dextroamphetamine (19.6%) and atomoxetine (17%) (Table 1). These three medications also showed the greatest increase in tweets over the years, as seen in **Figure 1.** Conversely, Methylphenidate was the drug with the highest number of posted tweets in the Spanish dataset (52.4%), followed by atomoxetine (13.6%) and clonidine (8.7%) as shown in **Table 1.**

Overall, stimulants had higher engagement (The tweet engagement is measured through the Like/Tweet and RT/Tweet ratios, representing the average number of likes and retweets obtained per tweet. These ratios evaluate content popularity and virality based on the interactions received) than non-stimulants, with higher RT/Tweet and Like/Tweet ratios. Dextroamphetamine had the highest Like/Tweet ratio (376.97) in English tweets, while Like/Tweet ratio of clonidine (1.91) and atomoxetine (1.12) topped the ratios in Spanish tweets.

Table 1. Number of tweets, ratio like/tweet and retweet/tweet classified by stimulant and non-stimulant drugs used in attention deficit hyperactivity disorder (ADHD)

Drug	Total original tweets (English + Spanish)				English original tweets				Spanish original tweets			
	n (frequency)	% (percentage)	Ratio like:tweet	Ratio retweet:tweet	n (frequency)	% (percentage)	Ratio like:tweet	Ratio retweet:tweet	n (frequency)	% (percentage)	Ratio like:tweet	Ratio retweet:tweet
Stimulants	183571	74.78	97.68	16.33	166726	75.21	106.98	17.81	16845	70.86	5.65	1.74
Amphetamine	14136	5.76	43.30	10.34	12073	5.45	50.02	11.89	2063	8.68	3.99	1.30
Dextroamphetamine	43779	17.83	374.25	61.59	43457	19.60	376.97	62.03	322	1.35	6.77	2.40
Lisdexamfetamine	11432	4.66	21.69	1.90	9437	4.26	26.08	2.24	1995	8.39	0.96	0.26
Methylphenidate	114224	46.53	6.02	1.17	101759	45.90	5.94	1.07	12465	52.44	6.65	2.04
Non-stimulants	61896	25.22	13.49	2.87	54969	24.79	15.04	2.87	6927	29.14	1.18	2.87
Atomoxetine	41007	16.71	1.85	0.35	37782	17.04	1.91	0.25	3225	13.57	1.12	1.55
Guanfacine	8918	3.63	1.57	0.19	7310	3.30	1.84	0.19	1608	6.76	0.38	0.19
Viloxazine	1462	0.60	0.88	0.10	1438	0.65	0.88	0.09	24	0.10	0.96	0.83
Clonidine	10509	4.28	70.75	15.33	8439	3.81	87.64	17.37	2070	8.71	1.91	7.03
Total	245467	100			221695	100.00			23772	100		

Content analysis and evolution through time per user type:

In English tweets, patients were the most common users (44.4%, n=98,517), while in Spanish tweets the type of user was more evenly distributed, including patients (23.75%, n=5,647), healthcare professionals (25.2%, n=5,990), and institutions (19.75%, n=4,696)**.** Methylphenidate was the most posted drug among patients in both English (45.9%, n=101,759) and Spanish (52.44%, n=12,465) tweets **(Figure 2).** This pattern was also seen among healthcare professionals, with methylphenidate being the most discussed drug in both languages (11.96%, n=12,171 in English; 17.42%, n=2,171 in Spanish)**.** In English tweets, healthcare professionals also frequently mentioned dextroamphetamine (13.31%, n=5,786) and atomoxetine (15.94%, n=6,023), while in Spanish tweets, discussions by healthcare professionals were spread across multiple medications, including lisdexamfetamine (68.97%, n=1,376) and guanfacine (60.32%, n=970)**.** Among English tweets from healthcare institutions, the focus was primarily on methylphenidate and atomoxetine, whereas Spanish tweets from healthcare institutions showed a more even distribution among different medications as shown in (**Figure 2).**

Related to the activity on X of the different user subgroups, the data showed a steady increase in tweet volume across all user types over the years. In English tweets **(Figure 3),** *patients* exhibited the highest growth, with tweet volumes rising rapidly, especially after 2010. Tweets from *healthcare* *professionals* grew steadily, while those from *institutions or entities increase* more slowly. In Spanish tweets **(Figure 3)**, *patients and healthcare professionals* exhibit similar growth patterns, with tweet volumes increasing rapidly until 2012 and then continuing to grow at a more gradual pace. Tweets from *institutions or entities* in Spanish also increase steadily but remain the lowest in volume compared to other user types.

