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‘People Like Us’: Gendered Network Structures and Assortative Mixing among Artistic Gatekeepers in The Electronic Music and Digital Arts in The Low Countries (2016-2022)

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Abstract

This thesis investigates gender-based network structures and assortative mixing or homophily and whether other factors reinforce this in electronic music and digital arts, in the Low Countries between 2016 and 2022. Stakeholders and researchers have often identified these phenomena as crucial contributing factors to the staggering lack of diversity in these fields. However, no meticulous Social Network Analysis (SNA) has been performed so far. Therefore, using supervised machine learning and Named Entity Recognition (NER), a gatekeeper network is constructed based on (implicit) mentions of and replies to others in tweets. Its topology and communities are visualised using ForceAtlas2 and Louvain Clustering. The visualisations and accompanying statistics indicate gendered network structures. Moreover, the roles men and women gatekeepers occupy in the network reflect existing gendered occupational segregation in the creative industries. Connecting gatekeepers, identified more often as being women, are essential to disrupt feedback loops, in which artistic gatekeeping practices are informed by relationships with trusted, similar peers that, in turn, shape the network structure. This research also demonstrates a tendency towards gender-based connections – impeding women gatekeepers most – which is even stronger when combined with territorial and professional similarity, *i.e.* ‘people like us’, increasingly since the pandemic, again worsening women’s position in this field.

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Chapter 1
Examining Gender Inequality in Electronic Music and Digital Arts

Over the past two decades, scholarly research has consistently highlighted the presence of structural gender inequality in the music industries[2], as demonstrated by the significant underrepresentation of women and gender-expansive people compared to men, both in performing and non-performing roles (Davies, 2001; Edmond, 2023; Leonard, 2017; Purnelle, 2019; Topaz et al., 2022; Vanhaverbeke, 2015; Whipple & Coleman, 2021).

Gender inequality[3] in the music industries is often attributed to the prevalence of cisgender men-dominated gatekeeper networks, perpetuated by informal connections and a culture that excludes women and gender-expansive persons (Abfalter & Reitsamer, 2022; Brinkmann, 2003; Edmond, 2019; Gritter, 2016; Harauer et al., 2003; Hennekam, 2022; Hooper, 2019; Mullens & Zanoni, 2019, pp. 8-10). In these networks, non-performing gatekeepers, such as artistic directors, bookers, and curators[4], hold significant decision-making power about artistic and income-generating opportunities for artists (Keunen, 2013). Therefore, to attain Diversity, Equity and Inclusivity (DEI), it is crucial to examine how gender bias in these decision-making processes is shaped by a possible 'gendered networked structure' of the music industries, *i.e.* what could be the network causes of this phenomenon (Ehrich et al., 2022, p. 5; Marin & Wellman, 2016, p. 17).

One often-mentioned contributing factor to the continued discriminatory practices of gatekeepers in the music industries is 'homophily' or assortative mixing. This concept is a widely studied and essential principle of social networks, structuring not only information flows and communities but also ties (McPherson et al., 2001, p. 415). "Homophily is defined as the tendency for people to seek out or be drawn to others who are similar to themselves. The people's networks tend to be more homogeneous than heterogeneous such that the communication between similar people occurs more frequently than with dissimilar people" (Khanam et al., 2022, pp. 8811-8812). Attributes used to investigate homophily among people in a network include value homophily, such as attitudes, beliefs, and behaviour, and status homophily, such as race, ethnicity, age, religion, education, occupation, and gender (Kegen, 2013, p. 63).

In this chapter, I will explore the existing research on gender inequality and (electronic) music and digital art, identify gaps in knowledge and highlight new directions suggested in recent literature. I will then explain why Social Network Analysis (SNA) might offer new insights by examining the structural properties of networks. Before delving into gendered notions of gatekeeping and analysing network dynamics, I will establish the boundaries of this field and demonstrate how networks can change over time. Finally, I outline my research questions and methodology and address the evolving language regarding gender.

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[2] This study assumes an everyday use of 'digital arts' and 'music industry'. However, since the latter might reinforce dominant voices and fails to recognise its diversity and underrepresented niches, which can perpetuate inequality, 'music industries' will be used (Williamson & Cloonan, 2007, pp. 305-307, pp. 314-318).

[3] Equality or fairness focuses on treating everyone equally, having equal rights and opportunities, and seeking equal outcomes. Equity emphasises providing targeted interventions to achieve fairness and justice, considering individual or group differences and historical disadvantages (D'Ignazio & Klein, 2020, pp. 59-60).

[4] In the music industries, venues rely on bookers to schedule performances, while in-house concert promoters manage, promote, and produce events in addition to booking artists. Independent concert promoters perform comparable tasks but also secure suitable venues. For clarity, I will only use promoter and curator (Cliche & Wiesand, 2003, pp. 27-28).

Established Research Perspectives

Much academic literature has emerged in the past decades on gender inequality in the creative industries. However, research on gender in electronic music and digital arts is limited; Tara Rodgers' *Pink Noises: Women on Electronic Music and Sound*(2010) and Rebekah Farrugia's *Beyond the Dance Floor: Female DJs, Technology, and Electronic Dance Music Culture* (2012) remain groundbreaking. Recent research has supplemented their research, mainly informed by practices in the influential German electronic music scene (Grund & Noeske, 2021; Sanio & Wackernagel, 2019). In the Low Countries, researcher Hannah Bosma's (2003, 2006) and QO-2 director Julia Eckhardt's (2017 and 2018) studies are notable exceptions compared to the near total absence of gender in the few ethnomusicological and (pop)cultural studies on (electronic) music.

Additionally, a genre or discipline categorisation can elicit and perpetuate gender inequalities, shaping professional values and influencing access, distinction, and career development options for performers and professionals (Alacovska & O'Brien, 2021; Koren, 2022; McLaughlin, 2015; McLeod, 2001; Schmutz & Faupel, 2010; Werner et al., 2020, pp. 641-642). Nevertheless, given the commonalities with the broader music sector, the existing research framework on gender in the music industries discerned by Ann Werner et al. (2020), provides suitable guidance for this research. Starting from a specific understanding of gender rather than from a historical timeline, the authors have identified three main strands of feminist research on gender in the music industries: the empiricist, the standpoint, and the poststructuralist tradition.

The Empiricist Feminist Research Tradition

In this approach, the dominant focus of predominantly women researchers and activists has been on representation and visibility through mapping gender proportions and the rediscovery of pioneers, including in the electronic music scene and digital arts (Abtan, 2016; Borchert, 1997; Bosma, 2006; Cox et al., 2018; Džuverović, 2016; Eyene, 2019; Farrugia, 2012; Fure, 2016; Greie-Ripatti, 2014; Grund & Noeske, 2021; Herrera, 2021; Klassen, 2021; Mazierska, 2020; Metzelaar, 2004; Morgan, 2017; Niebur, 2010; Niebur, 2021; Olszanowski, 2012; Rodgers, 2010; Rovner, 2020; Tumat, 2021; Werner et al., 2020, p. 637).

Highlighting the disproportionately low representation of women performers (Hooper, 2019, pp. 133-134; The TroubleMakers, 2022; von Braun, 2019) and adding women's accomplishments proved to be valuable, particularly in electronic music and digital arts, where their achievements were previously and are still overlooked by primarily men researchers (Dunn, 1992; Licht, 2019; Luening, 1968), minimised (Emmerson, 2018; Holmes, 2020; Reynolds & Press, 1995; Ross, 2007; Saunders, 2009; Sterne, 2012; Toop, 2018), discussed in a derogatory manner (Collins et al., 2013; Shapiro & Lee, 2000), in the context of appearance (Clayton et al., 2003) or from an essentialist viewpoint (Werner et al., 2020, p. 641).

Furthermore, this approach may lead to stereotyping women electronic musicians (Kohl, 2021; Morgan, 2017), distracts from fundamental issues, such as the canonisation of masculine aesthetic criteria (Werner et al., 2020, p. 639) and does not offer solutions or methodological tools for exposing gendered power imbalances and knowledge production (Borchard & Treydte, 2019, p. 133). In response to the latter observation, recent research (Baillie et al., 2022; Bennett, 2022; de Boise et al., 2022; Johnson & Dewey, 2020; Tang, 2022; Wall-Andrews & Luka, 2022) has assessed the impact of policies and interventions to

redress gender imbalances, such as the Keychange Initiative, where festivals commit to gender-equal programming (McGee, 2022).

This emphasis on the underrepresentation of women musicians and professionals in the music industries has also resonated in media coverage. However, the media tends to treat the statistics presented as a self-explanatory panacea and lately has tended to focus on high-profile cases of sexual harassment while failing to expose the underlying structural problems (Edmond, 2019; Fairlamb & Fileborn, 2020; online Supplement 1).

The Standpoint Feminist Research Tradition

This approach seeks to challenge power inequalities, gender bias, and discrimination in the music industries by incorporating knowledge from marginalised groups to effect tangible change (Gross, 2022; Werner et al., 2020, p. 637). Furthermore, exclusionary strategies employed by gatekeepers and their underlying assumptions, such as homophily, concerning booking and hiring practices (Cliche & Wiesand, 2003; Dent, 2020; Kahlert, 2021; Willrodt, 2016, p. 8), ingrained (gendered/essentialist) notions about 'musical quality', and the impact of marginalisation on the accessibility of 'music spaces' are examined. Within these spaces, agents often rely predominantly on same-gender social networks within the music industries' economic systems (Bennett, 2022; Cliche & Wiesand, 2003; Farrugia, 2012, p. 7; Gavanas, 2013; Hooper, 2019; Khazam, 2019; Leonard, 2017; Schmutz & Faupel, 2010; Werner et al., 2020, pp. 640-641).

Furthermore, topics such as industry values and gendered socialisation (Conde, 2003; Gadir, 2017; Mullens & Zanoni, 2019; Vanhaverbeke, 2015), misconduct and work environments (Crabtree, 2020), media representation of women musicians (Davies, 2001; Faupel & Schmutz, 2011; Whipple & Coleman, 2021), and overarching gender policies in the creative industries (Cameron, 2015; Duffin, 2021), are addressed. However, this approach risks 'othering' of actors who deviate from the white cis-gender male heterosexual norm (Werner et al., 2020, p. 641).

Poststructuralism, Intersectionality and Cyberfeminism

Previously, the contributions of women performers and professionals in music remained largely invisible in popular and academic music historical reviews, except for some pioneering research in gender studies and among activists. However, in the 1990s, influenced by poststructuralist theories, a paradigm shift occurred in (ethno-)musicology (Koskoff, 2005). This strand of research emphasises concepts and parameters such as language, difference and contradiction (Gray, 2022; Horn, 2013) and explores the notion of gender as performativity and constructed (Borchard & Treydte, 2019). However, focusing solely on how subtle discriminatory or stereotypical language, *e.g.* in media (Davies, 2001; Mangani, 2021) and lyrics (Bretthauer et al., 2007), shapes perceptions, assumptions, prejudices, and practices related to gender might – according to some researchers and activists – overlook the pursuit of a political and material change, or even perpetuate inequality (Edmond, 2023; Grund, 2021; Werner et al., 2020, p. 642).

This critique aligns with researcher Annie Goh's 2014 understandable observation – when frustration concerning the underrepresentation of women in electronic music first emerged outside academia and activism – that poststructuralist feminist theory often seems confined to abstract academic discourse, disconnected from real (material) concerns. Therefore, Goh has proposed a more radical sound-based perspective rooted in the long-standing cyberfeminist critique, particularly in the context of digital arts, to challenge the

dominant discourse that portrays the use of technology as an inherently masculine competence. Since the 1970s, cyberfeminists have called out the 'toys for boys' paradigm in electronic music and digital arts (Eyene, 2019, p. 6; Werner et al., 2020, p. 642). Starting from gendered notions of technology and the audio-technical discourse, in *Tinkering with cultural memory* (2015), Tara Rodgers addresses issues related to visibility and representation, challenging the concept of 'women' as a monolithic entity and contributing to a subtler understanding of gender dynamics in technology-driven electronic music and digital arts. These cyberfeminist insights[5] are becoming increasingly relevant, given the rapid developments of digital technologies and their integration across all musical genres. Werner et al. (2020) also do not address the emerging 'new materialism' in feminist research since the turn of the century, used, *e.g.* to examine Björk's music (Degórski, 2022) or the 'hidden' commonalities in the work of women electronic musicians and digital artists (Khazam, 2019).

The leading literature on gender and electronic music stems mainly from the first two traditions discussed above, while it might not always be possible to make clear distinctions. Considering research on gender inequality in digital arts, similar developments are observed, with a focus on pioneers, trailblazers and canonisation (Cox et al., 2018; Dunn, 1992; Spaninks, 2019) in the slipstream of Linda Nochlin's seminal 1973 article *Why Have There Been No Great Women Artists?*, statistics on underrepresentation (Brinkmann, 2003; Georgiou, 2018), work conditions (Conde, 2003) and discourses around gender, technology and cyberfeminism (Paul, 2018).

Embracing New Paradigms: A Digital Humanities Approach

Despite years of meticulous language dissection, counting, and challenging power inequalities in the music industries, the intended change towards gender equity seems to be falling short of expectations (Berkers & Hoegaerts, 2019, p. 4; Scharff, 2021; von Braun, 2019). In addition, decades of gender studies, grassroots activism, and advocacy from famous electronic music artists like Björk (Hopper, 2015) and the Blessed Madonna (Vincentelli, 2017) have not advanced DEI in the creative industries. Moreover, the current lopsided media narrative, a lack of persistent political engagement, emerging #MeToo-fatigue, so-called anti-woke sentiments, and entrenched industry interests that resist change threaten to diminish attention again.

Several scholars have, therefore, proposed a digital humanities approach to shed new light on the underlying gendered network structures that might contribute to the epistemic invisibility of women (Davies, 2019; Meirelles et al., 2018; Werner et al., 2020, p. 644). This could help overcome the existing knowledge and data gaps, which I will elaborate on in Chapter 2. While what exactly constitutes a digital humanities approach has yet to be discerned, embedding automated data collection and advanced computational methods in SNA for humanities research has proven to help extract relevant information and patterns from massive (unstructured) data and thus answer questions about phenomena previously deemed elusive such as reputation or networks of influential actors (Foka, 2022; Fraiberger et al., 2018) or homophily in networks (Hanusch & Nölleke, 2018; Khanam et al., 2022; Nanayakkara, 2021, p. 40; Tindall et al., 2022). Therefore, this novel approach might offer a more multi-dimensional comprehension of the supposed gendered network structures and gender-based assortative mixing in electronic music and digital arts. It could also ease the

[5] Poignantly, in 1997, some leading cyberfeminists formed an international alliance named *Old Boys Network* (Spaninks, 2019, p. 51).

burden of laborious counting, which, so far, has been chiefly conducted by women without compensation (Barna, 2022, p.113; D'Ignazio & Klein, 2020, pp. 173-201).

An Emerging Field: Boundaries and Gender Dynamics

Before applying Social Network Analysis (SNA) to the constructed network of gatekeepers in electronic music and digital arts in the Low Countries, it is crucial to establish the boundaries of this field and its two subfields. Moreover, I examine the impact of various possible factors on the awareness of gender inequalities within the boundaries of this network, such as gendered occupational divisions in the creative industries, romanticised perceptions of the field, the enduring (subconscious) association between technology and masculinity in electronic music and digital arts, and the influence of divergent societal attitudes and policies on gender between adjacent fields. In addition, I look at the potential effects of recent major social events, including the #MeToo movement and the Covid-19 pandemic, on the field. By analysing these factors, a better understanding of the contextual dynamics shaping DEI (un)awareness within these digital culture fields can be gained.

A Fluid (Interdisciplinary) Field

In order to identify potential gatekeepers, the field's boundaries need to be established. Due to the lack of a shared definition, a so-called emic viewpoint or realistic delineation determines a community membership based on insider's beliefs, values, and practices, is applied. For this research, it is coupled with a positional approach, using professional involvement as a gatekeeper and territorial delineation as criteria for inclusion in the network and a relation-based approach by adding gender and professional field (Basov, 2020; Knoke & Yang, 2020, pp. 21-22; Marin & Wellman, 2016, p. 12).

As a result, the boundaries of the field remain relatively fluid and include professionals active in experimental and contemporary electronic music, electroacoustic music and sound art, media art, video art, bio art, net art, generative art, art-as-files, AI-based art, and certain forms of performance art, such as live audio-visual performances. These genres and art forms are usually developed in a not-for-profit and/or subsidised context and engage critically and/or artistically with the technology used. Conversely, those involved in genres like trance, hardstyle, and certain types of tech art, immersive art, or NFTs (Non-Fungible Tokens) as collectables and financial assets have been excluded from this network because they operate in commercial and entertainment realms while using technology merely as a means. A telling example of the troublesome demarcation is the recent controversy surrounding Refik Anadol's immersive work, which some consider a legitimate art form. In contrast, others view it as a crowd-pleaser "as repulsive as a bag of Haribo bananas" (den Hartog Jager, 2023).

Despite their shared historical origins, tools, language and ecosystem of labs, residencies, media art festivals and supporting organisations, the fluid, often multi- and interdisciplinary nature of many electronic music and digital art practices presents difficulties in securing adequate funding for organisations and artists. While the Flemish and Dutch governments recognise the fields' significance, both cultural and innovation funding might apply. Furthermore, academic and policy research on electronic music and digital arts has often failed to examine its intersection. This lack of interdisciplinary focus in funding and research complicates gathering numerical data (Brinkmann, 2003, p. 238). In addition, the electronic music and digital art scene is fuelled by global networks of curators, festivals, and

collaborative projects involving cross-border gatekeeping practices. However, research and data on gatekeepers from an international perspective are very scarce (Conde, 2003).

Gendered Gatekeeping and Feedback Loops

Qualitative research on cultural gatekeepers across Europe has highlighted that informal, even 'cliquish' gendered networks of peers and other symbolic gatekeepers hold a greater significance in arts and media than in many other professional domains (Cliche & Wiesand, 2003, p. 15). This practice has also been observed in the Low Countries (Berkers & Hoegaerts, 2019, p. 4; Everts et al., 2022, p. 5; Miedema, 2022; Mullens & Zanoni, 2019, pp. 21-22; Vanhaverbeke, 2015). Expanding on definitions by Foster et al. (2011) and the renowned French sociologist Pierre Bourdieu (1984), according to Emma Hooper (2019), gatekeepers are individuals "who mediate not only between artists and audiences but also between artists and *opportunity*" (p. 137). This broad definition allows a wide range of professionals to take on the gatekeeper role, for instance, radio DJs, A&R managers, funding agency board members, festival programmers and bookers, as well as artistic directors, programmers, PR managers, artist managers, label owners, and music coordinators at radio stations and music critics. Additionally, individuals may fill multiple gatekeeper roles simultaneously or sequentially (Keunen, 2013, pp. 307-310).

The creative industries, including the music industries and digital art, often claim to be meritocratic, inclusive, and avant-garde. Thus, anyone, regardless of gender, could hold a gatekeeper position. However, field research and academic studies (Davies, 2001, pp. 302-316; de Boise et al., 2022, pp. 271-272; Edmond, 2019, p. 83; Gadir, 2017; Gill, 2002; Mullens & Zanoni, 2019; Taylor & O'Brien, 2017) have shown that this is not always the case, particularly regarding gender equality in the workplace. Contrary to the rise of popular (neo-)post-feminist discourses such as the widely criticised 'girl power' (Leonard, 2017; Vanhaverbeke, 2015, p. 25) and META's COO Sheryl Sandberg's 'lean in feminism' (Sandberg & Scovell, 2014), gender stereotypes persist and contribute to gendered occupational segregation. Women are still often confined to supporting and organisational roles, while men dominate in technical, managerial, and artistic gatekeeping roles (Duffin, 2021; Gross, 2022; Hennekam, 2022; Henry, 2009; Hesmondhalgh & Baker, 2015; Leonard, 2017; Mullens & Zanoni, 2019; Parsley, 2022; Vanhaverbeke, 2015, p. 43).

"It is here, with this festival programmer, and others like him (including the ones who are 'her's) that the stickiest problem sit" (Hooper, 2019, p. 136). Men – and women and gender-expansive gatekeepers who have internalised male perceptions of gatekeeping – may perpetuate biased artistic programming and recruitment practices even if they consider their practice as DEI or are convinced of the need for more DEI. These views may, in turn, be based on persistent opinions within their homogeneous networks, often referred to as the 'old boys network'. Such homogeneous networks often shape and reinforce – as in a feedback loop – the professional practices and decision-making of gatekeepers. Kadushin (2012, p. 14) has labelled this the 'chicken-and-egg problem', or as Marin and Wellman (2016) put it, social scientists can explain macro-level patterns "not simply as a large number of people acting similarly because they are similar, but as a large number of people acting on one another to shape one another's actions in ways that create particular outcomes" (p. 13). Thus, studying the structural features that determine the interactions and information flow between gatekeepers in a network can reveal how the network itself might constrain individual decision-making and perpetuate gender disparities in artistic decision-making (Ehrich et al., 2022, p. 6; Kegen, 2013, pp. 65-66; Shoemaker & Vos, 2009, p. 115).

Lastly, it is essential to note that ‘passion’ plays a vital role in the work ethics of creative industries professionals. As a result, the formation of ties in this field might resemble that of voluntary or leisure organisations. According to McPherson et al. (2001, pp. 432-433), this type of organisation offers a combination of ‘structurally induced and choice-produced homophily’. However, the research also points out that when there is shared membership in a voluntary organisation, ‘non-homophilous ties can be as effective as same-sex contacts in providing support’ (McPherson et al., 2001, p. 434). It is, therefore, necessary to consider whether the constructed network is more like a professional network, in which work-related sex segregation still prevails and creates strong baseline homophily, or whether the network has more characteristics of a voluntary organisation or an amalgamation of both.

Gender, Content and Country

McPherson et al. (2001, pp. 429–437) stated that less intimate, professional content-based relationships might be more gendered than close ties, such as those in families. As a result, gatekeepers in electronic music and digital arts may tend to have more gender-homogeneous relationships within their respective fields. These intertwined attributes of gender and professional field can, in turn, significantly impact network and community structures, acting as powerful forces that promote homophily (Labatut & Orman, 2018; McPherson et al., 2001, pp. 422-424). Therefore, can the reconstructed network highlight gendered network communities within each professional field in this study? Although the art world has a slightly higher proportion of authoritative female gatekeepers than the music industries (Treviño et al., 2017), does this trend also apply to the technology-driven niche of digital arts?

