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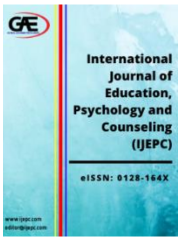

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GLOBAL ACADEMIC EXCELLENCE

THE ROLE OF SOCIAL MEDIA INFLUENCERS IN PROMOTING STEM AWARENESS AND POLICY REFORM: A SOCIAL NETWORK ANALYSIS APPROACH

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Abstract:

STEM fields are the driving force in advancing society and providing opportunities for personal and professional growth, from medical breakthroughs to new transportation methods. STEM fields are crucial in innovations and technological advancements that have improved our lives. As the world changes and new challenges arise, the importance of STEM education and careers will only grow. By now, STEM topics are widely discussed on Twitter. Use Twitter to share worldwide news, research, and insights about STEM fields. Therefore, this study aims to discuss online interaction, social networks, and perspectives twitters on STEM fields and even the women in STEM from conversations on Twitter by analyzing the Twitter data. The NodeXL Pro software was used to visualize the network visualization on network participation, especially women in STEM education, within Twitter data. The betweenness centrality to identify the top influencer in STEM conversation on Twitter. The top words in a tweet, the top 10 hashtags, and the most mentioned words on STEM were identified. The research findings demonstrated the existence of higher measures of connection and interaction with others on Twitter. Hence, a better comprehension is needed to understand the power of social media; tended to interact more frequently with all students than most participants from specialist backgrounds.

Keywords:

Hashtag, Social Media Influential, Social Network Analysis (SNA), STEM, STEM Awareness, Twitter, Women in STEM

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Introduction

STEM education has become a global priority because of its fundamental importance in innovation, economic competitiveness and societal progress. Educators and policymakers may promote better learning outcomes and reforms that reflect the distinctive characteristics of STEM by recognizing the complex interactions among these disciplines (Croak, 2018). Social networking in its current form has progressed quickly enough to create new options for connection, knowledge exchange, and professional growth by changing how people also in STEM connect with each other along with their fields (Eid & Al-Jabri, 2016; Struweg, 2022). With the advances of social media, these platforms have become highly effective means of increasing public awareness of STEM (Science, Technology, Engineering, and Mathematics). (Mueller-Herbst et al., 2020). Twitter and other social media platforms have been identified as important tools which promote informal learning outside the classroom setting, allowing for interaction between intersecting networks of learners, educators, and professionals (Struweg 2022; Mojumder & Sadri, 2021). Twitter has played a crucial role in establishing professional connections, increasing visibility, and career development for the STEM sector as it allows an opportunity to share knowledge and expertise freely (Struweg, 2022). On Twitter, discussions about STEM frequently revolve around hashtags and influencer-driven content. However, these conversations often prioritize trends over deeper engagement with essential STEM education policies or practices, leading to a lack of substantive discourse (Smith & Lee, 2023). Influencers are critical to building these new online, ad-hoc communities that, even outside a formal education setting, can elevate the awareness and value of the importance of STEM to innovation and economic development in the broader society (Allen & Peterman, 2019). Not only are these interventions effective for inspiring interest in STEM; they also serve such a purpose among women and minorities groups underrepresented within STEM because systemic barriers exist within these fields (Sadri, A. M. (2020).

That potential for visibility is equally important because women have always had less visibility and opportunity in STEM than men (Huang et al., 2020). As proven by Huang et al. (2020), disparities between females and males in courses and countries are well documented across the disciplines: in the number of authors, female and male, their productivity, award of their nourishments, their citations, recognition, and salary. Though women represented just 12% of active authors in 1955, the figure steadily increased over the past century, surpassing 35% by 2005 (Fig.1A). Women are 15% of math, physics, and computer science and 33% of psychology, but these aggregate figures hide huge disciplinary disparities (Fig. 1B) Huang et al. (2020). There are huge differences from country to country, however, with the share of scientists who are female 28% in Germany and parity at 50% in Russia (Huang et al., 2020). While significant strides have been made in both genders pursuing STEM fields, stark gender imbalance and inequality continue to be seen as STEM students face hidden score bias in both educational and professional settings (Huang et al., 2020). Given this knowledge, it is not surprising that research shows women continue to face recognition and advancement obstacles in STEM (Casad et at., 2021). Thus, social media can become a better accessible and equitable space to create a professional profile for female talent in STEM fields through promotion of their work and collaboration (Christou & Parmaxi, 2023).

