An Empirical Investigation into Music Listening Behaviour in the Presence of the Network Effect

A thesis

submitted in fulfilment

of the requirements for the degree

of

Doctor of Philosophy in Management Systems

at

The University of Waikato

by

Mona Ghaffari

2023

Abstract

The rapid expansion of online platforms has revolutionised the digital media industry, transforming the way people consume digital content and interact with each other and the platforms. The network effects (NEs) play a vital role in the success of online platforms, fostering user collaboration and interest exchange, thereby creating a positive feedback loop that influences user behaviours and contributes to a platform's success. However, initial studies exploring the NEs phenomenon primarily focused on network size, predating the widespread adoption of online platforms, and thus providing little insight into the application of NEs in the online platform context. Furthermore, despite extensive studies on online platforms, established theoretical constructs and practical frameworks that integrate other variables contributing to NEs in online platforms are lacking.

The thesis consists of three research chapters that significantly contribute to the study of NEs and their influence on users' online music listening behaviours. In the first study, a systematic and rigorous approach was adopted to develop an NEs measurement scale. Drawing on social network and social action theories, we developed a novel NEs model with two subconstructs: social network structure and social action. An empirical research design was applied using the data of 200 Last.fm users. We employed a combination of partial least squares (PLS) path modelling and an expert focus group to validate the model. The results supported the validity and reliability of the developed NEs model.

The second study addressed the scarcity of longitudinal analysis related to the evolving nature of NEs and the lack of empirical research to measure the impact of NEs on online music listening behaviours. We examined the NEs construct from our first study to show the impact of NEs on Last.fm users' music listening behaviours cross-sectionally and longitudinally. The research method used was partial least square-structural equation modelling (PLS-SEM) of data obtained from Last.fm within two time intervals, targeting 1,708 users. Our study found

that NEs positively influence users' music listening behaviours, including the quantity, variety, and novelty of their music consumption. Specifically, the multigroup analysis revealed that the positive impact of NEs on users' music listening behaviours becomes stronger over time. Furthermore, as the social network structure strengthens and users engage in more social actions, there is a carryover effect on NEs at subsequent times.

The third study explored the impact of COVID-19 on online music listening behaviours in relation to listeners' social interactions. We analysed the online music listening behaviours and social interactions of 37,328 Last.fm users in 45 countries before and after the first wave of confinement, using robust causal inference methods: difference in differences (DiD) and two-way fixed effects (TWFE). The results revealed that, in response to COVID-19, there was a decline in the quantity, variety, and novelty of music consumption, with a shift towards mainstream artists. However, our analysis also found that users with more online social connections and communications exhibited the opposite behaviour. This study provides guidance for the development of innovative design strategies for digital media, including music, movies, and games.

Acknowledgements

I would like to express my deepest gratitude to all those who have supported and guided me throughout my PhD journey and the completion of this thesis. Without their unwavering encouragement and assistance, this accomplishment would not have been possible.

First and foremost, I am immensely grateful to my chief supervisor, Dr Gohar Khan, for his invaluable guidance, expertise, and continuous support. His profound knowledge, patience, and mentorship have been instrumental in shaping my research and helping me to achieve my best.

I sincerely appreciate the privilege of working with my co-supervisors, Dr Shivendu Pratap Singh and Dr Bruce Ferwerda. I want to extend my gratitude for all the insightful feedback and comments they provided, which have been invaluable in guiding me throughout this academic journey.

To my family as a whole, your love, encouragement, and understanding have been the bedrock of my achievements. I am blessed to have such a supportive and loving family, and I cannot thank you enough for being my constant source of strength.

To the love of my life, Milad, who has been my pillar of strength, my confidant, and my source of motivation. Your unwavering belief in me and your unwavering support during the highs and lows of this journey have been invaluable. Moreover, your exceptional contribution in teaching me the skill of writing code for data collection has been instrumental to the success of my research.

I would like to extend my heartfelt appreciation to the faculty members and staff at the University of Waikato, specifically the Waikato Management School, who provided a nurturing academic environment and various resources essential for my research.

I am incredibly grateful to my amazing friends, who have been by my side throughout this journey, offering their endless support, encouragement, and priceless friendship that have made this academic journey not only possible but also a truly enjoyable experience.

I would like to thank Professor Markus Schedl for providing me with the invaluable dataset that has greatly contributed to the success of my research. I also thank Dr Brantly Callaway and Dr Pedro Sant'Anna for their patient and insightful responses to my inquiries regarding the development of my research method.

Furthermore, I want to acknowledge the invaluable contribution of my proofreader, Elizabeth Ardley, whose keen eye for detail and insightful suggestions greatly enhanced the clarity and coherence of my thesis. Her expertise and dedication to ensuring the accuracy and quality of my work are deeply appreciated.

While my academic journey has brought me to New Zealand, I want to address my home country Iran and acknowledge my fellow Iranian women who, despite the challenges they face, continue to strive for freedom and equal rights. The determination and resilience exhibited by Iranian women inspire me to contribute to positive change and advocate for their empowerment. I firmly believe that every individual deserves the opportunity to live a life of their choosing, free from oppression and discrimination.

In conclusion, I acknowledge the contributions and support of each and every individual who has played a role in shaping my academic journey. I am determined to utilise my academic endeavours to contribute to positive change and strive for a world where everyone can enjoy the freedoms and equal rights they deserve, both in Iran and beyond.