One of the most fundamental sources of homophily is geographic proximity: people tend to have more contact with those physically close to them (McPherson et al., 2001, pp. 429-430). Despite notable cultural, bureaucratic, and psychological differences between Flanders and The Netherlands, the two regions have a rich history of cross-border cultural cooperation and mobility based on their shared language and history (Grob & Klok, 2019). Moreover, while one can potentially connect with anyone worldwide through technological advancements, geographical proximity remains essential in the creative industries, as the COVID19-pandemic has highlighted.

However, this cross-border exchange of people and ideas may be less established in more niche areas such as electronic music and arts (Franssen, 2019). Will this lack of cross-border exchange be reflected in the constructed network? Additionally, is there a correlation between territory and gender? For instance, the Keychange Pledge (Keychange, 2023) has, at the time of writing, only a few signatories from the Low Countries, mainly from The Netherlands. This absence may suggest that the issue of gender disparity in the music industries is more recognised in The Netherlands.

From #Metoo to Post-pandemic Reality

Studies conducted by McPherson et al. (2001, pp. 428-437), as well as more recently by Foka (2022) and Ehrich et al. (2022), have emphasised the significance of integrating dynamic SNA to advance research on gender inequality. This study spans from 2016, predating the #MeToo movement, to 2022, coinciding with the end of the COVID-19 lockdowns – that heavily weighted on the cultural sector – and funding terms in Flanders and the Netherlands. How have these events impacted this gatekeeper network?

Not until 2014 did the issue of gender disparity in the music industries gain more widespread attention (von Braun, 2019). Then, first coined by activist and rape survivor Tarana Burke in 2006, the hashtag #MeToo became omnipresent on Twitter and other social media outlets in 2017 following the publication of numerous allegations of abuse of power, sexual abuse, violence, and gender-related harassment in the cultural workplace or education. Despite a handful of high-profile cases of misconduct and allegations of sexual abuse discussed in mainstream media (Philips, 2019; Snapes, 2019), #MeToo has yet to resonate deeply within the music industries and digital arts.

At the end of 2021 and early 2022, the COVID-19 pandemic gradually came under control. Research has demonstrated that the pandemic has disproportionately impacted women's professional and economic status compared to men in the music industries. The latest research confirms that post-pandemic, women's position in the music industries has hardly improved (Das, 2022; Kahlert, 2021; The TroubleMakers, 2022). Moreover, as Fione van Gestel, the head of promotion at Universal Music Benelux, recently pointed out, the 'tight-knit old boys' network' persists in the music industries (Vinckx, 2022).

Research Questions: A Summary

Existing literature suggests that the network of artistic gatekeepers in The Low Countries' electronic music and digital art scene is heavily dominated by men. This inequality is expected to be even more prevalent among gatekeepers based in Flanders/Brussels and primarily involved in music. The following chapter will provide a comprehensive outline of the rationale behind using Twitter data to construct and analyse a network through which I hope to answer the following questions:

(RQ1) Can large data from Twitter and advanced computational methods be utilised to construct and analyse a network of gatekeepers in the electronic music and digital art scene in the Low Countries? What are this approach's potential benefits and limitations?

(RQ2a) How does the network structure, including its topology and communities, provide evidence of gender bias in The Low Countries' electronic music and digital art scene?

(RQ2b) To what extent is assortative mixing reinforced based on the interconnected factors of gender and the professional field (music versus art) in the context of this study?

(RQ2c) To what extent is assortative mixing reinforced based on the interconnected factors of gender and territory of work (Flanders/Brussels versus The Netherlands) in the context of this study?

(RQ3) How have the #MeToo movement and the COVID-19 pandemic affected assortative mixing in the electronic music and digital art scene in The Low Countries?

(RQ4) How can the results of this study inform potential strategies to interrupt feedback loops and combat gender bias in the electronic music industries and digital arts in the Low Countries?

Methodology: Network Modelling

This thesis aims to construct a network and analyse its topology and communities over time through a graph representation model of the network. Network modelling is flexible and can be used for many types of networks (Alamsyah & Rahardjo, 2021; Casalegno, 2021; Khanam et al., p. 8814). And while network visualisation may uncover obscured patterns (Raad & Chbeir, 2018), a range of (statistical) measurements will help understand the network topology and assortative mixing. In this respect, it is also crucial to acknowledge that parasocial activities visualised in a constructed network merely reflect gendered gatekeeping patterns in the actual world (Knoke & Yang, 2020, p. 24).

A Graph Representation

The constructed network for this study will be a one-mode network comprising Twitter accounts of humans (nodes) and their gender, territory, and professional field. Organisational accounts will be included if they have a single (professional) actor. Ties, vertices or edges among gatekeepers will be formed based on the parasocial interactions on Twitter, specifically, 'mentions' and 'replies', offering a multiplex view (Hu et al., 2018, p. 3273; Kadushin, 2012, pp.35-36). Furthermore, as relations on Twitter are not necessarily reciprocal, the ties are directed from the account that mentions or replies to another account, and the weight of each node is determined by the aggregated number of mentions and replies (Dahlan & Terras, 2020, pp. 160-161; Foka, 2022, p. 26; Grandjean, 2016, p. 2; Marin & Wellman, 2016, p. 15), which can be used as a measure of influence.

Social networks also tend to display a community structure where vertices can be grouped into disjoint or overlapping sets, with edges within communities outnumbering those between them. Community detection, a primary task of SNA, helps identify cohesive groups and reveals features such as the overall connectivity, structural holes and the position of nodes acting as bridges that connect different communities (Aggarwal & Murty, 2021, pp. 558-559; Bedi & Sharma, 2016, pp. 115-116; Kadushin, 2012, pp. 186-204; Pan et al., 2019, p. 121586; Zhang & Peixoto, 2020).

Collecting and Processing Data

First, to identify gatekeepers for this study, a purposive non-probabilistic sampling method will be used to manually select artistic directors, promotors, and curators at publicly funded organisations based on official publications and supplemented by independent gatekeepers known in the field. The second step will consist of collecting the tweets by these actors between 1 January 2016 and 31 December 2022. For the data collection, bespoke Python tools will be used to scrape tweets containing mentions and replies. In her research, Foka (2022) has demonstrated the possibility of extracting not only explicit mentions – indicated with an @ symbol on Twitter but also implicit mentions from the tweet text, using Named Entity Recognition. The latter is a Natural Language Processing (NLP)-technique to extract information from unstructured data, thus providing meaningful insights from large datasets; too large for humans to process. For this task, the widely adopted Dutch and English spaCy models (https://spacy.io/usage/models) will be used (Foka, 2022, pp. 5-6).

However, before adding implicitly named actors to the list of nodes, the tweets should be reduced to relevant tweets using a classifier, as described in Chapter 3. After further cleaning and significant transformation, a node list and a weighted, asymmetric adjacency list will be created. Lastly, attributes will be added to the nodes. Crowdsourcing and automated techniques have been proposed to extract temporal, spatial, and gender

attributes from user-generated (textual) data such as Twitter's location and description. These approaches may yield incomplete or varied data and might be especially problematic regarding gender given the often simplified binary framework (D'Ignazio & Klein, 2020, pp. 105-115), disregarding gender self-identification and multilingual datasets. However, to speed up the gender identification process, I applied one of the most accurate tools, Gender-Guesser (Sebo, 2021).

Visualisations, Topology, Assortative Coefficient

Created in 2008, Gephi (version 0.10) has become a leading open-source and powerful package for network visualisation and analysis of extensive networks with attributed nodes (Bastian et al., 2009). Filters can be applied to appealingly visualise a network and its communities (Ehrich et al., 2022; Foka, 2022, pp. 4-9; Grandjean, 2016; Heymann, 2018; Meirelles et al., 2018, p. 90). In addition, it provides built-in layout algorithms, such as ForceAtlas2. This algorithm – which was developed for large scale-free networks – uses attraction and repulsion forces to arrange and position elements in a visual representation, emphasising the importance of connections between actors rather than the actors themselves while ignoring all attributes (Decuypere, 2020, pp. 8-9; Heymann, 2018, pp. 930-931; Jacomy, 2019).

Visualisation. However, before implementing ForceAtlas2, the Fruchterman Reingold algorithm will be deployed to detangle the network and improve visual readability (Grandjean, 2016). Next, with carefully adjusted settings (Jacomy et al., 2014; Khokhar, 2015, pp. 66-73) to balance and optimise the visual representation, ForceAtlas2 was applied, followed by the built-in Louvain-clustering algorithm to detect communities. The latter offers two main advantages: it computationally efficiently partitions large networks and can detect smaller communities (Knoke & Yang, 2020, p. 118; Menczer et al., 2020, pp. 168-169).[6] However, it also has a tendency to merge small, weakly connected communities into larger components, as well as producing many communities with almost indistinguishable values (Barabási & Pósfai, 2016, p. 35). Furthermore, a dynamic analysis will be performed using Gephi, which can provide an impression of how the constructed network developed between 2016 and 2022 (Saganowski et al., 2018). Another consideration is that emerging patterns, *e.g.* for communities, can result from irregular fluctuations rather than being meaningful (Nanayakkara et al., 2021, pp. 40-47).

Topology. Despite Gephi's popularity, there is an ongoing debate about its transparency. Some argue that the tool acts as a black box, potentially hiding biases from the user (Bastian et al., 2009, pp. 8-9; Ehrich et al., 2022; Foka, 2022, p. 4; Grandjean, 2016; Heymann, 2018; Jacomy, 2019; Meirelles et al., 2018, p. 90). Additionally, beyond ten nodes, it becomes increasingly challenging to examine network topology and discern intricate patterns from a visualisation (Blank et al., 2021; Kadushin, 2012, p. 27, pp. 48-62). Therefore, topology and other measurements will be calculated, mainly using Gephi. First, the network's size or the number of nodes and edges must be considered. The average weighted degree for the network, and more particularly, the distribution of the weighted degrees – the sum of in-degree (received mentions) and out-degree (given mentions) – for each node can confirm whether the constructed gatekeeper is a scale-free network and displays a so-called 'power distribution' indicating growth of the number of edges and nodes

[6] For this thesis, no exhaustive discussion of the affordances and drawbacks of all tools and algorithms, is provided. Grandjean's guide (2016), Jacomy's blog (2023) and the Gephi Cookbook (Khokhar, 2015) were consulted to identify potential pitfalls, *e.g.* carefully layering edges and nodes is essential to enhance node visibility during topology analysis, and by consensus, clockwise directed curved edges are used for directed graphs.

over time and a tendency for preferential attachment: the more ‘popular’ a node is, the more likely it is to receive, in this case, new mentions and replies (Kadushin, 2012, pp. 113-119; Menczer et al., 2020, pp. 133-135; Zaidi et al., 2018, p. 59).

Connectivity. The density tells what portion of all possible direct edges between the nodes are actually present in the network. The greater the density, the more likely a network is to be considered a close-knit network, a source of social support and an effective transmitter of, *e.g.* information. Density must be considered in relation to the size of the network (Kadushin, 2012, p. 29) and also relates to the average path length or the measure of how information flows in the network. Based on the shortest path length between any two nodes, the diameter indicates the maximum shortest path length a node can have with any other node in the network (Kadushin, 2012, pp. 32-34). Two other essential network properties are the average clustering coefficient – which calculates the probability for a node that its neighbours are each other’s neighbours – and connectedness, which can help understand the level of trust, support and information flow, which are crucial in gatekeeping practices. In this respect, weak ties are also considered, which might also reveal interesting structural information (Kadushin, 2012, p. 30).

Centrality. Eigenvector centrality calculates a node’s influence based on the importance of its neighbours. Examining attributes of the most influential nodes can provide insights into the perceived gender homophily of these nodes in the network (Bokunewicz & Shulman, 2017, pp. 210-211; Caldarelli & Chessa, 2016, p. 84, pp. 178-180; Kadushin, 2012, pp. 66-73; Khokhar, 2015, pp. 115-152; Peng et al., 2018, p. 22; Riquelme & González-Cantergiani, 2016, pp. 951-961). Harmonic Closeness Centrality, which returns the average distance from a given starting node to all other nodes in the network, tells us who connects different communities. It has been argued that women need to occupy these brokering positions to benefit from network opportunities (Ehrich et al., 2022, p. 6; Kadushin, 2012, pp. 66-73, pp.178-180). This variant of betweenness centrality accommodates unconnected graphs.

Community detection. Equally, clustering network communities is useful in comparing structural components, mainly to analyse ‘gendered communities’ (Atzmueller, 2018; Ehrich et al., 2022, pp. 2-3; Grandjean, 2016). The modularity score – its challenges are discussed by Kadushin (2012, pp. 79-80) and Foka (2022, Supplement Material, p. 12) – indicate the degree to which a network is clustered into non-overlapping groups or well-defined communities. Examining how these communities are based on similar attributes may reveal something about homophily.

Assortative mixing. To determine whether the calculated assortativity coefficient is structurally significant, it should be compared with the values obtained from a randomised version of (the subset of) the network. This comes with a few limitations. First, to assess structural significance, a simplified method of rewiring the edges in the network to create a randomised version was used. As Carstens and Horadam (2016, p. 337) highlighted, this approach could introduce biased sampling, especially on small graphs. And although new classes of assortativity coefficients for directed weighted networks have recently been proposed, they are still experimental (Noldus & Van Mieghem, 2015, pp. 527-528; Pigorsch & Sabek, 2022; Yuan et al., 2021). Given these considerations, the assortativity coefficient initially proposed by Newman and implemented in the *networkx* library will be deployed (Hagberg et al., 2008).

Temporal Analysis. Finally, snapshots of the network at different time points will be captured to observe any changes within the studied timeframe. As Zaidi et al. (2018) aptly

stated, “However, it may still be simplistic to analyse intricate temporal patterns. Yet, we seek to address a straightforward question” (p.63).

Evolving Language and Contentious Categorisation

In a 1970 opinion piece in The New York Times, composer and longtime gender equity advocate Pauline Oliveros called out critics and scholars who referred to women composers as ‘lady composers’, condemning their condescending language use. And she wondered: What critic speaks of male composers? Today, this question remains relevant. Although women composers are no longer called lady composers, othering through to explicit use of woman or female as an adjective still emphasises the ingrained association of composer, producer or musician with men. Furthermore, as Harauer et al. (2003) point out, “the female musician in music’ approach risks reducing complex gender identities to one essentialist element, namely biological sex” (p. 69), while the recently more often used ‘woman musician’ or ‘woman curator’ implies a more social and cultural perspective and can encompass gatekeepers who identify as a woman and thus acknowledge the challenges, experiences, and perspectives that come with being a woman in the music and, more broadly, creative industries. Therefore, in the theoretical section, I will mainly use woman and man as adjectives (Best, 2022). However, for the statistical analysis, I use cisgender male, cisgender female, and gender-expansive[7]. I am aware that this labelling fails to fully represent individuals who identify as any other gender not explicitly mentioned here and who are equally facing discriminatory practices on all levels in the creative industries (D’Ignazio & Klein, 2020, pp. 105-115; Werner et al., 2020, p. 643). Lastly, we chose the intersection of gender, location and occupational field rather than an intersectional approach that examines gender, class and ethnicity. The latter two, as well as age and functional capacity would be very challenging to infer from our dataset.

[7] In the most recently updated version of this thesis, other-gendered has been replaced by gender-expansive.

Chapter 2
Leveraging Twitter Data to Map Gatekeeper Networks

The first chapter discussed the dominance of men gatekeepers in the networks in music industries and digital art and identified the research gaps impeding a better understanding of their gendered structures and possible gender homophily. These networks are essential for gatekeepers in decision-making, and online platforms like Twitter help gatekeepers establish their position by building social capital and accumulating and showcasing symbolic capital. And while there are many advantages to leveraging Twitter data to map gatekeeper networks, there are also some limitations and concerns.

Gatekeeping Practices in Creative Industries

Gatekeeping theory was developed by German-American psychologist Kurt Lewin (Cliche & Wiesand, 2003, pp. 9-19) in the mid-twentieth century and is further elaborated on by scholars in different disciplines. Cliche and Wiesand (2003, pp. 18-19) have defined gatekeepers within the context of creative industries. Gatekeepers hold a pivotal role in decision-making within an organisation or field. The criteria for their decision-making process are underpinned by both their professional frameworks and subjective reasoning. Conversely, their decisions significantly impact the creation and dissemination of symbolic value and the establishment of reference frames within a field. Due to the emergence of digital technologies, particularly social networking platforms that allow user-generated content, new gatekeeping processes carried out by freelancers and amateurs emerged in addition to those established by individual gatekeepers associated with institutions.

Decision-Making Strategies

Generally, gatekeepers' decision-making practices are influenced by many factors, including job type, role conceptions, existing decision-making strategies, mental models, values, attitudes, and ethics (Shoemaker & Vos, 2009, p. 115). Studies on the creative industries have mainly focused on how gatekeepers' cognitive conceptions, demographic characteristics, educational backgrounds, accumulated expertise, personal beliefs, social and cultural capital, and occupational networks shape their decision-making processes (Davies, 2001; Keunen, 2013; Leonard, 2017; Vanhaverbeke, 2015; Whipple & Coleman, 2021). These factors can reinforce each other in decision-making processes, such as how gatekeepers perceive 'quality' or 'taste'[8], which are often also heavily gendered concepts (Hooper, 2019, p. 138; Keunen, 2013, pp. 106-146).

Gatekeepers in the creative industries need to balance artistic integrity or reputation and mitigating economic risk by trying to distinguish themselves through their 'own' taste while simultaneously facing pressure to generate revenue streams (De Roeper, 2010; Hooper, 2019, pp. 137-140; Keunen, 2013, pp. 147-201). The COVID-19 pandemic has once again highlighted this precarious trade-off. To mitigate risks and seek/sustain reputation,

[8] For his study, I will not delve into the existing and recent theoretical frameworks about 'taste' proposed by Bourdieu (1984), Lizardo (2006), and O'Brien and Ianni (2022).

building social capital through embeddedness, allowing for the gathering of external data and becoming influential through accumulating and showcasing symbolic capital have become essential to support adequate decision-making (Foster et al., 2011; Lizé, 2016).

Success Through Embeddedness

Twitter enables gatekeepers to build networks or social capital (Gross, 2022, p. 170; Syn & Oh, 2015). In addition, social networking sites facilitate gathering and exchanging information. This network of trusted relationships often comes with reciprocity and obligations based on economic power balances. However, shared and recognised cultural, social and symbolic capital are also indispensable. For example, such networks disseminate information about an artist's quality and, thus, reduce uncertainty (Hooper, 2019, pp. 139-140; Keunen, 2013, pp. 202-230). At the same time, this 'second order selection process' – aimed at reducing risk and complexity – carries the risk of conformism when cultural norms that reinforce existing structures of prejudice and aesthetic ideals become pervasive. Moreover, since gatekeepers often turn to people they know and trust when making decisions, this risk mitigation system might perpetuate entrenched and discriminatory patterns (Keunen, 2013, pp. 250-288).

Gatekeepers might also embrace embedding as a strategy to mitigate the risk of being overshadowed by metric-driven approaches. Keunen (pp. 106-146) noted earlier in 2013 that the music industries, driven by a romanticised self-image, resists a data-centric approach that could undermine the perceived value of artistic gatekeeping based on 'quality' and personal taste. However, the gatekeepers' attitude towards metrics in decision-making is ambiguous, given that they also increasingly consider statistics from streaming services and artists' social media (Baym et al., 2021; Osborne & Laing, 2021; Prey, 2020).

Influence: Acquiring and Displaying Symbolic Capital

Gatekeepers rely – passively and actively – on trusted external sources to gather information for decision-making. While this type of information was traditionally shared over coffee dates, at venues, and at festivals, now it has become part of online social information sharing. Moreover, gatekeeping now not only involves filtering information (Shoemaker & Vos, 2009, p. 117) but also continuously sharing the most relevant and 'hip' information showcasing taste and acumen to enhance social and symbolic capital (Hooper, 2019, p. 139; Schreiber & Rieple, 2018, p.24).

Although recommendation engines are increasingly being used, human gatekeepers continue to play a crucial role in the creative industries. The canonisation of artworks still relies heavily on human tastemakers with enough symbolic capital to be considered authoritative (Glowacki, 2023, pp. 98-99; Schedl et al., 2021). However, in the digital age, the value of an artist's work is now also determined by their online visibility and virality. Gatekeepers in this network use their conversations about artists performing at concerts and festivals, new releases, exhibitions, and emerging talent to assert their status as tastemakers among their peers while also promoting the artists they book for events or include in exhibitions. By doing so, a gatekeeper can contribute to the artists' viral success and simultaneously enhance their cultural tastemaking status.

Ultimately, in the pursuit of accumulating and displaying cultural and symbolic capital, the act of 'agrandissement' to boost one's perceived status on social media has become essential (Schreiber & Rieple, 2018, pp. 20-24; Syn & Oh, 2015, p. 558). However, this self-promotion is often viewed as a predominantly masculine trait, while women who exhibit

confidence and assertiveness may not be taken seriously, reinforcing the ‘authority gap’ stemming from gender biases, discrimination, and societal expectations about gender roles (Berkers & Hoegaerts, 2019, p. 4; Sieghart, 2022). In turn, this pattern might increase homophily in gatekeepers’ networks online, while women are discouraged from participating in online spaces, mainly because they are more vulnerable to gender-based abuse (Dhrodia, 2018). Combined with structural network properties, this may hinder the accumulation of symbolic capital for women gatekeepers.

Examining Gatekeeping in a Digital Ecosystem

As a communication network, relationships on Twitter are not defined as friendships but reflect different levels of information exchange (Menczer et al., 2020), which, as mentioned above, is part of economic and artistic risk-mitigating strategies between gatekeepers. Therefore, to gather the most appropriate Twitter data and outline a temporal network, it is necessary to delineate which Twitter communication levels gatekeepers in electronic music and arts use to obtain their goals.