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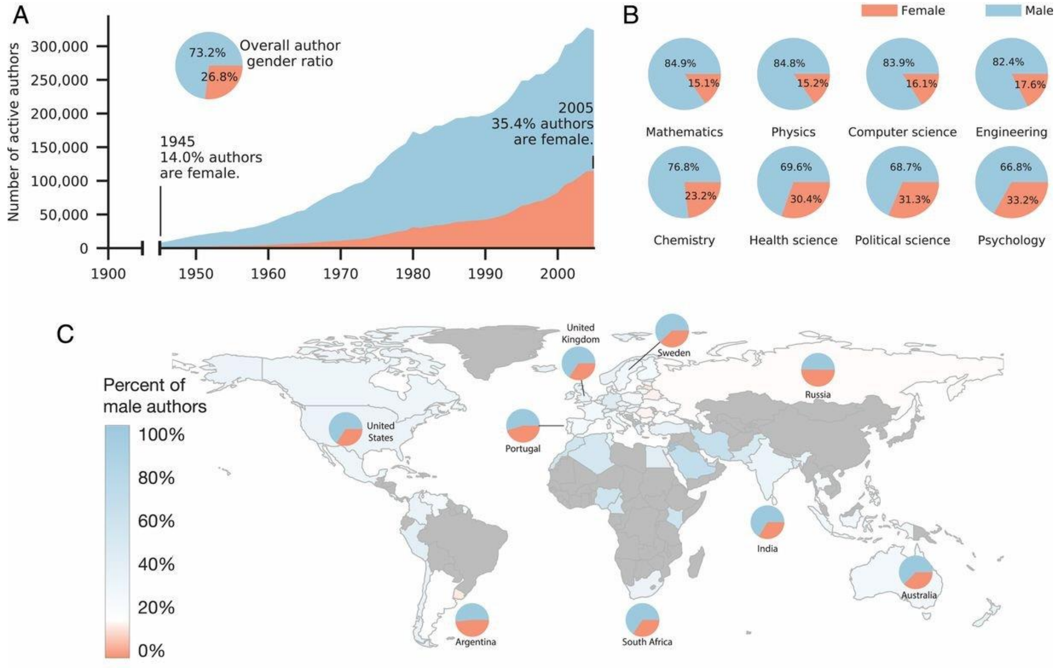

Figure 1A: The Number of Active Female (orange) and Male (blue) Authors Over Time and The Total Proportions of Authors.
Figure 1B and 1C: The Proportion of Female Authors in Several Disciplines (B) and Countries (C).

Source: Adapted from : "Historical Comparison of Gender Inequality in Scientific Careers Across Countries and Disciplines," by Huang, J., Gates, A. J., Sinatra, R., & Barabási, A. L. (2020). *Proceedings of the National Academy of Sciences*, *117*(9), 4609-4616. (https://doi.org/10.1073/pnas.1914221117). Copyright 2020 by Publisher.

The advent of social network analysis (SNA) has experienced a rapid rise in the past years, thanks to crossover research fields and ever-increasing data availability (Struweg, 2022). In this respect, network science provides tools that may be useful in addressing central challenges of the social media space including identifying influencers, conversational shapes and visualizing complex networks (Croak, 2018). SNA sees social media as a network of networks, drawing attention to the recurrent themes and relationships that develop within online communications. Although many early studies in SNA were concerned with basic social networks such as familial or community relationships, recent literature has turned towards more complex networks found in organisational and online settings (Struweg, 2022). While a variety of topics have been explored through SNA including the diffusion of innovations (First and Harad, 2007), social movements (James, Roodhouse, and Southeman 1996), and structures of online communities (Jones 2014) there are few studies using SNA to examine women in STEM despite gender parity remains unaddressed (Casad et at., 2021). Women have played a major part in creating digital learning innovations, like creating e-learning platforms and educational software (Butler et al. 2023). Yet despite these contributions, women are still underrepresented across much of the digital learning landscape within the domain of STEM education. This disparity is attributed to many reasons such as bias in education systems, lack of access to resources, and stereotypes that exclude women from STEM oriented events (Casad et at., 2021). For example, grading and evaluation often provide grade penalties to women in STEM even when the quality of their work is comparable to men (Roper, 2019), which affects their

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self-esteem and career paths. Further, being excluded from activities related to STEM such as coding clubs and robotics competitions deprives women of acquiring essential skills, which therefore hinders their competiveness in the field (Butler et al., 2023; Butler & Green, 2023).

With these issues, it is essential to recognize the contributions of women in STEM education and for online learning to thrive. An inclusive and effective educational system can be created by galvanizing women with STEM careers while also ensuring there is equal access to resources. This is where social media platforms such as Twitter can be crucial to promote connections made and women in STEM (Butler & Green, 2023). A social network analysis was conducted to examine twitter network dynamics and content patterns surrounding STEM discussions as the goal of this paper. Using Twitter activity as a data source, this paper targets to conduct a SNA via network insights and content insights around the STEM issues in Twitter conversation. Twitter served as a platform with current events and trends for researching the information flow. So, this research's objectives were: (1) To determine the critical influential actors in Twitter as a social network in #STEM conversation. (2) To spot the key topic of STEM topic-related discussion based on Twitter users and their interactions on Twitter (3) To describe the degree distribution of the relationships between Twitter users in the STEM conversation.

