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Identifying Neurodevelopmental Disorders through Social Media Algorithms

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Abstract

In the context of the evolving digital landscape, this research paper explores the operations of social media algorithms and their potential to identify individuals with neurodevelopmental disorders. Neurodiversity is a significant aspect of contemporary mental health discussions in the digital age. The primary objective is to unravel the mechanisms of social media algorithms and assess their capacity to identify users diagnosed with neurodevelopmental disorders. Employing a dual-method approach, both quantitative and qualitative methodologies were utilized. A quantitative survey targeted general social media users, collecting 143 valid responses to gauge their interactions with algorithm-generated content. Simultaneously, a qualitative survey involved interviews with artificial intelligence specialists, providing expert insights into algorithmic functionality. The analysis revealed that social media algorithms operate on recommender systems, categorizing content based on users' historical preferences. However, these algorithms lack the inherent capability to identify neurodevelopmental disorders. Instead, user-interacted content influences subsequent algorithmic recommendations.

Keywords

Neurodevelopmental Disorders, Mental Health, Well-Being, Digital Technology, Social Media

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1. Introduction

In the continually evolving digital landscape, social media platforms have become integral to daily life, prompting increased interest in exploring their potential contributions to various facets of human well-being, particularly mental health (Kennefick, 2022). Within this context, neurodevelopmental disorders, encompassing conditions such as autism spectrum disorder, attention-deficit/hyperactivity disorder, and intellectual disabilities, present unique challenges that demand innovative approaches for identification and support. The role of social media algorithms has come under scrutiny as a potential avenue for identifying individuals who may be diagnosed with neurodevelopmental disorders (Farsi, 2021). Basting vast user bases and diverse content offerings, social media platforms provide an unprecedented opportunity to glean insights into users' behaviors, preferences, and interactions (Frey et al., 2022). The algorithms powering these platforms possess the inherent capacity to process immense amounts of data, enabling personalized content delivery based on users' historical engagements and inferred interests (Chapman et al., 2020). This capability sparks curiosity about whether social media algorithms can recognize patterns in user behavior indicative of neurodevelopmental disorders (Aldhyani et al., 2022).

To many, neurodiversity signifies various concepts closely related to an "ecological society" where

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minority brains are valued and supported in finding their niche (Blume-Jensen et al., 1998; Singer, 1999). Neurodiversity encompasses perceived variations in cognitive, affectual, and sensory functioning, differing from the majority or 'neurotypical' population (Chapman, 2020). This study focuses on identifying neurodiversity in individuals through social media algorithms, particularly considering the rise in diagnoses among young adults, especially since the COVID-19 lockdowns (Luo et al., 2021). Concurrently, the online activity of the population increased from 50% to 70% during this period (Beech et al., 2020), with suggestions linking this surge to neurodevelopmental disorder diagnoses (Chapman et al., 2020; Davenport & Kalakota, 2019). Young adults, the largest demographic on social media (Vogels et al., 2022), reportedly use it for research, possibly explaining these observations within this specific group.

However, the connection between social media algorithms and neurodevelopmental disorder detection is a complex and multidimensional subject requiring thorough examination (Morris-Rosendahl & Crocq, 2022). It is crucial to differentiate between neurodevelopmental disorders and mental illnesses; the former affect brain structure and development without being inherently dangerous but influencing behavior and social lives. Neurodiversity, as an umbrella term, includes conditions such as dyspraxia, dyslexia, attention deficit hyperactivity disorder, dyscalculia, autistic spectrum, and Tourette syndrome (Clouder et al., 2020). The increase in neurodevelopmental disorder diagnoses may be linked to the concurrent rise in social media usage. Common neurodevelopmental disorders include ADHD and autism (Scandurra et al., 2019), characterized by socio-behavioral traits that complicate identification (Mengi & Malhotra, 2021). Recent advances in artificial intelligence, specifically machine learning techniques, have enhanced the diagnostic process.

Social media platforms monitor user behavior, curating personalized feeds raising privacy concerns (Zhang et al., 2021). While no specific studies address this, existing research explores the impact of social media on users' mental health and prediction techniques for analyzing online sentiments, including suicide ideation detection (Aldhyani et al., 2022). As exemplified by Frey et al. (2022), adolescents have studied Tourette syndrome through the lens of social media, exploring the development of tics after exposure. Furthermore, examining recommendation systems, discussed in the next section, adds depth to understanding the intersection of social media and neurodevelopmental disorders. This study explores the potential of social media algorithms in diagnosing neurodevelopmental disorders, posing questions such as: Can social media algorithms identify neurodivergent users? How well do these platforms comprehend their users and recognize such complex characteristics? The exploration will examine the integration of machine learning in these systems, focusing on factors influencing content suggestions on social media. The study's objectives include:

1. Identifying individuals receiving neurodevelopmental disorder-related content suggestions.
2. Examining the content seen by individuals diagnosed with a neurodevelopmental disorder on their social media pages.
3. Identifying factors contributing to the platforms' accuracy in content recommendations.

2. Literature review

This research paper examines the operations of social media algorithms and their potential to identify individuals with neurodevelopmental disorders.

2.1 Phenomenon of online diagnosis

2.1.1 An Era of "Free Education"

The internet has ushered in an era often described as "free education." The accessibility of online platforms, ranging from medical websites and forums to social media groups, has democratized information dissemination (Frey et al., 2022). Individuals are now empowered to seek insights into various medical conditions, including neurodevelopmental disorders, without the need for formal medical training or consultation. During the global COVID-19 pandemic, the activity of users online increased significantly (Beech et al., 2020), and online learning was prioritized during this period. Social media emerged as a crucial tool for research, including health-related subjects (Farsi, 2021), and this usage saw a surge along with increased social media activity (Beech et al., 2020). TikTok, notably, experienced a rise in popularity during the Covid-19 pandemic (Grandinetti, 2021). Despite the benefits, online content is often criticized due to the potential for spreading misinformation (Parveen & Varma, 2021). Therefore, even though social media provides users access to a wealth of information, scrutiny remains essential.