Medical content

Based on the content of the tweets, English tweets had a higher percentage of discussions related to inappropriate medication use (49.64%) compared to Spanish tweets (23.75%), as shown in (**Figure 4)**. Similarly, treatment adherence was a prominent topic of discussion, with 44.65% of English tweets covering this compared to 30.03% of Spanish tweets. Both languages displayed similar proportions of mentions regarding drug efficacy, with 26.66% for English and 32.18% for Spanish. Side effects were noted in 23.97% of English tweets but were less frequently mentioned in Spanish in 15.14%. Most notably, a significant contrast was observed in the mentions of psychiatric diagnoses, which were present in only 19.76% of English tweets compared to 34.26% of Spanish tweets.

Other type of content

Based on the data in **Figure 5,** English tweets showed a significant prevalence of requests and offers related to various medications, with methylphenidate, lisdexamfetamine and atomoxetine being the most discussed medications, representing 53.31%, 49.20%, and 42.48% of the related tweets, respectively. A noteworthy number of tweets also appeared to trivialise the use of these medications, including dextroamphetamine (54.37%), clonidine (45,92%) and amphetamine (32.74%). A prominent presence of advocacy content was also observed, containing notably material related to amphetamine (37,10%) and clonidine (27.41%). Regarding tweets posted in Spanish, they exhibited a substantial amount of advocacy content, particularly regarding the studied medications, notably viloxazine at the forefront (100%), followed by guanfacine (96.64%). Similarly, a substantial percentage of Spanish tweets focused on request and offer, particularly regarding methylphenidate (50.65%) and atomoxetine (48.90%). Furthermore, there was a notable emphasis on content that trivialised medications, with amphetamine being among the top medications receiving such attention (20.07%), followed by methylphenidate (15.33%).

Discussion:

In this study, we analysed tweets posted on X over 15 years (2006-2022) that mentioned the approved stimulant and non-stimulant medications for ADHD in both English and Spanish. Our findings indicate a predominance of tweets in English and greater activity surrounding stimulant medications compared to non-stimulants. Methylphenidate was the most frequently mentioned drug, particularly by patients, who appear to be the most active group of users in English. In contrast, Spanish-language tweets exhibited a greater diversity of user types, with a notable increase in participation from healthcare professionals. Additionally, there was a higher prevalence of tweets related to the inappropriate use of these medications in English. In both languages, a substantial volume of requests and offers for these medications was observed.

In our study, we found that ADHD medications, particularly stimulants, generate more discussion on X in English than in Spanish, suggesting a higher interest or visibility of these treatments in English-speaking countries compared to Spanish-speaking ones. In both languages, stimulants such as methylphenidate are the most frequently mentioned medications, aligning with global prescription trends [15,35]. Moreover, a significant proportion of English-language tweets come from patients, which could indicate greater active participation and awareness regarding ADHD diagnosis and treatment in these countries. This increased visibility of ADHD medications in English-language tweets corresponds with the higher prescription rates in English-speaking countries, such as the USA, compared to Spanish-speaking countries, like those in Latin America or Spain [6,35]. Several factors have been proposed to explain these differences, including disparities in access to diagnosis and treatment across regions [36–38] and political factors [39]. The immediate access to such information through social media analysis presents a major challenge and offers immense potential to be fully explored.

It is important to highlight that, in addition to their effectiveness in managing the core symptoms of ADHD, stimulant medications have been shown to impact patients' quality of life and productivity positively [8,11,12,40]. In our study, the low frequency of mentions regarding side effects may reflect a favourable perception of the tolerability profile of these medications, as reported in the scientific literature [41,42]. However, this observation could also indicate a potential lack of awareness or knowledge about the adverse effects they may entail. For instance, Moran et al. concluded that stimulants could be associated with low (0,10% with methylphenidate;0,21% with amphetamines) but significant adverse events, such as psychosis [43]; similar results were also described more recently by Hamard et al., also describing a higher risk of psychotic symptoms, with amphetamine rather than with methylphenidate [44]. This finding is particularly relevant, as our study found few explicit references to ADHD diagnosis in the tweets, while both languages—especially English—contained substantial content related to the misuse and trivialisation of these medications. This highlights the need for greater awareness of the potential risks associated with the misuse of these medications, particularly among adolescents and young adults, since there has been a growing number of news reports about drug misuse in this age group, especially during exam periods [45,46].