Literature Review

Twitter

Twitter has become a strong research tool where people across different backgrounds have been integrated to get updates on events, trends & discussions happening (Brown & Clark, 2021). Twitter is a microblogging site where the discovery of different topics takes place through hashtags—keywords or phrases that are attached to the "#" symbol and group posts on similar subjects. Hashtags are essentially metadata tags with a purpose of making it easier for users to find specific topics, engage in dialogue with popular voices, and even monitor conversations around issues they care about or are studying (Smith 2020). Users can click on hashtags to get a stream of tweets related in order to witness the diverse perspectives providing people with access to information in real time. This has turned Twitter into a powerful resource for the insight, information and discussion of various topics such as education, politics and science (Brown & Clark, 2021). Twitter for STEM @STEMtwitter: Twitter provides an accessible and interactive space for educators, researchers, and students to exchange knowledge and resources and promote news in the context of Science, Technology Engineering & Math (STEM). Hashtags such as #STEMEducation and #WomenInSTEM, for instance, have nurtured niche communities that address issues, discuss success stories, and promote gender equity in the discipline (Johnson et al., 2019). STEM-related conversations on Twitter tend to discuss surface-level trends or hashtag activism rather than analyzing policies, curriculum innovation, or mechanisms that could influence STEM education outcomes (Smith & Lee, 2023). Moreover, Twitter allows users to follow and subscribe to leading accounts in order to stay up-to-date on major trends, new papers, or live conversations (Miller 2022). Additionally, this aspect serves to provide networking opportunities and exchange of knowledge, while also aiding in professional development through providing a platform for users to interact with specialists and learn the ins-and-outs of industry practices (Taylor & Lee 2021). New results reveal that these Twitter influencers are essential in shaping perceptions of STEM fields and inspiring others to foster STEM careers (Wao et al., 2023). The influencers' communication style and ability to connect with their audience relatable establish a rapport that creates trust

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and motivation (Wao et al., 2023). Misinterpretation and oversimplification lead to the misrepresentation of scientific ideas and STEM careers (Nguyen & Catalan, 2020).); thus, some research on Twitter with respect to STEM topics has been conducted.

Social Network Analysis (SNA)
It has been observed that the coronavirus pandemic has provided a significant boost to the digital transformation of education, stressing that technology must be used for teaching and learning (Khor & Dave, 2022). With the development of education and educational technology, now many research interests focusing on Social Network Analysis (SNA) in the field of education have been attracted to this meta-analysis study. SNA is an interdisciplinary toolset that examines social relationship structures by employing mathematical and computational methods around individuals or organizations. By using this method, researchers are able to analyze the diffusion of information and influence as well as micro and macro group formations within the social network (Freeman, 2004).

A SNA is a particularly strong analytical toolbox for examining relational data about educational problems and provides such a tool in the context of examinations around women and STEM (science, technology, engineering, and mathematics) education. SNA can use connecting data of one or more kind to help visualize complicated associations between participants within a network (classroom, social media site, professional community) (Wasserman & Faust, 1994). These can then be represented graphically through sociograms, graphs, and matrices (Hanneman et al., 2005), allowing researchers to detect interaction and relationship patterns. SNA has been previously applied to study student interaction and engagement implications for how they impact classroom interactions or learning outcomes (Kassens-Noor,2030).

SNA offers several important metrics to analyse social structures including degree centrality (number of connections an individual has), betweenness centrality (how much a person bridges other individuals in the network) closeness centrality (how fast an individual to reach others) and eigenvector centrality, which captures the influence based on their connection to other well-known nodes (Borgatti et al., 2018). These enable educators and researchers to gain insight into the organization and functionality of learning communities so that they may be able to enhance student engagement and collaboration (Carolan, 2014).

Along with these network centrality measures, SNA also pays attention to the triads—groups of three connected people—which can show the tendencies to cluster and create sub-groups of interest. These insights are especially useful in understanding what social barriers exist and in facilitating group-based learning within educational spaces (Scott, 2017). Educators can leverage SNA to find who are influential actors in student groups, allowing them to implement tailored interventions that promote inclusive collaboration and equal representation of student voices in the process (Prell, 2012).

In addition, SNA is not limited to traditional classroom environments and can easily transfer into online websites such as Twitter. Organizations and researchers use the hashtags on Twitter for tracking of topics of interest leading to analysis patterns of information flow and ideas spread across communities such as #WomenInSTEM or#EdTech (Gruzd et al., 2018). SNA offers a data-driven approach to studying social interactions in education, as it enables researchers to see how information moves through networks and who or what person influence

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are (Smith et al., 2020). In SNA overall, SNA is used too infrequently to specifically investigate STEM education on social media or to assess the impact social media communities can have on education outcomes. Current research tends to be more focused on generic user behavior or popularity metrics of influencers rather than establishing any correlation between these insights and the actual improvement in STEM learning or inclusivity (Kimmons et al., 2018). The absence of a system to translate findings from social network analysis into evidence-based policy and curriculum and, equally, the absence of a robust evidence base—is a key challenge to be met.

Methods

Design and Sample

The study was carried out by quantitatively analyzing Twitter data on STEM by society. The sample was drawn from English language tweets from June 2020 to November 2023 to reflect how society used social media as a new way of communicating STEM. In this study, SNA was used to facilitate the identification of social networks consisting of nodes with which actors are connected through shared values, visions, ideas, social contacts, and disagreement.