Fostering Intimate Relationships and Influence

In addition to public tweets, Twitter’s API provides several ways to measure user interaction, such as following/friends, retweets, mentions, replies and quote tweets, where a tweet is quoted and commented on. Hashtags, adding friends to lists, liking tweets, and marking tweets as favourites are also discernible indicators. Since 2015, Twitter also provides the possibility of including text in retweets (‘quote retweet’), bringing both together. This feature allows for retweeting, commenting and mentioning the original poster in the same tweet (Caldarelli & Chessa, 2016, p. 79; Dahlan & Terras, 2020, pp. 160-161; Esteve Del Valle et al., 2022, p. 737; Foka, 2022, p. 26; Grandjean, 2016, p. 2; Hanusch & Nölleke, 2019, p. 28; Lee et al., 2020, p. 6244; Riquelme & González-Cantergiani, 2016, pp. 950-954).

The most significant levels of communication on Twitter for building social and symbolic capital are mentions and replies. By actively and frequently sending out tweets with mentions or replies, one can substantially grow their network and thus social capital (Aguilar-Gallegos et al., 2022, p. 128). Moreover, composing a mention or reply requires considerable time and effort, making it a much more intimate and active form of interaction than, *e.g.* retweets (Bokunewicz & Shulman, 2017, p. 209). This also suggests that the account being mentioned or replied to is of interest to the author’s followers and is worthy of attention. As a result, mentions and replies reflect a commitment to building trust-based relationships while also seeking visibility, both of which are crucial to success in gatekeeping practices. Furthermore, Twitter is sometimes compared to a radio: it can serve as a background noise that requires little attention, but the latter can be claimed by mentioning another user in a tweet through an @, also inviting the other user to engage in a conversation (Crawford, 2012, p. 83; Khanam et al., 2022, p. 11). Lastly, mentioning is a way of emphasising, acknowledging, and crediting another Twitter user, which is vital for embedding oneself in the social network.

Twitter behaviour shows differences between demographic groups. Studies indicate that about a quarter of tweets contain mentions, with men using mentions slightly more than women (Wood-Doughty et al., 2017, pp. 4-5). In addition, men tend to engage in social media interactions for reciprocity, while newer users use it for personal gain, including acquiring symbolic capital (Syn & Oh, 2015, pp. 558-566). Generally, users with a significant following on social media are seen as individuals or institutions with more influence within

the network. They are more effective in spreading information, building a high reputation and accumulating symbolic capital compared to users who follow many accounts but have no significant following themselves (Grandjean, 2016, p. 4; Riquelme & González-Cantergiani, 2016, p. 960).

Assortative Mixing on Twitter

Homophily or assortative mixing within a network, where individuals tend to connect with others who share similar traits, significantly influences gatekeeping practices and information dissemination. The joint influence of node preferences and meeting opportunities shapes these homophilic social network connections. Gender-based assortative mixing within a network is considered noteworthy if it deviates from the expected 'meeting opportunities' based on the near-equal distribution of men and women (Currarini et al., 2016; McPherson et al., 2001, p. 419).

Although social media platforms offer the opportunity to connect with diverse individuals worldwide, research suggests that homophily tends to increase on these platforms (Khanam et al., 2022, p. 8818). This might also impact the flow of information and, subsequently, the accumulation of social and symbolic capital. Majority groups are found to have more homophilic networks compared to minority groups, with, relating to gender, men usually forming the majority. As a result, majority groups are more effective in gathering information and disseminating their symbolic capital faster (Kegen, 2013, p. 63; Lutter, 2015; McDonald, 2011).

However, the presence of 'inbred homophily' may complement this 'closure pattern', resulting in minority (women and gender-expansive) gatekeepers having more allies who share similar traits than expected (McPherson et al., 2001, p. 416, pp. 419-429; Khanam et al., 2022, pp. 8819-8827). This may explain why, especially in the early days of Twitter, women and other minorities formed dedicated Twitter communities rather than remaining isolated or seeking a stronger position within existing majority networks (Rodgers, 2010). These segregated networks offered users safe spaces to mobilise each other for political action and social change (Carstensen, 2014, p. 489). Therefore, it is key to investigate whether homogeneity within gender minority groups among gatekeepers on Twitter is greater or less than expected.

From Data Gap to Dataset

In electronic music historiography, "social and professional networks, limiting definitions and achievement standards influence the inclusion or exclusion of individuals" (Rodgers, 2010, p. 15). This highlights the inherent political aspects of determining who is recognised, counted or documented within the field. Portraying power imbalances in the collection and accessibility of data, in 2017, the artist Mimi Onuoha displayed The Library of Missing Datasets (Dutch Edition) at the Utrecht media art festival Impakt. The installation featured a plain filing cabinet with empty hanging folders. Each folder was labelled with a topic lacking data, often relating to disadvantaged groups in history and society. Through this thought-provoking installation, Onuoha emphasised the absence of diverse and inclusive datasets and drew attention to persistent data collection and access inequalities.

Defining Gender Equity Progress

Onuoha's installation also captured the contemporary views that emerged in the late 2000s and gained momentum around 2012. Activists, journalists and community researchers

became increasingly convinced that the availability of more diverse quantitative data would reveal the extent of gender inequalities in music and art. In turn, it was believed that the insights gained from those statistics about gender proportions of performers and non-performers would spur positive change. This approach remains prevalent despite a shift towards more realistic expectations regarding the potential impact of these new, diverse datasets over the past five years. For the scholar Michelle Conceison (2022), this "documenting and establishing the state of the 'diversity crisis in the music industries' represents only the first stage of research" (p. 6).

The reliance on more diverse datasets and descriptive statistics without regard to contextual and statistical intricacies raises questions about whether an increase in female and gender non-conforming artists can be unequivocally labelled 'progress'. Scholars such as Conceison (2022, p. 28) and Rae et al. (2017) emphasise the need for studies that include clear indicators and benchmarks to measure such progress. In addition, these scholars stress the importance of more collaboration between the music industries and researchers to improve the quality of methodologies and data sources. Although for marketing purposes, extensive data and statistics to support decision-making in today's music industries, including on DEI, are collected, this data is, in many respects, not easily accessible to researchers and often comes with ethical concerns (Schwarz & Johansson, 2022).

Magic Numbers

Before discussing possible new computational approaches to address persistent data gaps, a concise overview of the findings gleaned from quantitative research conducted in recent years will be provided, and data gaps will be identified. Apart from observing the exclusion of many gender-expansive identities, LGBTQIA+ and BIPOC people in many studies, in her metastudy, Conceison (2022, p. 7) found a representation of 15%-20% of women in various roles. This percentage is slightly higher than the magical 13%, as cultural studies scholar Christina von Braun (2019, p. 136) coined it in 2014.

Electronic Music. Biannually, on International Women's Day, community organisation female:pressure – founded in 1998 by Vienna-based musician Susanne Kirchmayr aka Electric Indigo – publishes its crowdsourced FACTS survey on gender equality in performing roles in electronic music. The first FACTS survey was published in 2013. In its 2023 report, female:pressure concluded that the percentage of female and gender-expanding performing artists in electronic music has increased from a bit over 9% to almost 30% in a decade. The perceived 'progress' in gender representation within the electronic music field may be reassuring to those with gatekeeping roles. But, as noted, the lack of standardised benchmarks within the field renders the meaning of these numerical indicators ambiguous, threatening to erase the urgency of redressing the gender balance.

Since 2020, data on the gender identity of the festival curators has been added to the FACTS survey. Subsequently, female:pressure's statistics team The TroubleMakers discovered a slightly positive correlation between a mixed or all-female curatorial team and the proportion of women and non-binary performers. However, this conclusion should be accompanied by some methodological remarks. The included festivals are mostly located in the Global North, outliers (such as the Berlin-based Heroines of Sound festival, which has an almost 100% women line-up) might skew results, and possible correlations have not (yet) been statistically tested. The most recent FACTS report (The TroubleMakers, 2022, pp. 30-34) refers to additional studies confirming these dismal statistics.

Digital Arts. Compared to the electronic music scene, the findings in the field of digital arts are more encouraging. However, empirical data on this issue still needs to be explored. In 2016, Heather Dewey-Hagborg and fellow artists in the field of digital arts published an op-ed in the newspaper *The Guardian*, urging the directors and curators of the prestigious Austrian Ars Electronica festival to address the glaring gender inequality among participating and award-winning artists. Niki Georgiou's study (2018) supports Dewey-Hagborg's observations. This data analysis of digital arts festivals in the Global North between 2012 and 2017 revealed that, on average, 32% of the participating artists, whether working individually or collaboratively, were identified as women. Using statistical methods, Georgiou (2018, p. 28) concludes that 'that the possibility of the existence of occupational sexism in the digital arts field is high'. Meanwhile, empirical data on non-performing roles in this context is still largely absent, leaving a gap in the understanding of gender representation in various roles in the digital art field.

The Low Countries. Most research on gender disparity in the Low Countries focuses on performing roles (Berkers & Smeulders, 2018; Berkers et al., 2019; Hilliaert & Hesters, 2016; Mulder, 2022). Data about gender (in)equality of electronic music and arts gatekeepers or non-performing roles in the Low Countries is almost non-existent. For both territories, research by Kunstenpunt (Flanders/Brussels) and Boekmanstichting (The Netherlands) only considers the male-female categories. Furthermore, it is not clarified if the data is based on self-assigned gender or labelled by the researchers.

In its most recent *Cultuurmonitor* on the domain of music (Michael & Roosblad, 2023), the Boekmanstichting publishes key figures about gender proportions for different roles in pop music venues. There is no distinction between artistic and business directors, nor for genre or funding status. So, based on available evidence, among the directors in 2019, only 23% were labelled as women. For programmers, this percentage was slightly higher at 35%. Unfortunately, data about gender proportions among curators in museums and institutions or organisations for visual arts in The Netherlands, including digital arts, is unavailable. However, in 2018, only 6% were women at the director's level in visual arts. The most recent research on digital arts in The Netherlands (Virtueel Platform, 2011) lacks details on gender proportions.

For all arts organisations structurally funded by the Flemish government, including those with electronic music and digital arts as focal points, only 25% of the artistic directors are female. The *Cijferboek Kunsten* also provides a more detailed overview of gender proportions in directions for the music sector. In all grant categories, over half of the organisations have an exclusively male board of directors. In four categories, even more than 75%. In the two highest grant categories, 86% of the organisations at the time of publishing had an all-men direction (Janssens et al., 2018, pp. 392-397). Although this broad category of music organisations does not precisely coincide with the organisations considered in this study, it indicates the gender disparity at decision-making levels.

Digital Humanities Approaches

The previous section shows a strong need for more pertinent data to quantitatively investigate gender-specific network structures among electronic music and digital arts gatekeepers. Online supplement 2 provides a brief overview of existing empirical studies that use social media data to study the music industries. However, these studies have not utilised SNA to reconstruct and examine a network of gatekeepers in the music industries, let alone within specific genres. At a much smaller scale of measurement, Donker's research (2019)

highlights the specific role of the artist manager as a lynchpin in artist networks, albeit primarily based on Spotify data.

Therefore, this study will lean on the methodological approaches in other occupational fields. These include other creative industries (Bokunewicz & Shulman, 2017; Ehrich et al., 2022; Foka, 2022), the health (Lee et al., 2020), agricultural (Aguilar-Gallegos et al., 2022) and nonprofit sector (Benabdelkrim et al., 2020), politicians (Esteve Del Valle, 2022; Esteve Del Valle et al., 2022), scientific networks (Dahlan & Terras, 2020; Grandjean, 2016; Walter et al., 2019), journalism (Hanusch & Nölleke, 2019; Lauw et al., 2010), think tank members (Tchubykalo et al., 2021), and tech communities (McDonald & Anderson, 2020).

Harnessing Twitter's Data Potential

In the early days of the internet, blogging became popular for sharing information about various topics, including music and art. By the late 1990s, Dutch and English blogs had not only become essential information sources but also served as communities. 'Bloggers' soon complemented existing categories of gatekeepers (Jetto, 2015). So when Twitter emerged in the mid-2000s as a condensed version of blogging, many of these bloggers quickly adopted the platform (Levy, 2023).

Declining Use. In recent years, Twitter has faced several controversies, which has led to a decline in its usage among the general audience and, thus, most likely also among users in the music industries in the Low Countries (imec, 2022; Nederpel & Pauw, 2023). This drop is reflected in this study, as some of the long-term users on the exemplar list of gatekeepers discontinued their accounts while I was actually collecting data. As the issues of missing nodes and the representativeness of Twitter in occupational networks have been widely discussed (Bokunewicz & Shulman, 2017, p. 2015; Grandjean, 2016, p.12), Foka (2022) has demonstrated that gatekeepers who are not or are no longer present on the platform can still be inserted in a constructed network based on implicit mentions.

Noisy and Missing Data. The extracted data from Twitter is also susceptible to flaws, such as noise, including personal messages, jokes, and other non-relevant interests (Grandjean, 2016, p. 2). An initial exploration of the collected data for this study revealed tweets about politics, sports, and complaints about the service industry. Although techniques have been proposed to reduce noise, implementing these techniques was beyond the scope of this thesis (Chaki et al., 2020; Injadat et al., 2016; Nanayakkara et al., 2021; Tiwari & Kumar, 2020). Furthermore, missing or spurious nodes, missing relations, or falsely aggregated or disaggregated data may pose significant problems in network research, including using archival data such as historical tweets (Knoke & Yang, 2020, pp. 42-49). Nevertheless, this study explores whether a novel approach can mitigate the impact of missing nodes.

Other Potential Platforms. As Twitter's popularity wanes as a space for public communication and debate, can other social media platforms provide an alternative for constructing and analysing an attributed network? Additionally, in the Low Countries, unlike the Anglo-Saxon world and Germany, gatekeepers seem to be less involved in extensive Twitter discussions about the state of the field and developments in music genres and digital arts. While the professional networking platform LinkedIn – founded in 2003 and now owned by Microsoft – offers a wealth of (more) structured information about professional roles, location, affiliations, and education, accessing LinkedIn's data has become increasingly difficult due to restricted access (Gatto & Almasi, 2021; Smith, 2022). Unlike Twitter, few

users have fully public accounts on LinkedIn. The same legal and technical obstacles apply to using Facebook. Alternative platforms, such as Discord, Mastodon and TikTok, are unsuitable for the studied timeframe because of their recent creation, limited number of users in the sample or legal obstacles. Additionally, obtaining data from these platforms can be laborious for researchers, *e.g.* Instagram's API caters primarily to content creators and marketers, providing limited research opportunities.

Challenges for Responsible Data Use

Privacy and ethics in data collection have received increased attention in academia and society (Tindall et al., 2022, p. 272). Regulations such as the European Data Protection Directive (Carrigan et al., 2021, p. 9) have been implemented to restrict the use of data while offering some flexibility for scientific research. However, striking a balance between maintaining privacy and collecting data to understand social issues remains a challenge. Questions arise about handling public and non-public data and the choices made regarding anonymisation so that the underrepresented groups can continue to benefit from this dataset.

Twitter Data = Public Data?

Online social media networks have significantly blurred the boundary between public and private, mainly because users often trade in their anonymity and access to and control of their data for perceived network advantages, including establishing more or less 'intimate' relationships. Few users will be aware or give express consent that third parties can access their data for different purposes by so-called Unknown End Users, including researchers, even if they choose a pseudonym or create a separate online identity (Aguilar-Gallegos et al., 2022, pp. 120-121; Chaki et al., 2020; Macnish, 2018, pp. 778-780; Tindall et al., 2022, p. 282; Tzouramanis et al., 2018, pp. 769-777). Most exemplar users in this research operate under their given name, an easy-to-decipher abbreviation or a nickname while also mentioning their real name. Only a few users in the sample have set their settings to anonymous; their tweets are absent in the dataset.

However, as Grosser (2017) has noted: "Social media in particular has conditioned many to not only accept high visibility, but to desire it" (pp. 4-5). High visibility ensures power and, subsequently, influence within the online network to influence, which is vital to gatekeepers. This deliberate public exposure and ambiguity around the notion of 'public data' has led some researchers to conclude that data used from Twitter are 'up for grabs' (Kadushin, 2012, p. 189; Tindall et al., 2022, p. 282). However, the fact that the 'public data' is accessible through Twitter's API does not make data mining a straightforward process, as it often deals with sensitive data. And what is factual information to one person can be sensitive to another person or even do harm individuals when disclosed through pattern mining (Macnish, 2018, pp. 778-780; Tindall et al., 2022, p. 282; Tzouramanis et al., 2018, pp. 769-777).

Anonymisation and Node Re-Identification

In social network analysis, collecting personal data and attributes is indispensable; with big data, actors might not be aware of it (Kadushin, 2012, p. 189). Some researchers (Aguilar-Gallegos et al., 2022; Foka, 2022) that examine key actors in constructed networks have included personal data, such as personally identifiable information (PII), *i.e.* their name and Twitter username (Kamińska, 2022). These researchers want to test assumptions about

influential figures or organisations and examine information flows and success within networks (Fraiberger et al., 2018). In other studies, these data are often anonymised. However, recent research on machine learning node re-identification attacks in assortative networks (Horawalavithana et al., 2019, p. 18; Kefi & Perez, 2018; Tindall et al., 2022; Topaz et al., 2022; Zook et al., 2017) has demonstrated that adding binary and or multiple attributes to anonymised data points increases the risk of node re-identification – which is not the case in this study –, which is amplified by a conjunction of network topology and node placement. Even advanced privacy-preserving data presentation methods have not proven airtight when sophisticated machine-learning techniques are being deployed for node re-identification. Alternative options for robust node anonymisation remain still poorly understood (Ziemkiewicz et al., 2020, pp. 247-248).

In this study, personal data collected included names, gender, territory and professional field. However, the network visualisations in this thesis will be aggregated, and names and attributes will not be disclosed. After carefully considering the reproducibility of this research, the value of the dataset for further research, the closure of Twitter's free API, the need to establish a foundation for research that might also benefit the underrepresented groups in electronic music and digital arts and the potential harm for the exemplars and their alters (Tindall et al., 2022, p. 282), I have decided to make the Twitter dataset available for other researchers upon request. The data management plan (see Supplement 4) details the ethical aspects of collecting, storing, processing and accessing this potentially sensitive personal data.

Chapter 3
Curating a Relevant Dataset

Following a review of prior research and identifying knowledge and data gaps preventing a better understanding of the potential underlying gendered network structures and gender homophily leading to the underrepresentation of women in the electronic music and digital arts in the Low Countries, the upcoming chapter will elaborate on the collection of a new, relevant dataset. Inspired by Amalia Foka's 2022 research, this study shows that collecting data to constructing a fairly representative gatekeeper network is feasible using advanced computational methods. Again, this data collection, cleaning and transformation process highlights the underrepresentation of women gatekeepers in the real world and among Twitter users.

Curating a Representative Exemplar Sample

As demonstrated in Chapter 2, there is little available data on gender in non-performing roles in the creative industries in the Low Countries. Unlike other fields (Ehrich et al., 2022; Foka, 2022), no listings of influential gatekeepers in the Low Countries exists. Due to the lack of such lists and especially given the field's blurred boundaries, parameters had to be determined to arrive at a representative sample.

Selecting Institutions and Organisations

First, I aimed to collect artistic directors, curators and promoters at organisations receiving operational or multi-year project grants during the above-mentioned time frame. One challenge was differentiating between organisations focusing on electronic music and digital arts and those showcasing diverse music genres and art disciplines. Therefore, I focused on how organisations position themselves linguistically and in terms of programming. Due to the vastly different funding structures between the two territories, a cautious approach ensured that the levels at which the gatekeepers operated remained comparable. Next, additional sources were consulted to identify independent bookers and curators.[9]

Flanders / Brussels[10] In Flanders, cultural funding is primarily public and centrally organised, including through Brussels' Flemish Community governing body. Therefore, three sources proved to be useful. First, the list of organisations with an (inter)national appeal and scope that applied for and received funding in the framework of het Kunstendecreet, which covers organisational and programming costs for the subsequent five or ten years. Verifying the foundation behind each public cultural institution was done through the public Kruispuntbank van Ondernemingen. Civil servants and expert committees assess plans and advice on grants, with the Secretary of State for Culture making the final decision. Top-rated institutions are separately evaluated and receive subsidies under a management agreement. Short and long-term project grants are also allocated. Decisions are then published on the Flemish government website.

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[9] Online Supplement 2 offers a comprehensive list of links to the mentioned sources for this section.

[10] As a result of the federalisation of cultural authority in Belgium and the constitutional power of the French and Dutch language communities in Brussels, cultural organisations identifying as Flemish or bilingual can receive subsidies from the Flemish government. Furthermore, Brussels organisations might receive funding from more than one authority, including the Flemish government, the VGC, French-identifying Fédération Wallonie-Bruxelles or the COCOF (French Community Commission in Brussels).

The list is extended by the relevant organisations that receive direct operations funding from the Vlaamse Gemeenschapscommissie (Flemish Community Commission or VGC) in Brussels. The VGC decides on a case-by-case basis resulting in decisions published yearly on different dates. To double check, the member list of the Brussels Kunstenoverleg, the association of employers of publicly funded cultural institutions, was browsed. Thirdly, the Flemish domestic affairs agency also provides budgets for long-running projects in Brussels under Polsslag Brussel – Projecten voor Brussel (Pulse Brussels – Projects for Brussels), which supports, *e.g.*, the LISTEN electronic music festival.

Before 2018, all Flemish provinces had their own cultural policies, but since then, these responsibilities have been transferred to either the Flemish or local level. Due to this change and the fact that relevant organisations also received subsidies from the Flemish government, I have since excluded this policy level. Moreover, I refrained from including locally funded organisations, as their influence rarely extends beyond the local level. Finally, Belgian federal-level culture funding primarily supports major cultural heritage museums and cultural diplomacy events such as the Europalia festival and EU presidencies. These large-scale events, including electronic music and digital arts, are usually curated by freelance staff.

The Netherlands. Contrary to the Flemish funding framework, in the Netherlands, even larger cultural organisations might primarily receive funding from local authorities and executive funding authorities such as Mondriaan Fund, Creative Industries Fund and Fonds Podiumkunsten. In addition to these revenue streams, Dutch cultural organisations often rely on funding from philanthropists and private foundations. In addition to decisions made by the Basic Infrastructure (BIS) for a very limited number of organisations with national or supra-national importance and the executive authorities mentioned, I systematically examined the four-year cultural plans and funding decisions of the five largest Dutch cities, namely Amsterdam, Rotterdam, The Hague, Eindhoven, and Utrecht. It should be noted that organisations often seek funding from multiple levels and funding bodies. Since organisations for electronic music and arts are newcomers to the cultural infrastructure, most of them still need to gain sufficient status to access BIS funding.