2.1.2 Neurodevelopmental Disorders Definition

Western Michigan University defines neurodevelopmental disorders as "a group of conditions in which the growth and development of the brain are affected" (Al-Mawee et al., 2021). This impact extends to various aspects of an individual's life, including language, emotions, behavior, self-control, learning, and memory. The category includes autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD), among others. While officially recognized in psychiatry in 1820 (Lord et al., 2020), references to these disorders date back to the late 1700s, notably in "Der philosophische Arzt" by physician Melchior Adam Weikard, mentioning symptoms akin to attention deficit. "Behaviors consistent with autism were described long before the diagnostic category was named and defined by Leo Kanner in 1943 and Hans Asperger" (Morris-Rosendahl & Crocq, 2022). Diagnosing neurodevelopmental disorders, particularly for socio-behavioral symptoms (Song et al., 2019), and can be influenced by an individual's background.

2.1.3 Neurodevelopmental Disorders Online Diagnosis

During the COVID-19 lockdown, people spent more time on social media, leading to increased information exchange on various subjects, including mental health (Al-Mawee et al., 2021; Luo et al., 2021). The subsequent rise in neurodevelopmental disorder diagnoses can be attributed to increased public awareness of their existence and the complexity of their diagnosis. Social media became a platform for users to witness and engage with the stories of neurodivergent creators and health professionals (Mengi & Malhotra, 2021). However, the absence of regulations on mental health-related content raises concerns about potential misdiagnoses. While social media can provide valuable information, it prompts the question of whether relying solely on its content is sufficient. Additionally, mirroring behaviors observed on social media (Frey et al., 2022), further complicates the discernment of users' behavior. All these factors necessitate careful consideration in understanding the dynamics of online neurodevelopmental disorder diagnoses.

2.2 Dissection of the Social Media Algorithms

2.2.1 Understanding Machine Learning

Integrating artificial intelligence into various industries extends to machine learning, a fundamental component of AI (Schwalbe & Wahl, 2020). Operating within artificial intelligence, machine learning is a discipline that utilizes data to address inquiries. This field encompasses various model types, each suitable for distinct scenarios or tailored to specific objectives (Kim et al., 2021). The machine learning process involves data collection, feature extraction, and data partitioning for training and testing, culminating in utilizing diverse model types to achieve accurate predictions (Parveen & Varma, 2021).

2.2.2 How Machine Learning is Implemented in those Platforms?

Social media networks employ machine learning to recommend content to their users, specifically in recommendation systems (Chen & Wang, 2021). Machine learning in recommendation systems involves filtering data on the platforms. These systems analyze users' behavior and context to display targeted content (Javed et al., 2021). While some recommendation systems do not utilize artificial intelligence, AI significantly enhances the accuracy of recommendations in general, ensuring a better outcome. Integrating AI into widely-used platforms like Facebook and TikTok illustrates AI's interconnectedness, portraying its role as a collaborative partnership between humans and machines rather than a standalone entity (Grandinetti, 2021). Neural collaborative filtering (NCF), a general model for user-item interactions in recommendation systems, is one such machine learning model enhancing recommendation systems. It relies on several layers of artificial neural networks (ANN), also known as multi-layer perceptron (Frey et al., 2022).

An example is AutoRec, an autoencoder that distinguishes itself by capturing complex and nonlinear relationships. Unlike matrix factorization, neural networks excel in handling continuous functions. ConvMF, another example, enhances rating prediction accuracy by integrating convolutional neural networks into matrix factorization. It has been used to recommend hashtags, among other applications (Farsi, 2021).

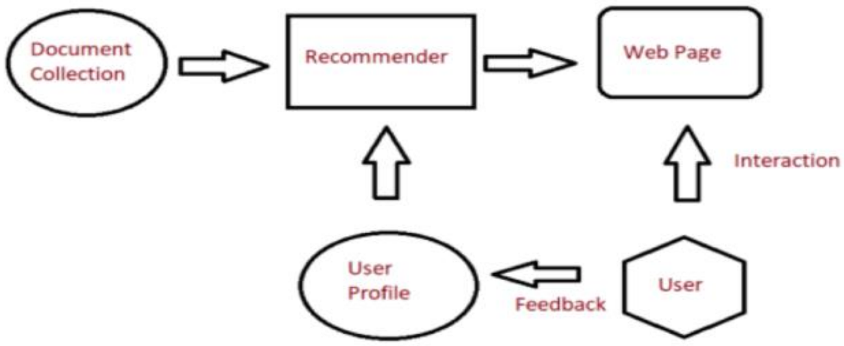


Figure 1 Example of recommendation system simplified

It is embedded in platforms such as Instagram and Twitter. Recommendation systems also suggest friends or people to follow. Various types of machine learning algorithms are utilized in recommendation systems, including XGBoost and CatBoost algorithms, which are known for their high accuracy, and others like The Random Forest and Light GBM (Parveen & Varma, 2021). Shopping platforms also employ recommendation systems to enhance the customer experience, predicting current preferences based on past activity. Similarly, in collaboration with social media, these systems utilize users' interactions with content to make predictions. Social media platforms understand users through their activity (Neyaz et al., 2020) and construct feeds designed to attract and retain users. The ultimate goal is to keep users on the platform as long as possible, and content that captivates users contributes to fulfilling this mission. TikTok is an example of an effective platform (Grandinetti, 2021). Its formula of short videos, combined with an AI-powered algorithm, retains users for extended periods, prompting some to raise concerns about the platform's addictiveness (Qin et al., 2022).