Data Collection

In this study NodeXL Pro was used to answer the research question based on the fundamental theory of SNA. The study used a stepwise approach (data collection, data processing and analysis) to provide network and content insights on STEM discussions on Twitter. Advanced network metrics (e.g., betweenness, closeness and eigenvector centrality) were computed in NodeXL Pro, a computational tool used for analysing and visualising social networks to capture the influence and connectivity of key actors within the network (Hansen et al., 2019). Such metrics serves to uncover the functionality of the individual nodes (users) in the network, i.e. they allow us to find out who are influential users and bridging nodes that form connections between different subgroups (Freeman, 1979). Beyond network metrics, NodeXL Pro offers content analysis capabilities that allowed for a thorough analysis of textual data (e.g. hashtags, URLs, and word pairs contained in tweets). Time-series analyses to identify patterns and trends overtime, top items (most frequent words, hashtags and links) to summarize the leading themes in the STEM conversation on Twitter. Such an emphasis on the structure of networks and a consideration for content insights is critical to both understanding dissemination of information and identifying topics where STEM discussions are most resonating (Gruzd & Haythornthwaite, 2013). Because community structures are prevalent in real-world networks, they investigated the community structure of the network using the Clauset-Newman-Moore algorithm based on modularity optimization (Clauset et al., 2004). Here, modularity optimization is utilized by this algorithm to divide the network into clusters–or communities of Twitter users who are more tightly connected to each other than others in different clusters. Mapping these clusters allows us to look deeper into the nature of STEM conversations among different user groups and how possible echo chambers may arise within such communities (Fortunato, 2010).

In answering the network insights, the analysis uncovered key user accounts that are central to conversations around STEM, influential groups that are forming clusters, as well as aggregate structural characteristics of these clusters. To understand the content, the study explored common hashtags, URLs and words over the entire network and also within each cluster to see what people were talking about. Such a practice is consistent with earlier studies that have

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proposed hashtags and keywords as markers of the virality of topics and the flow of information in social media (Bruns & Burgess, 2015). The unstructured data is extracted from Twitter through an R package able to download tweets using Twitter v2 — Academic Research API, which allows querying the full archive of Tweets. Tweets were included for data collection if they contained specific STEM-related keywords, such as “digital,” “STEM,” “#STEM” learning, students and “#digital”. The tweets within this study were posted from June 2020 through to November 2023, giving that temporal duration a significant amount of time over which we could observe trends and changes in STEM discourses. To better understand how messages spread across verified users, unverified users in the dataset are included, since the datas provide rich insights when discussing the same topic online (Zhu et al., 2011). Overall, the data set consisted of 89,853 tweets, retweets and replies with 19,662 unique Twitter users (including those mentioned/replied) engaged in conversation. Imported this data to NodeXL and simple they draw a network graph that shows how users are connected in love cluster in line with topics of STEM. These visualizations yield deep insights into the internal dynamics of STEM on Twitter, including who are the influential users, the flows of discussion, and themes at their center (discussed in more detail in subsequent sections).

Data Analysis

19,662 tweets of the Twitter dataset were imported in professional version, NodeXL Pro (Ahmed & Lugovic, 2019) for analysis. Afterwards, an SNA study of this dataset (composed of "vertices" and "edges") was performed to discover its structural and relational properties. Vertices (or, nodes, agents, entities) are the individual users/organizations/events or items in the social media environment who interact with each other (Struweg, 2022). Conversely, edges (or links or ties) reflect the connections across these entities to encapsulate all the possible interactions that distinguish the network. The initial step was to visualize the network structure in NodeXL Pro. This visualization uncovered dense clusters of users who often responded to each other, revealing sub-groups within the wider STEM discussion on Twitter. Clustering helps to understand the structure of communities in a network and who are the central nodes in these communities (Scott, 2017). Use the clusters to see how information flows and influence within specific nested groups in the STEM-themed community on Twitter (Or too big, so find sub-groups). Then, to quantify the relative importance of each node within the network, centrality is measured. Another example is betweenness centrality which helps in figuring users who act as bridges between other clusters. Information flows across these users from one part of the network to another and thus they embody Structural Holes making them Volatiles in STEM conversations (White & Borgatti, 1994). It is particularly relevant in social media studies, as measuring betweenness centrality can identify people or accounts that bridge otherwise disconnected communities and provide the greatest potential for spreading information (Freeman 1979).

Unlike Gephi, in-degree and out-degree measures were computed because it is important to analyze directed networks, such as Twitter, which was also included in the centrality analysis. In-degree centrality is the number of connections a user has directed toward them and is often interpreted as popularity (Wang et al., 2010). Accounts that are in the center of high degree centrality are often nodes or celebrities who have a wide range of appeals. The out-degree centrality, on the other hand, counts how many connections are directed away from a user and finds people who are very interactive or highly proactive in terms of connecting with others in the network. Having a high out-degree centrality means that the user is either a major communicator or an influencer of their community (Wasserman & Faust, 1994). The analysis

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went beyond degree centrality, looking at closeness and eigenvector centrality as well. Closeness centrality refers to averages how proximity are from any node in relation to the rest of nodes of the network. High closeness centrality indicates that a user is a short distance from interacting with all other users, placing them in an optimal position for spreading timely information (Struweg, 2022). Conversely, low closeness centrality means a user has high-connectedness and is "just one hop away from many others" thus high-reach and accessible to the community. On the other hand, eigenvector centrality puts more weight on links to well-connected nodes. This measure not only values the size of a user s connections, but also that they are connected well to central figures outside of their immediate area (Bonacich, 2007). This one is extremely useful in pinpointing users that exist within influential circles.