Based on this observation, the prevalence of tweets related to the inappropriate use of stimulant medications may not only indicate substance abuse but also point to unregulated access to these medications. Our analysis identified a substantial volume of requests and offers for these medications in both languages, supporting the hypothesis of an active illicit market. This issue is not isolated, as previous studies have demonstrated the utility of social media in monitoring the consumption of substances such as alcohol and the misuse of opioids [47,48]. Therefore, these findings highlight the importance of considering more robust pharmacovigilance strategies. In this regard, studies like that of Song et al. have proposed using social media as a potential tool for pharmacovigilance due to the immediacy and broad access to information it offers, compared to traditional methods [49].

The dissemination of accurate scientific information on social media could be a key strategy to mitigate the inappropriate use of these medications. While some articles discuss the effective dissemination of medical content on social media [50], others emphasise the need to optimise the quality, reach, and impact of such strategies [51]. Our study suggests that patients are the most frequent group posting tweets in English, underscoring the importance of educating this population segment about the risks associated with misuse. Based on this observation, we believe providing evidence-based information on X would be highly beneficial, allowing the public, especially patients, to make informed decisions and better understand the risks of using non-prescribed stimulants. In this context, the active participation of healthcare professionals on social media could be highly valuable in countering misinformation and providing science-based guidance. Fortunately, we have observed an increase in the presence of these professionals on X, particularly in Spanish-language tweets. This rise in healthcare professional engagement could be a positive step toward creating a more informed online environment where medication discussions are better aligned with clinical guidelines and available scientific evidence. Strengthening this trend is crucial to ensure that knowledge shared on social media contributes to a better understanding and management of ADHD and that patients receive reliable and relevant information for their health.

Principal Results

In this study, we reviewed tweets from X between 2006 and 2022 that discussed stimulant and non-stimulant ADHD medications, in both English and Spanish. The results showed that English tweets were more frequent, with stimulant medications being the main focus compared to non-stimulants. Methylphenidate was the most frequently mentioned drug, particularly by patients, who were the most active group in English-language discussions. Conversely, Spanish tweets featured a wider range of users, with a noticeable increase in contributions from healthcare professionals. Additionally, there was a higher rate of discussions about the misuse of these medications in English. In both languages, there was also a significant number of tweets requesting or offering these drugs

Limitations:

The findings of this study should be interpreted in light of several limitations. First, we included only tweets in English and Spanish, which may limit the representation of global diversity. Second, some of the medications analysed are also used to treat other conditions, like hypertension, highlighting the need for more precise identification of diagnoses mentioned in the tweets to improve the accuracy of the results. Additionally, it is possible that a significant portion of marginalised populations or older adults may not have access to X, potentially excluding these groups from the analysis.

Nonetheless, our study presents several strengths that contribute to the robustness of the findings. First, the analysis covers tweets spanning 16 years, providing a comprehensive view of trends and discussions over an extended period. Second, we classified the tweets by user type, allowing for a more nuanced understanding of who engages in these conversations, such as patients, healthcare professionals, and others. Third, by analysing tweets in both English and Spanish, we were able to highlight important linguistic and cultural differences in the discussion of ADHD medications, offering insights into varying regional perspectives. Finally, the content analysis enabled us to delve deeper into the nature of the discussions, identifying key themes such as medication use, misuse, and public perceptions, which are critical for understanding broader social dynamics surrounding ADHD treatments.

Conclusions:

Our study highlights the value of social media, particularly the X platform, as a useful tool for exploring perceptions and behaviours related to the use of ADHD medications. While we observed a higher prevalence of mentions of stimulant medications, reflecting their widespread use, there was also a trend toward inappropriate use and trivialisation. These findings suggest the need to enhance public education on the potential risks associated with these medications. Leveraging social media monitoring can provide healthcare professionals with deeper insights into patient discussions surrounding the prescribed medications, facilitating more informed conversations in clinical settings and potentially improving the doctor-patient relationship. This approach may help optimise therapeutic management and support treatment adherence.

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Conflicts of Interest

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References

1. Faraone, S. V. et al. The World Federation of ADHD International Consensus Statement: 208 Evidence-based conclusions about the disorder. Neurosci. Biobehav. Rev. 128, 789–818 (2021).
2. Sonuga-Barke, E. J. S. et al. Annual Research Review: Perspectives on progress in ADHD science - from characterization to cause. J. Child Psychol. Psychiatry 64, 506–532 (2023).
3. Karalunas, S. L., Antovich, D., Miller, N. & Nigg, J. T. Prospective prediction of developing internalizing disorders in ADHD. J. Child Psychol. Psychiatry 64, 768–778 (2023).
4. Torrens, M. et al. Clinical practice guideline on pharmacological and psychological management

of adult patients with depression and a comorbid substance use disorder. Adicciones 34, 128–141 (2022).

