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# Investigating Innovation Diffusion in Gender-Specific Medicine: Insights from Social Network Analysis

Katharina Baum · Annika Baumann · Katharina Batzel

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**Abstract** The field of healthcare is characterized by constant innovation, with gender-specific medicine emerging as a new subfield that addresses sex and gender disparities in clinical manifestations, outcomes, treatment, and prevention of disease. Despite its importance, the adoption of gender-specific medicine remains understudied, posing potential risks to patient outcomes due to a lack of awareness of the topic. Building on the Innovation Decision Process Theory, this study examines the spread of information about gender-specific medicine in online networks. The study applies social network analysis to a Twitter dataset reflecting online discussions about the topic to gain insights into its adoption by health professionals and patients online. Results show that the network has a community structure with limited information exchange between sub-communities and that mainly medical experts dominate the discussion. The findings suggest that the adoption of gender-specific medicine might be in its early

stages, focused on knowledge exchange. Understanding the diffusion of gender-specific medicine among medical professionals and patients may facilitate its adoption and ultimately improve health outcomes.

**Keywords** Health data · Gender-specific medicine · Social network analysis · Diffusion of innovations · Twitter

## 1 Introduction

With healthcare being one of the most innovative industries (Grassano et al. 2021), the advent of new knowledge is common. Recent medical developments include the recognition of gender-specific medicine, a medical subfield focusing on sex and gender disparities in clinical manifestations, outcomes, treatment, and prevention of diseases (Legato 2003). Sex and gender differences impact various illnesses, including cardiovascular disease, cancer, stroke, Alzheimer's, diabetes, and depression (Mauvais-Jarvis et al. 2020). These differences may arise from sex-related factors like hormone-driven immune responses and gender-related factors like lifestyle and socioeconomic conditions (Gebhard et al. 2020). As the symptoms of some diseases differ significantly between men and women, a lack of awareness and, as a result, inadequate treatment can have life-threatening consequences for patients (Regitz-Zagrosek 2006). Therefore, understanding the extent to which gender-specific medicine is being adopted by the medical community and examining stakeholder discussions can help promote the adoption of new medical practices that take into account sex and gender differences.

However, to date, biological factors (sex differences) and sociocultural aspects (gender differences) that affect men and women differently have received limited attention

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in research and practice and are even less known to the general public (Baggio et al. 2013). In fact, the discussion of this phenomenon has largely been limited to researchers and professionals in the field, leaving the broader public uninvolved and unengaged (Mauvais-Jarvis et al. 2020). Gender-specific medicine, a topic that originated in the 1980s but still lacks widespread implementation today (Mauvais-Jarvis et al. 2020), is not the only healthcare innovation characterized by slow diffusion and adoption. On average, it takes about 17 years from the conclusion of clinical research to reach 50 percent adoption in clinical practice (Balas and Boren 2000). Importantly, timely recognition, dissemination, and adoption of innovations in healthcare is essential. This critical aspect is illustrated by a study showing that of all the articles on a particular liver disease published between 1945 and 1999, 19 percent were considered outdated by the year 2000, and 20 percent were found to be incorrect (Balas and Chapman 2018). Understanding the diffusion of medical innovations can help accelerate their adoption by identifying barriers and facilitators (Afraz et al. 2021). Therefore, shedding light on the diffusion of information about gender-specific medicine can play an important role in advancing its adoption by researchers and practitioners alike.

A theoretical underpinning for how innovations spread has been developed by Rogers (1976), who defines innovation as any novel idea, practice, or object. His Innovation Decision Process Theory details how innovations are accepted or rejected over time. According to Rogers (2003), innovations disseminate through diffusion, a process by which they spread among members of a social system via communication channels (Oldenburg and Glanz 2008). The term “diffusion” originates from physics, which describes the stochastic spread of objects from a place of higher concentration to a lower concentration. This terminology has since been adapted to many contexts concerned with how new practices, technologies, or ideas spread through a population or social system, such as sociology, economics, and marketing (Rosenberg 1972; Strang and Meyer 1993). The Innovation Decision Process Theory outlines five stages of innovation diffusion: knowledge, persuasion, decision-making, implementation, and confirmation (Lee 2004; Rogers 2003). These stages span from the initial exposure to innovation toward its adoption and, finally, to the stage of seeking reassurance post-adoption (Rogers 2003). In this regard, influential individuals can play a crucial role in the diffusion of innovations. They occupy central or bridging positions in networks and can acquire and disseminate large amounts of information, which may speed up the adoption process (Cavusoglu et al. 2010; Probst et al. 2013).

Social networking sites (SNSs), defined as online platforms that allow individuals to create profiles, connect with

other users and share content, interests and activities within a virtual community, could be a potential facilitator for the diffusion of health innovations (Boyd and Ellison 2007). These platforms have revolutionized healthcare communication, enabling physicians, patients, and healthcare organizations to inform, discuss, and seek advice on health-related topics online (Yan et al. 2015). Due to their role in disseminating information, public SNSs are especially relevant in this context. Here, Twitter<sup>1</sup> offers unique opportunities for spreading health information since several platform affordances promote information flow. For example, communication in the form of tweets and the use of links and hashtags enable efficient information intake by the user, as messages are easy to process and fast to read (Gleason 2013). Furthermore, hashtags facilitate following, joining, and engaging in conversations around a specific topic, which allows virtual communities to form around a shared interest (Bruns and Burgess 2011; Xu et al. 2015). Interaction is further enabled through reply, retweet, quote, and mention functions. These affordances make Twitter an especially prominent forum for exchanging information on health-related topics such as gender-specific medicine (Pershad et al. 2018). The network is used by academics, practitioners, and patients alike (Choo et al. 2015; Erskine and Hendricks 2021), all of whom are relevant stakeholders in spreading and adopting knowledge about this topic.

Given Twitter’s significant role in disseminating health information, examining the existing discourse about gender-specific medicine can provide information about this innovation’s adoption level in the medical community. The topics being discussed, the flow of information, and the network structure may all yield insights into the stage of the innovation cycle that gender-specific medicine is currently in. Furthermore, studying influential users can provide insights into the type of actors who dominate the discussion and how they direct the flow of information. In this study, building on the Innovation Decision Process Theory, we examine the spread of information about gender-specific medicine on SNSs to draw conclusions about the medical online community’s awareness and adoption of the topic. In particular, we ask the following research questions: (1) *What information about gender-specific medicine is shared among network members?* (2) *What stage of adoption is gender-specific medicine currently in?* (3) *Who are the influential users in the network, and how do they contribute to disseminating information on gender-specific medicine?*

To answer these questions, we collected a Twitter dataset that reflects the network of discussions on gender-

<sup>1</sup> At the time of data collection, the platform was known as Twitter. However, it has since been renamed to X. Throughout this study, we will refer to the platform by its name at the time of data collection.

specific medicine. Using social network analysis, we can uncover connections and interactions among the individuals in the network. This allows us to shed light on how information is disseminated within the network, which is pivotal for understanding how innovations spread. A qualitative analysis of the tweets reveals insights into the information discussed within different network sub-communities. Further, we identify influential users in the network and examine their strategies to disseminate information.

This study makes several important theoretical and practical contributions. From a theoretical perspective, it adds to the literature on how health-related content spreads on SNSs (Singh et al. 2020; Roy et al. 2020). Our study further contributes to the growing domain of social media analytics in the Information Systems (IS) field, in which researchers use social media data to gain insights about patterns in communication (Stieglitz et al. 2014, 2018). We add to this literature by using social media data to analyze the innovation diffusion of an emerging topic in healthcare. Further, we add to the IS literature on innovation diffusion (O Riordan et al. 2009; Parameswaran et al. 2023) by examining how gender-specific medicine has been adopted by the various stakeholders contributing to the discussion within the Twitter network. Regarding practical contributions, insights from our research can benefit public institutions, such as ministries of health or medical associations, to measure public knowledge on gender-specific medicine and plan health literacy campaigns accordingly. Further, insights about the diffusion of innovation in gender-specific medicine among the medical community and patients might help facilitate its adoption. In addition, identifying influential actors in the network might help spread awareness campaigns more effectively by directly targeting users who can act as significant information multipliers.

## 2 Theoretical Background

### 2.1 Gender-Specific Medicine: A Healthcare Innovation

Gender-specific medicine is one of the most pressing recent innovations in the healthcare field (Schiebinger and Klinge 2015). This growing stream of research is concerned with studying and eliminating sex and gender disparities in medicine (Legato 2003; Oertelt-Prigione 2020). While many factors influence a person's health, two of the most important are sex and gender (Regitz-Zagrosek 2012). Sex refers to biological characteristics such as chromosomes, genes, anatomy, and hormones. Gender, on the other hand, is a social construct. It refers to the norms, behaviors, and

roles associated with being male or female (Baggio et al. 2013). Although both variables are critical to healthcare, they have long been neglected (Baggio et al. 2013). Historically, biomedical studies, clinical trials, and drug development primarily focused on male subjects, including cells, mice, and men (Clayton 2016). This bias stemmed from the assumption of cellular uniformity between sexes, leading medical studies to generalize findings for both sexes.