Within recommendation systems, Recurrent Neural Networks (RNNs) constitute another model. RNN-based recommendation systems can anticipate users' preferences over specific timeframes (Chancellor & De Choudhury, 2020). This proficiency arises from RNNs' capability to handle sequential data, enabling recommendation systems to structure and analyze the evolution of user interests over time, thus facilitating the prediction of engaging content (Chen et al., 2021). In recommendation systems, active learning emerges as a crucial strategy for accurately discerning users' preferences. Every correlation established between users and items within a recommender system, particularly those derived from explicit ratings or implicit interactions, is paramount in characterizing user preferences and significantly influencing the system's overall performance (Zhang et al., 2021). Platforms employ reinforcement learning within their recommendation systems to enhance user engagement, introducing a long-term perspective. This approach treats the recommender system as a learning agent, with user behaviors corresponding to states and system-generated recommendations representing actions. Feedback from users on recommendation outcomes, such as click-through rates or time spent on webpages, serves as the reward, encapsulating the essence of reinforcement learning (Zhang et al., 2021). In essence, reinforcement learning centralizes users within the recommendation process, promoting an environment that optimizes user satisfaction. Some individuals may hesitate to provide authentic information, deviating from the accuracy of the recommendations (Zhang et al., 2021).

2.2 Exploration of How Machine Learning is used in the Diagnosis of Neurodevelopmental Disorders

Artificial intelligence finds applications in diagnoses and mortality risk assessment, disease outbreak prediction, and surveillance, among other areas. Its pivotal components in diagnoses encompass expert systems, machine learning, natural language processing, and signal processing (Schwalbe & Wahl, 2020). Machine learning emerges as the most widely used technique for diagnoses, with advancements in deep neural networks enhancing the accuracy of high-performance machine learning algorithms in deciphering complex problems (Taddy, 2018). This technology aids in overcoming the limitations of the field by diagnosing, preventing, and treating mental illnesses and disorders through its machine techniques (Farsi, 2021; Frey et al., 2022). The Bayesian model takes center stage in psychiatry, a classification algorithm making predictions based on prior knowledge. Logistic regression illustrates the link between two variables, while the decision tree visualizes different outcomes from a series of decisions (Liu et al., 2020). The Support Vector Machines model tackles complex classification, and deep learning surpasses its predecessors, utilizing multiple machine-learning algorithms to solve the most complex problems. It is particularly adapted to large data models (Liu et al., 2020). Whether connecting underlying causes, evaluating links between variables, or predicting psychiatric readmission, these algorithms achieve up to 96% accuracy rates.

For instance, the decision tree algorithm diagnoses obsessive-compulsive disorder by investigating micromolecular variations, brain structure changes, and particular neural circuits in MRI scans. Data collected after phenotype switches in patients aid in identifying behavioral changes (Liu et al., 2020). Deep learning algorithms can identify autistic individuals based solely on their brain activation patterns (Liu et al., 2020). Long short-term memory, in particular, stands out as a deep neural network that diagnoses autism more effectively than convolutional neural networks (CNNs) and multilayer perceptron (MP). It identified autistic individuals with 100% accuracy in a group of neurotypical and autistic people (Khullar et al., 2021). Autism Spectrum Disorder (ASD) can also be diagnosed through mobile game plays using classification with random trees, distinguishing neurotypical children from neuroatypical ones (Deveau et al., 2022). Existing models of automated diagnosis for Attention Deficit Hyperactivity Disorder (ADHD) include tests under multiple scenarios, accelerating processes for practitioners when performed before appointments, and acting as a pre-assessment (Chen et al., 2021). Combined with professionals' opinions, it can increase accuracy from 85% to 95% (Tachmazidis et al., 2020). Another method of diagnosing ADHD involves a web application that captures pupil biometrics while the participant completes a task (Khanna & Das, 2020). It is both accessible to a wider range of people and time-efficient.

The presence of a female phenotype for autism adds complexity to the diagnosis process, as methodologies and tools predominantly rely on Occidental males (Lockwood Estrin et al., 2021).

Other minorities are also affected by these biases. Another barrier to the diagnosis of Neurodevelopmental Disorders (NDDs) is the lack of access to psychiatry services in rural areas. Even though they have the same percentage of people on the spectrum as urban areas, their means are limited (Deveau et al., 2022). The gender gap in diagnosis extends to other disorders, such as ADHD, where manifestations of symptoms differ. Hyperactivity, for example, is not always as expressive among girls and women as among boys and men due to social conditioning (Kennefick, 2022). The lack of widespread awareness results in a higher rate of "missed" diagnoses among girls and women (Chronis-Tuscano, 2022). Artificial intelligence's accuracy levels, along with its versatility and adaptiveness, prove its potential for broad use, ensuring increased access to healthcare in general (Chronis-Tuscano, 2022).

3. Methodology

The objectives are to identify the demographic to whom the algorithm directs NDD-related content and to comprehend the process. To achieve these objectives, the researcher performed the following actions:

1. Developed a survey targeted at social media users.
2. Engaged in discussions with professionals specializing in machine learning, social media, and psychiatry.

3.1 Survey

As previously mentioned, this study is exploratory. Its primary goal is to examine the relationships between different variables and determine the recipients of NDD-related content from the algorithm. The inquiry explores whether a specific demographic exists and whether users' behaviors influence these recommendations. The researcher crafted questions to analyze correlations between users' habits, identities, and the content visible on their social media feeds. The survey intentionally reached all social media users, avoiding a more specific target group. This approach ensures diverse responses, facilitating comparisons across different demographics. The survey was distributed through the researcher's personal social media channels and shared with the business school students.

It is categorized into four (4) parts, containing a total of 29 questions:

User ID: Questions concerning the age, gender, and location of the users were pivotal for understanding the demographic targeted by the algorithm with NDD-related content. Cognitive status inquiries were deferred, considering that not all participants are familiar with neurodevelopmental disorders, so a separate section was dedicated to it.