Excluded organisations. Finally, after thorough consideration, I have excluded funding committees or grant assessors. Although they hold significant power in shaping the cultural landscape, their experts are often already active in the field or have a legal, financial, or organisational background, making their inclusion less relevant. Finally, it should be noted that while the Netherlands and Belgium are renowned for their mega-electronic music festivals, such as Tomorrowland or Mysteryland, these festivals operate in a commercial realm and are not eligible for cultural funding. Additionally, they target a different audience and mainly present genres we have previously excluded.

Limitations. Following the steps above, I compiled a list of about a hundred organisations in electronic music and arts in the Low Countries. However, I found that some renowned and emerging organisations were lacking. Organisations might deliberately refrain from receiving public funding and instead seek funding through, *e.g.* technological innovation programs or private and international sources. Another challenge I faced, particularly in the Netherlands, is that several leading electronic music festivals and clubs are operated by private companies, making it necessary to browse the Chamber of Commerce database and LinkedIn. While they showcase alternative and cutting-edge electronic music and digital art, they are often banned from cultural funding.

An Attributed List of Exemplar Gatekeepers

To examine the networked structures among gatekeepers based on attributes such as gender, location, and professional field, a list including all those who are artistically responsible for the programming in the above-identified institutions or organisations was needed. I used funding application summaries, organisational and institutional websites, and LinkedIn profiles to track gatekeepers. Additionally, it proved to be relatively straightforward to identify the gender, location, and professional field of the artistic gatekeepers based on real-life knowledge or publicly available information from social media profiles.

However, the strategy outlined above excluded freelance curators and bookers – where in the precarious creative industries many might take on different roles simultaneously, including that of journalist, researcher or communications officer. To identify members of this category, I mapped the members of three Facebook groups: Strange Overtone, Worm Sound Studio, and The Dutch and Electronic Music Network. The latter was founded by Sietse van Erve, the label owner of Moving Furniture Records, the leading experimental electronic music label in The Netherlands, and curator at Ruisburo, a series of electronic music concerts. This group comprises 364 members, including artists, small label owners, non-funded organisations, and representatives of funded organisations. In this group, a list of venues with their respective promoters was circulating. This proved to be a valuable source of information, especially regarding younger gatekeepers or gatekeepers with another geographical background who do not readily acquire a formal position as a gatekeeper. I also used female:pressure's bi-annual list of electronic music festivals, which includes Dutch and Flemish festivals. Additionally, based on my field knowledge, I added some gatekeepers with acknowledged practices or audiences beyond their regions or city to ensure geographical diversity.

Using these various sources, I compiled a list of 248 unique exemplars. Of these exemplars, 205 are affiliated with an organisation, while 43 are unaffiliated. The proportion of exemplars from the Netherlands (159) and Flanders/Brussels (85) is more or less in line with the respective populations (circa 18 million Netherlands versus circa 8 million Flanders/Brussels). Additionally, four exemplars were active in both territories. Of the listed gatekeepers, 177 are men, 71 are women – skewing the meeting opportunity – and no (self-assigned) gender-expansive people were identified. While 136 gatekeepers are curators or bookers in a formal or informal sense, 112 held the formal role of artistic director. Regarding the field, 109 are mainly focused on music, 95 are on arts, and 44 operate at the intersection of art and music. Notably, 45 exemplars were missing from the list in 2016, while 37 had dropped out of the field by 2022. Moreover, 32 organisations had multiple identified artistic directors or curators simultaneously or consecutively.

The List of Exemplar Twitter Accounts

Of the 248 unique exemplars I studied, 152 (61.29%) have a Twitter account. Among these users, 151 have a single Twitter account. One exemplar had two accounts for different roles, with one primarily used at the beginning of the timeframe and the other mainly used at the end. Regarding territory, 92 exemplars work in The Netherlands, 59 in Flanders, and one is active in both regions. Only over half of the artistic directors on the initial list have a Twitter account. However, among formal and informal curators, 82% of the 112 in the sample have a Twitter account, which could be related to the need for and display of symbolic capital, as discussed in Chapter 2. The gender ratio of exemplars with a Twitter account is 109 men to

43 women, comparable to the gender ratio in the initial list. In terms of professional interest, 73 exemplars work in the music industries, 54 in the arts, and 25 operate in both fields.

Building a Relevant, Contextualised Dataset

Based on this curated exemplar list, I collected all historical tweets of these exemplars between 1 January 2016 and 31 December 2022. Due to Twitter's processing speed limitations, I had to perform this task in three batches between 15 January 2023 and 28 February 2023. The collected dataset then underwent essential cleaning and transformation stages to ensure its usability for visualisation and analysis. In the following sections, I elaborate on the challenges and limitations during the six key cleaning and transformation steps.[11]

Scraping Data

After conducting tests using various Twitter scraping tools, including Twarc and Twitter's own application, I ultimately decided to use Twint. The latter is a well-documented open-source intelligence tool that is used by researchers, journalists and activists and is less affected by Twitter rate limitations (Benabdelkrim et al., 2020, p. 6; Bruns et al., 2017, p. 1). Its other significant advantage is the abundance of additional metadata in the output, including separate columns with usernames, IDs and screen names of Twitter users mentioned in tweets and replies. Twint also allows immediate data saving in various formats, including csv and Pickle. During scraping tweets, Twint provided additional information, such as the tweet count for each user and whether any deleted tweets were encountered, and it generated a notification when an exemplar did not have a public Twitter account, ensuring awareness of such cases. After collecting the tweets, I inspected each of the three batches and concatenated them.

All tweets from all exemplars with a public Twitter account were gathered for the entire period, regardless of their current or past affiliation with the organisation. As I mentioned, one possible motivation for maintaining a Twitter presence is expanding one's network. Additionally, not all exemplars were (yet) equally active or, conversely, only created a Twitter account over the time of the surveyed period. These so-called lurkers or 'listeners' should not be dismissed: as an audience that checks in regularly, they encourage others to post (Crawford, 2012, p. 81).

Cleaning and Contextualising

It was crucial to understand each variable accurately to guarantee accurate representation and proper handling of the – essentially unstructured – Twitter data. This understanding enabled us to implement correct headers, assign appropriate data types to the respective columns and return a complete, consistent dataset. Primarily due to a parsing error in the third batch, there were minor differences in the metadata output, affecting the consistency of the columns and data types. Thus, I ensured data types such as DateTime were consistent, duplicates were removed, and empty fields got a NaN value. Metadata columns (detailed in the notebooks) that contained no information or duplicated data in other columns were also removed. Finally, some columns needed to be renamed. Each batch then included 25 columns. The 'mentions' and 'reply_to' columns are significant for this research. Both columns contain information on any Twitter accounts mentioned or replied to in the tweet.

[11] All steps can be reproduced with the Python notebooks in Online Supplement 4.

This information includes the screen name or username, name and user ID. At this stage, the Twitter dataset consisted of 202.740 tweets from 137.660 conversations by 124 users. All metadata are listed and annotated in Table 3.1.

Table 3.1
Overview Metadata Twitter Dataset

Metadata	Description	Datatype	Unique values
tweet_id	Unique id for each tweet	integer	202.740
conversation_id	Unique id for each conversation	integer	137.660
tweet_url	Unique URL of the tweet	string	202.740
created_at	Format: yyyy-mm-dd hh:mm:ss timezone	timestamp	200.186
hour	At what time do exemplars tweet	string	23
day	At what day do exemplars tweet	string	7
language	ISO codes for languages, based on automatic detection by Twitter	string	45
user_id	Unique id for a user	integer	124
user_id_str	Unique id for a user in string format	string	124
username	Also referred to as screen_name	string	124
name	Real-world name of a user	string	124
place	Geo-location coordinates based on the location of IP-address	dictionary	674
tweet	The tweet's content, including hashtags, mentions, emoji's and links	string	201.931
mentions	List of user_id, username and name per mention	string	25.434
reply_to	All user accounts that are replied_to	string	21.399
replies_count	Number of replies of a tweet	integer	-
retweets_count	Number of retweets of a tweet	integer	-
likes_count	Number of times a tweet is liked	integer	-
quote_url	Link to original tweet in case of retweeting with comment	string	14.837
photo	Unique URL of a photo in a tweet	string	24.350

Metadata	Description	Datatype	Unique values
video	Indicates if a tweet contains a video or not	bool	-
thumbnail	Link to the video	string	25.982
link	Link to a webpage outside of Twitter	string	62.259
hashtags	Hashtags used in a tweet	list	15.480
cashtags	Cashtags used in a tweet	list	6

Identifying Relevant Tweets

Before extracting the implicit mentions, only the relevant tweets, *i.e.* the tweets about music and art, needed to be identified. Although Twitter tends to generate non-random communication patterns due to individuals feeling strongly connected to specific topics or demographic groups (Bruns et al., 2017, p. 2), tweets about politics, sports and complaints about public transport were omnipresent. However, manually selecting the relevant tweets was impractical, given the dataset's size. To address this, I employed Stochastic Gradient Descent (https://scikit-learn/stable/modules/sgd.html; Aabbar, 2021), using a training set of 2500 tweets to classify tweets as either 'musicarts' or 'other'. This approach yielded 84.971 tweets that were deemed relevant. This resulted in several exemplars being excluded from the analysis because their tweets were not classified as relevant.

However, this approach came with a few limitations. First, preprocessing every relevant language used in the tweets was beyond the scope of this study. Therefore, only Dutch and English stop words were removed, and lemmatisation was based on the built-in English NLTK-lemmatiser, which did not seem to impact Dutch words significantly. Second, after testing a few models, the highest average accuracy of 74% was achieved with SGD. The ambiguity of words such as 'track' or replies containing only generic words like 'yep,' 'haha,' 'idd,' 'prachtig' ('beautiful' in Dutch), and 'cool' may have contributed to this lower score. However, the precision was relatively high, meaning many tweets labelled 'musicart' were genuinely about art or music. Therefore, I considered this result sufficient.

Extracting Implicit Mentions

A further step involves extracting the implicit mentions from the relevant tweets. This process focuses on identifying and extracting mentions of users that are implicitly referenced in the tweets, going beyond the explicit mentions using the '@' symbol by applying Named Entity Recognition (NER). This approach is just one example of the various automated techniques for mining supplementary data from large (unstructured) datasets that have become available recently (Blank et al., 2021; Injadat et al., 2016; Nanayakkara et al., 2021).

Given the dataset is mostly bilingual – English and Dutch – I applied the widely used Spacy Large English and the Spacy Large Dutch models to extract the implicit mentions. The English model returned 104.154 unique values, while the Dutch model returned 52.169. While many names seemed to be correctly extracted, the list with extracted names was noisy. In order to extract all additional proper nouns, all values that started with @ were first discarded since they were already included. Next, only the values that consisted of two words that both started with an upper case or three words containing common prefixes to

last names such as ‘Van’, ‘Der’, ‘Den’, ‘De’, ‘van’, ‘der’, ‘den’, ‘de’ (it was enforced that if a string contained three words, the first and last word needed to have a capital), were selected. After generating a list of unique values for each language (8.823 for English, 8.279 for Dutch), both were combined, and duplicates were dropped. In total, 12.284 unique values were extracted and added to the dataset.

Organising Nodes and Edges

To use the data in Gephi, the dataset was transformed into a separate node list and adjacency list. The node list includes exemplars, (implicitly) mentioned users and replied-to users. Each entity was assigned a new ID, and columns for gender, territory, professional field, gatekeeper status and role were added. These attributes in the node list dataset were pre-filled with the most common values and were, if necessary, updated in the next step. The final node list consists of the following fields for each entity: name, username, ID, gender, territory, professional field, gatekeeper status and role.

Only instances where the sample users (implicitly) mentioned or answered others were considered for the edges. This process involved extracting the relevant tweet for each mention or reply from the respective columns, even when multiple actors were mentioned or replied to within the same tweet. As a result, I obtained 288.796 tweets, out of which 64.569 contained a mentioned or replied-to actor. For each tweet ID, a new random ID was assigned. Additionally, the nature of each edge was added to a separate column. Some columns were renamed to ensure proper importing of the adjacency list into Gephi, and a ‘year’ column was extracted to facilitate temporal analysis. The edge or adjacency list includes the following information: source_username, source (new user ID), target_username, target (new user ID), year, created_at, edge_id, and edge_type.

Refining Node List

During a preliminary data exploration, many actors in this open systems network with unclear boundaries (Kadushin, 2012, p. 17) turned out to belong to the music industries or the art world but are not primarily associated with electronic music or digital arts. This limitation exposed a flaw in the classification model that was not specific enough about electronic music and digital arts. In addition, the dataset of 15.140 nodes included individuals involved in policy-making and legislation in the broader cultural sphere, as well as cultural organisations, arts institutions, venues and labels.

To address these concerns, I used the clustering algorithm present in Gephi to make a crude distinction between relevant and irrelevant nodes. Additionally, I observed that the actors within the network often displayed their cultural capital by mentioning international – and sometimes deceased – composers, filmmakers, writers, visual artists, and researchers. Furthermore, I encountered duplicate nodes because ‘implicit mentions’ often resulted in misspelt names. This additional step resulted in 10.588 relevant nodes and 13.826 edges.

Exploratory Data Analysis

Table 3.2. summarises the impact of each step in order to arrive at an adequate, relevant dataset. From the original pool of 203.644 tweets, I distilled 64.596 relevant rows. These can include duplicate tweets if, *e.g.* they contain both a reply to and an implicit mention. Out of the initial list of exemplars, 111 remain. However, it should be noted that exemplars without Twitter accounts or those who do not tweet about music may still be included in the dataset if

other exemplars mention them. Furthermore, I intercepted several additional actors by mining implicit mentions, aligning with the intended goal.

Table 3.2
Summary Results from Data Collection and Transformation

Step	1	2	3	4	5	6	Gephi
Number of unique exemplar accounts	248	152	124	116	116	111	n/a
Number of tweets/edges	n/a	n/a	203.644	202.649	84.971	64.569	13.826
Total tweets with mentions	n/a	n/a	70.404	70.193	14.565	40.214	n/a
Total tweets with replies_to	n/a	n/a	75.874	69.420	7.536	29.520	n/a
Total implicit mentions	n/a	n/a	n/a	n/a	11.673	33.039	n/a
Unique mentions	n/a	n/a	n/a	n/a	n/a	8.250	n/a
Unique replies	n/a	n/a	n/a	n/a	n/a	6.528	n/a
Unique implicit mentions	n/a	n/a	n/a	n/a	n/a	12.111	n/a
All unique actors	n/a	n/a	n/a	n/a	n/a	15.140	10.588
Top language	n/a	n/a	NL	NL	NL	NL	n/a
Proportion tweets top language	n/a	n/a	49.50%	50%	50%	53.50%	n/a

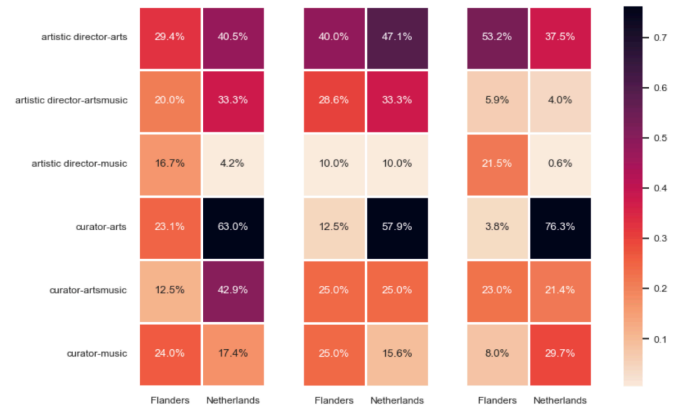
In the original dataset, Twitter was able to detect 45 different languages, with 100.691 tweets in Dutch and 78.066 in English. Other, mainly Western European languages and dialects were also identified, with 3.861 tweets whose language Twitter could not trace. Throughout the data transforming process, the proportion of tweets detected as Dutch also increased from slightly less than 50% to nearly 54%. In addition to English (42%), less than 1% consists of French and German tweets and even lower proportions for other languages and dialects. Furthermore, Twitter automatically detected 674 unique places, represented as geo-coordinates, although these consisted of IP -addresses rather than actual locations and were, therefore, not very helpful.

By determining which days and hours experience the highest level of Twitter activity, insights on the professional status of the gatekeepers and whether there is a relationship with sector-related activities, such as attending concerts and exhibitions, can be found. In the original dataset, the majority of tweets were sent on Wednesday, Thursday, and Friday,

with the weekend also showing a significant number of tweets, which is when most cultural activities take place. The same applies to the final dataset, with a notable peak on Fridays. In the original dataset, a substantial number of tweets were sent between 8 am and 9 am and between 8 pm and 9 pm, while the frequency of tweets quickly decreased after 10 pm. However, a significant number of tweets were also sent during the daytime. In the final dataset, most tweets were concentrated in the morning, gradually declining in the afternoon. Another peak was observed at 6 pm, followed by a gradual decrease in tweet frequency after 9 pm. Therefore, this network might be a mix of a professional and a leisure network.

Before delving into the network analysis of the obtained data, it is essential to closely examine the proportion of female exemplars in various roles, fields, and territories at different stages of transforming the dataset. These stages include all selected exemplars, exemplars with Twitter accounts, and the remaining exemplars after completing phase five of the data transformation. In Flanders, an increase in the proportion of female exemplars among art directors and directors/curators working at the intersection of music and art was observed. However, the proportion of female curators in art (3.8%) and female promoters in music (8%) remains significantly low. On the other hand, in The Netherlands, a higher proportion of female curators in art and music appeared to tweet about music and art. Nonetheless, this dataset showed a lower representation of female directors in all fields and curators in the music and art intersection, given that they apparently tweeted less about the field. These findings highlight the lack of female representation among artistic directors and curators in the music field across the territories included in the sample, particularly in the context of Twitter usage.

Figure 3.1
Proportions of Women Gatekeepers



Note: This heatmap represents the proportion of women exemplars compared to the total number of gatekeepers with (left) all women exemplars in curated list, (middle) all women exemplars with a public Twitter account, (right) all women exemplars with a Twitter account in final exemplar list.

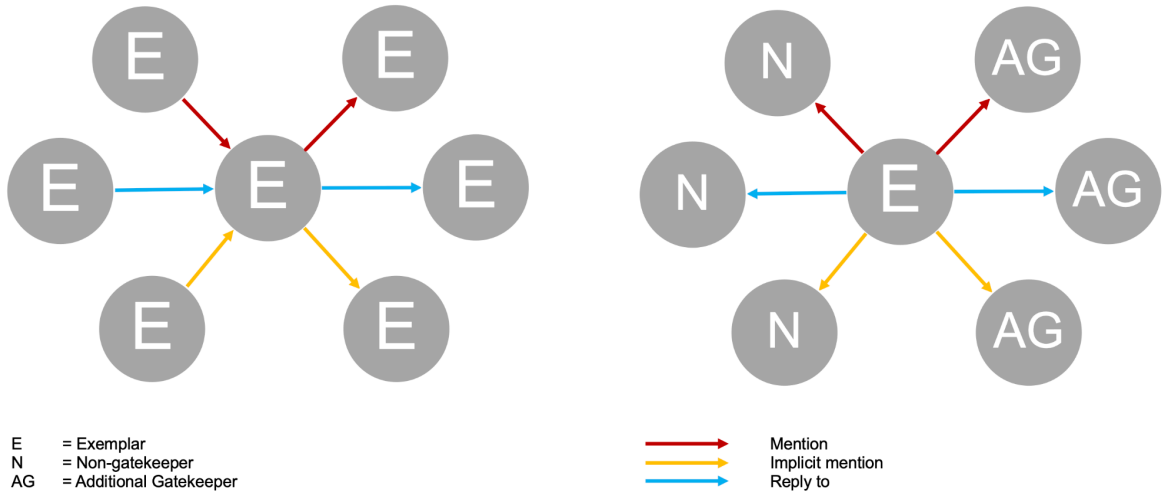
Chapter 4
Uncovering Gendered Network Structures, Communities and Connections

In Chapter 3, it became apparent that a wealth of historical tweets can be collected from known gatekeepers with public Twitter accounts (nodes), providing (implicit) mentions and responses that define the relationships (edges) between gatekeepers and other actors underpinning the constructed network. The visualisations and accompanying statistics point to gender-specific network structures, confirming previous qualitative research. Moreover, the roles taken by women and men gatekeepers in the network reflect the existing gender segregation in the creative industries. Finally, this research demonstrates a trend towards gender-based connections becoming stronger when combined with shared geographic and professional backgrounds. While this gender-based assortative mixing by 2020 seemed to diminish, this trend has increased again since the COVID-19 pandemic.

Constructing a Gatekeeper Network

In the extended network of 10,587 nodes, 47.23% were implicitly mentioned, while 31.43% were mentioned, and 21.33% replied to. Of the original 248 examples, 111 – accounting for 283 edges – are part of this extended network. The 13,821 remaining edges reflect two specific communication patterns, as shown in Figure 4.1. All exemplars mention or reply to others, so-called out-degree. Most exemplars, additional gatekeepers and non-gatekeepers receive mentions or replies, so-called in-degree. Together, they indicate an actor's popularity. However, the research design skews this extended network towards in-degree, which might impact results.

Figure 4.1
Examined Communication Patterns



An Attributed Gatekeeper Network

The gatekeeper network was distilled from the extended network, and attributes were added to the former's nodes. Although challenging, my expertise in the field facilitated the efficient

completion of this task. An actor's position within a network is often influenced by whether or not they have a formal role (Kadushin, 2012, pp. 38-39). Therefore, in the original exemplar list, clear boundaries for the still-fluid field by adopting this formal definition of gatekeeper were set. However, gatekeeping practices extend beyond these boundaries as gatekeepers do not operate in isolation but rely on an entire ecosystem, mainly when gathering information, *e.g.* from authoritative critics and journalists.