Last, NodeXL Pro was used to compute the clustering coefficient, which indicates a natural tendency of nodes in a network to cluster together into tightly knit groups. Once a user-to-user network has been built, the high clustering coefficients suggest that users clustered together do interact with each other frequently suggesting they are closely linked groups, with some potential influence over discussions of specific topics (Watts & Strogatz, 1998). Visualising these clusters on the network graph allows researchers to explore community structures and dynamic sub-groups behind the Twitter STEM conversation. Conclusion In short, NodeXL Pro performed detailed calculations of important social network measures in the interactions occurring on Twitter about STEM activities. These metrics, each providing unique insights into user influence: 1) Betweenness centrality; 2) In-degree and out-degree centrality; 3) Closeness centrality; and 4) Eigenvector centrality and community structure (5—Clustering coefficient), combine to provide a robust characterization of STEM-related communication on Twitter.

Results
19,662 tweets were extracted on STEM topics from individual users and organisations (a total of 2790) for social network analysis. A graph of the network visualisation was created using NodeXL Pro to represent the structure of interactions within this dataset (Figure 1). In this graph, every colored circle corresponds to a unique Twitter user and the lines connecting these circles indicate interactions — whether replies, mentions, or retweets between users. In total, we identified 4,328 groups where a group is defined as a community or cluster of Twitter users who have often interacted with each other over tweets on the STEM topics. This graph accentuates the manner in which Twitter acts as a network for establishing and redefining ad hoc communities that are able to spread (disseminate) knowledge across boundaries of distance, ethics, culture and expression (Ahmed & Lugovic, 2019).

The social network analysis involved identifying users that serve as bridges within such communities—i.e., influential users able to facilitate information flow between otherwise disconnected end-points in the network by calculating betweenness centrality, a portability of this pairwise similarity across all groups (White & Borgatti, 1994). Those with top scores in betweenness centrality are thought to be the information gatekeepers and influencers in that network, since they are responsible for controlling (and amplifying) the flow of information across these various clusters. The vast majority of the key influencers were based in the US or UK although as you can see below there was also representation from regions around the globe like Africa and Switzerland. The worldwide participation is a testament to Twitter as the digital gathering place for diverse throughts in STEM and ideas across borders (Struweg, 2022).

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Apart from studying individual influencers, The study also discovered some popular hashtags which motivated engagement on the network. As Twitter is a microblogging site, hashtags are an important tool for classification and discovery of similar topics to make the experience easier by allowing users to follow tweets on particular topics or join in on specific conversations (Wang, Tan, & Zhang, 2010). Top hashtags used throughout the dataset were #STEM, #digital, #AI, #womeninSTEM, #womenintech,#tech,#edtech,#influence and#IoT and#ML. These hashtags can be seen as important issues related to discussions about STEM, including popular emerging areas such as artificial intelligence (AI) and the Internet of Things (IoT) as well as diversity and inclusion by emphasizing women in STEM and technology (Scott, 2017). Through analyzing these hashtags, researchers will learn about the most prominent topics and themes in Twitter STEM.

Broadly, this analysis highlights some of the utility provided by social network analysis within digital communities. This type of research, which includes mapping user interactions, was applied to understand conversations in STEM fields on social media sites such as Twitter by identifying influential users and hashtags. These analyses possess a fundamental framework for institutions, policymakers, and organizations seeking to interact with, or influence the STEM community who do so in a more directed fashion (Wasserman & Faust, 1994).

Network Visualization Graph

Figure 1 shows a social network analysis of tweets. The directed graph obtained when one users follows another user, it created a directed edge from the follower to the followed users. The graph (Figure 1) represents a network of 19662 twitter users whose tweeted "STEM" at different context who were replied to, mentioned, retweeted or quoted related to STEM, women, women in digital and women in STEM.