Social Media Input: This section aims to uncover the users' preferred social media platforms, recognizing that each platform employs distinct algorithms. The survey included Instagram, Facebook, Twitter, TikTok, LinkedIn, Reddit, and Quora. Distinguishing between users' favorite and most used platforms was essential. Participants may default to specific platforms, and the researcher sought insights into which apps users genuinely enjoy. Exploring whether users' activity on both platforms aligns was crucial in assessing the impact on user engagement. Questions about saving, liking, and commenting habits aim to discern the influence of user interactions on their feeds. Additional inquiries about download times and usage duration were posed to evaluate potential impacts on the platform's understanding of users.

Neurodivergence Knowledge: Questions in this section revolve around when participants learned about NDDs, whether they are diagnosed with one or a mental illness, their relatives' conditions, and their overall interest in the subject. The aim is to identify correlations between the timing of individuals' awareness of neurodevelopmental disorders and their diagnoses. While user ID and neurodivergence knowledge could have been consolidated, a deliberate decision was made to introduce the latter later in the survey.

Neurodivergence Content: Finally, inquiries about the frequency of NDD-related content on users' pages, how they interact with it, whether they actively seek it, and if they disclose their interest or NDD diagnosis on their platforms. This section examines users' interactions with and expression of neurodivergent content on social media.

3.2 Interviews

The interviewees were comprised of an algorithm engineer and a psychiatry resident who also served as a machine learning consultant. Questions during the interviews centered on their utilization and understanding of artificial intelligence, specifically in the context of social media. These questions were carefully crafted to adapt conversations and elicit detailed responses. In the interview with the psychiatry resident, inquiries also inquired neurodevelopmental disorders, assuming familiarity with the subject matter. Notably, the researcher faced challenges securing an available social media professional for an interview within the allotted timeframe. For this study, the interviewees were anonymized as "Participant A" and "Participant B."

Participant A, referred to for anonymity, is a psychiatry resident based in Paris. His academic background encompasses studies in bioengineering before he transitions to psychiatry. Practical experience gained through internships exposed him to diverse machine learning applications, particularly interfacing with computers and analyzing biosignals like electroencephalographic and electrocardiographic signals. Additionally, he contributes as a part-time machine learning consultant for a startup specializing in personalized psychiatry solutions.

Participant B, identified for confidentiality, serves as an algorithm engineer at a prominent Chinese e-commerce platform. With a foundation in mathematics, he specializes in mathematical optimization and holds a master's degree in artificial intelligence. His academic journey included an exchange program in China focusing on AI. Following this, he worked in the data science sector in Paris for several years before returning to China. His current role revolves around refining search algorithms for the e-commerce platform.

4. **Results and Analysis**

4.1 Data collection

4.1.1 Respondent profile

A total of 144 individuals participated in the survey, with 143 completed forms retained for analysis. The breakdown is as follows.

Table 1: Age

Age groups	Percentage
15 to 17	4.2%
18 to 24	56.6%
25 to 34	30.1%
35 to 44	7%
45 to 62	2.1%

Table 1 highlights that the majority (56.6%) of participants fall within the 18 to 24 age range.

Table 2: Gender

Gender	Percentage
Men	17.5%
Women	71.3%
Nonbinary	11.2%

Table 2 indicates a notable majority of female participants, precisely 71.3%. Men constitute 17.5%, and 11.2% identify as nonbinary.

Table 3: Location

Location	Percentage
Europe	71.33%
United Kingdom	6.99%
North America	17.4 8%
Saudi Arabia	0.7%
Africa	2.1%
Asia (Turkey)	0.7%
Oceania	0.7%

Table 3 reveals that a substantial majority of respondents are in Europe. Furthermore, 71.33% learned about neurodevelopmental disorders more than 3 years ago, 9.1% within the last 3 years, and 13.3% through the survey. A small percentage discovered it on their social media—24.82% for the favorite platform and 27.73% for the most used one.

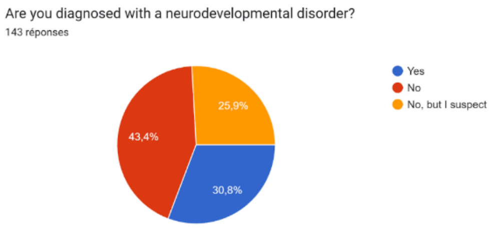
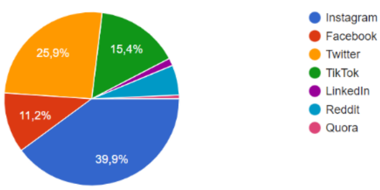


Figure 2: Respondents' status

According to Figure 2, 30.8% of the respondents are neurodivergent, 43.4% are not, and 25.9% are questioning. Among those, 5 were diagnosed less than 3 months ago, one between 3 and 6 months ago, 2 between 6-12 months ago, 21 between one and 3 years ago, 14 more than 3 years ago, and one person did not specify. 49.6% have someone diagnosed with a neurodevelopmental disorder in their close circle. Additionally, 32.86% are diagnosed with a mental illness, and 84.6% cited mental health as one of their interests. Finally, 62.9% have an interest in neurodevelopmental disorders.

4.1.2 Social Media Input



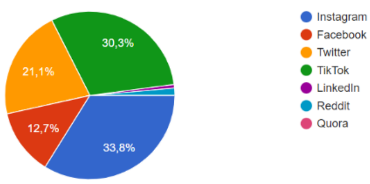


Figure 3: Respondents' favorite social media

Figure 4: Respondents' most used social media

According to Figures 3 and 4, Instagram takes the biggest slice of the pie, being the favorite social media of almost 40% of the participants, followed by Twitter (25.9%). Instagram also emerged as the most used social media, but the margin of TikTok increased between the questions, going from 15.4% to 30.3%.