Furthermore, gatekeepers might often fulfil multiple roles simultaneously or sequentially. For example, a PhD researcher may curate an exhibition, journalists are sought after to compile playlists and offer line-up suggestions, policymakers can influence decisions, and label owners have the power to determine which artists to include on their roster. In addition, the latter might organise events featuring their associated artists to supplement revenue. Finally, while so-called amateurs may have only limited professional involvement in the electronic music and digital arts, they have often acquired substantial symbolic capital through their friendships with promoters, curators and journalists, encyclopaedic knowledge, outspoken opinions shared on social media due to the emergence of user-generated content, and generally 'being always in attendance'. Therefore, I have included not only the identified additional formal gatekeepers but also amateurs, researchers, policymakers, journalists/critics and label owners from the Low Countries and abroad.

Although statistical predictions can estimate gender or location based on the proximity of nodes, this approach can lead to self-fulfilling predictions. However, to accelerate the process of assigning gender, I used Gender Guesser (Sebo, 2021), checking for self-assigned gender on other social media in case no gender was returned or knowing that the gender must be different. And recently, there has been a noticeable trend among male artists using artist names typically associated with females, such as Seth Horvitz adopting the name Rrose, confusing Gender Guesser. As discussed in Chapter 1, I categorised genders into (cisgender) male, (cisgender) female, other, none (organisations) and mixed (bands). Regarding the territory attribute – Twitter metadata yielded poor results – I used The Netherlands, Flanders, Low Countries, and 'other'. The professional field attribute has been compartmentalised into music, art and multidisciplinary.

Exploring the Gatekeeper Network

The applied methodology has proven effective in constructing a gatekeeper network (RQ1). Six original exemplars dropped from the list during the transformation process reappeared in the node list of the gatekeeper network because they were either (implicitly) mentioned or received answers from other exemplars. 177 additional formal electronic music and digital arts gatekeepers were identified and added. Of these, 91 work in The Netherlands, 27 in Flanders, while three of them work across the entire Low Countries, and an additional 56 are located elsewhere but are actively engaged with the scene in the Low Countries. The gender ratio consists of 106 men and 71 women gatekeepers. Most of the added gatekeepers work in music (91), followed by art (77), and nine other formal gatekeepers work at the intersection of music and art. Furthermore, 65 journalists (53 male / 12 female), seven policymakers (five female, four male), seven amateurs (all male), 21 researchers (14 man / five woman / one gender-expansive), and 45 label owners (41 male and four female) were added.

While the proposed approach has successfully led to constructing a hitherto unmapped gatekeeper network, it also exhibits some limitations. Firstly, the supervised categorisation of tweets and the subsequent selection of relevant nodes may be more

appropriate for an entire sector or a more significant segment of society rather than a niche and still fluid field. A more sophisticated approach or a combination of methods may ensure higher accuracy in the automated selection of relevant tweets and nodes, minimising the need for manual pruning due to noisy data. Furthermore, it is observed that younger, and to a lesser extent, women gatekeepers are not being fully captured by using Twitter. For gatekeepers who already have a certain status and use this platform to enhance their influence; it may only be worthwhile to include actors from underrepresented demographic groups if those are, *e.g.* trendy, emerging artists or 'rediscovered women pioneers'.

A Visual and Topological Perspective

A visual and topological exploration of this constructed network will help discover to what extent its structure and associated measurements explain the persistent gender inequality among gatekeepers of electronic music and digital arts in the Low Countries. Furthermore, I will focus on specific network partitions to delve deeper into more intricate structural elements. Table 4.1 (p. 47) summarises all measurements related to the topology, community structure of the extended network, exemplar network, gatekeeper network, and each relevant network partition discussed in the following paragraphs.[12]

Do Network Structures Prevent Diversity?

Overall, the density and network diameter show that the gatekeeper network (Figure 4.2) is sparse and dispersed. Unsurprisingly, this is often the case in many real-world networks (Menczer et al., 2020, pp. 20-21), and also holds for the creative industries in the Low Countries, which still lack a dedicated organisation or platform and rely on different channels for funding (Moonshot, n.d.). The sparsity in the constructed network might hinder connectivity, coordination, cooperation and efficient information flow. The gender, professional and territorial partitions display the same sparsity and dispersion, except for women gatekeepers and gatekeepers in arts and multidisciplinary practices. The average path length is equally aligned with what can be expected in real-world networks (Menczer et al., 2020, pp. 50-52). This indicator for the efficiency of the information flow amounts to only a few steps (2.925) and decreases when the size of the network through partitioning decreases. However, this decline is more pronounced in the female partition and is not correlated when looking at the Flemish/Brussels gatekeepers. Thus, location and gender might play a role in defining sparsity and density. However, given the small size of some partitions, this cannot simply be interpreted as a small-world network where everyone knows each other.

Scale-free Network. Rather than such a small world network, the distribution of average weighted degrees (Online Supplement 5) within the gatekeeper network and all its partitions display a power law distribution indicating a scale-free network. The latter network type has two specific characteristics: the network can grow by adding new nodes, and preferential attachment, meaning existing important and/or influential nodes have a higher probability of engaging new nodes than nodes with less leverage, increasing their social capital in addition to the efforts mentioned above, such as drawing the attention of alters (nodes connected to the scrutinised node) by (implicitly) mentioning them – who might be honoured to receive a mention or reply from an influential node – and eliciting a response. Through the network structure, such influential actors are thus inherently more successful in

[12] Due to the extremely low number of nodes, I opted not to create a partition specifically for gender-expansive actors and actors working in both territories, as this would result in uninformative visualisations and statistics.

accumulating social and symbolic capital. In most cases, the result of the combination of network structure and the aforementioned efforts would be a continuous growing influence. Nevertheless, the decline in Twitter use might flatten this preferential attachment development.

Influence. Based on their Eigenvector centrality, the twenty most influential actors form a homogeneous group situated at the network's core: these are all Dutch men from the music field, except for one male gatekeeper with a multidisciplinary practice (Figure 4.2). Among these most influential, 11 were part of the initial exemplar network, while among the added influential gatekeepers, I primarily found journalists and 'amateurs'. Equally not surprising, the relationships within these partitions show the highest levels of strength, as indicated by the average weighted degree for each division. Strikingly, the average weighted grade for the subnetwork of male Dutch gatekeepers (44,523) is significantly higher than that of the entire gatekeeper network (25,488) and many times higher than that of the female (7,313), Flemish/Brussels (4,407) and art gatekeepers (1,677). The Dutch partition has the highest average weighted degree (43,794). The influence of this homogeneous group on the network is undeniably strong. However, it is equally important to consider how receptive they are to actors with other characteristics and their contribution to promoting cohesion within the network.

Embeddedness. As discussed in Chapter 2, gatekeeper success also depends on embeddedness in a network of trusted alters. The average clustering coefficient reveals more about local clustering patterns in a network by indicating the extent to which nodes tend to conglomerate together locally. Additionally, this tendency is often stronger than expected on social media platforms since they might recommend friends of friends (Menczer et al., 2020, pp. 58–59). Across the whole gatekeeper network, only a weak positive tendency towards clustering (0.169) is found. However, this trend is moderately strong (0.316) among Dutch male music gatekeepers, yet another indicator for potential success as a gatekeeper if belonging to this group, thus gaining more influence and a higher ability to attract new nodes.

However, as observed in the literature and from anecdotal evidence, network closure, producing tightly connected actors that exclude other actors by cliquish behaviour, is rampant in the music industries. The high prevalence of triangles – groups of three nodes where each node is connected to the other two nodes – in the subset of the Dutch male music gatekeepers confirms this, while they are hardly existent in the female, Flanders/Brussels and art/multidisciplinary partitions. If all female gatekeepers across both territories for arts and multidisciplinary practice are considered, triangles are entirely lacking. These findings confirm that there is a tendency among male gatekeepers, particularly those from the Dutch music industries, to exhibit limited openness in engaging with gatekeepers possessing different characteristics.

Connectivity. One advantage of a sparse network is that it is often robust and resilient. Indeed, the loss of a node does not immediately cause the network to collapse because alternative routes to other nodes are available. This observation also applies to reality, where the scenes for electronic music and digital art in the Low Countries lack a

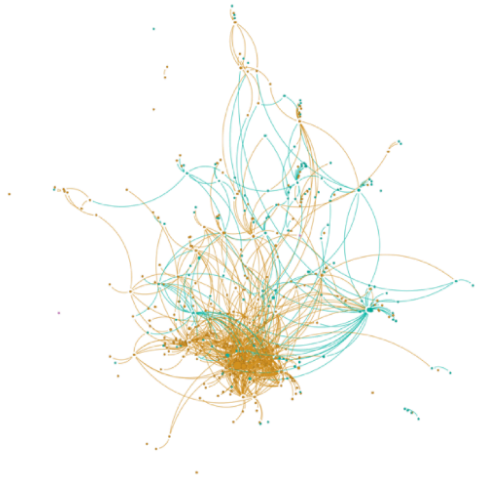
Figure 4.2
Gatekeeper Network with Influential Nodes (2016-2022)

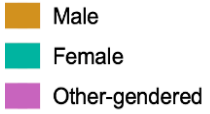
Note: The size of the nodes (0 – 1.0) reflects the Eigenvector Centrality, while the colour of the nodes reflects the community they belong to. The tie colour is based on the source node, mentioning or replying to another node.

Figure 4.3
Gatekeeper Network with Connector Nodes (2016-2022)

Note: The size of the nodes (0 – 1.0) reflects the Harmonic Closeness Centrality, while the colour of the nodes reflects the community they belong to. The tie colour is based on the source node, mentioning or replying to another node.

Figure 4.4
Gatekeeper Network by Gender (2016-2022)





Note: The size of the nodes (0 – 1.0) reflects the Eigenvector Centrality, while the colour of the nodes reflects their gender. The tie colour is based on the source node, mentioning or replying to another node.

single authoritative figure which has control at all levels, shaping careers, exerting significant policy influence or unilaterally dictating the discourse in these domains.

However, sparsity impedes not only the spread of new information and innovation but also accessibility and connectivity. In this gatekeeper network, 5% of the total components are weakly connected, i.e. these components are mainly dependent on indirect paths, as opposed to strongly connected components, where each node in the graph can be reached from every other node via directed paths (Khokhar, 2015, pp. 135-136; Menczer et al., 2020, pp. 43-44). This proportion is higher in the male and Dutch partitions but much higher in the other partitions of the network, indicating that the network's cohesion depends on very specific gatekeepers.

The larger nodes in Figure 4.3. show these bridging gatekeepers. Almost all are situated in the periphery and even among isolates (nodes with 0 degree). Moreover, based on the 20 nodes with the highest Harmonic Closeness Centrality, these actors display a higher diversity than the 20 most influential actors. Of these, 12 were Flemish/Brussels gatekeepers, only seven music gatekeepers and a balanced gender representation. Moreover, actors previously not labelled as exemplars emerge as connectors offering access to all actors in the gatekeeper network.

Gender Homogeneous Communities?

In the previous section, it was found that influential nodes are most likely Dutch male gatekeepers from the music industries, whose position is affirmed through a complex interplay of the characteristics of a scale-free network and specific communication behaviour on Twitter to gain social and symbolic capital. They are also firmly embedded and connected among themselves, which is another benchmark for success as a gatekeeper. However, they have a relatively limited propensity to engage with gatekeepers with different attributes, possibly perpetuating existing views on gender and music in this community. Moreover, they hardly act as connectors to other communities, possibly beyond this network of gatekeepers, that can produce fresh perspectives and innovative practices. The question is whether the same applies to communities in the network. After automatically detecting communities through Louvain clustering, the gatekeeper network nodes' arrangement and interactions uncannily resemble the real-world network, despite ignoring the attributes. Louvain clustering has some flaws – as outlined in Chapter 1 – and despite the weak tendency for communities to be clearly distinguished (0,250), five particularly notable communities arise.

The largest group (dark teal) at the network's core is characterised by an almost homogeneous composition (male, Dutch, music). This group revolves around established electronic music genres and includes diverse practices that emerged or gained recognition in the mid-1990s. Renowned international labels such as raster-noton, Edition Mego, Planet Mu, and Dutch label Moving Furniture Records and Flemish (K-RAA-K)3 label are part of this community. This group covers genres such as (dark) ambient, (minimal) techno, glitch, breakcore and drum'n'bass, and other forms of abstract electronic music production. These 'alternative mainstream' within the electronic music scene is programmed at both specialised and niche cultural venues and commercial platforms, ranging, *e.g.*, from STUK (Leuven), Berghain (Berlin), DGTL festival (Amsterdam) to Rewire Festival (The Hague). Its producers are strongly committed to digital music equipment and have often pursued formal education in music or technology rooted in European or North American epistemological systems.

Adjacent to the core group appears an olive cluster representing more contemporary, emerging and interdisciplinary forms of electronic music. In their programming or other

activities, these forward-thinking and more diverse gatekeepers actively explore electronic music venturing outside the boundaries of the established electronic music by, *e.g.* transcending the global north music paradigm or music created by women and gender-expansive artists. Compared to the established electronic music scene, this community partly intertwines with the equally diverse digital arts community, as observed in the network's upper middle part. This convergence is mainly centred around media arts festivals and European-funded networks for multidisciplinary and media art. The diverse range of practices – from bio-art to live AV performances – within the digital art domain is reflected in the smaller subcommunities, only connected through bridges, often original exemplars. Thus, this community is not dependent on a few central nodes or shaped by a densely connected core. In these groups, most actors are encountered that ensure connectivity and cohesion in the network (Figures 4.2 and 4.3).

In the top-left region, the emerald green cluster further called the Brussels community, demonstrates subtle connections to Flemish gatekeepers who hold influential positions in prestigious, publicly funded organisations and various policy-making bodies, with a close connection to Brussels as a locus of power. This community exhibits more dispersion, as some actors are located more closely to the specific music genres or disciplines they engage with. On the periphery of the forward-thinking electronic music gatekeepers, a subcommunity of the Brussels community working at a distinct group of cultural organisations that adopt a more commercial approach, exists. Furthermore, a few nodes are active in sound art and can be found on the bottom right, close to sound art actors in the bright blue community.

The latter is positioned a little sideways of the network. This community mainly contains actors focused on 'serious' electronic composed, electroacoustic music and sound art, as is frequently showcased in renowned venues like Bozar (Brussels) Concertgebouw (Bruges) or Muziekgebouw aan 't Ij (Amsterdam) and thought at institutions such as Sonology (The Hague) or Kask (Gent). This community is predominantly centred around a single node. Moreover, this community maintains limited connections with other communities, setting it apart.

Assigning node colours based on gender and overlaying this information with the gatekeeper network (Figure 4.4), keeping the community structure in mind, reveals an unmistakable gendered pattern. More specifically, the established electronic music in the core network and the Brussels group is dominated by male gatekeepers. A mixed ratio was found among the forward-thinking and serious electronic music gatekeepers. The digital arts group is also mixed but with a predominance of female gatekeepers. Male gatekeepers are primarily present in specific digital arts, such as NFTs (Non-Fungible Tokens).

Quantitative Validation of Qualitative Research Findings

Overall, this is a sparse and dispersed network, with a large core predominantly consisting of successful – through their influence and embeddedness – male gatekeepers and overlapping with the established electronic music community. These specific gatekeepers mainly communicate among themselves, being less open to new voices and fresh information. Moreover, the actors in this community rarely act as connectors. Conversely, among the actors that hold the network together and provide easy access to the entire breadth of the network and beyond it, primarily women, multidisciplinary and niche actors are found. This phenomenon reflects the gendered work segregation observed in previous research: women in creative industries often cover positions aimed at ensuring smooth

operations. An open attitude and cultivating a vast network – not seldom out of necessity – can facilitate this bridging role.

The above visualisations and metrics corroborate what previous studies have indicated: the dominance of male gatekeepers in the studied creative industries network, especially in the music industries and the most technologically cutting-edge subcommunities in digital arts. Therefore, the next section will explore whether and how this pattern might contribute to gender-based assortative mixing. In addition, examining the interaction between location/territory and the professional field, intertwined with gender, may potentially provide further valuable insights.

Detecting Gender-Based Assortative Mixing

To test gender homophily or gender-based assortativity mixing, the assortativity coefficient, introduced by the renowned network scholar Newman in 2002, is used. This coefficient quantifies the extent to which nodes in an attributed network associate with similar others and is represented on a scale from -1 (strong negative tendency) to 1 (strong positive tendency). The overall assortativity coefficient for this gatekeeper network (RQ2a) reveals a weak, almost moderate tendency (0.2616) for nodes to connect with nodes of the same gender. This finding is statistically significant compared to the random network, where no trend towards gender homophily is observed. Based on existing research, a more pronounced overall tendency for assortative mixing based on gender was anticipated. It should be noted that this outcome does not suggest a correlation between gender homophily and gatekeepers and the established lack of DEI for performers in the studied fields.

Assortative Mixing in Music and Art

Hence, it is worth exploring whether specific subsets (Table 4.2) of the network show a stronger tendency towards gender homophily or whether gender-based homophily among gatekeepers can be refuted as one of the underlying factors contributing to inequality in electronic music and digital arts. Therefore, the gatekeeper network was divided by professional fields, *i.e.* music and arts/multidisciplinary gatekeepers. The latter groups are combined as all the actors primarily work in arts institutions, organisations, or media art festivals.

The gender-based assortativity coefficient in the overall gatekeeper network and among the subset of music gatekeepers (0.2687) indicates a low inclination towards assortative mixing. Among arts and multidisciplinary gatekeepers, there is a very weak tendency (0.1608) to connect nodes with similar gender characteristics, suggesting this is perhaps less important for relationships between nodes to form. This observation aligns with the phenomenon discussed in Chapter 2, where members of a minority group in a network might seek affiliation with nodes in the majority group that have similar attributes.

Furthermore, as mentioned earlier, this gatekeeper network simultaneously exhibits professional and leisure/voluntary network characteristics, especially since professionals share their influence increasingly with amateurs. Generally, while gender homophily may play a role in gatekeeping practices within professional networks, shared interests within the leisure networks may substantially influence support and trust more than gender. The assortativity coefficients for the gatekeeper network (0.4840), its male partition (0.4533), and its female partition (0.4755) confirm this positive correlation for all three, indicating a moderate to an almost strong tendency for professional field-based assortative mixing or

‘interest homophily’ for different genders, being also substantially higher than expected when compared to a random network.

Diverging Gender Equality Policies and Assortative Mixing

Furthermore, the question (RQ2c) arose about whether gender-based assortative mixing between the gatekeepers in both territories, given the varied social and policy developments in the Netherlands and Flanders/Brussels regarding DEI in the creative industries. In other words, do Flemish/Brussels gatekeepers associate more with other gatekeepers of the same gender, or is this the case in the Netherlands? Across the network, a slightly moderate positive correlation (0.2991) between gender and location is observed. A moderate positive trend for assortative mixing was identified in each region, with slightly higher levels in Flanders/Brussels (0.3705) compared to the Netherlands (0.3060).

Moreover, a strong positive correlation (0.6088) exists between gender and professional fields in Flanders and Brussels. Gatekeepers tend to establish ties with fellow gatekeepers within the same field and territory. A similar, though slightly weaker, inclination is seen in the Netherlands. In both regions, the positive assortativity (0.4338) correlation for gender and field far exceeds what would be expected by the randomisation of the subsets of the network. In conclusion, the highest tendency to assortative mixing happens among gatekeepers whose attributes are all three similar, or ‘people completely like us’.

Evolving Trends

So far, this analysis has looked at the constructed network from a static perspective. However, social networks are dynamic, especially when the nodes and edges come from social media platforms. Unfollowing or de-friending occurs regularly, often due to disagreements on specific topics. Meanwhile, algorithms – whose properties are often considered a black box – play an essential role by recommending potential interesting actors. Furthermore, the aim of this thesis was to discover how social movements and global events influenced the evolution of the network of gatekeepers in the Low Countries’ electronic music and digital art scene. Therefore, three snapshots were analysed: 2016 (before the #MeToo movement gained momentum), 2017-2019 (the aftermath of the #MeToo movement) and 2020-2022 (the Covid-19 pandemic years), as represented by Figures 4.5, 4.6 and 4.7.

Overall, minimal changes regarding communities occur, except for a sharp drop in activity within the Brussels community from 2017 onwards. In the established electronic music group, two subcommunities emerge: curators/bookers on the one hand and other gatekeepers such as journalists on the other hand. A causal relationship with real-world developments remains unclear. While Twitter use is generally declining, the connecting actors (labels) might have turned to other platforms, such as Instagram or LinkedIn. In the three snapshots, the colour of the nodes is based on gender, confirming that the male dominance in the gatekeeper network seems to remain unchanged.

As noted earlier, the constructed gatekeeper network exhibits characteristics of a scale-free network, allowing for preferential attachment (Jacomy et al., 2014). In examining the latter feature – by comparing the gender of the most influential actors for each snapshot – several trends emerge. First, over time this group remains very homogeneous. Second, having a formal position as a gatekeeper within an organisation positively affects Eigenvector centrality. In addition, labels and festival organisers may experience periods of popularity followed by less success. Over time, international actors seem to become more

prominent than local actors. Finally, music journalists become more present overall, with new voices sometimes rapidly gaining influence in the field. Given the low receptivity to innovation in this group of influential actors, it might be worthwhile to investigate the content of their tweets in order to establish how they accommodate their audience. Another notable observation is that there is consistently only one woman gatekeeper among the influential actors for each timeframe. This suggests that it remains challenging for women to establish and maintain a significant presence as an influential actor, possibly related to the infamous authority gap.

Similar observations can be made regarding the highest rankings for weighted degrees, or the sum of the received and given mentions and replies. However, over the past three years, professionals have largely left music conversations on Twitter to amateurs, while exemplars involved in digital arts, particularly those associated with NFTs, have gained more clout. Lastly, the lack of out-degrees was not as detrimental to non-exemplars as expected: in 2016, 9 gatekeepers among the actors with the highest weighted degree were non-exemplars; in subsequent years, 7 of the 20.

Finally, the evolution of gender-based assortative mixing over the past seven year is examined. In 2016, a moderate positive (0.3746) tendency, contributing to barriers for women and gender-expansive gatekeepers in the network, as discussed above, was observed. Between 2017 and 2019, however, this trend weakened (0.2072), while from 2020, gender homophily in the network (0.2664) resurges, aligning with the mentioned societal and economic developments impacting gender equality, including #MeToo fatigue and a general backlash against women and minority rights. Gender-based assortative mixing is significantly higher for each time frame than expected. While this poses no obstacle for actors in the majority group to accumulate and gain social, symbolic, and economic capital, research has shown that it can have detrimental effects on all other actors belonging to minority groups. In the final chapter, building upon these findings, will be discussed how gendered network structures intersect with other previously identified causes of gender inequality in electronic music and digital arts. Subsequently, policy recommendations to foster a more diverse and equitable future in the studied field, will be presented.