5. Posner, J., Polanczyk, G. V. & Sonuga-Barke, E. Attention-deficit hyperactivity disorder. Lancet Lond. Engl. 395, 450–462 (2020).
6. Chan, A. Y. L. et al. Attention-deficit/hyperactivity disorder medication consumption in 64 countries and regions from 2015 to 2019: a longitudinal study. EClinicalMedicine 58, 101780 (2023).
7. Caye, A., Swanson, J. M., Coghill, D. & Rohde, L. A. Treatment strategies for ADHD: an evidence-based guide to select optimal treatment. Mol. Psychiatry 24, 390–408 (2019).
8. Faraone, S. V. et al. The World Federation of ADHD International Consensus Statement: 208 Evidence-based conclusions about the disorder. Neurosci. Biobehav. Rev. 128, 789–818 (2021).
9. Cortese, S. et al. Comparative efficacy and tolerability of pharmacological interventions for attention-deficit/hyperactivity disorder in children, adolescents and adults: protocol for a systematic review and network meta-analysis. BMJ Open 7, e013967 (2017).
10. Bellato, A. et al. Systematic Review and Meta-Analysis: Effects of Pharmacological Treatment for Attention-Deficit/Hyperactivity Disorder on Quality of Life. J. Am. Acad. Child Adolesc. Psychiatry S0890-8567(24)00304–6 (2024) doi:10.1016/j.jaac.2024.05.023.
11. Fleming, M. et al. Educational and Health Outcomes of Children Treated for Attention-Deficit/Hyperactivity Disorder. JAMA Pediatr. 171, e170691 (2017).
12. Keilow, M., Holm, A. & Fallesen, P. Medical treatment of Attention Deficit/Hyperactivity Disorder (ADHD) and children's academic performance. PloS One 13, e0207905 (2018).
13. Abdelnour, E., Jansen, M. O. & Gold, J. A. ADHD Diagnostic Trends: Increased Recognition or Overdiagnosis? Mo. Med. 119, 467–473 (2022).
14. Polanczyk, G. V., Willcutt, E. G., Salum, G. A., Kieling, C. & Rohde, L. A. ADHD prevalence estimates across three decades: an updated systematic review and meta-regression analysis. Int.

J. Epidemiol. 43, 434–442 (2014).

15. Shellenberg, T. P., Stoops, W. W., Lile, J. A. & Rush, C. R. An update on the clinical pharmacology of methylphenidate: therapeutic efficacy, abuse potential and future considerations. Expert Rev. Clin. Pharmacol. 13, 825–833 (2020).
16. Ferrin, M. et al. Medication adherence and persistence in children and adolescents with attention deficit hyperactivity disorder (ADHD): a systematic review and qualitative update. Eur. Child Adolesc. Psychiatry (2024) doi:10.1007/s00787-024-02538-z.
17. Acosta, D. L. et al. Nonmedical use of d-Amphetamines and Methylphenidate in Medical Students. P. R. Health Sci. J. 38, 185–188 (2019).
18. Alfonso-Fuertes, I. et al. Time Spent on Instagram and Body Image, Self-esteem, and Physical Comparison Among Young Adults in Spain: Observational Study. JMIR Form. Res. 7, e42207 (2023).
19. Carabot, F. et al. Understanding Public Perceptions and Discussions on Opioids Through Twitter: Cross-Sectional Infodemiology Study. J. Med. Internet Res. 25, e50013 (2023).
20. Alvarez-Mon, M. A. et al. Analyzing Psychotherapy on Twitter: An 11-Year Analysis of Tweets From Major U.S. Media Outlets. Front. Psychiatry 13, 871113 (2022).
21. de Anta, L. et al. Assessment of beliefs and attitudes about electroconvulsive therapy posted on Twitter: An observational study. Eur. Psychiatry J. Assoc. Eur. Psychiatr. 66, e11 (2023).
22. Chart-Pascual, J. P. et al. Areas of interest and sentiment analysis towards second generation antipsychotics, lithium and mood stabilizing anticonvulsants: Unsupervised analysis using Twitter. J. Affect. Disord. 351, 649–660 (2024).
23. Alvarez-Mon, M. A. et al. Assessment of Antipsychotic Medications on Social Media: Machine Learning Study. Front. Psychiatry 12, 737684 (2021).
24. de Anta, L. et al. Areas of Interest and Social Consideration of Antidepressants on English Tweets: A Natural Language Processing Classification Study. J. Pers. Med. 12, 155 (2022).