Table 4: Social Media Inputs

Social media downloads	Favorite	Most used
Less than 3 months ago	2.8%	2.14%
3-6 months ago	2.1%	2.86%
6-12 months ago	6.29%	3.57%
1-3 years ago	30.77%	35%
More than 3 years ago	58.04%	56.43%

Table 4 illustrates that most participants downloaded social media more than 3 years ago. Globally, there are similarities between the moments individuals download their favorite social media and those they use the most. 30.77% of participants downloaded their favorite social media more than 1-3 years ago, and the most used were 35%. 6.29% of participants downloaded their favorite social media more than 6-12 months ago; the most used were 3.57%; 2.1% of participants downloaded their favorite social media more than 3-6 months ago, and the most used were 2.86%. Lastly, 2.8% of participants downloaded their favorite social media less than 3 months ago; the most used were 2.14%.

Table 5: Social Media Representation

Social media representation	Favorite	Most used
5	19	16
4	53	54
3	44	35
2	20	31
1	7	7

Table 5 shows that the difference in numbers is not significant. Nineteen people indicated "5" for their favorite, compared to 16 for the most used. Fifty-three chose "4" for the favorite, while 54 did so for the most used. Forty-four participants picked "3" for the favorite, contrasting with 35 for the most used, and 20 individuals selected "2" for the favorite instead of 31 for the most used. This suggests that more users tend to identify with their favorite social media than their most used one. Lastly, 7 people on both sides do not feel their social media represents them.

Table 6: Frequency of the Posts

Frequency of the posts	Favorite	Most used
Everyday	10	10
At least once a week	11	13
At least once a month	16	13
Now and then	62	52
Never	44	53

Table 6 illustrates that 44 participants never post on their favorite social media, compared to 53 for their most used. Sixty-two participants post "now and then" on their favorite platform, whereas 52 do so on their most used. Sixteen individuals post on their favorite social media at least once a month, while 13 do so on their most used. Eleven participants post at least once a week on their favorite social media, as opposed to 13 on their most used, and 10 participants post every day on their favorite social media, similar to the count on their most used.

Table 7: Frequency of the Comments

Frequency of the comments	Favorite	Most used
Every time	2	2
Very often	12	12
Often	25	20
Rarely	71	75
Never	33	33

Table 7 illustrates that 33 participants never commented on their favorite social media, compared to 33 for their most used. Seventy-one participants rarely comment on their favorite platform, while 75 do so on their most used. Twenty participants commented often on their favorite social media, compared to 20 on their most used. Similarly, 12 participants commented very often on their favorite social media, compared to 12 on their most used, and 2 comments every time on their favorite social media, similar to 2 on their most used.

Table 8: Frequency of Saving Posts

Frequency of saving posts	Favorite	Most used
Every time	10	14
Very often	37	44
Often	46	41
Rarely	30	27
Never	20	16

Table 8 illustrates that 20 participants never saved posts on their favorite social media, compared to 16 for their most used. Thirty participants saved posts on their favorite platform, while 27 did so on their most used. Forty-six participants were post-saving very often on their favorite social media, compared to 44 on their most used, and 10 participants were saving posts every time on their favorite social media, in contrast to 14 on their most used.

Table 9: Time Spent

Time spent	Favorite	Most used
1-3 hours a day	66.2%	81
3-6 hours a day	27.46%	47
6-12 hours a day	5.63%	10
+12 hours a day	0.007%	2

Table 9 illustrates that most participants spend 1-3 hours a day on social media. Then, participants spend 3-6 hours a day, while 5.63% spend 6-12 hours a day. A negligible percentage spends more than 12 hours on social media.

Table 10: People who see NDD-Related content

People who see NDD-related content	Favorite platform	Most used platform
Never	17.48%	15.38%
Rarely	31.47%	26.57%
Often	17.48%	20.28%
very often	16.08%	16.08%
Everyday	17.48%	21.68%

Table 10 illustrates that most participants started seeing NDD-related content on their feeds one to 3 years ago.

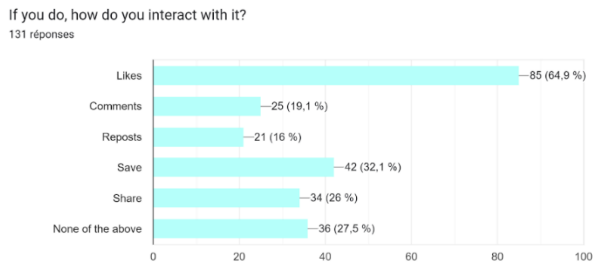


Figure 5. Respondents’ social media interactions

Figure 5 shows that participants who see NDD-related content mostly like it (64.9%). Thirty-two point one percent (32.1%) save it, 26% share it, and the remaining comment and repost. Twenty-seven point five percent (27.5%) do not interact with it.

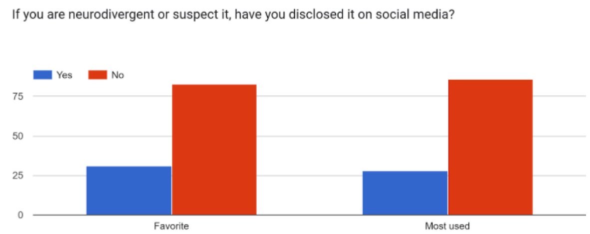


Figure 6. Respondents’ NDD disclosure

Figure 6 shows that only 27.19% of the participants who are diagnosed or suspect that they have a neurodevelopmental disorder have disclosed it on their favorite social media. The percentage is similar for the most used platform (24.56%). Thirty-seven point zero six percent (37.06%) have already looked for NDD-related content in their favorite social media search bar, and 41.26% on their most used one. Forty-nine point sixty-five percent (49.65%) of the participants look for mental health-related content in their search bar, versus 53.15% on their most used one.