But medicine is not sex- or gender-neutral. Sex and gender differences occur in a wide range of diseases. Cardiovascular disease, cancer, pulmonary disease, stroke, Alzheimer's disease, diabetes, or depression are all affected by sex and gender (Mauvais-Jarvis et al. 2020). In cardiovascular disease, for example, heart failure in women often goes undiagnosed because of diverging symptoms (Baggio et al. 2013). While there is a substantial overlap in symptoms of cardiovascular diseases like acute cardiovascular syndrome, some of the symptoms vary between men and women, which leads researchers to conclude that symptoms should no longer be classified as "typical" or "atypical" (van Oosterhout et al. 2020). Further, osteoporosis is often overlooked or misdiagnosed in men because more studies have been conducted in women (Baggio et al. 2013).

Health outcomes further vary based on whether individuals identify with binary or non-binary gender identities. Gender encompasses social, cultural, and psychological traits linked to being male or female, while gender identity reflects one's internal sense of being masculine, feminine, or a mix of both (Morrow and Messinger 2006). Studies indicate that transgender individuals whose gender identity differs from their assigned sex at birth (Stryker et al. 2008), especially those identifying as non-binary, experience poorer health outcomes compared to those with binary gender identities (Reisner and Hughto 2019). Scholars further call for not only integrating sex and gender into medical research and practice but also considering how they intersect with factors like culture, ethnicity, and socioeconomic status, as these significantly influence health (Subramaniapillai et al. 2024). Incorporating sex and gender into medical approaches benefits all individuals more effectively than a one-size-fits-all approach (Regitz-Zagrosek 2012).

Over time, the focus on male specimens as the norm for healthcare trials has begun to shatter, and the need to include additional variables such as sex and gender in health research has become apparent (Legato 2003). As early as the 1980s the US National Institutes of Health and the Food and Drug Administration recognized that most diagnostic and therapeutic strategies were geared toward men (Regitz-Zagrosek 2011). Despite this, sex and gender biases persist in medicine, and the topic is as relevant as

ever (Yakerson 2019). This gap has become evident during the COVID-19 pandemic, where only 21% of the planned clinical studies explicitly proposed sex and gender balance as recruitment criteria and only 17.8% of published studies included sex as an analytic variable (Brady et al. 2021). These disparities are further reflected in medical school curricula, most of which do not adequately address how sex and gender affect disease and treatment, hindering physicians' ability to effectively care for their patients (Henrich and Viscoli 2006; Mauvais-Jarvis et al. 2020; Regitz-Zagrosek 2012). For example, a recent survey found that most German medical faculties do not teach the impacts of gender on health and treatment (Wortmann et al. 2023). However, medical professionals are not the only ones missing out. Mosca et al. (2013) report that women's awareness of symptoms of cardiovascular disease remains low. In 2020, Mauvais-Jarvis et al. (2020) note that the impact of sex and gender on human health and disease is consistently undervalued, inadequately researched, and insufficiently utilized within medical practice. On its website, the Office of Research on Women's Health (2021) states: "Much is known about the influences of sex and gender on health and disease; however, much more is unknown." These examples illustrate that although sex and gender differences in medicine have been known since the 1980s, the adoption of gender medicine in medical research and practice has been slow.

Recently, sex and gender disparities in medicine have gained increased attention, with coverage expanding from academic journals to mainstream media. For instance, the German newspaper Die Zeit now reports on health-related gender inequalities (Eisenreich 2021), and BARMER, a German health insurance company, has launched an advocacy campaign against unequal medical treatment of men and women (Tutzer 2021). Internationally, outlets like The New York Times and The Guardian have also addressed this issue (Jackson 2019; Rabin 2019). The COVID-19 pandemic has further emphasized differing impacts on men and women, raising public awareness of gender disparities in healthcare (Gebhard et al. 2020). However, despite these developments, gender-specific medicine is only gradually being adopted in clinical practice (Henrich and Viscoli 2006; Regitz-Zagrosek 2012) and remains largely unfamiliar to the general public (Mauvais-Jarvis et al. 2020).

## 2.2 Diffusion of Innovations

Adopting new knowledge and innovations while phasing out outdated practices is crucial in advancing healthcare. Improving patient outcomes relies on identifying valuable innovations, disseminating them effectively, and integrating them into medical practice (Balas and Chapman 2018).

Despite high volumes of medical research, the rate at which new insights are incorporated into medical education and the treatment of patients can be slow: On average, the time required from the completion of clinical research to achieve 50 percent adoption in clinical practice is approximately 17 years (Balas and Boren 2000). Consequently, understanding the dynamics of innovation diffusion within healthcare holds significant importance for academics and practitioners alike.

The process of how innovations are adopted has been researched extensively in various fields, including the healthcare sector (Sahin 2006; Milella et al. 2021). One of the most widely used theories to explain innovation diffusion was introduced by Rogers (1976). According to Rogers, an innovation is any idea, practice, or object that appears new to an individual or other unit of adoption (Rogers 2003). The Innovation Decision Process Theory (Rogers 2003) describes the process by which an innovation is accepted or rejected over time.

According to Rogers (2003), innovations spread through a process called diffusion, where they propagate through communication channels within a social system (Oldenburg and Glanz 2008). Adopting innovations is a gradual process that involves evaluating its benefits against uncertainty and the current solution (Rogers 2003). The Innovation Decision Process Theory outlines several stages: the *knowledge stage*, where initial exposure to an innovation and information gathering occurs actively or passively (Rogers 2003), and the *persuasion stage*, where favorable or unfavorable attitudes toward the innovation are formed (Rogers 2003). Unlike the knowledge stage, which is mainly characterized by cognitive mental activity, the predominant type of thinking about the innovation in this stage is affective (Rogers 2003). In the *decision stage*, adoption or rejection takes place (Lee 2004), followed by the *implementation stage* in the case of adoption (Lee 2004). Finally, in the *confirmation stage*, reassurance about the decision is sought (Rogers 2003).

In the medical field, the Innovation Decision Process Theory has been used to describe the adoption of several novel technologies and ideas. For example, the model can accurately explain nurses' behavior while using a novel computerized care system (Lee 2004). Further, the theory was applied to identify barriers and facilitating factors for adopting a novel integrated care and funding model for mental health in Germany (Afraz et al. 2021). Another study conceptualized the diffusion of innovations from clinical research to implementation in medical practice by building on the five innovation stages (Balas and Chapman 2018).

Besides its application in healthcare, the Innovation Decision Process Theory is often used to explain technology diffusion. In the domain of IS, the diffusion of novel



technologies has been studied in various contexts. For example, researchers have examined how innovations spread in digital worlds (O Riordan et al. 2009), how the process of early-stage diffusion of codependent IT innovations can be explained (Parameswaran et al. 2023), or how the diffusion of an IT innovation is linked to the visions of organizations (Miranda et al. 2015). Our study extends this research by focusing on the healthcare domain, particularly by shedding light on innovation diffusion in the emerging field of gender-specific medicine.

### 2.3 Analyzing Innovations Diffusion in Gender-Specific Medicine Using Online Networks

The widespread use of SNSs has fundamentally changed how we communicate and share information, including how we talk about health (Cain and Mittman 2002). Thus, the stakeholders involved in the diffusion of innovations concerning gender-specific medicine may now use SNSs to share, disseminate, and promote information about the topic.

Adopting innovations like gender-specific medicine involves various stakeholders, including policymakers, public health agencies, physicians, scientists, academic institutions, and patients (Cain and Mittman 2002). These stakeholders play crucial roles in assessing, providing, researching, and educating about new medical innovations. On SNSs, these stakeholders now have tremendous opportunities to connect and collaborate with others, actively participate in discussions, and disseminate or receive health-related information (Eysenbach 2008). For example, politicians educate on health-related legislation, public health agencies monitor outbreaks and run campaigns (Kriek et al. 2011), and healthcare providers form virtual communities, share educational resources, and exchange professional insights (Choo et al. 2015). Patients harness these platforms to access professional knowledge, understand individual health factors, seek advice, and form supportive communities for diseases like breast or prostate cancer (Himmelboim and Han 2014; Chen et al. 2018; Sugawara et al. 2012). Further, health organizations promote literacy and engage with consumers (Park et al. 2013), benefitting from Twitter's accessibility and user base as a cost-effective outreach tool. Therefore, analyzing online discussions on Twitter can yield valuable insights about the adoption of gender-specific medicine among the relevant stakeholders.

One way to analyze such conversational networks on SNSs is social network analysis. Social network analysis, rooted in graph theory, defines social entities as nodes and their communication through arbitrary interaction as links (Wasserman and Faust 1994). This analysis can be a powerful tool in investigating the diffusion of innovations

because it focuses on understanding relationships and interactions between individuals or entities within a network (De Nooy et al. 2018). Network analysis provides insights into how information spreads through networks, which is crucial to understanding innovation diffusion. It offers a set of methods and metrics to measure the structural properties of social networks, such as the presence of communities (Freeman 2004).