25. Riese, F. M. & Keller, S. Supervised, Semi-supervised, and Unsupervised Learning for Hyperspectral Regression. in Hyperspectral Image Analysis : Advances in Machine Learning and Signal Processing. Hrsg.: S. Prasad 187–232 (Springer Nature, 2020). doi:10.1007/978-3-030-38617-7_7.

26. Nguyen, D. Q., Vu, T. & Tuan Nguyen, A. BERTweet: A pre-trained language model for English Tweets. in Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations (eds. Liu, Q. & Schlangen, D.) 9–14 (Association for Computational Linguistics, Online, 2020). doi:10.18653/v1/2020.emnlp-demos.2.

27. Rosa, J. de la et al. BERTIN: Efficient Pre-Training of a Spanish Language Model using Perplexity Sampling. (2022).

28. Kulakowski, M., Frasincar, F. & Cambria, E. Sentiment Classification of Cryptocurrency-Related Social Media Posts. IEEE Intell. Syst. 38, 5–9 (2023).

29. Tian, Y., Zhang, W., Duan, L., McDonald, W. & Osgood, N. Comparison of pretrained transformer-based models for influenza and COVID-19 detection using social media text data in Saskatchewan, Canada. Front. Digit. Health 5, 1203874 (2023).

30. Abal, R., Soria Quijaite, J. & Peña, L. Twitter Sentiment Analysis with Machine Learning for Political Approval Rating. in 377–397 (2024). doi:10.1007/978-3-031-53549-9_37.

31. Limaylla-Lunarejo, M.-I., Condori-Fernandez, N. & Luaces, M. R. Requirements classification using FastText and BETO in Spanish documents. in International Working Conference on Requirements Engineering: Foundation for Software Quality 159–176 (Springer, 2023).

32. Kim, M. G., Kim, M., Kim, J. H. & Kim, K. Fine-Tuning BERT Models to Classify Misinformation on Garlic and COVID-19 on Twitter. Int. J. Environ. Res. Public. Health 19, 5126 (2022).

33. Wei, J. & Zou, K. EDA: Easy Data Augmentation Techniques for Boosting Performance on Text Classification Tasks. (2019).

34. World Medical Association. World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects. JAMA 310, 2191–2194 (2013).

35. Raman, S. R. et al. Trends in attention-deficit hyperactivity disorder medication use: a retrospective observational study using population-based databases. Lancet Psychiatry 5, 824–835 (2018).

36. Madsen, K. B., Ersbøll, A., Olsen, J., Parner, E. & Obel, C. Geographic analysis of the variation in the incidence of ADHD in a country with free access to healthcare: a Danish cohort study. Int. J. Health Geogr. 14, (2015).

37. Slobodin, O. & Masalha, R. Challenges in ADHD care for ethnic minority children: A review of the current literature. Transcult. Psychiatry 57, 468–483 (2020).

38. Yang, K., Flores, M., Carson, N. J. & Cook, B. Racial and Ethnic Disparities in Childhood ADHD Treatment Access and Utilization: Results From a National Study. Psychiatr. Serv. appips202100578 (2022) doi:10.1176/appi.ps.202100578.

39. Ramos-Quiroga, J. A. et al. The Prevalence and Treatment of ADHD in Spain: A Retrospective Cohort Analysis. J. Atten. Disord. 27, 273–282 (2023).

40. Boland, H. et al. A literature review and meta-analysis on the effects of ADHD medications on functional outcomes. J. Psychiatr. Res. 123, 21–30 (2020).

41. Pliszka, S. R. et al. The Texas Children's Medication Algorithm Project: revision of the algorithm for pharmacotherapy of attention-deficit/hyperactivity disorder. J. Am. Acad. Child Adolesc. Psychiatry 45, 642–657 (2006).

42. Scheffler, R. M., Hinshaw, S. P., Modrek, S. & Levine, P. The global market for ADHD medications. Health Aff. Proj. Hope 26, 450–457 (2007).

43. Moran, L. V. et al. Psychosis with Methylphenidate or Amphetamine in Patients with ADHD. N. Engl. J. Med. 380, 1128–1138 (2019).