4.1.3 Interviews

While Participant A is familiar with neurodevelopmental disorders (NDDs), it's crucial to note that he does not work directly with them. The discussion with him encompassed several key themes, including artificial intelligence in the medical field, machine learning applications, NDD-related content on social media, social media algorithms, and potential biases in diagnoses. The conversation with Participant B inquired distinct topics, primarily focusing on search algorithms, machine learning applications, and metrics associated with social media.

5. **Analysis**

5.1 Survey

Upon examining the preferred social media platforms and the most frequently used ones among participants, TikTok's percentage saw a twofold increase when transitioning from one category to another. Only a small percentage of participants have permitted social media to track their activities on other platforms. Interestingly, user habits exhibit minimal variations across different platforms.

Consequently, the outcomes are more closely associated with individual user personalities than with the attractiveness of the platforms.

Table 11. Favorite and most used social media for each age group

Age group	Favorite	Most used
15-17	Instagram	Instagram Twitter
18-24	Instagram	TikTok
25-34	Twitter	Twitter
35-44	Instagram	Facebook
45-62	X	X

Table 12. NDD content visualization based on cognitive status

		Have a NDD		Do not have an NDD		Are questioning	
NDD-related content		Favorite	Most used	Favorite	Most used	Favorite	Most used
YES	Everyday	17	16	0	0	8	15
	Very often	11	14	3	3	9	6
	Often	9	10	9	11	7	8
	Total	37	40	12	14	24	29
NO	Rarely	6	3	29	29	10	6
	Never	1	1	21	19	3	2
	Total	7	4	50	48	13	8

Table 13. NDD content visualization based on cognitive status in percentage

		Have a NDD		Do not have an NDD		Are questioning	
NDD-related content		Favorite	Most used	Favorite	Most used	Favorite	Most used
YES	Everyday	38.636%	36.36%	0	0	21.62%	40.54%
	Very often	25%	31.818%	4.838%	4.838%	24.32%	16.216%
	Often	20.45%	22.727%	14.516%	17.74%	18.9%	21.62%
	Total	84.1%	90.9%	19.4%	22.6%	64.86%	78.38%
NO	Rarely	13.63%	6.818%	49.77%	49.77%	27.027%	16.216%
	Never	2.27%	2.27%	33.87%	30.64%	8.11%	5.405%
	Total	15.9%	9.1%	80.6%	77.4%	35.14%	21.62%

5.2 Participants who see NDD-related content

5.2.1 Favorite Social Media

Out of the 73 participants who confirm regularly encountering NDD-related content, a significant majority are associated with neurodevelopmental disorders (NDDs). Specifically, 50.68% have a diagnosed neurodevelopmental disorder, and 32.9% suspect that they might have one. The demographic skews young, with 43.83% falling between 25 and 34 and 39.7% aged 18 to 24. Additionally, 50.7% of these participants report having a mental illness, and a noteworthy 90.4% express an interest in mental health. Almost 70% have a relative who is neurodivergent. In terms of when they became aware of NDDs, 17.8% learned about it over 3 years ago, 31.5% between 1 to 3 years ago, 2.74% between 6 to 12 months ago, 1.37% between 3 to 6 months ago, and 5.48% within the last three months. Examining their social media preferences, 31.5% favor Instagram as their primary social network, followed by 27.4% on Twitter, 21.9% on Facebook, and 19.18% on TikTok. A majority (53.4%) registered on their chosen platform over 3 years ago, with 35.6% between 1 and 3 years ago. Regarding privacy settings, 32.8% have linked their social media accounts to their personal information, 61.6% have not, and the remainder are unsure. Furthermore, 43.8% have linked their phone numbers to the platform. A notable 19.18% grant the application permission to follow their activities on other platforms.

Concerning self-representation, a striking 80.8% believe that their favorite social media platform represents them adequately, scoring between 3/5 and 5/5. Analyzing posting behavior, the majority (43.8%) post content "now and then," while 9.6% post content at least once a day, with a similar frequency for "at least once a week." Additionally, 16.4% post content "at least once a month," and 27.4% never post. Regarding engagement, 34.25% comment on posts regularly, while 65.75% rarely or never comment. A substantial 65.75% regularly save posts. Regarding time spent on their favorite social media, 58.9% spend 1-3 hours a day, 34.25% spend 3 to 6 hours, 5.48% spend 6 to 12 hours, and the remaining individuals spend more than 12 hours.

5.2.2 Most Used Social Media

In the cohort of participants consistently encountering NDD-related content, 58% identify as neurodivergent, while 35% harbor suspicions of such identification. Age distribution reveals that 43.37% fall within the 18 to 24 age bracket, 40.9% are aged 25 to 34, 3.6% are aged 15-17, 10.8% are between 35 to 44, and the remaining 45 to 62 years old. The predominant awareness of NDDs occurred over 3 years ago for 78.3% of participants, with 28.9% gaining awareness through social media. Notably, 67.47% report having a relative who is neurodivergent, and 50.6% disclose having a mental illness. Furthermore, 94% express an interest in mental health, and 80.7% hold an interest in NDDs. Examining their most used social media platforms, similar percentages are observed but are ranked as follows: TikTok (33.73%), Instagram (26.5%), Twitter (20.48%), and Facebook (19.27%). Most participants downloaded these platforms one to 3 years ago (38.55%) and over (53.01%). Regarding privacy settings, 31.33% have linked their social media accounts, and 44.58% have linked their phone numbers to the platform. Additionally, 18.07% authorize their most used application to follow their activities on other platforms. A noteworthy 69.87% rate their social media representation as 3/5 to 5/5.