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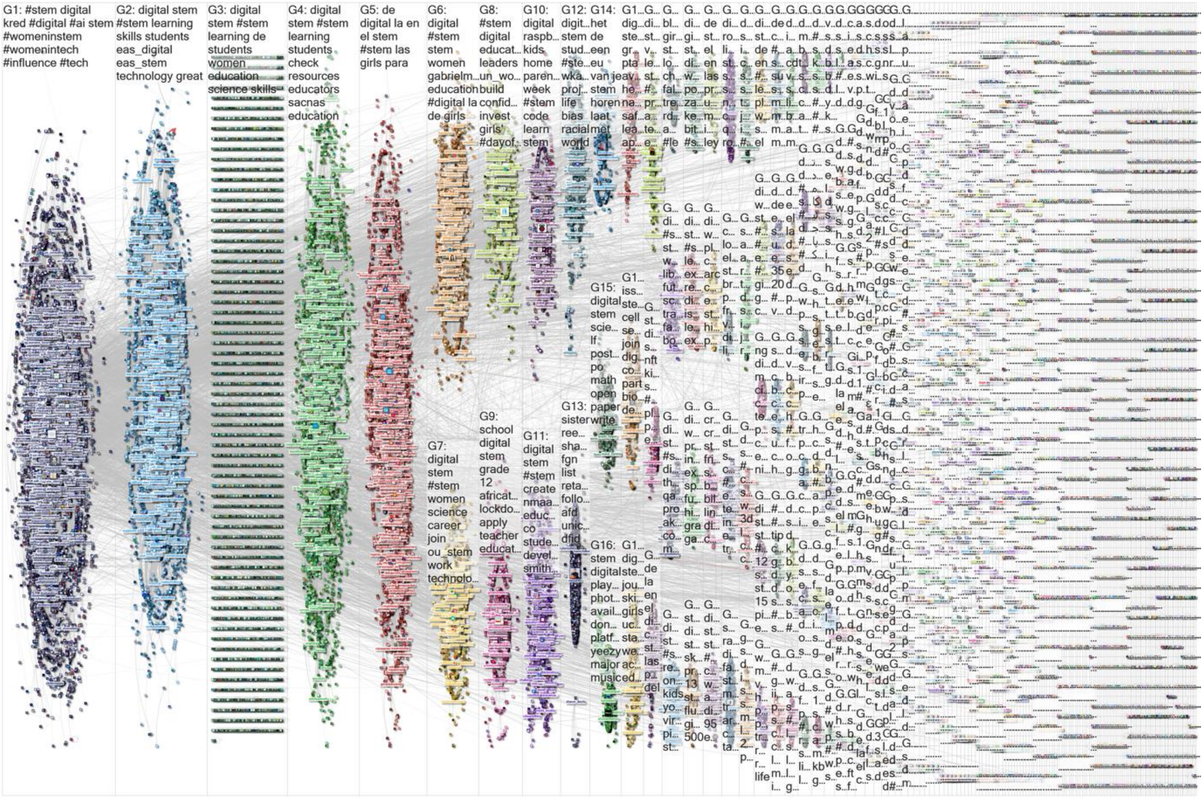

Figure 2: Network Visualization Graph

Figure 2: The main clusters of community talking about STEM-related topics on twitter during the time period being studied. The clusters indicate hubs of activity in the STEM-related Twitter network and also between community clusters differ in their interconnectedness and influence (Figure 1). Based on major and basic data-based clustering here, colours of biggest clusters are used to colour the elements as above, and the sizes and centralities in network determine their size as well. All clusters have some interactions, and these patterns show where certain types of STEM conversations are centered within their own hub or surrounded by peripheral groups and demonstrate how the community structure surrounding discourse about STEM on Twitter. Group 1 (shown in purple) was the largest cluster with 6,700 users, which corresponded to 34.08% of the total sample size. There is a high communication density in this particular group: 8,542 unique edges and 41,948 duplicate edges (repeat contacts). Kaggle – the dataset has 4,717 self-loops which indicates users interacting with their content. The density score of Group 1 is a high rate of 0.000 which indicates that it was the lowest density score as compared to possible connections versus actual connections, meaning not all members interacted with other members directly, something which is common for networks that have large groups (Ahmed & Lugovic, 2019). With all Group 1 numbers being large and their density values being high, this group appears to be a discussion center for STEM, with lots of connected users here. The second biggest cluster: Group 2 (highlighted in blue — visualized): 5,418 users; 27.56% of the network. Among these, 6,111 are unique edges and 17,194 are duplicate edges; it also contains 2,823 self-loops. Group 2 has a density score of (0.0000) which also means that it is not actually a group at all but again sprawling with some connection across subgroups, similar to Group 1. The large number of interactions that occur within Group 2

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indicates that it also is an important channel for distributing STEM-related content, but it is less interactive than Group 1.

More low-interconnectivity Groups 4 and 5 account for 21.58% and 20.36% of the network, respectively. For Group 4, the number of users is 4244 which has a density of (0.000), For Group 5 it is almost similar as they have only around 4004. These smaller groups however show a trend of double linking between each other and back to the larger groups, representing episodic dialogue across clusters while functioning more as independent centres of debate. That shows, also in method group 4 and 5, to high proximities of users within STEM conversation forming local sub-communities (Struweg, 2022). Along with those central groups, a big, isolated group (Group 3) was also detected. In Group 3, the users are out of the main network, with 3,676 unique edges and 6,648 self-loops in this group implies that these users only interacted their tweets. But Group 3 does not have reciprocal links with other groups, indicating that the users who were tweeting on STEM topics were doing it clumsily through active isolation of the rest of Twitter. Group 3 consists of 4,693 single-vertex components which are users with no outward connections (i.e. these accounts have zero edges to any other user in the dataset). This indicates that they may be independently tweeting about STEM-related topics but not engaging with users discussing them within a larger conversation. Such an isolated group pops out in the network graph as a ring of disconnected nodes on the fringes representing a class of Twitter users who talk about STEM review, but do not interact with the networks at their center (Scott, 2017).