When it comes to studying how information spreads through networks, several characteristics are essential. One is the degree of centralization of the network's underlying structure. In highly centralized networks, only a few users dominate the information flow (Barabási 2009; 2016). Another critical network property is the distribution of connections or the degree. Typically, this shows a highly skewed pattern: A small number of nodes with many connections, followed by a trailing tail of nodes with very few connections (Barabási 2016). Here, the average degree is the average number of edges per node, which informs the network's connectivity. The average path length measures the average number of steps along the shortest path for all possible pairs of nodes in the network. Smaller numbers indicate that information travels more efficiently (Jackson 2008). Another centrality metric is the betweenness centrality, which focuses on nodes that are important connecting points in the network (Burt 2018). Betweenness centrality measures the shortest paths passing through a particular node. A high betweenness centrality shows a node's significance for information flow since many paths traverse the node (Freeman 2002). Similarly, the density level strongly affects a network's information flow. In dense networks, individuals maintain close ties with others and form highly concentrated communities (Himmelboim et al. 2017). A network's diameter denotes the largest distance and measures how far information must travel to reach the whole network (Jackson 2008). The clustering coefficient describes how many nodes cluster together and form groups (Jackson 2008). Furthermore, it is common to find individuals who do not communicate with their peers (Wasserman and Faust 1994). These so-called isolates are disconnected and cannot receive information through social exchange (Haythornthwaite 1996).

Social network analysis has been applied across various domains to explore innovation diffusion. Bolici et al. (2020) examined innovation spread in tourism via Twitter exchanges, while Kolleck (2013) studied sustainable education adoption through social networks. Broader applications of social network analysis include analyzing information diffusion about COVID-19 (Singh et al. 2020), H1N1 (Chew and Eysenbach 2010), and Ebola outbreaks (Roy et al. 2020). Further studies looked into online debates among pro- and anti-vaxxers (Himmelboim et al. 2020), online breastfeeding discussions (Moukarzel et al.

2020), and the dissemination of information on tobacco use (Chu et al. 2019), and cancer (Wang et al. 2020). In summary, stakeholders in gender-specific medicine increasingly use platforms like Twitter for communication, and social network analysis aids in understanding innovation diffusion of this topic.

## 2.4 The Role of Influential Users in Innovation Diffusion Online

When examining the diffusion of innovations, certain user types are of interest. Rogers' (2003) innovation diffusion theory outlines a classification system for individuals based on when they adopt an innovation, consisting of five distinct categories. *Innovators* lead the adoption of new ideas, with *early adopters* following suit, often taking on leadership roles to spread innovations. The *early majority* waits for widespread acceptance, while the *late majority* adopts innovations after they have become commonplace. *Laggards* are the final group to adopt innovations (Rogers 2003).

In the study of information diffusion in online social networks, the extension of these five types of users by the concept of *influential users* has attracted substantial interest (Cha et al. 2010). Influential users are those who not only adopt ideas but also significantly facilitate their dissemination (Cavusoglu et al. 2010; Probst et al. 2013). Therefore, they are essential to the diffusion of innovations because they can speed up the adoption process (Goldenberg et al. 2009). Influential users occupy central or connecting positions in networks and, therefore, have access to and can forward a great deal of information (Haythornthwaite 1996). Influential actors may include celebrities, news media, social activists, politicians, or sports figures (Cha et al. 2010; Bakshy et al. 2011). Several studies have demonstrated that influential users exist in online discussions about health-related topics, such as emergency medicine (Riddell et al. 2017), information about Ebola (Liang et al. 2019) and COVID-19 (Kim and Valente 2021), or vaccine debates (Featherstone et al. 2020).

Different methods exist for identifying influential users, reflecting the complex nature of influence (Cha et al. 2010). For instance, follower count serves as one metric for audience size (Cha et al. 2010), while others assess the number of connections to neighboring nodes as an indicator of rapid information dissemination (Boulet and Lebraty 2018). A key distinction lies between a user's centrality in a network and their bridging of different network segments (Araujo et al. 2017). Highly *central users* possess numerous connections and play pivotal roles in information exchange (Boulet and Lebraty 2018). Acting as hubs, they facilitate extensive knowledge transmission, which is crucial in time-sensitive scenarios like crisis

communication (Fan et al. 2021). Further, users bridging structural gaps between disconnected groups, known as *information brokers*, facilitate cross-community information flow (Araujo et al. 2017). Their absence could impede inter-group communication, which emphasizes their significance. Research on platforms like Twitter (Bakshy et al. 2011) and YouTube (Liu-Thompkins and Rogerson 2012) underlines the vital role of information brokers in social media information dissemination. Even with an average or below-average amount of connections, targeting an audience in a bridging position enhances information diffusion (Bakshy et al. 2011).

Identifying influential nodes in social networks has broad implications. For example, addressing a select group of influencers in viral marketing can efficiently promote new products (Goldenberg et al. 2009). In health communication, understanding influential users aids in assessing information credibility and refining communication strategies (Kim and Valente 2021). For gender-specific medicine, studying influential users offers insights into the type of actors who dominate the discussion and highlights structural obstacles hindering knowledge dissemination.

## 3 Methodology

### 3.1 Data Collection and Search Term Selection

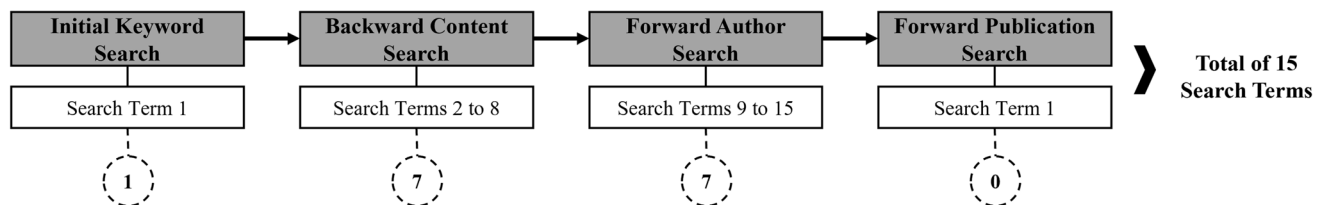
We collected publicly available tweets containing 15 different search terms (see Table 1) from Twitter from January 1 to May 31, 2021. We deliberately chose a more extended sampling period compared to other literature from the health awareness field (e.g., Araujo et al. 2017; Himelboim et al. 2020), which is often focused on events. Since the discussion on gender-specific medicine is an ongoing process of actors raising awareness (Legato 2003), we collected tweets over a 5-month period to ensure the connectivity of the tweets and users. We collected only tweets written in English. To select the search terms, we adopted a search strategy similar to those used in literature reviews (e.g., Webster and Watson 2002), constituting of four steps: (a) Initial keyword search, (b) backward content search, (c) forward author search, and (d) forward publication search (see Fig. 1).

Following this approach, we (a) started with the term “gender-specific medicine” in all its possible spellings. (b) We then scanned the tweets obtained from the first search term for further clues about other popular terms and hashtags used in the field. This strategy identified seven additional search terms (see Table 1, rows 2–8). (c) We then conducted an author-centric forward search through the Twitter profiles of the 16 most prominent individuals and organizations in the field based on their academic

**Table 1** Search terms and descriptive statistics of the final data sample

No	Search terms	Tweets	Thereof original	Users	Replies	Mentions	Retweets	Quotes
1	(#GenderSpecificMedicine OR “gender specific medicine” OR #GenderMedicine OR #GenderedMedicine OR (“gender specific” medicine))	208	67	310	115	148	106	8
2	(“precision medicine” OR #PrecisionMedicine) (sex OR gender)	562	95	406	83	224	426	14
3	(#GenderDataGap OR “gender data gap”) *	326	62	420	159	42	264	7
4	#HeartDiseaseInWomen	36	7	43	1	22	25	4
5	#SexDifferences OR #SexDifference	1469	283	1375	180	600	1087	69
6	#SexMatters	673	45	680	132	166	529	42
7	(#GenderBias OR “gender bias”) * -#WomenInSTEM - leadership -promotion	3673	739	4322	1118	1290	2449	127
8	#MedicalBias	71	46	145	33	34	8	6
9	#SABV	1956	251	1492	396	647	1577	82
10	(#GenderDifferences OR #GenderDifference)*	27	14	27	0	8	12	1
11	#HerHeartMatters	3698	618	1840	809	2484	2655	299
12	#SexAndGender *	279	57	318	50	176	183	24
13	“sex & gender” * -transphobia -trans -transgender -transsexual -dysphoria	2114	445	2804	975	1317	1217	79
14	#SexBias	57	9	72	22	17	43	1
15	#GenderData *	114	28	103	2	26	77	7
TOTAL		15,263	2745	14,357	4075	7201	10,658	770
TOTAL (w/o duplicates)		15,061	2695	12,709	4014	6950	10,526	769

\*(rehabilitation OR vaccine OR diagnosis OR health OR medicine OR clinical OR therapy OR treatment OR disease OR illness OR symptoms OR prevention)

**Fig. 1** Illustration of the search term selection process

activity and/or activity on Twitter,<sup>2</sup> which yielded seven additional search terms. (d) We inspected keywords of 60 research papers from 2021 covering the topic of gender-specific medicine authored or co-authored by the people identified in the previous step. None of those publications led to the identification of new hashtags, but previously identified terms could be detected. We regarded the re-occurrence of familiar content without detecting new information as an indicator of saturation (Webster and Watson 2002), leading to a final selection of 15 search strings (see Table 1).