Analyzing posting behavior, the majority (37.35%) posts content "now and then," followed by those who never post (32.53%), those who do “at least once a month” (10.84%), “at least once a week” (9.64%), and “at least once a day” (8.43%). Regarding engagement, 57.83% rarely comment on posts, 16.87% do so often, 14.46% never comment, and 8.43% comment very usually. The majority frequently saves posts (31.33%), often (28.92%), and rarely (19.28%). Concerning the time spent on social media, more than half (50.6%) spend 1-3 hours, 39.76% spend 3-6 hours, 8.43% spend 6-12 hours, and the remaining spend 12 hours and more. Globally, more people encounter NDD-related content on their most used platform, with participants diagnosed with NDDs having the highest percentage, followed by those questioning and those not diagnosed.

5.3 Participants Who Are Neurodivergent

A demographic breakdown reveals that 77.27% of the participants identifying as neurodivergent are women, 4.55% are men, and 18.18% identify as non-binary. The predominant age group is "25-34" (45.45%), followed by 36.36% aged 18 to 24, 11.36% aged 35 to 44, 4.55% aged 45 to 62, and the remaining participants fall into the "15-17" age group. Regarding geographic distribution, 68.19% of neurodivergent respondents reside in Europe, with a substantial portion in France (56.82%). The distribution continues with 20.46% in America (15.91% in the US and 4.55% in Canada), 6.82% in the UK, and 2.27% in Algeria and Australia.

5.3.1 Favorite Social Media

Among the 44 individuals diagnosed with a neurodevelopmental disorder, 84.1% actively engage with NDD-related content on their favorite platform. The frequency breakdown is as follows: 38.64% daily, 25% very often, 20.45% often, 13.64% rarely, and 2.27% never. Instagram emerges as the preferred platform for 29.55%, with Twitter and Facebook securing 25%. Following closely are TikTok (11.36%), Reddit (6.82%), and LinkedIn (2.27%). Notably, 75% rate their favorite social media with at least 3/5 for how well it represents them. Additionally, 52.27% downloaded it over 3 years ago, while 34.09% did so between 1 and 3 years ago. Other details include 45.45% linking their phone number to the platform, 20.45% authorizing activity tracking, and 56.82% spending 1-3 hours daily on their favorite application. A significant 47.73% have disclosed their neurodivergence on this platform, with the majority posting content "now and then" (45.45%) and 20.45% never posting. Engagement metrics include 84.09% commenting on posts, with 47.73% doing so rarely, and 77.27% saving posts, including 22.73% rarely.

5.3.2 Most Used Social Media

All neurodivergent participants (100%) encounter neurodevelopmental disorders-related content on their most used platform regularly. The frequency distribution is 40% every day, 35% very often, and 25% often. Twitter claims the top spot as their most used platform (31.82%), followed by Instagram and Facebook at 25%, and TikTok at 18.18%. A significant 65.91% rate their most used social media with at least 3/5 in terms of representation. Regarding platform usage, 63.64% signed up over 3 years ago, 27.27% between one and 3 years ago, and 45.45% linked their phone number to the platform. Additionally, 13.64% authorize activity tracking. Time spent varies, with 45.45% spending 1-3 hours, 40.91% spending 3-6 hours, 11.36% spending 6-12 hours, and the remaining spending more than 12 hours. Notably, 43.18% have disclosed their neurodivergence on this platform, with the majority posting content "now and then" (43.18%) and 25% never posting. Engagement metrics mirror the favorite platform, with 81.82% commenting on posts, including 50% rarely, and 84.09% saving posts, including 25% rarely.

5.4 Interviews

The responses from Participant A are indicated in blue, while Participant B's are highlighted in yellow.

Table 14: Machine learning

Machine learning
- Machine learning is a subfield of artificial intelligence.
- You have two types of machine learning: Supervised and unsupervised. For the first one, you need really clean data
- “Unsupervised learning, you give the data as they are and you let the system try to understand if there is any pattern inside. So you don't give any previous knowledge, you let the computer try to find his knowledge about it.”
- “Problems with unsupervised models is that they don't have such a good performance as supervised models. That's why for now we need we need labels”
- “An AI model is a mathematical function with some parameters inside. For example, linear regression is the simplest machine-learning model. And so in a linear regression, you could have different parameters that you want to optimize. So you have the slope of the curve and if you have an end dimensions and slopes for all the different dimensions. These are the parameters of the model and a machine learning model is what you want to do when you train”
Artificial intelligence in the medical field
- The use of artificial intelligence is not widespread in the medical sector
- There is a data problem “We have problems in terms of the data, how they are

recorded, how they sometimes don't match each other…the way we save data also in hospitals is unstructured”

- There is a legal perspective to take into consideration when it comes to the responsibility of the decisions. “And the problem also is that medicine will be the same, in the sense you can create systems that advise doctors, but they don't make medical decisions. Therefore, it's just extra data the doctor receives to decide because in another case you will need to understand who is guilty. It's the doctor, it's the machine, it's the software, it's the hospital.”

NDD-related content on social media

“The problem of TikTok is that since the goal of videos is to attract attention, especially for neurodivergent stuff there is a lot of non-reliable content because it's very easy to say "You have trouble concentrating, You feel like you cannot interact with other people, that you cannot look at people in the eyes", things that are very, very common among everybody; that they are like. "OK, maybe you have autism"’’

“People are making videos based on some general Knowledge they have about autism that is shrunk to very peculiar traits that are common to anybody "

- Because the popular content mostly relies on blurry symptoms, it is important to take your concerns to a professional when possible

Biases of diagnoses

- To reduce the risk of incorrect diagnosis, it is recommended to take notes of the troubling symptoms, seek an expert, and ask which of them are related to a condition and which are not
- It is better to see specialists than psychologists because the diagnosis method of the latter mainly relies on a form whose score is supposed to indicate if the individual is neurodivergent or not. It is not enough.