Finally, it is interesting to see Group 3 isolated since this seems to fit the pattern in other social network analyses, where isolated groups are users who perhaps use Twitter as a one-way broadcast medium but do not really have access or connections into the core of the network itself. This type of content is commonly referred to in social media research as part of the wider category called "silent broadcasters," or users who transmit but do not receive. Such structure could reveal either a unidirection transfer of information or absence of integration to science-specific Twitter networks (White & Borgatti, 1994). Table 1 shows the summary of the most frequent words occurring in STEM tweets between June 2020 and November 2023. STEM, technology, innovation and education appear frequently — an emphasis on scientific endeavors and their use in human society. Common hashtags, including #STEM, #womeninSTEM, #AI, and #tech also highlight links between STEM fields and those related to digital technology, artificial intelligence (AI), and gender diversity. This prominence characterization indicates that interests of Twitter community on STEM are at technical progress and broader societal issues, including gender equity in technology occupations (Wang et al., 2010). Overall, the analysis of Twitter discussions on STEM indicates that it is a community with a non-simple structure that consisting of several highly interlinked cores, and some more diffuse isolated regions. Each main cluster represents an active sub-community participating in STEM conversation, and the influential users and hashtags lead engagement in and between groups. Such insights not only reveal how STEM topics are discussed on social media, but also indicate potential for additional research on information dissemination and community engagement in digital STEM education and advocacy.

The Top Occurring words during this time period, from June 2020 to November 2023 was shown in Table 1. It highlights mentions of STEM were made in conjunction with the scientific work that linked them to STEM.

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Table 1: Most Frequently Occurring Words.

Words	Entire Graph Count
digital	59335
stem	41073
#stem	24434
de	12716
learning	7965
students	7824
la	7278
en	7126
#digital	7030
girls	6218

The top popular occurring words in Group 1 were displayed in Table 2 below. Here, it can also be seen that many of these words centred on STEM around women.

Table 2: Top Word Pairs in Tweet in Entire Graph

Words	Entire Graph Count
kred, #influence	2565
stem, digital	2460
digital, learning	2173
Digital, skills	2010
Eli_krumova, kred	1894
#ai,#ml	1876
Digital,stem	1694
Stem, education	1595
De,la	1430

Table 3: The Top Popular Occurring Words Group 1

Words	No.
#stem	59334
digital	41073
womeninstem	7278
womenintech	7126
influence	7030

The most frequently occurring words in Group 2 (the second largest cluster of Twitter users) are highlighted in Table 4 below. It is important to note that the word-count numbers listed in Table 4 would also contain hashtags that used those words.

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Table 4: Most Frequently Occurring Words Group 2

Words	No.
digital	8427
stem	8167
learning	4320
students	3240
eas_digital	2906

The power of hashtags created in response to an event and to raise awareness become ad hoc online communities (Golbeck, Ash and Cabrera, 2017). The most frequently occurring hashtags overall are summarized in Table 5 below. These hashtags highlighted the STEM issue around the digital involvement of women in STEM.

Table 5: Most Frequently Occurring Hashtags

Words	Entire Graph Count
stem	24,284
digital	6,983
ai	3877
womeninstem	3,368
womenintech	3,097
tech	3,093
ehtech	2725
influnce	2540
ict	2535
ml	1945

The influential users were ranked by the betweenness centrality algorithm, indegree centrality, outdegree centrality, closeness centrality and eigenvector centrality using NodeXL as shown in Table 6

Table 6: Most Vertex Ranked by Betweenness Centrality, Indegree Centrality, Outdegree Centrality, Closeness Centrality and Eigenvector Centrality

Vertex	betweenness centrality	Indegree centrality	Outdegree centrality	Closeness Centrality	Eigenvector Centrality
Stem_ai	1432173282.00	12	1372	0.215	0.409
Un_women	209565123.20	628	1	0.182	0.409
enricomolonari	133557326.00	715	407	0.184	0.394
wef	107616674.40	520	5	0.184	0.250
africateengeek	104591057.00	641	45	0.173	0.030

Discussion

Building communities on Twitter, there have been lots of research done on how small networks develop and flourish in the localities of interest. Twitter is idiosyncratic, in contrast to other social media platforms; often users' group together to talk about events with hashtags circulating preferably as they happened, creating a space that merges the physical and digital world (Golbeck et al., 2017). This unique surrounding is perfect for conversation on varied topics e.g. STEM (Science, Technology Engineering and Math) that can capitalize with

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hashtags to develop a sense of community and bring about participation all in one small environment. The analysis aimed to do two main things and the first was to find influential actors in #STEM Twitter conversation as concerns the general architecture of STEM network.

The study used network analysis to analyze the structure and layout along with community detection and individual metrics of users participating in these discussions. Struweg (2022) explains that the connectedness of users with other users such as through mentions or retweets and replies can be mapped by using NodeXL software, which helps create clusters or communities in the network. The analysis identifies four main user groups: Group 1, Group 2, group 4 and Group 5. Using betweenness centrality, an indicator of how influential a user is due to their role as connector between different groups, the research finding found the following groups acted as some of top influencers in STEM conversation.