The complete list of search terms and the number of tweets, users, and interactions can be found in Table 1. To

ensure search results were concerned with gender-specific medicine, broad keywords that could potentially touch on a variety of adjacent topics (e.g., “gender bias”) were further refined by adding a search string with terms from the medical field.

### 3.2 Social Network Analysis and Identification of Influential Users

To conduct the network analysis, we used the Python package NetworkX to build the network (Hagberg et al. 2020). In our network, users serve as the nodes, and their interactions in the form of retweets, quotes, replies, and mentions are the links. Since we regard different interaction forms as connections between users, the network needs

<sup>2</sup> The full list is available from the authors upon request.



to visualize multiple ties between the same two actors. This characteristic is labeled multivariant and represented by a multigraph (Wasserman and Faust 1994).

After constructing the network using NetworkX, we followed the classification approach by Himelboim et al. (2017) to uncover the structure of discussions on gender-specific medicine. As opposed to previous approaches that were based on specific users and their positions in the network, this classification technique employs four network-level metrics (density, modularity, centralization, and the fraction of isolates) to classify networks into archetypes (Himelboim et al. 2017).

The literature distinguishes between six different network archetypes that yield information about information dissemination patterns (Smith et al. 2014): (1) Polarized crowds, with dense connections within groups but limited interaction across networks, leading to knowledge silos due to strong homophily. (2) Tight crowds, with high connectivity, enabling rapid information dissemination but risking redundancy. (3) Fragmented brand clusters, where users discuss a topic without interaction, resulting in low density and lacking hubs or community structure. (4) Clustered community networks, which emerge from diverse small conversations that represent diverse discussions. (5) Broadcast networks, with a centralized flow of information similar to traditional mass media. (6) Support networks, where one user interacts with many, fostering a free exchange of information.

Four steps are needed to define the network's structure and topology: Step 1 involves calculating the network's centralization, measured as the sum of all nodes' degree centrality divided by the number of nodes. A centralization of 0 implies equal degrees for all nodes, while 1 indicates all actors connected to a single node, as in a star-shaped network (Wasserman and Faust 1994). A centralization value of 0.59 or higher indicates high centralization, while lower values signify decentralization (Himelboim et al. 2017). If the network's centralization is below 0.59, step 2 measures density. Density ranges from 0 (no links between nodes) to 1 (fully connected network). Networks with a density of 0.12 or more are densely connected (Himelboim et al. 2017), potentially dominated by unified or divided clusters impacting information flow. High-density networks undergo step 3, measuring network modularity to assess overall connectivity. A modularity value of 0.29 distinguishes high from low modularity (Himelboim et al. 2017). This step is skipped for low-density networks. The final step calculates the share of isolates among all users to differentiate between sparse networks with few connected communities (clustered) and networks with many isolates and few clusters (fragmented) (Himelboim et al. 2017). The share of isolates is calculated as the proportion of users who do not interact with other users. An isolate share of

19% or higher indicates fragmentation, while values below 19% imply a clustered network structure.

We analyzed central users and information brokers to examine the influential users in the gender-specific medicine network. Central users were identified based on the degree of a node (Boulet and Lebraty 2018). In social network analyses on Twitter, degree is one of the most commonly used metrics to detect influential users. It has been employed, for example, to identify influential users during World Breastfeeding Week (Moukarzel et al. 2020). Information brokers are equally essential in the network for information flow since they connect two different audiences that might otherwise be separated. We identified information brokers in the network based on the betweenness centrality of a node (Boulet and Lebraty 2018). Betweenness centrality is also widely employed to detect influential users on Twitter. For example, in the context of images shared in vaccine debates, Milani et al. (2020) identified key actors by their betweenness centrality and in-degree.

Using a variety of metrics to detect the most influential users is not uncommon. Multiple centrality measures are often used to detect the most influential users in a network. In their social network analysis of health knowledge sharing, Xu et al. (2015) calculated in-degree, out-degree, and betweenness centrality as defining measures for analyzing the central participants. In this regard, it is important to note that the centrality measures correlate, especially with degree (Boulet and Lebraty 2018).

### 3.3 Qualitative Data Analysis

To understand the underlying themes discussed within the gender-specific medicine network, we relied on concepts from the general procedure of grounded theory coding (Corbin and Strauss 1990; Strauss and Corbin 1998). In the first step, to narrow the focus to the major thematic streams discussed, we selected the ten largest sub-communities of the complete network based on the Louvain method implemented in Gephi. The associated tweets were selected for those identified ten communities to code them following an open and axial coding procedure (Wiesche et al. 2017). Upon the first engagement with the qualitative data that the selected communities contributed, we used an open coding procedure to initially coarsely understand prevalent themes and concepts apparent in the data. In a subsequent step, we engaged in axial coding to get a more fine-grained understanding of the community discussion. Through this, we identified two major categories revolving around the framing of the tweet and the underlying concrete matter discussed. Hereby, the framing relates to how the matter is approached. Specifically, we identified the sub-categories of “personal story”, “raising awareness”, “announcing

events”, “sharing information pieces”, “popularizing networks”, and “other”. The category referring to the discussed matter relates to the actual content of the tweet at hand. Here, “heart health”, “neuro” (including mental health), “COVID-19”, “surgery” (including ICU care and emergency hospitalizations), “gender identity”, and “data gap” were identified as leading codes prevalent in the data. The categories and associated codes were then used to determine the overarching themes discussed within the sub-communities and to understand the underlying narrative approach to addressing each theme (see example codes in Table 2).

## 4 Results

In the following section, we summarize the results of our analysis using the methods described in the previous section. We outline the results of the social network analysis, starting with an overall network classification, followed by a deep dive into the network features and their implications for the information flow. Further, we present an analysis of the structure and content discussed in the largest sub-communities, including identifying influential users and their main strategy to distribute the topic of gender-specific medicine within the network.

### 4.1 Network Structure and Information Flow

For the social network analysis, we created a network comprising 12,603 nodes and 16,704 links (replies: 2240; mentions: 5243; retweets: 9221) to capture the network structure of gender-specific medicine conversations. As they do not contribute to information circulation, 585 self-loops were removed. A total of 503 isolates were detected. In-degree and out-degree yielded the same result, with an average of 1.6 links directed inwards and outwards between users. On average, 3.22 interactions on gender-specific medicine took place between individuals over five months. The resulting network is shown in Fig. 2.

In the following, we present the results of applying Himelboim et al.’s (2017) classification approach. The analysis shows that (1) Network centralization was very low (0.0002103). With values close to zero, the cut-off value of 0.59 for a highly centralized network was far from being met. Hence, our first observation was that the gender-specific medicine network is strongly decentralized. When further analyzing the distribution of relationships between users, we found that the weighted degree distribution of the network was characterized by a high number of nodes with a degree of 1 and by a short right tail of nodes with a higher

degree. Hence, the degree distribution followed a power law. The observed degrees varied between 1 and 759, where most nodes (8268 or 65.6%) had a degree of 1, and 1626 (12.9%) had a degree of 2.

Most users thus interacted with or were addressed by others only once, and mutual interaction rarely occurred. (2) The next stage involved an examination of the network density. As the network of gender-specific medicine was decentralized, it could be structured as one unified accumulation of users or divided into different camps (Himelboim et al. 2017). Results showed that density was low (0.0001052), far below the threshold of 0.12. Hence, we observed only a small interconnectedness compared to other networks. All values remained above the 0.0001 (0.01% of all possible connections) measured in the network on gender-specific medicine.

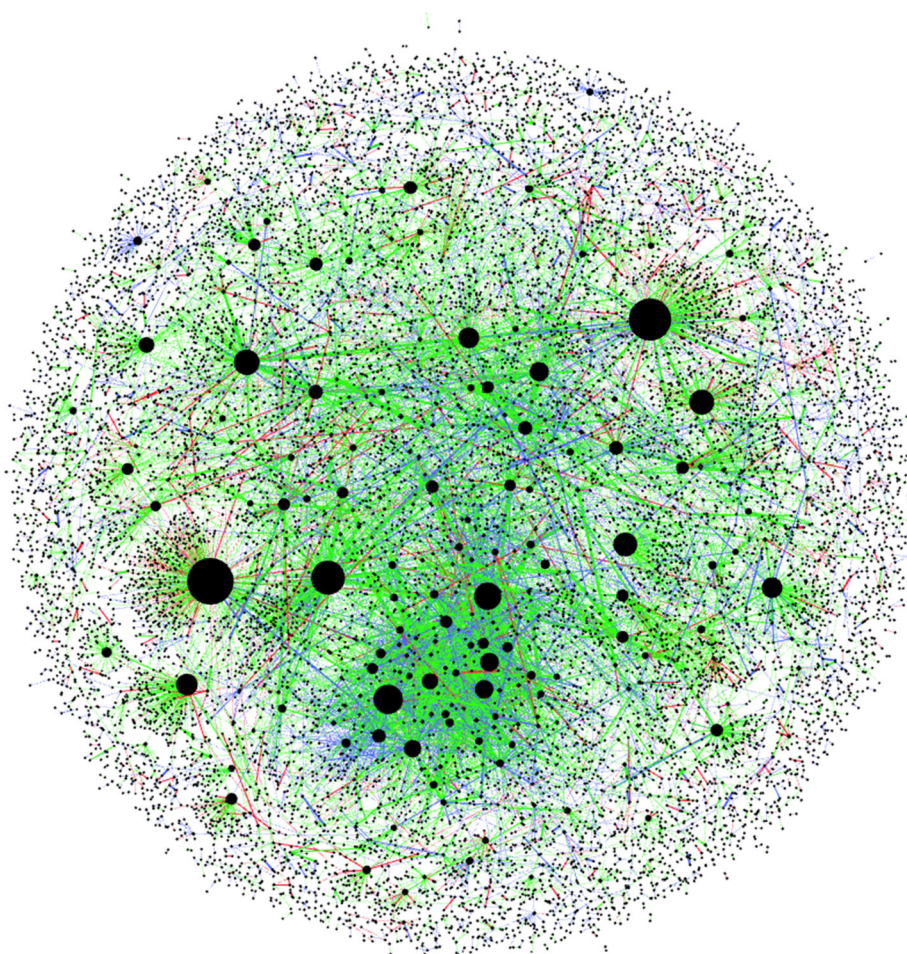
Our second finding is that the network of gender-specific medicine was decentralized and weakly connected. (3) Due to the low density of the network, step 3 was not performed; instead, the fraction of isolates was calculated. (4) The fraction of isolates in the network was at 3.99%. With the cut-off value for a high share of isolates at 19%, this finding implies that most individuals and organizations interacted with at least one other actor in the network, even though the interaction was likely to have occurred only once. Given the low share of isolates, we conclude that the network on gender-specific medicine presented some form of group connectivity, where a few moderately sized communities form around hubs (Himelboim et al. 2017). Hence, the network followed the topology of a community network. See Fig. 3 for a depiction of the steps in the analysis and resulting network structures.