Figure 4.5
Gatekeeper Network by Gender - 2016

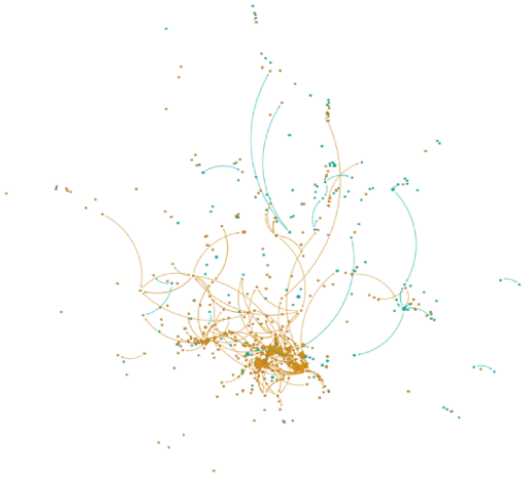
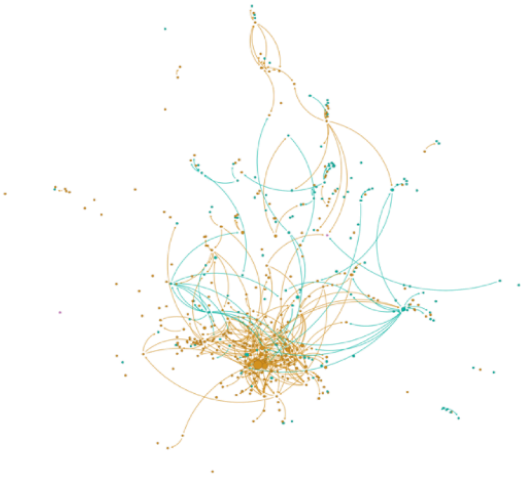
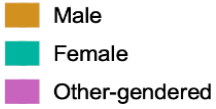


Figure 4.6
Gatekeeper Network by Gender - 2017-2019

Figure 4.7
Gatekeeper Network by Gender - 2020-2022





Note: The size of the nodes (0 – 1.0) reflects the Eigenvector Centrality, while the colour of the nodes reflects their gender. The tie colour is based on the source node, mentioning or replying to another node

Table 4.1
Overview topology measurements

				GATEKEEPER NETWORK PARTITIONS								
	Extended network	Exemplar network	Gatekeeper Network	Male	Female/gender -expansive	Music	Art/Multi-disciplinary	Dutch	Flemish/ Brussels	2016	2017-2019	2020-2022
Nodes	10.587	117	441	307 (70%)	134 (30%)	263 (60%)	171 (39%)	223 (50%)	81 (18%)	434 (98%)	434 (98%)	434 (98%)
Edges	13.821	283	981	688 (70%)	77 (8%)	670 (68%)	144 (15%)	546 (56%)	86 (9%)	179 (18%)	446 (46%)	405 (46%)
Topology												
Average degree	1,305	2,419	2,224	2.241	0,575	2,548	0,842	2,448	1,062	0,412	1,028	0,793
Average weighted degree	4,204	22,496	25,488	31,752	7,313	32,205	1,667	43,794	4,407	3,850	15,136	6,841
Network Diameter	7	8	7	7	2	6	4	7	5	5	8	9
Average Path length	3,108	3,110	2,925	2,662	1,238	2.569	1.895	2.687	1.661	1,922	3.265	3,444
Density	0	0,021	0,005	0,007	0,004	0,010	0.005	0.011	0.013	0,001	0,002	0,002
Weak connected components	7	27	22	46	72	25	63	22	29	302	195	209
Strongly connected components	10.522	88	406	284	133	236	168	197	78	429	410	419
Avg Clustering Coefficient	0,063	0,187	0,169	0,214	0,024	0,249	0,024	0.216	0.097	0,016	0,067	0,027
Transitivity	3.106	129	719	638	1	607	4	548	5	5	164	37
Number of paths (length: 2)	5.098.839	1.453	19.232	13.758	203	13.758	537	8.241	428	845	5.160	2.534

Communities Modularity	0,676	0,210	0,250	0.171	0.626	0.197	0.733	0.126	0.273	0,523	0.198	0.385

Table 4.2

Summary Assortative Coefficients

	Gatekeeper network	Male	Female / gender-expansive	Dutch	Flemish/Brussels	Music	Art/Multidisciplinary
Proportion male	70,28%	100%	0%	59,39%	59,44%	82,51%	51,46%
Proportion female	29,26%	0%	100%	22,19%	22,19%	17,49%	47,37%
Proportion other	0,46%	0%	0%	0,87%	0,83%	-	1,17%
Gender Assortativity							
Constructed network	0,2616	n/a	n/a	0.3060	0.3705	0.2687	0.1608
Random network	-0.0677	n/a	n/a	-0.0559	0.1044	-0.006	-0.0136
Territory Assortativity							
Constructed network	0.2991	0.2996	0.4319	n/a	n/a	0.3008	0.3405
Random network	-0.0036	-0.0352	0.0892	n/a	n/a	-0.0267	0.0150
Field Assortativity							
Constructed network	0.4840	0.4533	0.4755	0.4338	0,6088	n/a	n/a
Random network	0.0052	-0.0370	-0.0471	-0.0238	0.0791	n/a	n/a

Chapter 5
Disrupting the Feedback Loop for More Diverse Electronic Music and Digital Arts

The two main questions of this study have now been answered: Twitter data can be effectively used to construct a network of gatekeepers in electronic music and digital art in the Low Countries, including gatekeepers without a Twitter account. Moreover, I found underlying gender-specific network structures leading to gender-specific segregation within the network of gatekeepers in electronic music and digital art in the Low Countries between 2016 and 2022, which is also reflected in the gender-specific assortative mixing. This research offers new insights to address the aforementioned chicken-and-egg problem – *i.e.* disrupt feedback loops – and promote Diversity, Equity and Inclusion in these technology-driven fields. For example, more attention could be paid to less visible and influential gatekeepers with a more diverse network when developing and implementing policies. Additionally, more digital humanities research (RQ4), among others, can help determine precisely how these gender-specific network structures create or impede opportunities for artists, e.g. how notions of quality and genres as institutions spread are reinforced and used as exclusionary strategies in networks. The developed dataset offers opportunities to enhance this study.

From Focus on Proportions to Disrupting Feedback Loops

With the methods applied, it proved feasible to construct, then visualise and analyse a fairly representative network of gatekeepers in electronic music and digital art active in the Low Countries. For example, the constructed network is sparse and dispersed, reflecting the lively exchange of ideas and debates on the current state of electronic music and digital arts. Above, some limitations have been pointed out; in the last section of this chapter, I will outline how this approach can be refined and used more broadly.

In this scale-free network, influential nodes can increase their importance faster than less influential ones. Over the past seven years, all the most influential players were consistently located at the network's core, a close-knit community of men gatekeepers focused on established electronic music. To expand their symbolic capital and, thus, influence, they benefited not only from the strategic use of the Twitter algorithm and its communication options but also could take advantage of the specific type of network. Moreover, if gatekeepers in a subset of the network share all three attributes – gender, location and professional field – there is an inclination to mention or reply to each other on Twitter, which is also the case in this core group. Because this is the majority group that exerts its influence over the entire network, including by maintaining closer relationships with a group of similar gatekeepers who, in the real world, wield power as policymakers or by their economic status, this homogeneity among influential actors has important implications.

As aforementioned, only relying on 'people like us' to enhance success in a network is the risk of conformity, thus creating a feedback loop that stifles innovation by, in this case, perpetuating ingrained gendered views about 'quality' in electronic music and digital art. Our research has shown that such feedback loop risk caused by the network structure is present and may explain the persistently low proportion of female and gender-expansive gatekeepers and artists in electronic music and digital art in the Low Countries, often still

barely exceeding the magic threshold of 13%. More research should reveal whether there is also a correlation between cultural programming and the network structure presented here.

Besides influencing cultural programmes, it is not inconceivable that this network structure also reinforces (subconscious) ideas and strategies contributing to the exclusion of new actors, such as the concept of genre as an ‘imaginary institution’ (Lehmann, 2022, pp. 177-178). Imaginary institutions might create a sense of commonality among these influential nodes that consider themselves gatekeepers of what constitutes quality and boundaries of electronic music and digital art. Delineating its community of rightful guardians necessitates exclusion but can also result in ‘totalitarian traits’. However, genres – even as institutions – change over time, challenged by newcomers. This process might threaten the sense of commonality even more by rejecting or avoiding those who do not belong to the community due to their divergent opinions and practices, labelling new or alternative approaches as ‘too poppy’, ‘too superficial’, ‘too artistic’, ‘too serious’ or simply lacking overall quality. This dismissal is illustrated by the fact that most influential nodes seemingly make no effort to strengthen cohesion and communication with other communities, possibly threatening the ‘institution’ and thus preventing more diversity in the electronic music and digital art scene.

This dominance of the male core group also contributes to the marginalisation of women and gender-expansive gatekeepers. The latter face more significant challenges in penetrating the core community of influential individuals. As aforementioned, not only are they seen as ‘different’, but based on gender stereotyping, their authority and taste – including their judgement about ‘quality’ – continued to be questioned. Furthermore, they might feel less inclined or are even discouraged from using the above-mentioned strategies to acquire more symbolic capital, including ‘aggrandisement’. However, in this sparse network, these gatekeepers essentially hold everything together and, through their open-mindedness and network beyond the gatekeeper network, have the potential to introduce fresh perspectives and new voices. The fact that this role is predominantly held by women gatekeepers should be no surprise. Earlier research on the gendered segregation of roles in the creative industries has already shown that women are mainly assigned behind-the-scenes roles, ensuring the smooth functioning and development of the field with their perceived feminine and even maternal qualities, such as organisational skills. As mentioned above, these bridge actors also have the potential to add to the desired DEI goals advocated by many artists, creative industry professionals, society, funding bodies and decision-makers.

Thus, based on the research findings, it can be inferred that network structures – along with entrenched notions about genre and gendered divisions of labour within the creative industries and a higher prevalence of gender homophily than expected – contribute to the lack of diversity, equity, and inclusion among gatekeepers in the electronic music and digital arts in the Low Countries. However, it does not offer a conclusive answer to Kadushin’s (2012, p. 14) chicken-and-egg problem, where the interconnectedness of individuals makes it challenging to determine whether internalised, shared norms and characteristics are the underlying cause of homophily or if the latter is a consequence of their structural location within the network. Instead, this research suggests a complex interplay between the two phenomena. Lastly, its significance lies in emphasising that to attain a more diverse future in electronic music and digital arts in the Low Countries, the focus needs to shift from influential figures and representation numbers to disrupting the at least partially network structure-induced feedback loop and highlighting the role of

gatekeepers with a more diverse social capital and cultural background, acting as connectors.

Attaining Equity: Some Policy Recommendations

The conclusions of this research not only support the anecdotal evidence and the qualitative research conducted earlier about gendered network structures but also serve as a reminder that the currently diluted focus on gender equality in the creative industries, in particular electronic music and digital arts, must be addressed if the field is to attain gender equity in the music industries and digital arts by the end of this decade. The above observations give rise to some recommendations that may contribute to this goal and go beyond quota – however important this is – for gatekeepers and performing artists.

A first recommendation to break the feedback loop is for policymakers and organisations to recognise women and gender-expansive gatekeepers, or those active in smaller subcommunities of non-consecrated forms of electronic music and digital arts, as pivotal bridges between the communities with access to peripheral and potentially more diverse communities. Focussing more on significant though under-recognised social capital instead of visible symbolic capital undoubtedly requires more commitment to identifying these ‘connectors’ and courage as inviting these gatekeepers into the overarching gatekeeping-decision-making processes and giving them an equal position as the hitherto dominant groups might remain challenging. In addition, supporting international mobility for women and minority gatekeepers to attend multidisciplinary encounters and knowledge exchange with a clear purpose and where preparation time and attendance are financially compensated are required.

Furthermore, at a time when electronic music and digital arts seem to be gaining momentum and becoming mainstream, its professionalisation – through top-down policies and grassroots initiatives – calls for more diversity, equity and inclusivity. Having such strategies in place as an organisation is frequently a requirement when applying for grants. Therefore, these connectors and their cross-border and cross-disciplinary practices need to be acknowledged and included right now in the design of new policies and professionalisation strategies, as they can contribute to distorting the still prevailing pattern of assorted mixing. Conversely, professionalisation could also enhance the flow of knowledge and research, creating a greater sense of urgency. The field often seems unprepared and caught off guard by new developments. Despite extensive research on gender inequality in the creative industries taking off around 2010, it was only in 2017 that it appeared on the creative industries’ agenda and attracted the attention of numerous gatekeepers.

Thus, to improve knowledge, enhance connectivity, raise awareness about current societal issues and foster a more diverse field, it would be helpful to establish a more organised and acknowledged diverse, cross-border and cross-disciplinary field. Numerous initiatives are underway to map the field, including efforts to arrive at a definition of the field. However, the downside of such professionalisation could be that, if not adequately and sufficiently broadly defined from the outset, only influential gatekeepers with power, prestige, and symbolic capital— given what is now known about the demographic makeup of this group — would dominate the discourse, also on DEI. In contrast, the actual gatekeepers capable of bringing diversity may be overlooked, perpetuating the feedback loop. Moreover, it would be regrettable to create a division between electronic music and digital arts, as well

as between Flanders/Brussels and the Netherlands, as this would weaken the field's potential strength, especially in these international fields.

Lastly, it is essential to investigate the prevalence and impact of feedback loops within the specific subsets identified in this study and develop a tailored approach based on those findings. A complex interplay of network structure shaped by the fluidity of the field, prevailing gendered norms and values with significant segregation and gender homophily is observed, subsequently impeding any structural change, as evidenced by the temporal analysis. Hopefully, with the aforementioned recommendations, this impasse can be overcome.

Refining and Enhancing the Digital Humanities Approach

To enhance and refine this digital humanities approach, one possible direction is to include additional levels of communication on Twitter, such as friends and followers. While it would allow for a more comprehensive understanding of emerging communities outside this gatekeeper network, potentially revealing more diverse perspectives, this would complicate the temporal analysis, as mentioned. Furthermore, including historical tweets from Twitter's inception would place current observations about gendered structures and possible shifts in gender homophily in a broader temporal framework.

Moreover, the gatekeeper network in the Low Countries is part of a more extensive international network. Labels, agencies and public relations firms operate worldwide and now – mainly due to cost-efficiency strategies – from headquarters abroad, foregoing local representatives. Examining this international network of gatekeepers from a gender perspective could yield a more in-depth understanding of gender dynamics in electronic music and digital arts in a global context. By examining these networks globally, deeper insights into how individuals tend to associate and form connections based on shared geographical locations and ethnic backgrounds could be gained, which can engender discriminatory practices. Lastly, a multimodal approach – examining the relationship between human and institutional gatekeepers within the broader context of this network – would be a valuable addition to uncovering gender dynamics in hiring practices, curating and programming.

Within the limitations of this thesis, I could not pay in-depth attention to more detailed temporal developments. It would be valuable to go deeper into this aspect and investigate how different types of interactions, such as (implicit) mentions and replies – included in the dataset –, are influenced by or subject to gendered structures and gender homophily. Another area of interest is improving tweet classification by implementing alternative methods to increase accuracy. As not all demographic groups are equally active on Twitter, and not all gatekeepers actively participate on the platform, integrating data from other social networks, such as LinkedIn and Instagram, could be insightful and could, for example, also be helpful to map the entire creative industries or digital culture in the Low Countries, including gaming, virtual reality, performances and labs, workshops and residencies as places of production. This visual representation would not only enhance the understanding of policymakers, industry participants, researchers and stakeholders but also shed light on the sector's complex composition and extensive reach from both an artistic and economic perspective.

Combining the data from this study with data from other social networks could also lay the foundation for an alternative tool where a gatekeeper gets recommendations – taking

into account privacy considerations – for new connections based on where the gaps in terms of diversity occur in their network.

Twitter is often considered a valuable treasure trove for researchers. To ensure continuity in case the platform undergoes significant changes or becomes inaccessible in the future, it is essential to develop datasets independent of Twitter, especially regarding underrepresented communities or topics that would leave the proverbial hanging folders in filing cabinets empty. This dataset of approximately 200.000 original tweets related to an emerging field in the music industries and arts I collected for this research will be available to other researchers upon request and offers myriad avenues for future research. As some scholars have recently pointed out (Hellsten & Leydesdorff, 2020; Himelboim et al., 2017), automated analysis of Twitter content could enrich future research in this domain, such as uncovering actor-subject networks. The dataset also lends itself to sentiment and discourse analysis, e.g., on the above-mentioned prejudices and notions about quality and genres as institutions.

Furthermore, exploring additional data available through the Twint scraping process but not included in this analysis, such as the content of shared photos and videos and their spread, analysing hashtags and studying the languages used in content would be intriguing. Another analysis opportunity is to delve into the content of tweets to examine the prevalence of the ‘agrandissement’ mechanism. In addition, this dataset can also contribute to research on network causes of possibly gendered decision-making processes by gatekeepers, thus enriching existing empirical research focused on the gender proportion among performing and exhibited artists. Altogether, this research highlights the importance of further in-depth quantitative and qualitative research, more tailored policy interventions and increased social awareness to attain a more diverse, equitable and inclusive electronic music and digital arts field in the Low Countries.

Bibliography

Aabbar, A. (2021, December 6). *Tweets binary classification*. Github. https://github.com/adnaneaabbar/TweetsBinaryClassification

Abfalter, D., & Reitsamer, R. (Eds.). (2022). *Music as labour: Inequalities and activism in the past and present*. Routledge.

Abtan, F. (2016). Where is she? Finding the women in electronic music culture. *Contemporary Music Review*, *35*(1), 53–60. https://doi.org/10.1080/07494467.2016.1176764

Aggarwal, M., & Murty, M. N. (2021). *Machine learning in social networks: Embedding nodes, edges, communities, and graphs*. Springer.

Aguilar-Gallegos, N., Klerkx, L., Romero-García, L. E., Martínez-González, E. G., & Aguilar-Ávila, J. (2022). Social network analysis of spreading and exchanging information on Twitter: The case of an agricultural research and education centre in Mexico. *The Journal of Agricultural Education and Extension*, *28*(1), 115–136. https://doi.org/10.1080/1389224X.2021.1915829

Alacovska, A., & O'Brien, D. (2021). Genres and inequality in the creative industries. *European Journal of Cultural Studies*, *24*(3), 639–657. https://doi.org/10.1177/13675494211006095

Alamsyah, A., & Rahardjo, B. (2021). *Social network analysis taxonomy based on graph representation*. Arxiv. https://arxiv.org/pdf/2102.08888.pdf

Atzmueller, M. (2018). Community detection and analysis on attributed social networks. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 322–330). Springer. https://doi.org/10.1007/978-1-4939-7131-2_110194

Baillie, G., Fileborn, B., & Wadds, P. (2022). Gendered responses to gendered harms: Sexual violence and bystander Intervention at Australian music festivals. *Violence Against Women*, *28*(3–4), 711–739. https://doi.org/10.1177/10778012211012096

Barabási, A.-L., & Pósfai, M. (2016). *Network science*. Cambridge University Press.

Barna, E. (2022). Emotional and relational labour in music from a feminist perspective. In D. Abfalter & R. Reitsamer (Eds.), *Music as labour: Inequalities and activism in the past and present* (pp.112–127). Routledge.

Basov, N. (2020). The ambivalence of cultural homophily: Field positions, semantic similarities, and social network ties in creative collectives. *Poetics*, *78*, 101353. https://doi.org/10.1016/j.poetic.2019.02.004

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *Proceedings of the International AAAI Conference on Web and Social Media*, *3*(1), 361–362. https://doi.org/10.1609/icwsm.v3i1.13937

Baym, N. K., Bergmann, R., Bhargava, R., Diaz, F., Gillespie, T., Hesmondhalgh, D., Maris, E., & Persaud, C. J. (2021). Making sense of metrics in the music industries. *International Journal of Communication*, *15*(24), 3418–3441. https://doi.org/https://doi.org/10.5167/uzh-203937

Bedi, P., & Sharma, C. (2016). Community detection in social networks. *WIREs Data Mining and Knowledge Discovery*, *6*(3), 115–135. https://doi.org/10.1002/widm.1178

Benabdelkrim, M., Levallois, C., Savinien, J., & Robardet, C. (2020). Opening fields: A methodological contribution to the identification of heterogeneous actors in

unbounded relational orders. *M@n@gement*, 4–18. https://doi.org/10.37725/mgmt.v23.4245

Bennett, A. (2022). Programming with gender parity in call-based new music festivals. In L. Kouvaras, M. Grenfell, & N. Williams (Eds.), *A century of composition by women* (pp. 263–276). Springer. https://doi.org/10.1007/978-3-030-95557-1_14

Berkers, P., & Hoegaerts, J. (2019). Editorial: Music, gender, inequalities. *Tijdschrift voor Genderstudies*, *22*(1), 1–6. https://doi.org/10.5117/TVGN2019.1.001.BERK

Berkers, P., & Smeulders, E. (2018). *Gendergelijkheid onder muziekmakers in Nederland / Women music creators in the Netherlands*. Buma/Stemra.

Berkers, P., Smeulders, E., & Berghman, M. (2019). Music creators and gender inequality in the Dutch music sector. *Tijdschrift voor Genderstudies*, *22*(1), 27–44. https://doi.org/10.5117/TVGN2019.1.003.BERK

Best, S. (2022). Is the category of the 'woman artist' still helpful? In L. Kouvaras, M. Grenfell, & N. Williams (Eds.), *A century of composition by women* (pp. 191–205). Palgrave Macmillan. https://doi.org/10.1007/978-3-030-95557-1_10

Blank, C., McBurney, M., Morgan, M., & Seetan, R. (2021). A survey of big data techniques for extracting information from social media data. *Advances in Science, Technology and Engineering Systems Journal*, *6*(3), 189–204. https://doi.org/10.25046/aj060322

Bokunewicz, J. F., & Shulman, J. (2017). Influencer identification in Twitter networks of destination marketing organizations. *Journal of Hospitality and Tourism Technology*, *8*(2), 205–219. https://doi.org/10.1108/JHTT-09-2016-0057

Borchard, B. & Treydte, E. (2019). Genderforschung in der Musikwissenschaft: Eine (kritische) Bestandsaufnahme aus zwei Perspektiven. In S. Sanio & B. Wackernagel (Eds.), *Heroines of Sound: Feminismus und Gender in elektronischer Musik* (pp. 130–135). Wolke.