Group 1 and Group 2 constituted our biggest groups, both showing polerized opinions but high engagement. Group 1 was full of STEM advocates, people who promoted anything STEM related while Group 2 had more negatives around them, they often opposed some forms of STEM or certain areas of the STEM norms. The in-degree and betweenness centrality of Group 1 was highest proving its dominance in the conversation. Group 2: This was a smaller group that also talked a lot about things like "digital" and "STEM" but focused more on the topics of STEM education and digital learning. Both groups had low density (0.002), indicating that their engagement went beyond the immediate circle. The central focus for Group 1 was around supporting the participation of women in STEM, whereas Group2 more broadly addressed issues related to digital and STEM learning. In the time series analysis, the overall higher tweet volumes for these groups indicating the fluctuations of topics over time, likely based on changing interest or external triggers such as events. Topics such as "women in STEM," and "digital learning" and discussion around "STEM education" remained on the forefront, with high engagement found in the most widely used words and themes across groups. Remarkably, Group 1, the advocates, had continuous activity from June 2019 up until November 2022 which means their efforts were consistent despite the impact of COVID-19 pandemic on many societies. This supports the findings in Golbeck et al. (2017), Twitter will continue to serve as a key platform for building communities, even when all seems lost. Twitter played overall as a forum for STEM advocacy, further strengthening its ideal utility as a virtual community-building space.

Research shows that these digital spaces offer both moral and informational support, bettering the well-being of group members. Twitter presents women with a chance to engage, providing a remedy for the hindrances they sometimes encounter in academia or the profession. During the period of review, Group 1 consistently remained more active than other groups indicating that counter actors to STEM were less effective in their calls for action [12]. Differences also emerged when looking at tweets versus replies and retweets separately: while Group 1 had the highest number of original tweets, Groups 2,3 and 4 actually generated more retweets, indicating that they were sharing STEM knowledge with higher engagement as well as promoting their position to a larger audience. These groups were smaller in number, but Groups 2, 3 and 4 showed a considerable level of commitment to their positions, which also manifested itself in a growth on Twitter.

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For research question 2 and research question 3, content analytic techniques were employed with respect to text (research question 2), top terms and time series data (research question 3). This analysis revealed trends in conversations about science, technology, engineering and math (STEM) topics based on how users engaged with them and how closely connected those users are. Also the high network density in clusters indicated of opinion leaders. Core influencers were network users with high in-degree (forming ties to other members) and out-degree (having more connections) values while isolated users, who lack broad connectivity, have minimal impact on advances in the network visualization. These online communities were primarily built through hashtags, which created loose gatherings of users talking about the same topic and allowing them to congregate in virtual spaces (Golbeck et al., 2017). Common derivatives of the STEM conversation with identifiers such as #STEM, #Digital, #WomenInSTEM and #Tech became popular. This made participants part of a bigger community that had shared experiences, struggles and support encouraged through the use of these hashtags. Hashtags allowed women to talk about sexual discrimination or harassment methods in STEM fields, bringing social support and solidarity.

The other hashtag #Feminism raised gender issues related to STEM and provided a place for women to talk about their specific challenges. Not only did this ad hoc network fulfill the desire for belonging, it also increased awareness of gender-related problems in STEM and contributed to supportive as well as activist conversations (Golbeck et al., 2017). These Twitter community-building elements assisted in broadcasting feminist issues into the STEM discourse and facilitating sociocultural recognition (Cohen 2014). The analysis also shows gendered Twitter usage differences. For example, they discovered that female legislators on Twitter were more active communicators than males and typically expressed more positive sentiments than males. That may mean that women legislators more frequently discussed policy and gender issues, implying that Twitter opened up a space in which women could contribute to discussions of substance and advocacy in different ways from men. These findings expand prior research on Twitter as a platform that can foster relationship building and engagement across gender.

Conclusion

This study shows that social media can be applied to discussions about other current issues, particularly those relevant to STEM (Science, Technology, Engineering and Mathematics). In particular, social media — and the reach of voices that shape it — is an effective device for increasing interest in STEM-affiliated subjects. They also attract the interest of Influencers in STEM, whose work leads to greater public exposure and participation, laying the groundwork for future generations to pursue careers that are critical to improving life and growing our economy. This increasing awareness about the societal value of STEM is an indication of its role in driving education and economy policies for the future.

In addition, this study underlines the importance of more studies to establish a general methodological framework using Social Network Analysis (SNA) to analyze gender inequalities in STEM in a systematic manner. By utilizing an integrated Social Network Analysis (SNA) perspective, more informed details can be gained on how the structures that perpetuate gender inequality in STEM interact and consequently fill evidence gaps to inform policy change. Utilization of SNA allows researchers to analyze how network patterns, interactions, and influences affect gender representation in STEM which potentially can inform educational policy for a more equitable framework (Golbeck et al., 2017; Struweg, 2022).

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