In addition to the entirety of the communication flow, we also analyzed differences in the frequency of communication forms. This observation is valuable since the interactions hold different implications for the information flow. The most popular way of communicating information on gender-specific medicine was through retweets (9221 links). Due to Twitter’s retweet and quote button, reposting content is extremely easy, and users in the network on gender-specific medicine made great use of it. In contrast to retweets, replies were rarely sent (2240 links). While retweets are a form of replicating information, replies require active engagement with the content and thus present a higher activation barrier to overcome. Mentions connected users 5243 times.

**Table 2** Example tweets and codes for the categories framing and discussed matter

Example tweet	Framing	Matter
Dr. Sedlak speaking about debilitating chest pain from small vessel disease or coronary vasospasm. I was having chest pain 20 + times a day/night. It caused me to lose my first transplant. It is NOT benign. see: <a href="https://t.co/yYp0S21Ku0">https://t.co/yYp0S21Ku0</a> #HerHeartMatters #WearRedCanada #WearRedDay	Personal story	Heart health
Defining valid chronic stress models for depression with female rodents - in @BiologicalPsyc1 from @RCBagot -Pretty stark ! Publications per year broken down by sex for studies on chronic stress and depression between the years 2000 and 2019 #sabv <a href="https://t.co/EQn3GjUm0d">https://t.co/EQn3GjUm0d</a> <a href="https://t.co/o3qqZ9etzT">https://t.co/o3qqZ9etzT</a>	Sharing information pieces	Neuro
Lets educate our future docs about #sexandgender #sexmatters @laurenwalter @DeanoftheGreen @Brown_Emergency A sex and gender medicine in emergency medicine course: a novel elective for trainees <a href="https://t.co/M7X6uJ2wWl">https://t.co/M7X6uJ2wWl</a>	Announcing events	Surgery

**Fig. 2** Multi-directed network with link-color by interaction type and degree as node size. The network depicts a 5-month interval of discussions on gender-specific medicine on Twitter, with 12,603 unique users shown as nodes connected via 16,704 links; of those, 2240 replies (in red), 5243 mentions (in blue) and 9221 retweets (in green)



#### 4.2 The Structure and Themes of the Largest Sub-communities

To shed light on the underlying organizing structure of the gender-specific medicine network, we further investigated its division into sub-communities.

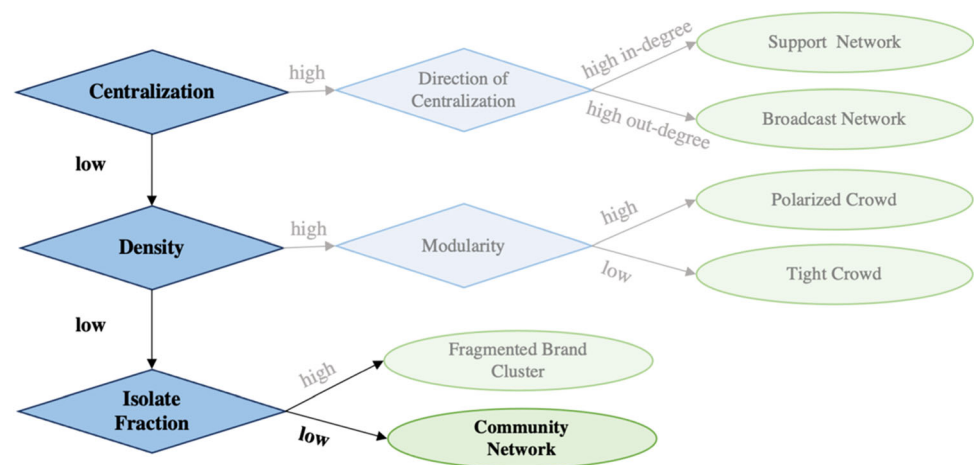
Using the Louvain method implemented in Gephi, we derived the ten largest sub-communities of the complete

network, covering 45.35% of all nodes and 56.34% of links within the entire network (see Fig. 4).

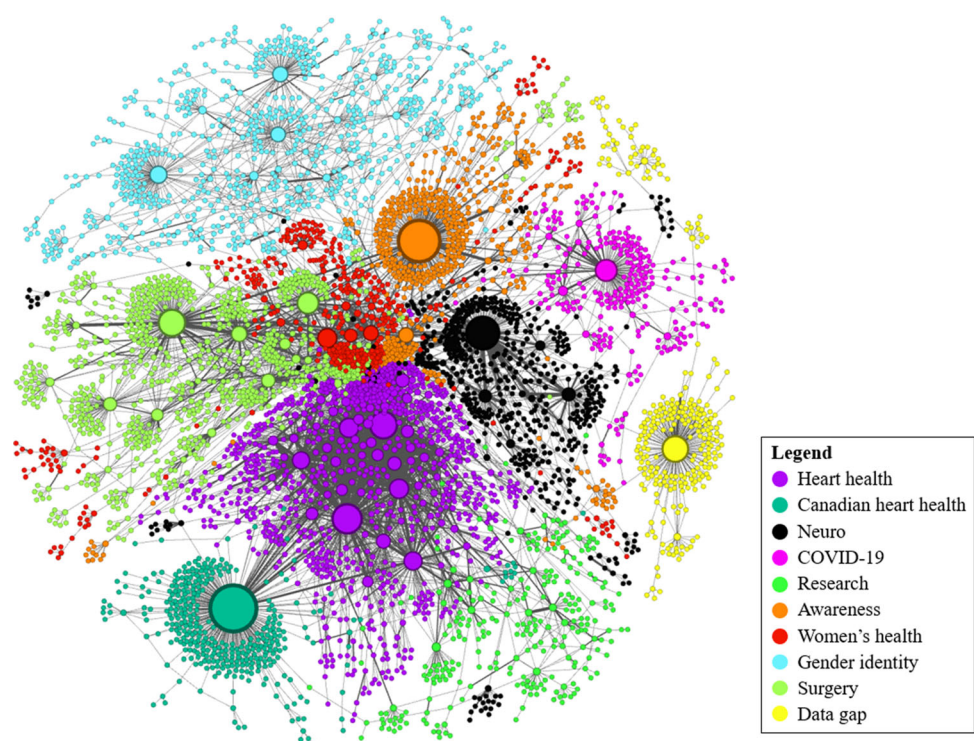
Here, some communities were characterized by several smaller nodes arranged around one central hub (e.g., turquoise, orange). In contrast, others had several opinion leaders (e.g., purple) or were organized in a relatively decentralized manner (e.g., light blue). Of all communities, the largest one across the ten selected sub-communities comprised 9.4% of the nodes and 17% of the links (purple).



**Fig. 3** Network classification process, illustration based on Himelboim et al. (2017)



**Fig. 4** Network of the ten largest sub-communities of the gender-specific medicine network, color-coded by community and degree as node size (with nodes representing unique users and links representing any form of interaction)



While no apparent significant discrepancies could be observed for the metric density across all communities, more striking differences existed for the diameter, average degree, clustering coefficient, and path length (see Table 3). In terms of structure, the purple community was characterized by several opinion leaders, as signaled by those nodes having a comparatively large degree. Furthermore, this sub-community had the largest average degree compared to all other communities, thereby signaling, in combination with the largest average clustering coefficient and one of the smallest diameters, that the nodes belonging to that community were well-connected and

often interacted with each other based on retweets, mentions, and replies.