Social media algorithm

- Social media algorithms just show you what attracts the most your attention
- “To the question Can social media predict a disorder? My answer is they can't. Even humans cannot predict some disorders because sometimes it's not very easy. But what can social media do very efficiently is give the doubt to people that they might have a problem that needs to be addressed... I wouldn't be against TikTok saying "I saw you watching a lot of videos on this topic, you might be interested in contacting some people just to have a chat to check"
- The broad idea is that most of the algorithms that you have in data science or AI, you can put them in different buckets depending on I would say the type of input and then the type of output that you would have for your algorithm. I would say natural language processing is mostly focused with like sentences or word input.
- “For social media, it's more about trying to optimize the time That people stay on the platform. Maybe you can try also to qualify the quality of the interaction of people on the platform. So maybe a click, how many videos are looking at, how many people they are adding as friends... So these are all kinds of metrics that could be taken.” It is based on these metrics that they recommend content to their users.
- “If you have been on a platform for a longer time, the platform has more data on you”
- The platforms also have data management constraints, so they are not going to keep all the data.
- Some metrics might be more important than others, The social media platforms intercept a lot of information, but they determine which ones they want to keep and which ones they need to let go.
- “You have usually what we call a life cycle or the data. So, it means that depending on the data that you have, it's stored in databases in tables and so these tables you will give them a life cycle. Which means that after a certain time, the old data will be deleted.”
- The prediction of content is a complex task. The most appropriate term would be “ranking” because this is what most social media do. They give priority to the content and put them in order with the most attractive at the top.
- “These predictions, they are using a lot of different features. Some of the features could be some intermediate predictions like “What are the characteristics of this person? What are the kind of topics he likes?” This is based on ordering past interactions that you have on the platform, it is based on your friends; If your friends like something, maybe you will also like this thing as well.”

Search systems

- There are search systems that use artificial intelligence and some others that do not
- It is not necessary for a search engine to use artificial intelligence, but AI-powered search engines are better at making recommendations.
- How they work: “You consider a typical natural language processing algorithm to be like a user query, so it's a text and what you want to have in the end is another text, another query.”
- “Every time you search for something, you have a model behind waiting for your query and you're using your query to make some predictions.

6. Discussion

Among individuals encountering content related to neurodevelopmental disorders (NDD) on their preferred social media platform, 50.8% are classified as Neurodivergent. Additionally, among participants diagnosed with a neurodevelopmental disorder, a significant 84.1% report exposure to NDD-related content on their favorite application. Notably, 58% of those encountering NDD-related content on their favored social media platform identify as Neurodivergent, while the entirety of individuals diagnosed with a neurodevelopmental disorder acknowledge viewing NDD-related content on their preferred application. The higher percentages observed for the most used social media suggest greater accuracy. It is also important to closely examine the social media inputs of each group and the other information provided. All participants engaging with NDD-related content are linked to it one way or another, either directly for neurodivergent individuals or those questioning or indirectly for those with relatives diagnosed with NDD, having an interest in mental health, etc. User interactions with their platforms are also crucial. The amount of screen time coupled with the moment they signed up is a sign that social media platforms have had time to adapt to their preferences. In an interview, Participant B mentioned that social media algorithms pick up different metrics, such as the amount of time spent on a video, actions taken with content, etc. Each platform has its data management, which selects data to intercept and uses it to recommend content later. They work with recommendation systems powered by AI, so their accuracy grows with the data they receive.

However, participant A suggests that this level of accuracy is insufficient for user self-diagnosis. Social media platforms merely recommend content based on users' interactions, and the routine exposure to NDD-related content on one's "For You page" or feed should not be the sole basis for a diagnosis. This is especially crucial given the prevalence of false information circulating online. Nevertheless, such exposure could serve as an initial step for a potential diagnosis in the future. Despite achieving a harmonious balance among the diagnosed, undiagnosed, and questioning participants, there was an imbalance in the number of individuals within each identity group. The majority of respondents were women, and there was an inadequate representation of individuals in the age groups at the extremes. Regrettably, the researcher was unable to interview a social media algorithm engineer. The study requires additional insights from professionals, particularly those directly interacting with social media platforms and algorithms. While this interaction was initially planned, it has not been executed.

Regarding the survey population, the researcher lacks a mechanism to verify the neurodivergent identity of participants. The absence of strict guidelines on how individuals receive their diagnoses, whether through self-assessment or by a professional, presents a challenge. Notably, self-diagnosis is accepted in the autistic community, primarily due to limited access to psychiatry services. The researcher trusted participants to provide accurate responses based on their situations. However, it remains uncertain whether some individuals who responded affirmatively or negatively may indeed be on the autism spectrum, and unfortunately, there is no means to validate this information.

7. Conclusion

The researcher's initial stance on "Can social media algorithms identify neurodiversity?" leaned toward a negative response. However, a persistent sense of curiosity drove the exploration of the outcome. This study has been remarkably enlightening, unveiling the operations of social media algorithms and their content recommendation systems. It has illuminated the boundaries within which neurodevelopmental disorders content operates online, emphasized the potential enhancement artificial intelligence can offer in psychiatric diagnoses, and underscored the reality of data challenges within the medical field. The mechanics of social media recommendations rely on sophisticated systems that categorize and deliver content based on user interactions. Integrating machine learning into social media significantly boosts user engagement, contributing to extended platform usage and the continual refinement of content feeds. However, in the context of diagnosing neurodevelopmental disorders within these platforms, this study has established that neither social media itself nor the content it houses is sufficient for accurate identification.

Nevertheless, it is crucial to recognize the positive impact social media has had and continues to have, aiding numerous individuals. Given social media's substantial role, platforms should consider certifying relevant content and incorporating disclaimers. Certain platforms, such as Twitter and TikTok, have already taken steps in this direction by introducing certification for news and safety disclaimers for potentially risky activities. This practice should be expanded to encompass mental health content and information about disorders.

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