44. Hamard, J. et al. Psychosis with use of amphetamine drugs, methylphenidate and atomoxetine in

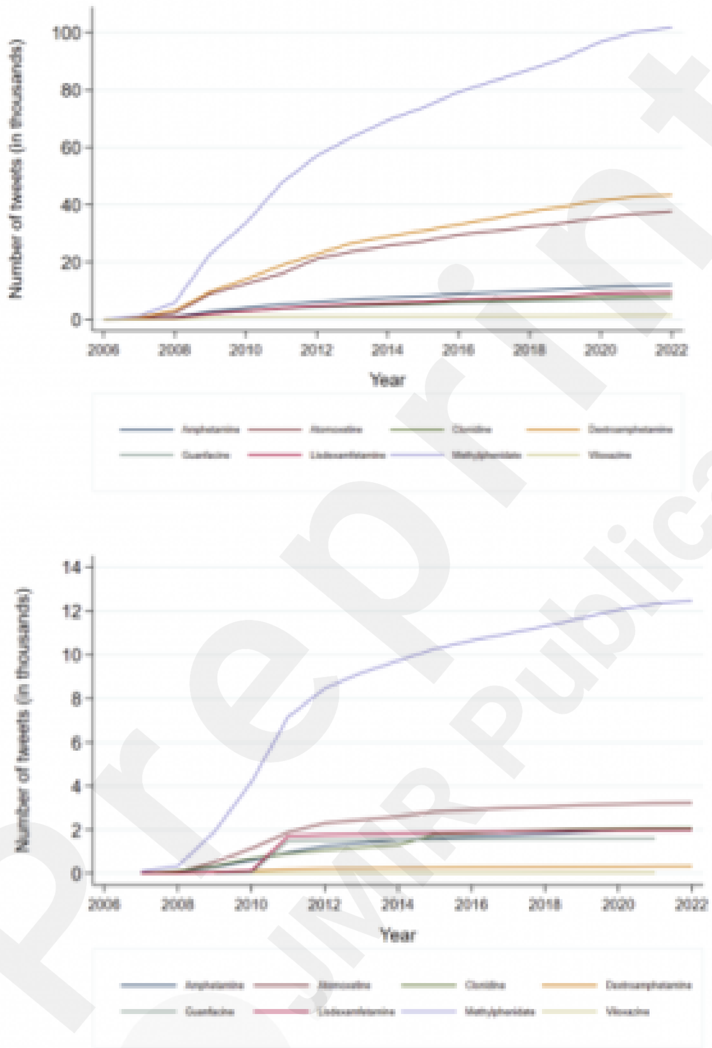
adolescent and adults. BMJ Ment. Health 27, e300876 (2024).

45. El Mundo. Empastillada con Concerta para aprobar los últimos exámenes. (2024).
46. US NEWS. ADHD Patients Could Face Disrupted Access to Meds Following Fraud. (2024).
47. Curtis, B. et al. Can Twitter be used to predict county excessive alcohol consumption rates? PLoS ONE 13, e0194290 (2018).
48. Sarker, A., Gonzalez-Hernandez, G., Ruan, Y. & Perrone, J. Machine Learning and Natural Language Processing for Geolocation-Centric Monitoring and Characterization of Opioid-Related Social Media Chatter. JAMA Netw. Open 2, e1914672 (2019).
49. Song, H. et al. Pharmacovigilance in China: Evolution and future challenges. Br. J. Clin. Pharmacol. 89, 510–522 (2023).
50. Castillo, L. I. R., Hadjistavropoulos, T. & Brachaniec, M. The Effectiveness of Social Media in the Dissemination of Knowledge About Pain in Dementia. Pain Med. Off. J. Am. Acad. Pain Med. 22, 2584–2596 (2021).
51. Faus, M., Alonso, F., Javadinejad, A. & Useche, S. A. Are social networks effective in promoting healthy behaviors? A systematic review of evaluations of public health campaigns broadcast on Twitter. Front. Public Health 10, (2022).