Borchert, G. (1997). American women in electronic music, 1984–94. *Contemporary Music Review*, *16*(1–2), 89–97. https://doi.org/10.1080/07494469700640101

Bosma, H. (2003). Bodies of evidence, singing cyborgs and other gender issues in electrovocal music. *Organised Sound*, *8*(1), 5–17. https://doi.org/10.1017/S135577180300102X

Bosma, H. (2006). Musical washing machines, composer-performers, and other blurring boundaries: How women make a difference in electroacoustic music. *Intersections: Canadian Journal of Music / Intersections : Revue Canadienne de Musique*, *26*(2), 97–117. https://doi.org/10.7202/1013229ar

Bourdieu, P. (1984). *Distinction: A social critique of the judgement of taste*. Routledge.

Bretthauer, B., Zimmerman, T. S., & Banning, J. H. (2007). A feminist analysis of popular music: power over, objectification of, and violence against women. *Journal of Feminist Family Therapy*, *18*(4), 29–51. https://doi.org/10.1300/J086v18n04_02

Brinkmann, A. (2003). Culture-Gates in music and new media arts in Germany. In *Culture-Gates: Exposing professional 'Gate-keeping' processes in music and new media arts* (pp. 219–254). ARCult.

Bruns, A., Moon, B., Münch, F., & Sadkowsky, T. (2017). The Australian Twittersphere in 2016: Mapping the follower/followee network. *Social Media + Society*, *3*(4). https://doi.org/10.1177/2056305117748162

Caldarelli, G., & Chessa, A. (2016). *Data science and complex networks: Real case studies with Python*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199639601.001.0001

Cameron, S. (2015). *Music in the marketplace: A social economics approach*. Routledge.

Carrigan, C., Green, M. W., & Rahman-Davies, A. (2021). 'The revolution will not be supervised': Consent and open secrets in data science. *Big Data & Society*, *8*(2). https://doi.org/10.1177/20539517211035673

Carstens, C. J., & Horadam, K. J. (2016). Switching edges to randomize networks: What goes wrong and how to fix it. *Journal of Complex Networks, 5*(3), 337–351. https://doi.org/10.1093/comnet/cnw027

Carstensen, T. (2014). Gender and social media: Sexism, empowerment, or the irrelevance of gender? In C. Carter, L. Steiner, & L. McLaughlin (Eds.), *The Routledge companion to media and gender* (pp. 483–492). Routledge.

Casalegno, F. (2021, February 23). *Graph Convolutional Networks*. Medium. https://towardsdatascience.com/graph-convolutional-networks-deep-99d7fee5706f

Chaki, J., Dey, N., Panigrahi, B. K., Shi, F., Fong, S. J., & Sherratt, R. S. (2020). Pattern mining approaches used in social media data. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, *28*(Supp02), 123–152. https://doi.org/10.1142/S021848852040019X

Clayton, M., Herbert, T., & Middleton, R. (Eds.). (2003). *The cultural study of music: A critical introduction*. Routledge.

Cliche, D., & Wiesand, A. (2003). Exposing and opening gates: Introduction and recommendations. In *Culture-Gates: Exposing professional 'Gate-keeping' processes in music and new media arts* (pp. 9–66). ARCult.

Collins, N., Schedel, M., & Wilson, S. (2013). *Electronic music*. Cambridge University Press.

Conceison, M. (2022). Studying diversity in the music industry. *Proceedings of the 2022 International Summit of the Music & Entertainment Industry Educators Association*, 4–32. https://doi.org/10.25101/22.12

Conde, I. (2003). Making distinctions: Conditions for women working in serious music and in (new) media arts in Portugal. In *Culture-Gates: Exposing professional 'Gate-keeping' processes in music and new media arts* (pp. 255–323). ARCult.

Cox, D. J., Sandor, E., & Fron, J. (Eds.). (2018). *New media futures: The rise of women in the digital arts*. University of Illinois Press. https://doi.org/10.5406/j.ctv8j4d3

Crabtree, J. R. (2020). *Tunesmiths and toxicity: Workplace harassment in the contemporary music industries of Australia and New Zealand* [PhD]. University of Technology Sidney]. https://opus.lib.uts.edu.au/handle/10453/148011

Crawford, K. (2012). Following you: Disciplines of listening in social media. In J. Sterne (Ed.), *The sound studies reader*. Routledge.

Currarini, S., Matheson, J., & Vega-Redondo, F. (2016). A simple model of homophily in social networks. *European Economic Review*, *90*, 18–39. https://doi.org/10.1016/j.euroecorev.2016.03.011

Dahlan, K., & Terras, M. (2020). A social network analysis of the oceanographic community: A fragmented digital community of practice. *Preservation, Digital Technology & Culture*, *49*(4), 159–181. https://doi.org/10.1515/pdtc-2020-0030

Das, S. (2022, May 4). When will a better future arrive for women in music? *MIDiA Research*. https://midiaresearch.com/blog/when-will-a-better-future-arrive-for-women-in-music

Davies, H. (2001). All rock and roll is homosocial: The representation of women in the British rock music press. *Popular Music*, *20*(3), 301–319. https://doi.org/10.1017/S0261143001001519

Davies, J. (2019). Creative industries research requires a new approach to data analysis. In S. Cunningham & T. Flew, *A Research Agenda for Creative Industries* (pp. 76–92). Edward Elgar Publishing. https://doi.org/10.4337/9781788118583.00012

de Boise, S., Edmond, M., & Strong, C. (2022). Gender and popular music policy. In S. Homan (Ed.), *The Bloomsbury handbook of popular music policy* (pp. 271–288). Bloomsbury. https://doi.org/10.5040/9781501345357

De Roeper, J. (2010). Serving three masters: The cultural gatekeeper's dilemma. *The Journal of Arts Management, Law, and Society*, *38*(1), 51–70. https://doi.org/10.3200/JAML.38.1.51-70

Decuypere, M. (2020). Visual network analysis: A qualitative method for researching sociomaterial practice. *Qualitative Research*, *20*(1), 73–90. https://doi.org/10.1177/1468794118816613

Degórski, P. (2022). Meaning mattering in Björk's Biophilia: An analysis from the viewpoint of Karen Barad's agential realism. *New Sound*, *59*(1), 71–88. https://doi.org/10.5937/newso22059071D

den Hartog Jager, H. (2023, March 22). Is het werk van de razend populaire Refik Anadol kunst? Of is het vooral lekker vies, zoals een zak Haribo-bananen? *NRC*. https://www.nrc.nl/nieuws/2023/03/22/refik-anadol-en-de-kunst-van-de-korte-kick-a4160155

Dent, T. (2020). Devalued women, valued men: Motherhood, class and neoliberal feminism in the creative media industries. *Media, Culture & Society*, *42*(4), 537–553. https://doi.org/10.1177/0163443719876537

Dewey-Hagborg, H., Wagenknecht, A., Røstvik, C. M., & High, K. (2016, September 12). Why women are asking a major art and technology festival to #KissMyArs. *The Guardian*. https://www.theguardian.com/science/the-h-word/2016/sep/12/ars-electronica-festival-gender

Dhrodia, A. (2018, March 21). What women want Twitter to know about online abuse. *HuffPost UK*. https://www.huffingtonpost.co.uk/entry/what-women-want-twitter-to-know-about-online-abuse_uk_5ab26c2fe4b0decad045f82b

D'Ignazio, C., & Klein, L. F. (2020). *Data feminism*. The MIT Press.

Donker, S. (2019). Networking data: A network analysis of Spotify's socio-technical related artist network. *International Journal of Music Business Research*, *8*(1), 67–101.

Duffin, C. K. (2021). Women in the music industries: The art of juggling. In L. Hamer (Ed.), *The Cambridge companion to women in music since 1900* (pp. 254–269). Cambridge University Press. https://doi.org/10.1017/9781108556491.021

Dunn, D. (1992). *Eigenwelt der Apparate-Welt: Pioneers of electronic art*. Ars Electronica.

Džuverović, L. (2016). Twice erased: The silencing of feminisms in Her Noise. *Women and Music: A Journal of Gender and Culture*, *20*(1), 88–95. https://doi.org/10.1353/wam.2016.0005

Eckhardt, J., De Graeve, L., Andersen, H., & Heylen, E. (Eds.). (2017). *The second sound: Conversations on gender & music*. umland.

Eckhardt, J. (Ed.). (2018). *Grounds for possible music: On gender, voice, language, and identity*. Errant Bodies.

Edmond, M. (2019). 'I think the main obstacles are men and older men'. In C. Strong & S. Raine (Eds.), *Towards gender equality in the music industry* (pp. 73–87). Bloomsbury Academic. https://doi.org/10.5040/9781501345531

Edmond, M. (2023). Enduring inequalities: Fifty years of gender equality talk in the media and cultural industries. *European Journal of Cultural Studies*, 136754942211453. https://doi.org/10.1177/13675494221145307

Ehrich, M. E., Burgdorf, K., Samoilova, Z., & Loist, S. (2022). The film festival sector and its networked structures of gender inequality. *Applied Network Science*, *7*(1), 20. https://doi.org/10.1007/s41109-022-00457-z

Emmerson, S. (Ed.). (2018). *The Routledge research companion to electronic music: Reaching out with technology*. Routledge.

Esteve Del Valle, M. (2022). Homophily and polarization in Twitter political networks: A cross-country analysis. *Media and Communication*, *10*(2). https://doi.org/10.17645/mac.v10i2.4948

Esteve Del Valle, M., Broersma, M., & Ponsioen, A. (2022). Political interaction beyond party lines: Communication ties and party polarization in parliamentary Twitter networks. *Social Science Computer Review*, *40*(3), 736–755. https://doi.org/10.1177/0894439320987569

Everts, R., Berkers, P., & Hitters, E. (2022). Milestones in music: Reputations in the career building of musicians in the changing Dutch music industry. *Poetics*, *92A*, 101647. https://doi.org/10.1016/j.poetic.2022.101647

Eyene, C. (Ed.) (2019). *Sounds like her: Gender, sound art & sonic cultures*. Beam Editions.

Fairlamb, H. M., & Fileborn, B. (2020). Experiences and perceptions of gender in the Australian music industry. *Perfect Beat*, *20*(1), 8-39. https://doi.org/10.1558/prbt.39800

Farrugia, R. (2004). *Sisterdjs* in the house: Electronic/Dance Music and women-centered spaces on the net. *Women's Studies in Communication*, *27*(2), 236–262. https://doi.org/10.1080/07491409.2004.10162474

Farrugia, R. (2012). *Beyond the dance floor: Female DJs, technology and electronic dance music culture*. Intellect.

Faupel, A., & Schmutz, V. (2011). From fallen women to Madonnas: Changing gender stereotypes in popular music critical discourse. *Sociologie de l'Art*, *OPuS 18*(3), 15-34. https://doi.org/10.3917/soart.018.0015

Festival 2017—Exhibition. *IMPAKT*. (n.d.). https://impakt.nl/nl/festival/2017/exhibition/

Foka, A. (2022). Constructing an artworld influencer network by mining social media. *Leonardo*, *55*(1), 24-29. https://doi.org/10.1162/leon_a_02094

Foster, P., Borgatti, S. P., & Jones, C. (2011). Gatekeeper search and selection strategies: Relational and network governance in a cultural market. *Poetics*, *39*(4), 247–265. https://doi.org/10.1016/j.poetic.2011.05.004

Fraiberger, S. P., Sinatra, R., Resch, M., Riedl, C., & Barabási, A.-L. (2018). Quantifying reputation and success in art. *Science*, *362*(6416), 825–829. https://doi.org/10.1126/science.aau7224

Franssen, S. (2019, November 20). Rondetafelgesprek Vlaams-Nederlandse samenwerking. *Gonzo (circus)*. https://www.gonzocircus.com/rondetafelgesprek-vlaams-nederlandse-samenwerking/

Fure, A. (2016). GRID: Gender research in Darmstadt a 2016 historage project. *Grid Darmstadt*. https://griddarmstadt.files.wordpress.com/2016/08/grid_gender_research_in_darmstadt.pdf

Gadir, T. (2017). Forty-seven DJs, four women: meritocracy, talent, and postfeminist politics. *Dancecult*, *9*(1), 50-72. https://doi.org/10.12801/1947-5403.2017.09.01.03

Gatto, J. G., & Almasi, P. (2021, January 6). Supreme court scraps LinkedIn data-scraping decision. *Bloomberg Law*. https://news.bloomberglaw.com/us-law-week/supreme-court-scraps-linkedin-data-scraping-decision

Gavanas, A. (2013). DJ technologies, social networks and gendered trajectories in European DJ cultures. In B. Attias, A. Gavanas, & H. Rietveld (Eds.), *DJ culture in the mix: Power, technology, and social change in electronic dance music* (pp. 51–77). Bloomsbury Academic.

Georgiou, N. (2018). *Gender inequality and the digital arts: How do sexism and gender biases influence female digital artists* [Master thesis]. Erasmus University Rotterdam.

Gill, R. (2002). Cool, creative and egalitarian? Exploring gender in project-based new media work in Euro. *Information, Communication & Society*, *5*(1), 70–89. https://doi.org/10.1080/13691180110117668

Glowacki, S. (2023). Distribution and emergent economies of software-based art. In G. Wijers & R. Somers Miles (Eds.), *A new era for the distribution of media art* (pp. 81–112). LIMA.

Goh, A. (2014). Sonic cyberfeminism and its discontents. *CTM*. https://www.ctm-festival.de/magazine/sonic-cyberfeminism-and-its-discontents

Grandjean, M. (2016). A social network analysis of Twitter: Mapping the digital humanities community. *Cogent Arts & Humanities*, *3*(1), 1-14. https://doi.org/10.1080/23311983.2016.1171458

Grandjean, M. (2023). *GEPHI: Introduction to network analysis and visualization [new video]*. https://www.martingrandjean.ch/gephi-introduction/

Gray, C. (2022). A hauntology of clandestine transmissions: Spectres of gender and race in electronic music. *Indian Journal of Gender Studies*, *29*(3), 319–334. https://doi.org/10.1177/09715215221111136

Greie-Ripatti, A. (2014). 101 women in electronic music. *CTM*. https://www.ctm-festival.de/magazine/101-women-in-electronic-music

Gritter, R. (2016, March 16). Column: 'Vrouwen zijn ok! Maar mannen net iets beter'. *NMTH*. https://nmth.nl/column-vrouwen-zijn-ok-maar-mannen-net-iets-beter/

Grob, L., & Klok, R. (2019). *Grensgevallen: Een inventarisatie van barrières in culturele uitwisseling tussen Nederland en Vlaanderen*. Overbruggen. https://www.overbruggen.info/uploads/Grensgevallen_Een-eerste-inventarisatie-van-barrieres.pdf

Gross, S. A. (2022). Women working in the music business: An alumni study. In D. Abfalter & R. Reitsamer (Eds.), *Music as labour: Inequalities and activism in the past and present* (pp. 159–174). Routledge.

Grosser, B. (2017). Tracing You: How transparent surveillance reveals a desire for visibility. *Big Data & Society*, *4*(1). https://doi.org/10.1177/2053951717694053

Grund, V. (2021). ‘Über das Hören erfolgreicher Musik’: Kritische Theorie, Avantgarde, Klangkompositionen und Gender. In V. Grund & N. Noeske (Eds.), *Musik und Klangkultur* (pp. 103–118). transcript Verlag. https://doi.org/10.14361/9783839447390-006

Grund, V., & Noeske, N. (Eds.). (2021). *Gender und neue Musik: Von den 1950er Jahren bis in die Gegenwart*. transcript Verlag.

Hagberg, A., Schult, D., & Swart, P. (2008). Exploring network structure, dynamics, and function using networkx. *Proceedings of the 7th Python in Science Conference*, 11–15.

Hanusch, F., & Nölleke, D. (2019). Journalistic homophily on social media: Exploring journalists’ interactions with each other on Twitter. *Digital Journalism*, *7*(1), 22–44. https://doi.org/10.1080/21670811.2018.1436977

Harauer, R., Eberherr, H., & Mayerhofer, E. (2003). Male gate-keepers, female artists and resistance, mechanisms of exclusion in serious music and new media arts in Austria. In *Culture-Gates: Exposing professional ‘gate-keeping’ processes in music and new media arts* (pp. 68–143). ARCult.

Hellsten, I., & Leydesdorff, L. (2020). Automated analysis of actor–topic networks on Twitter: New approaches to the analysis of socio‐semantic networks. *Journal of the Association for Information Science and Technology*, *71*(1), 3–15. https://doi.org/10.1002/asi.24207

Hennekam, S. (2022). Towards more inclusion in the music industry. In D. Abfalter & R. Reitsamer (Eds.), *Music as labour: Inequalities and activism in the past and present* (pp. 190–203). Routledge.

Henry, C. (2009). Women and the creative industries: Exploring the popular appeal. *Creative Industries Journal*, *2*(2), 143–160. https://doi.org/10.1386/cij.2.2.143/1

Herrera, I. (2021, April 29). The secret history of women in electronic music is just beginning to be told. *Pitchfork*. https://pitchfork.com/thepitch/the-secret-history-of-women-in-electronic-music-is-just-beginning-to-be-told/

Hesmondhalgh, D., & Baker, S. (2015). Sex, gender and work segregation in the cultural industries. *The Sociological Review*, *63*(1_suppl), 23–36. https://doi.org/10.1111/1467-954X.12238

Heymann, S. (2018). Gephi. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 928–941). Springer. https://doi.org/10.1007/978-1-4939-7131-2_299

Hilliaert, W., & Hesters, D. (2016, September 27). No women’s land? *Rekto:Verso*. https://www.rektoverso.be/artikel/no-women’s-land

Himelboim, I., Smith, M. A., Rainie, L., Shneiderman, B., & Espina, C. (2017). Classifying Twitter topic-networks using social network analysis. *Social Media + Society*, *3*(1). https://doi.org/10.1177/2056305117691545

Holmes, T. (2020). *Electronic and experimental music: Technology, music, and culture*. Routledge.

Hooper, E. (2019). The gatekeeper gap: Searching for solutions to the UK’s ongoing gender imbalance in the music industry. In S. Raine & C. Strong (Eds.), *Towards gender equality in the music industry: Education, practice and strategies for change* (pp. 131–144). Bloomsbury Academic.

Hopper, J. (2015, January 21). The Invisible Woman: A Conversation With Björk. *Pitchfork*.

https://pitchfork.com/features/interview/9582-the-invisible-woman-a-conversation-with-bjork/

Horawalavithana, S., Arroyo Flores, J., Skvoretz, J., & Iamnitchi, A. (2019). The risk of node re-identification in labeled social graphs. *Applied Network Science*, *4*(1), 33. https://doi.org/10.1007/s41109-019-0148-x

Horn, M. (2013). *Pressure and movements : Gender constructions in experimental electronic music* [Master Thesis]. Royal College of Music in Stockholm.

Hu, B., Jamali, M., & Ester, M. (2018). User behavior in online social networks: Influencing factors. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of Social Network Analysis and Mining* (pp. 3273–3285). Springer. https://doi.org/10.1007/978-1-4939-7131-2_359

imec. (2022). *Digimeter 2021: Digitale trends in Vlaanderen*. https://www.imec.be/sites/default/files/2022-04/IMEC_Digimeterrapport_2021.pdf

Injadat, M., Salo, F., & Nassif, A. B. (2016). Data mining techniques in social media: A survey. *Neurocomputing*, *214*, 654–670. https://doi.org/10.1016/j.neucom.2016.06.045

Jacomy, M. (2023, May 3). How to render a network map, part 1: black and white. *Reticular*. https://reticular.hypotheses.org/6381

Jacomy, M. (2019, May 13). Is Gephi a black box? *Reticular*. https://reticular.hypotheses.org/976

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLOS ONE*, *9*(6), e98679. https://doi.org/10.1371/journal.pone.0098679

Janssens, J., Leenknecht, S., & Ruette, T. (2018). *Cijferboek Kunsten 2018*. Kunstenpunt. https://wp.assets.sh/uploads/sites/4718/2019/12/cijferboek-web-lowres.pdf

Jetto, B. (2015). The evolution of music blogs: From a fan's passion to a promotional outlet. *International Journal of Music Business Research*, *4*(2), 49–74.

Johnson, N., & Dewey, M. (2020). Content targets work: A practical example of changing behaviours and processes in programming women composers. *Tempo*, *74*(292), 38–48. https://doi.org/10.1017/S0040298219001165

Kadushin, C. (2012). *Understanding social networks theories, concepts, and findings*. Oxford University Press.

Kahlert, H. (2021, March 8). Women making music: The COVID impact. *MIDiA Research*. https://midiaresearch.com/blog/women-making-music-the-covid-impact

Kamińska, J. (2022, March 9). Pseudonymization vs anonymization: Differences under the GDPR. *Statice*. https://www.statice.ai/post/pseudonymization-vs-anonymization

Kefi, H., & Perez, C. (2018). Dark side of online social networks: Technical, managerial, and behavioral perspectives. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 535–556). Springer. https://doi.org/10.1007/978-1-4939-7131-2_110217

Kegen, N. V. (2013). Science networks in cutting-edge research institutions: Gender homophily and embeddedness in formal and informal networks. *Procedia - Social and Behavioral Sciences*, *79*, 62–81. https://doi.org/10.1016/j.sbspro.2013.05.057

Keunen, G. (2013). *Alternatieve mainstream: Over selectiemechanismen in het popmuziekcircuit*. Lannoo Campus.

Keychange. (2023). *Music organisations*. Keychange. https://www.keychange.eu/directory/music-organisations

Khanam, K. Z., Srivastava, G., & Mago, V. (2022). The homophily principle in social network analysis: A survey. *Multimedia Tools and Applications*, 8811–8854. https://doi.org/10.1007/s11042-021-11857-1

Khazam, R. (2019). Genre and gender: New tendencies in contemporary electronic music. In E. Shimana (Ed.), *Hidden alliances / Versteckt Verbunden* (pp. 10–27). Hatje Cantz.