Topic-wise, the result of the coding process revealed that the purple community centered around heart health, with a striking majority of its associated tweets focusing on cardiovascular disease, followed by tweets combining the topic with a COVID-19 notion. In terms of framing, it could be observed that raising awareness of gender-specific heart health and the announcement of events or popularizing networks constituted the essential main methods followed. Notably, a comparatively large number of personal stories were shared within the cluster, providing a

**Table 3** Selection of metrics, themes, and hub(s) of the ten largest communities of the gender-specific medicine network

Community	Nodes	Edges	Degree	Diameter	Density	Clustering	Path length	Overarching theme	Hub(s)
Purple	1136	2461	4.3	8	0.004	0.519	3.473	Heart health	HeartDocSharon CWHHAlliance NicoleNickers11 thaiscoutinhoCV WomensHearts2 HeartInstitute
Turquoise	361	374	2.1	8	0.006	0.326	2.374	Canadian heart health	JustinTrudeau
Black	562	740	2.6	8	0.005	0.48	3.638	Neuro	womensbrainpro
Pink	276	321	2.3	11	0.008	0.381	3.403	COVID-19	GlobalHlth5050
Green	883	1109	2.5	11	0.003	0.338	3.975	Research	ShanskyLab BiologySexDiff
Orange	525	577	2.2	11	0.004	0.331	3.350	Awareness	sabraklein1998
Red	456	547	2.4	11	0.005	0.306	4.198	Women's Health	NIH_ORWH
Light blue	748	881	2.4	14	0.003	0.062	4.938	Gender identity	DalgetySusan LabWomenDec michelelemonoreEd
Light green	270	328	2.4	12	0.009	0.171	5.08	Surgery	/
Yellow	270	279	2.1	11	0.008	0.311	3.548	Data gap	QueenMab87

more personal take on the topic which, however, was still at a fairly low rate.

Turquoise, a community well connected to the purple sub-division of the network, was unique in terms of its structure since one central hub was observed, with almost all interactions happening based on this node. Here, the hub constituted a prominent figure in politics and, therefore, already enjoys high popularity. With this node tweeting about the Canadian Heart Health initiative, several other nodes retweeted this information from the turquoise and purple communities. Accordingly, a bridge function of this turquoise hub became evident since it connected the two communities based on the similar theme they shared.

Another sub-community dedicated to a central theme revolving around a specific body part was the community color-coded in black. Having the largest clustering coefficient of the community-top ten, its central theme concerned neuro-related topics with a particular focus on the Women's Brain Project and events organized by this network. The comparatively large clustering coefficient signaled a well-connected neighborhood, with almost half the possible links being present between neighboring nodes. While mainly certain events were shared within this community, research and general information on the Women's Brain Project were also commonly found.

Even though COVID-19 as a topic appeared to a certain extent in almost all other communities, the pink cluster focused explicitly on this theme. Next to cardiovascular diseases and neuro-related aspects, SARS CoV-2

constituted the third central topic area that centered around a specific disease, signaling its importance for raising awareness on the relevance of gender-specific medicine and being a critical use case where the importance of medical gender- and sex-differences became even more evident quite recently (Mauvais-Jarvis et al. 2020).

The three communities, green, orange, and red, were somewhat close concerning their metrics (with minor deviations) and shared certain similarities concerning the underlying themes. The orange community was rather generally themed with their primary purpose of raising awareness of gender-specific medicine, while the red community focused on themes related to raising awareness toward women's health. In contrast, the green community took a different approach by sharing research and similar information pieces. Importantly, those three communities were somewhat well-connected via bridges linking them with each other based on the affordances offered by the Twitter platform.

The light blue sub-community exhibited different structural aspects. This community showed the largest diameter across all communities, a relatively low average clustering coefficient, and a sizeable average path length. Even though the average degree was similar to other communities (apart from purple), it signaled a more substantial spread within the community, as indicated by several hubs that functioned as central opinion leaders. Within this community, gender identity and the general mistreatment of individuals based on sex and gender were



the main topics, with a majority of tweets sharing additional information in the form of research and other information pieces. Looking more closely into the issues discussed within this community, we observed that the main topic revolved around the critical issue that sex and gender are not the same and should not be treated as such, with some highlighting it under the lens of transgender. Most of the tweets from this community pointed to specific use cases where official surveys mismeasured, failed to measure, or mixed the two constructs.

A similar structural observation could be made for the light green community, which showed similar patterns to the light blue community in its associated metrics. Here, a focus on topics around surgery with a broad range of contexts (raising awareness, announcing events, sharing information pieces, or popularizing networks) could be observed.

Last, while being among the smallest among the top ten according to size, the yellow community clustered the topic area of the gender data gap and called for action to collect richer datasets that are not biased against a specific sex or gender.

Following the thematic analysis of the sub-communities based on the coding process and the structural analysis relying on methods from social network analysis, we then looked at the underlying interaction patterns among the communities (Table 4). Again, the purple community constituted the largest in terms of the absolute number of tweets (3259 tweets), followed by green (1245 tweets) and the black community (1190). This finding was generally unsurprising as purple and green were also the largest communities regarding the number of nodes (i.e., the number of unique users). Only the color-coded black community seemed to be more active compared to what its general size might suggest.

We classified all tweets according to the underlying type (original, retweet, quote, reply). Here, we observed mainly three classes of communities. The first class was characterized by being comparatively active in creating unique content while having fewer retweets (red community as signaled by the largest share of original tweets). The second class, which comprised most of the communities, still produced a fair share of original tweets while also being characterized by many retweets (purple, black, pink, green, orange, light green). The third class showed only a marginal amount of original tweets and a comparatively great share of user interactions via retweets, quotes, and replies (turquoise, light blue, yellow). Here, we could detect again the turquoise community's hubs-and-spoke character by having a central, single hub with whom all other connected nodes interacted mainly in the form of retweets. The largest share of replies was observed for two communities (light blue, yellow), signaling that users directly engaged with each other more often, facilitating discussions. Since the two communities revolved around the overarching themes of gender identity and gender data gap, it can be assumed that their topics were an immediate result of the increased direct interaction patterns, which generally seemed to ground more room for discussion. Turning toward the average feedback tweets received in the form of retweets, replies, likes, and quotes, the turquoise community stood out again. Here, its particular structural characteristics, having a central, popular hub with an extensive number of followers on the platform, resulted in the most considerable feedback received across all considered communities. Concerning the average number of likes and replies received per tweet, the runner-up community was orange, followed by purple. Surprisingly, the red community with the most significant number of original tweets had one of the lowest engagement rates, signaling that potentially

**Table 4** Interaction patterns of the ten largest communities of the gender-specific medicine network

Community	Number tweets	Original (in %)	Retweets (in %)	Quotes (in %)	Replies (in %)	Avg. retweet count	Avg. reply count	Avg. like count	Avg. quote count
Purple	3259	556 (17.06)	2,292 (70.33)	292 (8.96)	119 (3.65)	8.854	0.145	3.018	0.125
Turquoise	236	228 (2.19)	216 (94.74)	1 (0.44)	6 (2.63)	200.627	0.969	7.061	0.232
Black	1190	172 (14.45)	923 (77.56)	41 (3.45)	54 (4.54)	8.971	0.094	2.129	0.092
Pink	497	65 (13.08)	412 (82.90)	8 (1.61)	12 (2.41)	14.193	0.062	1.551	0.054
Green	1245	180 (14.46)	971 (77.99)	57 (4.58)	37 (2.97)	34.446	0.129	2.856	0.105
Orange	575	71 (12.35)	460 (80.00)	30 (5.22)	14 (2.43)	29.720	0.242	4.397	0.120
Red	771	219 (28.4)	501 (64.98)	34 (4.41)	17 (2.20)	8.429	0.073	1.764	0.080
Light blue	839	41 (4.89)	682 (81.29)	37 (4.41)	79 (9.42)	31.546	0.147	3.426	0.056
Light green	323	58 (17.96)	238 (73.68)	16 (4.95)	11 (3.41)	10.084	0.121	2.390	0.087
Yellow	174	2 (1.15)	149 (85.63)	3 (1.72)	20 (11.49)	106.563	0.339	2.839	0.126

structural aspects might be quite essential for innovations to spread through the network.

#### 4.3 Identifying the Influential Users of the Gender-Specific Medicine Network

In the next step, we turned toward individual users to better understand how information on gender-specific medicine spreads through the network (see Table 5). Further, we wanted to understand which users were the main contributors to the dissemination of information throughout the network. Based on the degree and betweenness centrality metrics (see Sect. 3.2), we first looked at the 15 most important central users and information brokers in the gender-specific medicine network. We saw a strong overlap between these two types of users, with eleven users fulfilling both important functions in the network.

Therefore, in our subsequent analysis, we focused on those eleven users to further understand their behavior in the network and shed light on how they spread the topic of gender-specific medicine across the network.

Among the eleven users, we found four accounts of academics, two advocacy institutions, and one journal. The remaining users were physicians, journalists, politicians, and involved citizens, representing each category once. Eight of the accounts were mainly dedicated to the topic of

gender-specific medicine, with only three of them being more general topic-wise. Six of the accounts belonged to the communities of “heart health” and “Canadian heart health,” which constituted an overrepresented topic among influential users. Naturally, influential users produced comparatively more content. However, a few users who were not primarily dedicated to gender-specific medicine only created very few pieces of information on the platform.