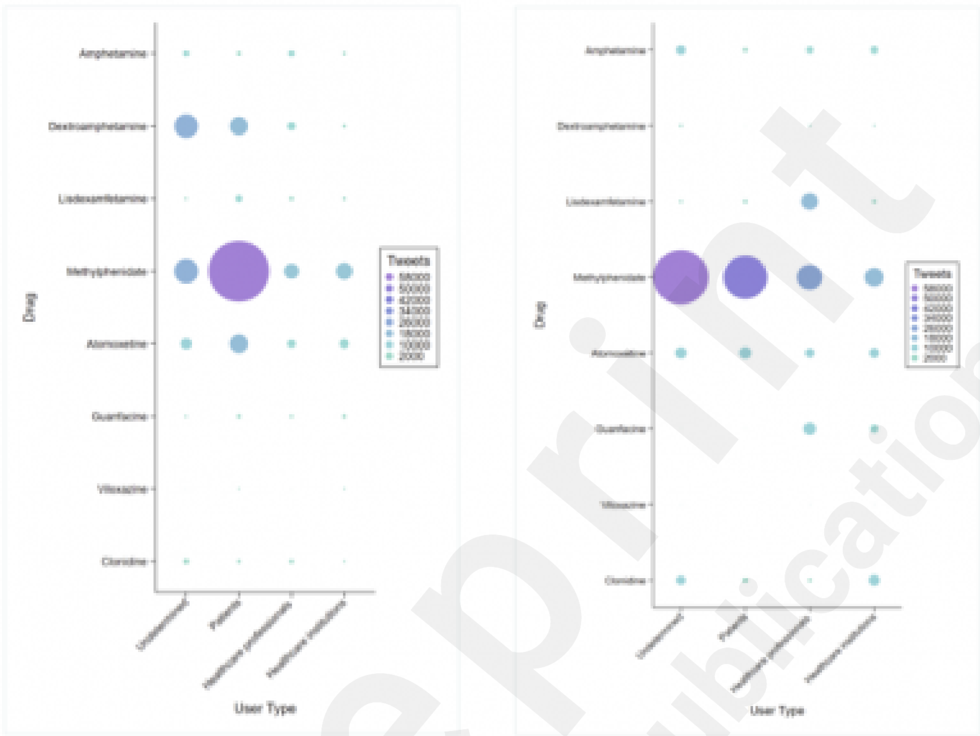
Supplementary Files

Figures

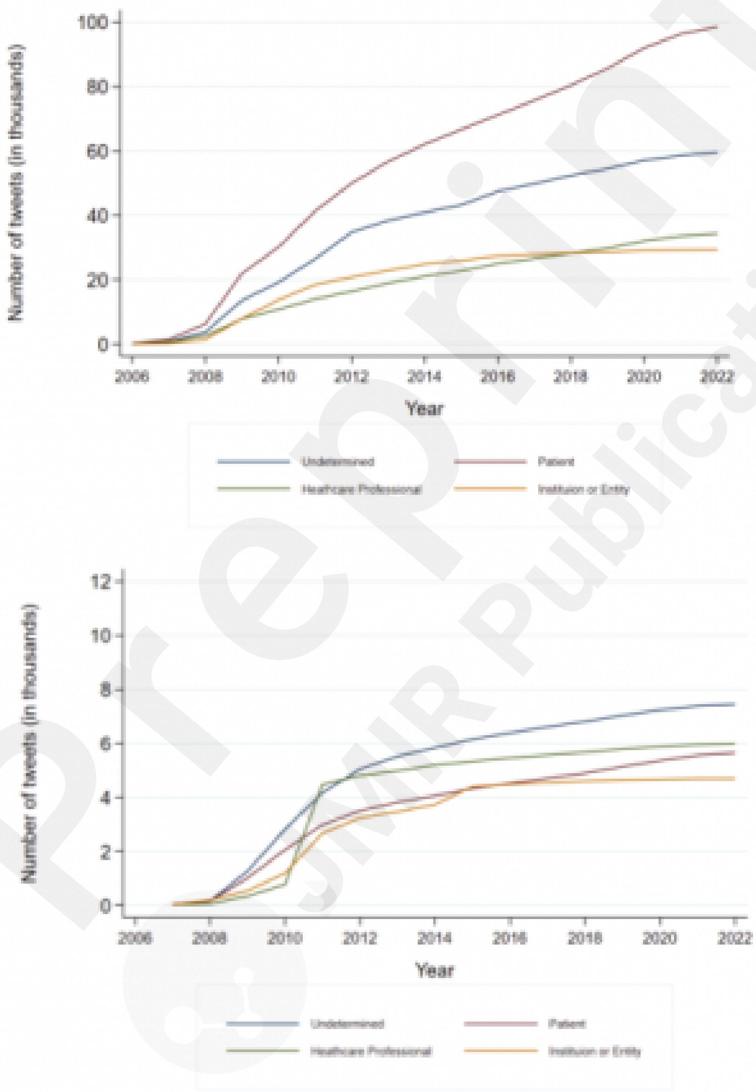
Annual frequency of English (Top panel) and Spanish (Bottom panel) tweets mentioning stimulants and non-stimulant drugs used for ADHD. Each colour represents a specific drug as indicated by the legend below.