Khokhar, D. (2015). *Gephi cookbook: Over 90 hands-on recipes to master the art of network analysis and visualization with Gephi*. Packt.

Klassen, J. (2021). Mikros für Sirenen: Von Cathy Berberian zu den Heroines of Sound: Zur Hör- und Sichtbarkeit von Künstlerinnen elektronischer Musik. In V. Grund & N. Noeske (Eds.), *Gender und Neue Musik: Von den 1950er Jahren bis in die Gegenwart* (pp. 137–156). transcript Verlag.

Knoke, D., & Yang, S. (2020). *Social network analysis*. SAGE.

Kohl, M.-A. (2021). A tool is a tool. Or Is It? Einige Gedanken über die Bedeutung von Stereotypen und Vorbildern. Ein Plädoyer für gegendiskursive Strategien in der Neuen Musik am Beispiel Pamela Z und Laura Mello. In V. Grund & N. Noeske (Eds.), *Gender und Neue Musik: Von den 1950er Jahren bis in die Gegenwart* (pp. 157–174). transcript Verlag.

Koren, T. (2022). The work that genre does: How music genre mediates gender inequalities in the informal work cultures of Amsterdam's nightclubs. *Poetics*, 101713. https://doi.org/10.1016/j.poetic.2022.101713

Koskoff, E. (2005). (Left out in) left (the field): The effects of post-postmodern scholarship on feminist and gender studies in musicology and ethnomusicology, 1990-2000. *Women and Music: A Journal of Gender and Culture*, *9*(1), 90–98. https://doi.org/10.1353/wam.2005.0009

Labatut, V., & Orman, G. K. (2018). Community structure characterization. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 371–383). Springer. https://doi.org/10.1007/978-1-4939-7131-2_110151

Lauw, H., Shafer, J. C., Agrawal, R., & Ntoulas, A. (2010). Homophily in the digital world: A LiveJournal case study. *IEEE Internet Computing*, *14*(2), 15–23.

Lee, S., Chung, J. E., Park, N., & Welch, J. (2020). Status and expertise in the structuring of reciprocal exchanges on Twitter: Replies, retweets, and mentions during national diabetes awareness month. *International Journal of Communication*, *14*(24), 6242–6265.

Lehmann, H. (2022). Genres as imaginary institutions. In M. Churcher, S. Calkins, J. Slaby, & J. Böttger (Eds.), *Affect, power, and institutions* (pp. 167–180). Routledge. https://doi.org/10.4324/9781003303770-12

Leonard, M. (2017). *Gender in the music industry: Rock, discourse and girl power*. Ashgate.

Levy, S. (2023, March 2). Startup T2 wants to terminate twitter. *Wired*. https://www.wired.com/story/plaintext-startup-t2-wants-to-terminate-twitter/

Licht, A. (2019). *Sound art revisited*. Bloomsbury Academic.

Lizardo, O. (2006). How cultural tastes shape personal networks. *American Sociological Review*, *71*(5), 778–807. https://doi.org/10.1177/000312240607100504

Lizé, W. (2016). Artistic work intermediaries as value producers: Agents, managers, *tourneurs* and the acquisition of symbolic capital in popular music. *Poetics*, *59*, 35–49. https://doi.org/10.1016/j.poetic.2016.07.002

Luening, O. (1968). An unfinished history of electronic music. *Music Educators Journal*, *55*(3), 43–145. https://doi.org/10.2307/3392376

Lutter, M. (2015). Do women suffer from network closure? The moderating effect of social capital on gender inequality in a project-based labor market, 1929 to 2010. *American Sociological Review*, *80*(2), 329–358. https://doi.org/10.1177/0003122414568788

Macnish, K. (2018). Ethics of social networks and mining. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 777–785). Springer. https://doi.org/10.1007/978-1-4939-7131-2_197

Mangani, A. (2021). Media bias against women in music: An empirical analysis of Italian music magazines. *Economia Politica*, *38*(2), 657–676. https://doi.org/10.1007/s40888-020-00188-3

Marin, A., & Wellman, B. (2016). Social network analysis: An introduction. In J. Scott & P. J. Carrington (Eds.), *The SAGE handbook of social network analysis* (pp. 11–25). SAGE.

Mazierska, E. (2020). Popular Viennese electronic music, 1990 – 2015: A cultural history. In M. Ahlers, L. Grünewald-Schukalla, A. Jóri, & H. Schwetter (Eds.), *Musik & empowerment* (pp. 271–274). Springer. https://doi.org/10.1007/978-3-658-29706-0_19

McDonald, D. M., & Anderson, J. E. (2020). A data science expert social network: From personal follower list to social network structure. *2020 Intermountain Engineering, Technology and Computing (IETC)*, 1–6. https://doi.org/10.1109/IETC47856.2020.9249094

McDonald, S. (2011). What's in the 'old boys' network? Accessing social capital in gendered and racialized networks. *Social Networks*, *33*(4), 317–330. https://doi.org/10.1016/j.socnet.2011.10.002

McGee, K. (2022). Gendered interventions in European jazz festival programming. In J. Reddan, M. Herzig, & M. Kahr, *The Routledge companion to jazz and gender* (pp. 190–204). Routledge. https://doi.org/10.4324/9781003081876-18

McLaughlin, A. R. (2015). *Navigating gender inequality in musical subgenres* [Master thesis]. East Tennessee State University. https://dc.etsu.edu/cgi/viewcontent.cgi?article=3989&context=etd

McLeod, K. (2001). Genres, subgenres, sub-subgenres and more: musical and social differentiation within electronic/dance music communities. *Journal of Popular Music Studies*, *13*(1), 59–75. https://doi.org/10.1111/j.1533-1598.2001.tb00013.x

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*, 415–444.

Meirelles, I., Schich, M., & Malina, R. (2018). Complex network analysis of arts and humanities. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 87–92). Springer. https://doi.org/10.1007/978-1-4614-6170-8_28

Menczer, F., Fortunato, S., & Davis, C. A. (2020). *A first course in network science*. Cambridge University Press.

Metzelaar, H. (2004). Women and 'Kraakgeluiden': The participation of women improvisers in the Dutch electronic music scene. *Organised Sound*, *9*(2), 199–206. https://doi.org/10.1017/S1355771804000287

Michael, J., & Roosblad, S. (2023, January 26). Muziek. *Cultuurmonitor*. https://www.cultuurmonitor.nl/domein/muziek/

Miedema, M. (2022, February 5). Seksisme in de muziekindustrie: De rot zit in het fundament. *3voor12*. https://3voor12.vpro.nl/artikelen/overzicht/2022/februari/Seksisme-in-de-muziekindustrie--de-rot-zit-in-het-fundament.html

Moonshot. (n.d.). Moonshot digitale cultuur. https://www.moonshotdigitalecultuur.nl

Morgan, F. (2017). Pioneer spirits: New media representations of women in electronic music history. *Organised Sound*, *22*(2), 238–249. https://doi.org/10.1017/S1355771817000140

Mulder, M. (2022). *De Nederlandse livemuziek monitor 2008-2019: Popconcerten en-festivals in het tijdperk tussen streaming en sluiting*. POPLIVE. https://www.poplive.nl/wp-content/uploads/2022/01/Nederlandse-Livemuziek-Monitor.pdf

Mullens, F., & Zanoni, P. (2019). 'Mothering the artist': Women artist managers crafting an occupational identity in the Flemish music industry. *Tijdschrift voor Genderstudies*, *22*(1), 7–26. https://doi.org/10.5117/TVGN2019.1.002.MULL

Nanayakkara, A. C., Kumara, B. T. G. S., & Rathnayaka, R. M. K. T. (2021). A Survey of Finding Trends in Data Mining Techniques for Social Media Analysis. *Sri Lanka Journal of Social Sciences and Humanities*, *1*(2), 37. https://doi.org/10.4038/sljssh.v1i2.36

Nederpel, A., & Pauw, T. (2023, January 28). De resultaten uit het social media onderzoek Nederland 2023. *Frankwatching*. https://www.frankwatching.com/archive/2023/01/28/socialmedia-onderzoek-2023/

Niebur, L. (2010). *Special sound: The creation and legacy of the BBC radiophonic workshop.* Oxford University Press.

Niebur, L. (2021). Case studies of women in electronic music: The early pioneers. In L. Hamer (Ed.), *The Cambridge companion to women in music since 1900* (pp. 199–212). Cambridge University Press. https://doi.org/10.1017/9781108556491.017

Noldus, R., & Van Mieghem, P. (2015). Assortativity in complex networks. *Journal of Complex Networks*, *3*(4), 507–542. https://doi.org/10.1093/comnet/cnv005

O'Brien, D., & Ianni, L. (2022). New forms of distinction: How contemporary cultural elites understand 'good' taste. *The Sociological Review*, 003802612211281. https://doi.org/10.1177/00380261221128144

Oliveros, P. (1970, September 13). And don't call them 'lady' composers. *The New York Times*. https://www.nytimes.com/1970/09/13/archives/and-dont-call-them-lady-composers-and-dont-call-them-lady-composers.html

Olszanowski, M. (2012). What to ask women composers: Feminist fieldwork in Electronic Dance Music. *Dancecult*, *4*(2), 3–26. https://doi.org/10.12801/1947-5403.2012.04.02.01

Osborne, R., & Laing, D. (Eds.). (2021). *Music by numbers: The use and abuse of statistics in the music industry*. Intellect.

Pan, X., Xu, G., Wang, B., & Zhang, T. (2019). A novel community detection algorithm based on local similarity of clustering coefficient in social networks. *IEEE Access*, *7*, 121586–121598. https://doi.org/10.1109/ACCESS.2019.2937580

Parsley, S. (2022). Feeling your way as an occupational minority: The gendered sensilisation of women electronic music artists. *Management Learning*, *53*(4), 697–717. https://doi.org/10.1177/13505076221091625

Paul, C. (Ed.). (2018). *A companion to digital art*. John Wiley & Sons.

Peng, S., Zhou, Y., Cao, L., Yu, S., Niu, J., & Jia, W. (2018). Influence analysis in social networks: A survey. *Journal of Network and Computer Applications*, *106*, 17–32. https://doi.org/10.1016/j.jnca.2018.01.005

Philips, A. (2019, February 15). Why are women underrepresented in music? Look to the Ryan Adams story. *Pitchfork*. https://pitchfork.com/thepitch/why-are-women-underrepresented-in-music-look-to-the-ryan-adams-story/

Pigorsch, U., & Sabek, M. (2022). Assortative mixing in weighted directed networks. *Physica A: Statistical Mechanics and Its Applications*, *604*, 127850. https://doi.org/10.1016/j.physa.2022.127850

Prey, R. (2020). Performing numbers: Musicians and their metrics. In D. Stark (Ed.), *The performance complex* (pp. 241–259). Oxford University Press. https://doi.org/10.1093/oso/9780198861669.003.0012

Purnelle, B. (2019). Vrouwen en muziek: Gimmick of gelijke kansen? *Tijdschrift voor Genderstudies*, *22*(1), 45–48. https://doi.org/10.5117/TVGN2019.1.004.PURN

Raad, E., & Chbeir, R. (2018). Sociograph representations, concepts, data, and analysis. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 2832–2842). Springer. https://doi.org/10.1007/978-1-4939-7131-2_402

Rae, C., Coles, A., & Hanna-Osborne, S. (2017). *Skipping a beat: Assessing the state of gender equality in the Australian music industry*. The University of Sydney. https://ses.library.usyd.edu.au/handle/2123/21257

Reynolds, S., & Press, J. (1995). *The sex revolts: Gender, rebellion, and rock 'n' roll*. Harvard University Press.

Riquelme, F., & González-Cantergiani, P. (2016). Measuring user influence on Twitter: A survey. *Information Processing & Management*, *52*(5), 949–975. https://doi.org/10.1016/j.ipm.2016.04.003

Rodgers, T. (2010). *Pink Noises: Women on electronic music and sound*. Duke University Press.

Rodgers, T. (2015). Tinkering with cultural memory. *Feminist Media Histories*, *1*(4), 5–30. https://doi.org/10.1525/fmh.2015.1.4.5

Ross, A. (2007). *The rest is noise: Listening to the twentieth century*. Fourth Estate.

Rovner, L. (Director). (2020). *Sisters with transistors* [Documentary]. https://sisterswithtransistors.com

Saganowski, S., Bródka, P., & Kazienko, P. (2018). Community evolution. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 357–370). Springer. https://doi.org/10.1007/978-1-4939-7131-2_223

Sandberg, S. & Scovell, N. (2014). *Lean in*. Random House.

Saunders, J. (Ed.). (2009). *The Ashgate research companion to experimental music*. Ashgate.

Sanio, S., & Wackernagel, B. (2019). *Heroines of Sound: Feminismus und Gender in elektronischer Musik*. Wolke Verlag.

Scharff, C. M. (2021). From unspeakability to inequality talk: Why conversations about inequalities may not lead to change. *Open Library of Humanities*, *7*(2). https://doi.org/10.16995/olh.4674

Schedl, M., Bauer, C., Reisinger, W., Kowald, D., & Lex, E. (2021). Listener modeling and context-aware music recommendation based on country archetypes. *Frontiers in Artificial Intelligence*, *3*, 508725. https://doi.org/10.3389/frai.2020.508725

Schmutz, V., & Faupel, A. (2010). Gender and cultural consecration in popular music. *Social Forces*, *89*(2), 685–707. https://doi.org/10.1353/sof.2010.0098

Schreiber, D., & Rieple, A. (2018). Uncovering the influences on decision making in the popular music industry; intuition, networks and the desire for symbolic capital. *Creative Industries Journal*, *11*(3), 245–262. https://doi.org/10.1080/17510694.2018.1490146

Schwarz, J. A., & Johansson, S. (2022). When music becomes datafied: Streaming services and the case of Spotify. In S. Homan (Ed.), *The Bloomsbury handbook of popular music policy* (pp. 289–304). Bloomsbury. https://doi.org/10.5040/9781501345357

Sebo, P. (2021). Performance of gender detection tools: A comparative study of name-to-gender inference services. *Journal of the Medical Library Association*, *109*(3). https://doi.org/10.5195/jmla.2021.1185

Shapiro, P., & Lee, I. (Eds.). (2000). *Modulations. A history of electronic music: Throbbing words on sound*. Caipirinha Productions.

Shoemaker, P. J., & Vos, T. P. (2009). *Gatekeeping theory*. Taylor and Francis.

Sieghart, M. A. (2022). *The authority gap: Why women are still taken less seriously than men, and what we can do about it*. W. W. Norton & Company.

Smith, Z. S. (2022, April 18). *Scraping data from linkedin profiles is legal, appeals court rules*. Forbes. https://www.forbes.com/sites/zacharysmith/2022/04/18/scraping-data-from-linkedin-profiles-is-legal-appeals-court-rules/

Snapes, L. (2019, February 14). The Ryan Adams allegations are the tip of an indie-music iceberg. *The Guardian*. https://www.theguardian.com/music/2019/feb/14/the-ryan-adams-allegations-are-the-tip-of-an-indie-music-iceberg

Spaninks, A. (Ed.). (2019). *Computer Grrrls*. MU.

Sterne, J. (Ed.). (2012). *The sound studies reader*. Routledge.

Syn, S. Y., & Oh, S. (2015). Why do social network site users share information on Facebook and Twitter? *Journal of Information Science*, *41*(5), 553–569. https://doi.org/10.1177/0165551515585717

Tang, Z. (2022). How female DJs and producers narrowed the gender gap in Electronic Dance Music: strategies and campaigns that have been successful in the last decade. *BCP Social Sciences & Humanities*, *20*, 473–485. https://doi.org/10.54691/bcpssh.v20i.2362

Taylor, M., & O'Brien, D. (2017). 'Culture is a meritocracy': Why creative workers' attitudes may reinforce social inequality. *Sociological Research Online*, *22*(4), 27–47. https://doi.org/10.1177/1360780417726732

Tchubykalo, E., Manfredi-Sánchez, J. L., & Sánchez-Giménez, J. A. (2021). Think tanks and political influence. How influencer networks and the specialization of power are represented on Twitter. *Tripodos*, *45*, 111–131. https://doi.org/10.51698/tripodos.2019.45p111-131

The TroubleMakers. (2022). *Facts 2022*. female:pressure. https://femalepressure.net/FACTS2022-femalepressure.pdf

Tindall, D., McLevey, J., Koop-Monteiro, Y., & Graham, A. (2022). Big data, computational social science, and other recent innovations in social network analysis. *Canadian Review of Sociology/Revue Canadienne de Sociologie*, *59*(2), 271-288. https://doi.org/10.1111/cars.12377

Tiwari, D., & Kumar, M. (2020). Social media data mining techniques: A survey. In M. Tuba, S. Akashe, & A. Joshi (Eds.), *Information and communication technology for sustainable development* (Vol. 933, pp. 183–194). Springer. https://doi.org/10.1007/978-981-13-7166-0_18

Toop, D. (2018). *Ocean of sound: Ambient sound and radical listening in the age of communication*. Serpent's Tail.

Topaz, C. M., Higdon, J., Epps-Darling, A., Siau, E., Kerkhoff, H., Mendiratta, S., & Young, E. (2022). Race- and gender-based under-representation of creative contributors: Art, fashion, film, and music. *Humanities and Social Sciences Communications*, *9*(1), 221. https://doi.org/10.1057/s41599-022-01239-9

Treviño, V., Giraud Voss, Z., Anagnos, C., & Wade, A. D. (2017). *The ongoing gender gap in art museum directorships*. Association of Art Museum Directors. https://aamd.org/sites/default/files/document/AAMD%20NCAR%20Gender%20Gap%202017.pdf

Tumat, A. (2021). Die Anfänge der Internationalen Ferienkurse für Neue Musik aus Gender-Perspektive. In V. Grund & N. Noeske (Eds.), *Gender und Neue Musik* (pp. 17–42). transcript Verlag. https://doi.org/10.1515/9783839447390-002

Tzouramanis, T., Kefallonitis, A., & Papageorgiou, G. (2018). Ethical issues surrounding data collection in online social networks. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 769–777). Springer. https://doi.org/10.1007/978-1-4939-7131-2_347

Vanhaverbeke, G. (2015). *Een verkennend onderzoek naar genderdispariteit in de muziekindustrie bij niet-performers in Nederlandstalig België* [Master thesis] Universiteit Gent.

Vincentelli, E. (2017, November 30). The Black Madonna, an activist D.J., wants to turn dance music upside down. *The New York Times*. https://www.nytimes.com/2017/11/30/arts/music/the-black-madonna-dj.html

Vinckx, J. (2022, February 24). 'Als enige vrouw in de crew moet je altijd beter zijn'. *NRC*. https://www.nrc.nl/nieuws/2022/02/23/als-enige-vrouw-in-de-crew-moet-je-altijd-beter-zijn-a4093075

Virtueel Platform. (2011). *Sectoranalyse e-cultuur*. Virtueel Platform.

von Braun, C. (2019). Die 'Magischen Dreizehn Prozent': Gender in der zeitgenössischen Musikszene aus kulturwissenschaftlicher Perspektive. In S. Sanio & B. Wackernagel (Eds.), *Heroines of Sound: Feminismus und Gender in elektronischer Musik* (pp. 136–149). Wolke.

Wall-Andrews, C., & Luka, M. E. (2022). Advancing equity in arts entrepreneurship: A case study on gender equity and empowerment in music production. *Artivate: A Journal of Entrepreneurship in the Arts*, *11*(1), 1–22. https://doi.org/10.34053/artivate.11.1.154

Walter, S., Lörcher, I., & Brüggemann, M. (2019). Scientific networks on Twitter: Analyzing scientists' interactions in the climate change debate. *Public Understanding of Science*, *28*(6), 696–712. https://doi.org/10.1177/0963662519844131

Werner, A., Gadir, T., & De Boise, S. (2020). Broadening research in gender and music practice. *Popular Music*, *39*(3–4), 636–651. https://doi.org/10.1017/S0261143020000495

Whipple, K., & Coleman, R. (2021). Facing the music: Stereotyping of and by women in US music journalism. *Journalism*. https://doi.org/10.1177/14648849211028770

Williamson, J., & Cloonan, M. (2007). Rethinking the music industry. *Popular Music*, *26*(2), 305–322. https://doi.org/10.1017/S0261143007001262

Willrodt, A.-L. (2016). *Gender and labour in the music industry: An exploration into why the music industry has a gender problem and what can be done to change it* [Master thesis]. University of Agder.

Wood-Doughty, Z., Smith, M., Broniatowski, D., & Dredze, M. (2017). How does Twitter user behavior vary across demographic groups? *Proceedings of the Second Workshop on NLP and Computational Social Science*, 83–89. https://doi.org/10.18653/v1/W17-2912

Yuan, Y., Yan, J., & Zhang, P. (2021). Assortativity measures for weighted and directed networks. *Journal of Complex Networks*, *9*(2), cnab017. https://doi.org/10.1093/comnet/cnab017

Zaidi, F., Muelder, C., & Sallaberry, A. (2018). Analysis and visualization of dynamic networks. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 58–69). Springer. https://doi.org/10.1007/978-1-4939-7131-2_382

Zhang, L., & Peixoto, T. P. (2020). Statistical inference of assortative community structures. *Physical Review Research*, *2*(4), 043271. https://doi.org/10.1103/PhysRevResearch.2.043271

Ziemkiewicz, C., Chen, M., Laidlaw, D. H., Preim, B., & Weiskopf, D. (2020). Open challenges in empirical visualization research. In M. Chen, H. Hauser, P. Rheingans, & G. Scheuermann (Eds.), *Foundations of data visualization* (pp. 243–252). Springer. https://doi.org/10.1007/978-3-030-34444-3_12

Zook, M., Barocas, S., Boyd, D., Crawford, K., Keller, E., Gangadharan, S. P., Goodman, A., Hollander, R., Koenig, B. A., Metcalf, J., Narayanan, A., Nelson, A., & Pasquale, F. (2017). Ten simple rules for responsible big data research. *PLOS Computational Biology*, *13*(3), e1005399. https://doi.org/10.1371/journal.pcbi.1005399

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