Turning toward content posting strategies of influential users, we observed varying behaviors across the eleven profiles. Profiles can either write their own tweets and share original content, retweet content from others to distribute external content within their network, or focus on interactions with other users in the form of replies and quotes. Similar to a reply where a user provides a written reaction to another user’s tweet, a quote also contains the original tweet the user replies to. First, two profiles dedicated to a broader range of topics (a journalist and a politician) produced only a marginal amount of content. Still, they engendered the most resonance regarding retweets, replies, and likes. While one profile produced a single original tweet, the other account focused on interaction with an audience based on two quotes related to gender-specific medicine. Due to their comparatively large audience, those users fulfilled the role of *distributors* who broadly

**Table 5** Top influential users in the gender-specific medicine network

Username	Type	GSM Focus	Community	Avg. #Retweets / Avg. #Replies / Avg. #Likes	# Tweets	#Original / #Retweets / #Replies + Quotes (in % of #Tweets)	Main Strategy
NicoleNickers11	Involved Citizen	Yes	Hearth health	5.42/0.45/4.75	132	27/76/29 (20.5%/57.6%/22.0%)	Facilitator
HeartDocSharon	Physician	No	Hearth health	7.08/0.33/5.50	121	18/53/50 (14.9%/43.8%/41.3%)	Interactive facilitator
womensbrainpro	Advocacy Institution	Yes	Neuro	4.61/0.26/6.93	121	58/47/16 (47.9%/38.8%/13.2%)	Facilitating creator
thaiscoutinhoCV	Academic	Yes	Hearth health	5.05/0.29/6.70	107	10/68/29 (9.4%/63.6%/27.1%)	Facilitator
BiologySexDiff	Journal	Yes	Research	4.02/0.09/5.28	102	66/28/8 (64.7%/27.5%/7.8%)	Creator
WomensHearts2	Academic	Yes	Hearth health	3.97/0.11/4.76	101	31/49/21 (30.7%/48.5%/20.8%)	Facilitator
CWHHAlliance	Advocacy Institution	Yes	Hearth health	4.99/0.19/8.23	96	38/38/20 (39.6%/39.6%/20.8%)	Balanced creator
sabracklein1998	Academic	Yes	Awareness	11.52/3.07/63.44	27	15/0/11 (55.6%/0.0%/44.4%)	Interactive creator
ShanskyLab	Academic	Yes	Research	20.42/1.11/29.42	19	4/14/1 (21.1%/73.7%/5.3%)	Facilitator
DalgetySusan	Journalist	No	Gender identity	62.5/2.5/178	2	0/0/2 (0.0%/0.0%/100.0%)	Distributor
JustinTrudeau	Politician	No	Canadian heart health	247/216/1460	1	1/0/0 (100.0%/0.0%/0.0%)	Distributor

GSM: gender-specific medicine

distribute the concept of gender-specific medicine, even though they were not focused on the topic.

In the case of the remaining users, we observed that none followed a single dominant strategy, combining sharing original tweets, retweeting content from others to act as facilitators, and interacting with other users in the form of replies and quotes to varying extents. Generally, we identified three different strategies that could be combined. We named the users who applied them as *creators*, *facilitators*, and *interactors*. First, creators are focused on sharing their content in original tweets. Facilitators retweet other users' content, enabling the spread of such tweets beyond the user's network when creating the tweet. Last, interactors bundle their energy by engaging with other users through replies and quotes. The three strategies can be arbitrarily combined, and if an approximately equal share of effort is distributed among those activities, it can be seen as a rather *balanced* approach.

In this regard, we identified four users who mainly acted as facilitators by focusing their actions on retweeting other users' tweets. Among those, three accounts constituted academics, and one belonged to an involved citizen. Primarily, three of those accounts belonged to the heart health community. In addition, one account belonging to an academic journal emphasized sharing original tweets, thereby creating unique content for its community. Three more accounts also followed the strategy to produce original tweets, even though not solely since they combined it with retweeting content and interacting with others. Last, one account belonged to the heart health community whose topics did not focus on gender-specific medicine but engaged with the community through interactions and sharing other users' content instead of creating it themselves.

In summary, among the top influential users who both served as central users and information brokers in the network, we observed various strategies to spread the concept of gender-specific medicine.

## 5 Discussion

### 5.1 Discussion of the Network Analysis

This study was conducted to explore and understand the content and network structure of Twitter communication about gender-specific medicine. We used social network analysis to investigate the dissemination of information in the network and thereby draw conclusions about the innovation diffusion stage of gender-specific medicine among the stakeholders participating in the discussion.

Following the network topology classification approach by Himelboim et al. (2017) presented in Sect. 3.2, we

sequentially calculated network *centralization*, *density*, and the *isolate fraction* to conclude that the network on gender-specific medicine corresponds to a clustered community network. This result implies diverse viewpoints among distinct communities but limited information exchange between clusters. The individual steps of the network classification and their implications for information diffusion are discussed below.

The gender-specific medicine network appears highly *decentralized*, with most nodes having similar connections and few users holding significant influence. This decentralized structure fosters egalitarian information sharing but also leads to knowledge silos with diverse opinions. However, the low network density results in slow and vulnerable information flow, relying on sparse connections. This lack of centralized coordination by official sources or leading figures limits information exchange, fostering homogeneous information circulation within communities.

Analyzing the network's *density* revealed that the gender-specific medicine network shows sparse connectivity, with the lowest level of interconnectedness compared to similar studies. For example, while the HPV vaccine debate on Twitter involved 39,000 users with a density of 0.0003 (Himelboim et al. 2020), our network, with 12,603 users, has a density of only 0.0001. Additionally, analysis of pro- and anti-vaccination content on Twitter showed densities ranging from 0.0011 to 0.0024 (Milani et al. 2020), significantly higher than our network's 0.0001 density. Despite Twitter's potential for interaction, engagement in gender-specific medicine primarily revolves around one-way information distribution, with minimal interactive dialogues.

The gender-specific medicine network exhibits a low *isolate fraction*, with only 3.99% of users not connected to others through replies, retweets, or mentions. This suggests that most individuals and organizations interact with at least one other actor in the network. While these few isolates lack social connections within the network, they still contribute to the conversation by posting content relevant to the topic. Their posts, originating from external sources, present a potential source of new information. Actively connected users in the network can expand their knowledge base by engaging with these 503 isolated users.

In summary, the network analysis revealed that the network follows a clustered community structure. Therefore, limited information exchange takes place, where information circulation is restricted by the decentralization and sparsity of the network, and communication happens in independent silos.

## 5.2 Discussion of the Sub-Community Analysis

As the network analysis revealed, the network on gender-specific medicine followed a clustered community structure. To further examine the sub-communities, we derived the ten largest sub-communities of the complete network using the Louvain method implemented in Gephi. We then performed a manual coding of the tweets to shed light on the topics that were discussed in the individual communities. Following this procedure, the top ten communities showed that almost all centered around a different thematic focus.

In particular, we observed several central themes revolving around specific medical fields (heart health, neuro, COVID-19, surgery), generally raising awareness on the topic and partially with a focus on women's health research (sharing research papers, gender data gap), or gender identity. The most prominent topic was women's heart health, discussed in a community of 1136 nodes and 2461 links, with users exchanging information on disease manifestations and participating in advocacy campaigns like Wear Red Canada. While topics like mental health and COVID-19 were raised, none received as much attention as heart health. However, discussions on Twitter lacked diversity regarding the broader impact of sex and gender bias in healthcare. The network's ten major communities did not fully encompass fields like immunology, pneumology, oncology, or hematology, which also show sex and gender differences (Mauvais-Jarvis et al. 2020; Regitz-Zagrosek 2012) but are not yet extensively discussed on the platform.

The emphasis on cardiology might stem from the data collection process, incorporating hashtags like #HeartDiseaseInWomen and #HerHeartMatters. The latter originated from the annual "Wear Red Canada" campaign by the Canadian Women's Heart Health Centre (CWHHC 2021), trending on Twitter Canada during its launch on February 13. Aligning with National Wear Red Day in the United States on February 5, 2021, and National Heart Health Month in February 2021 in Canada and the U.S., the selected hashtags and timeframe naturally directed the thematic focus toward cardiology.

The analysis of communities further highlights a stronger focus on gender-related disparities affecting women, potentially influenced by the prominence of discussions on women's heart health or the prevalence of the gender data gap in women's health research. While these disparities disproportionately affect women due to the data gap, it is crucial not to overlook their impact on men (Regitz-Zagrosek 2012). For instance, research on osteoporosis in men is lacking (Baggio et al. 2013), and mental health symptoms in men may be underestimated due to inadequate measurement tools, leading to insufficient treatment

(Harris et al. 2015). Additionally, men with melanoma have worse survival rates than women, suggesting a need for targeted prevention campaigns for this group (el Sharouni et al. 2019).

We further observed a scarcity of users sharing personal experiences regarding gender and sex-biased treatment, with most focusing on factual information. This differs from previous studies where users discussed personal stories, such as breastfeeding-related healthcare (Moukarzel et al. 2020) or Lupus (Pirri et al. 2020). The limited presence of personal narratives may stem from patients' and physicians' unfamiliarity with gender and sex disparities in medicine, leading to unawareness of biased treatment and its consequences (Regitz-Zagrosek 2012). Additionally, physicians may not recognize patients' varying symptoms for the same health condition.