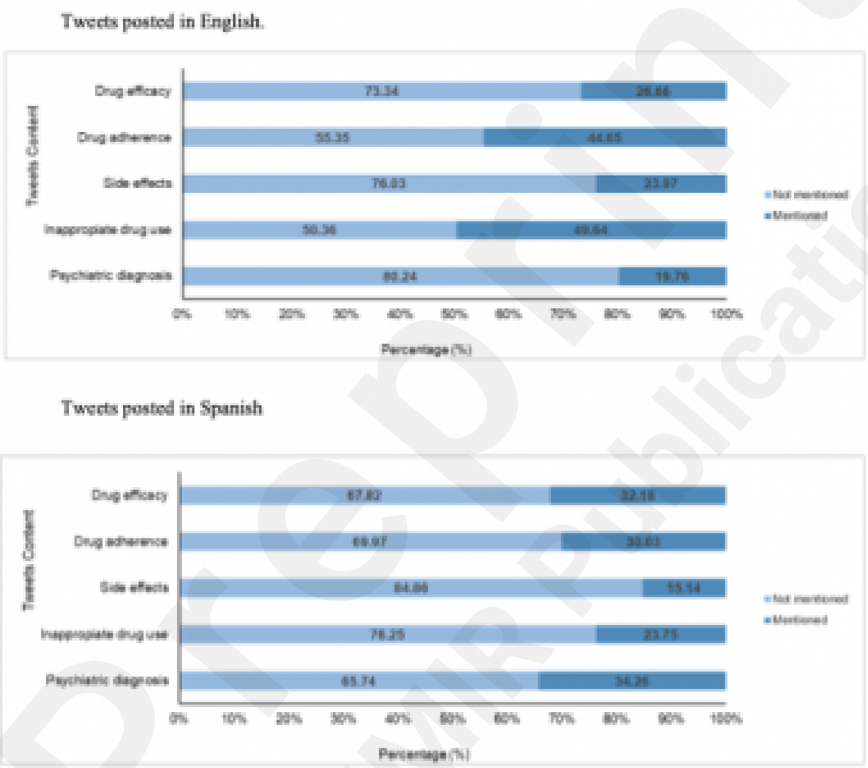
Tweets of stimulant and non-stimulant drugs used in attention deficit hyperactivity disorder (ADHD) classified by user type.



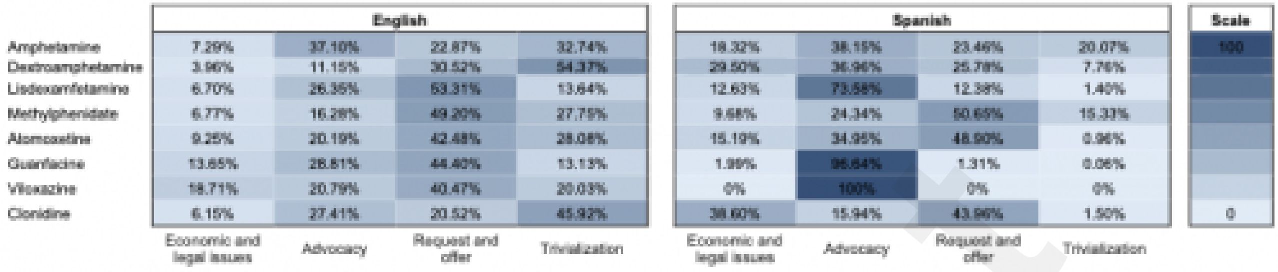
Annual frequency of English (Top panel) and Spanish (Bottom panel) tweets mentioning stimulants and non-stimulant drugs used for ADHD published by user type. Each colour represents the type of user, as indicated by the legend below.



Proportion of tweets posted of stimulant and non-stimulant drugs used in attention deficit hyperactivity disorder (ADHD) according to content topics of the study. Drug efficacy: Categorized tweets as effectiveness reported or did not mention efficacy. Drug adherence: Categorized tweets as good adherence reported or did not mention adherence. Side effects: Classified tweets as presence of side effects or did not mention side effects. Inappropriate use: Categorized tweets if they mentioned inappropriate use or did not mention inappropriate use. Understanding inappropriate use if they mentioned the use of the drug in a recreational way or clearly showing a different use rather than therapeutic.



Heatmap explaining percentage of tweets posted in English and Spanish of stimulant and non-stimulant drugs used in attention deficit hyperactivity disorder (ADHD) according to content topics of the study.



Multimedia Appendixes

Suplementary Material.
URL: http://asset.jmir.pub/assets/5fee453488bbc0c5fa61639e4ca0ad37.docx