One of the goals of gender-specific medicine is to personalize healthcare, aiming to customize healthcare based on an individual's genotypical and phenotypical (e.g., environment, lifestyle choices, relationships) characteristics (Vaz and Kumar 2021). The results of our study highlight the demand for such approaches, with a significant Twitter community discussing gender medicine and raising awareness of the need for medical research and treatment to consider gender.

In summary, we found that the communities revolved around distinct topics and often had a standalone position within the network, sharing only very few connections with other communities.

## 5.3 Discussion of the Influential Users

Lastly, this research aimed to identify key users that have a powerful influence over the information flow in the network. Individuals with academic and medical expertise largely dictate discussions on gender-specific medicine, with many influential users associated with heart health communities. These influencers employ various tactics, including sharing their content, retweeting others' posts, and actively engaging with their followers. In essence, our findings reveal a relatively homogeneous group of elite users shaping the discourse on gender-specific medicine through diverse influence strategies.

The high presence of scientific users aligns with previous research on health networks. Investigating influential users in networks formed from different health hashtags, such as #BreastCancer or #Alzheimers, Xu et al. (2015) find that advocates and healthcare practitioners dominate the discussions. Moreover, Himelboim and Han (2014) report that individual users rather than health organizations dominate the communication on breast and prostate cancer.

The prevalence of highly educated users, particularly from health and science fields, indicates that scientific

content dominates discussions in the network. Many influential users, often involved in medical or research-related activities, utilize Twitter to share scientific publications, promote colleagues' work, or raise awareness. A Canadian politician active in the Canadian heart health community is an exception among users from the medical field, suggesting untapped potential for government and political figures to disseminate information on gender-specific medicine to a broader audience. Supporting this idea, Chung (2017) indicates that health campaigns on Twitter benefit from involvement across various professional backgrounds. These findings imply that the gender-specific medicine network holds promise for distributing evidence-based information, offering advantages over other health networks that may lack factual basis. For instance, in discussions about COVID-19 on Twitter, significant involvement in generating and disseminating information came from non-expert users, potentially compromising credibility and accuracy (Kim and Valente 2021).

Influential users apply diverse strategies to shape the network, with no single strategy dominating. Non-medical experts primarily distribute content on gender-specific medicine, while medical professionals tend to create their content or facilitate sharing. Notably, none of the accounts solely employed interactive strategies, consistent with findings indicating infrequent use of interactive communication styles on Twitter (Triantafillidou et al. 2018). These results align with previous research suggesting that employing multiple communication styles enhances message reach in online networks (Tantawi et al. 2018).

#### 5.4 Overall Discussion: Diffusion of Innovation in Gender-Specific Medicine

The network analysis and the community detection yield information about the adoption stage of gender-specific medicine among the medical community and patients. Identifying the gender-specific medicine discourse as a clustered community network suggests that the innovation adoption stage is likely in a phase where multiple perspectives, approaches, and viewpoints are being actively explored and discussed. Currently, the multifaceted nature of the conversation indicates that the field is dynamic and diverse, with ongoing exploration of different aspects and potential applications rather than a uniform adoption or rejection of a single approach or viewpoint. This observation suggests that the innovation is currently in the early stages of adoption, likely in the knowledge stage. This stage is characterized by relevant stakeholders gathering and exchanging information about the innovation, with the predominant communication being rather fact-based and cognitive (Rogers 2003). In addition, as the analysis of the

sub-communities in the network implies, a wide range of topics exists that are addressed, further strengthening the assumption that the adoption of gender-specific medicine is in the knowledge stage. Moreover, patients' lack of personal stories hints at the topic being less well-known among the general public, again showing that widespread adoption has not happened yet. The analysis of the networks' influential users adds to this interpretation, with the discussion being dominated mostly by medical experts who share evidence-based information on the topic.

These findings suggest avenues for advancing the diffusion of gender-specific medicine. To enhance its spread, it is crucial for information to flow across community boundaries. Some nodes already serve as information brokers, facilitating connections between communities, particularly those sharing similar themes like heart health and awareness. However, deeper cross-community connections are more prevalent within these thematically closer sub-communities. Thus, fostering communication that transcends community-centric themes could unlock untapped potential for strengthening the innovation flow of gender-specific medicine. Twitter users express a growing interest in the topic of sex and gender differences in medicine, signaling an expanding research area. This indicates that tweet volume, network size, interconnectivity, and topic diversity will likely increase over time. Despite the network's vulnerability to disruption, it offers numerous opportunities for innovation diffusion through forming additional connections, especially between communities.

#### 5.5 Limitations

This paper is not without limitations. The data used for this paper relates to the hashtags and search terms we used for data collection. Although we employed a thorough search process to detect all relevant key terms, it is possible that we missed less frequently used hashtags or that some of the search terms captured tweets on closely related topics. Future research could expand search terms to include phrases like "gender-sensitive medicine", "diversity-sensitive medicine", or "diversity medicine" to cover intersectional aspects related to culture, ethnicity, minority status, and socioeconomic conditions. Additionally, the decentralization observed in our analysis may partly result from using various search terms, as seen in similar studies (Xu et al. 2015). However, given the breadth of sub-fields within gender-specific medicine, employing diverse search terms seems justified.

Over time, relevant hashtags in the discourse will evolve, requiring adjustments for future research. The findings are time-dependent, as seen in the prevalence of topics like heart health and COVID-19, prominent during



data collection in early 2021. Using different search terms or collecting data at another time may unveil varied patterns of information flow and debated topics.

Further, focusing on Twitter introduces differences compared to traditional sources like surveys or experiments. While the latter ensures data quality through researcher control, Twitter data presents nuances. Issues like algorithmic bias, polarization, and A/B testing by platform owners can affect data generation (Chen et al. 2022). Moreover, bot interventions and the spreading of fake news may further impact data quality (Chen et al. 2022). It is important to note that social media data, despite its large scale, may not fully represent the general public. Therefore, conclusions drawn from our research should be cautiously approached, recognizing that offline information flow on the same topic may differ structurally.

Moreover, our findings depend on Twitter's features and user demographics. Similar results may apply to platforms sharing Twitter's key features, like text-based communication, public profiles, and commenting capabilities. Platforms that bring together all relevant stakeholders in the gender-specific medicine discourse might also see similar trends.

## 5.6 Contributions

This study makes several important theoretical and practical contributions. First, it adds to the literature on the spread of health-related content on SNSs (Roy et al. 2020; Singh et al. 2020). It also deepens our understanding of discussions of gender-specific medicine on Twitter, which have been primarily addressed in the medical field (Mauvais-Jarvis et al. 2020). In addition, the results contribute methodologically to other studies that use social network analysis to understand the spread of information through SNSs, such as vaccination debates (Milani et al. 2020) or campaign monitoring and identification of key influencers in the World Breastfeeding Day discussion (Moukarzel et al. 2020). Further, the study is in line with the recent aim of the field of healthcare IT to examine how patients can take over a larger role in their healthcare (Fürstenau et al. 2023).

Our study adds to the field of social media analytics within the IS domain, where scholars leverage social media data to discern communication patterns (Stieglitz et al. 2014, 2018). Previous research has explored various aspects, including discussed topics, trends, influential users, and information diffusion (Susarla et al. 2012). In the area of information diffusion, researchers have, for instance, looked into how network position influences the spread of information (Susarla et al. 2012), the relationship between information diffusion and economic outcomes (Oh et al. 2016), or how expressed emotions impact information

diffusion (Zhang 2016). So far, this body of literature has mainly looked into the domains of business, crisis communication, journalism, and political communication (Stieglitz et al. 2018). We extend this literature by using social media data to examine the innovation diffusion of an emerging healthcare topic.

Further, by building on the Innovation Decision Process Theory, we add to the IS literature that applied this theory to examine technology diffusion. IS researchers have explored innovation diffusion in various contexts, such as the spread of innovations in digital worlds (O Riordan et al. 2009) and the early-stage diffusion of codependent IT innovations (Parameswaran et al. 2023).

Our research further offers practical implications for public institutions like health ministries or medical associations. Insights can aid in assessing public knowledge of gender-specific medicine and guiding the planning of health literacy campaigns. Given the lengthy process of translating research into policy and medical programs (Brownson et al. 2009) it is evident that education efforts targeting both practitioners and the public are crucial, with the potential to leverage SNSs for broad dissemination. For instance, national health campaigns could prioritize less-discussed topics, for example, by enhancing awareness of gender-specific symptoms like those of heart attacks among women. Understanding community structures enables tailored information delivery to users' specific needs while identifying influential users can enhance campaign effectiveness through their advocacy involvement.

Further, our findings have clinical implications for patients and healthcare professionals. Patients can benefit from education on gender-specific symptoms, enhancing prevention and treatment. Social media platforms provide a channel for patients to access new information they can discuss with their medical providers. Similarly, healthcare professionals can use social media discussions to stay updated on the latest research findings in gender-specific medicine, potentially informing their practice. Furthermore, our results highlight the need to raise awareness among medical professionals about gender disparities, which could accelerate the adoption of gender-specific medicine and benefit patients.

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