Woman, Life, Freedom

زن، زندگی، آزادی

Table of Contents

List of Tables

List of Figures

List of Original Papers

The research thesis encompasses three studies, which have led to the creation of five distinct papers. Throughout this research, I have been solely responsible for developing the research ideas, conducting data collection, performing data analysis, interpreting the findings, and composing the manuscripts. Each co-author's contribution is detailed in the co-authorship forms (Appendix B), wherein their involvement primarily lies in data analysis, findings interpretation, and manuscript editing.

The overview of the five research papers:

1. **Paper 1.** Music Oh my Music: A Network Perspective on Online Music Listening Behaviour

   Accepted and presented in the ACIS 2020 conference.

2. **Paper 2.** Covid-19 and Socially Connected Music Listeners: Social Dynamics of Music Streaming Platforms

   Accepted and presented in the INFORMS 2022.

3. **Paper 3.** The Network Effects Construct for Online Platforms: Toward an Integrated Theory, Metrics, and Mathematical Framework

   To be submitted to an A level journal.

4. **Paper 4.** The Impact of Network Effects on Online Music Listening Behaviours: A Longitudinal Study

   To be submitted to an A level journal.

5. **Paper 5.** The Impact of COVID-19 on Online Music Listening Behaviours in Light of Listeners' Social Interactions

   Published in the Multimedia Tools and Applications Journal.

Chapter 1 - Introduction, Thesis Aim, and Outline

1.1. Introduction

Network effects (NEs) are a widely recognised and extensively studied phenomenon in the field of information and communication technologies (ICTs) (Qiang et al., 2004). Initially, NEs were observed in communication technologies such as telephones and fax machines, referring to the concept that the value of a network increases as the number of users or participants within the network grows (Katz & Shapiro, 1985; Shapiro et al., 1998). However, with the invention of the Internet and technological advancements, NEs have become increasingly prevalent across various online platform businesses (Gregory et al., 2020). These platforms provide a venue for sharing content, interests, and social connections, thereby enhancing the value of the platform's products and services (Khan et al., 2019). Therefore, the traditional notion of NEs has faced criticism for its limitations in capturing the collaborative and interactive nature of modern networks, including its restrictive approach and neglect when solely focused on network size (Mandl, 2019).

These identified limitations firstly underscore the necessity of discussing the constraints associated with applying the traditional notion of NEs to online platforms. Subsequently, it is crucial that a new construct for NEs is developed that overcomes these limitations and provides a more comprehensive understanding of the phenomenon. The traditional notion of NEs has been subject to criticism for its simplistic measurement of network size as the sole determinant of NEs in emerging online platforms. Several issues underlie this criticism. First, the standard definition of NEs overlooks the fact that dominant platforms with strong NEs can be outcompeted by new entrants, leading to their eventual demise (McIntyre & Srinivasan, 2017). Success and market dominance in this new online market is not based solely on the number of users on a platform, thus challenging the traditional view of NEs (Hagiu & Rothman, 2016; Tucker, 2018). Another limitation of the traditional notion of NEs lies in its narrow focus on network size, neglecting the importance of social network structure within the network (Afuah, 2013). In fact, an individual's position within the network plays a crucial role in determining how much value they receive and contribute, thus highlighting the limitations of solely relying on network size as a measure of NEs (Afuah, 2013; Suarez, 2005).

Additionally, the traditional notion of NEs does not consider the impact of social interactions and their cascading effects on user behaviour on online platforms (De Vries et al., 2012). Users' observations and positive responses to others' behaviours create network externalities, contributing to a platform's value (Khan et al., 2019). The term social interaction in this context is defined by Godes et al. (2005) as "an action or actions that are taken by an individual not actively engaged in selling the product or service, and that impacts others' expected utility for that product or service" (pp. 416-417). The size hypothesis fails to capture these interdependent social actions, which can generate value even without continuous user acquisition. To effectively understand and leverage NEs in the online platform environment, it is necessary to go beyond the economic aspect of platforms and consider their technical architecture (Gregory et al., 2020). This is something that is missing in traditional NEs as they were primarily grounded in neoclassical economics, limiting their applicability in complex and dynamic online markets (Afuah, 2013).

Some studies have explored the social dynamics and network structure within online platforms, but the results have been limited. While the researchers have proposed theoretical models, variables, and discussions on this topic (Afuah, 2013; Gregory et al., 2020; Mcintyre & Subramaniam, 2009; Mitomo, 2017), empirical investigations have been scarce. Only a few researchers have conducted empirical validation of the results (e.g., Katona et al., 2011; Khan et al., 2019; Oestreicher-Singer & Zalmanson, 2013; Suarez, 2005), although they have considered a limited number of variables beyond network size. This study draws on the substantial theoretical research on social network and social action theories (Arnaboldi et al., 2016; Burt, 1982; Estrada & Knight, 2015; Fuhse, 2020; Liu et al., 2017) in order to develop a comprehensive NEs model that incorporates both dimensions. Additionally, to the best of our knowledge, no prior research has mathematically developed equations to measure NEs on online platforms, except for the work of Khan et al. (2019), which served as an inspiration for our mathematical NEs reference model.

Furthermore, the lack of comprehensive theoretical models for NEs on online platforms has created a significant research gap, hindering comprehensive analyses of user behaviour across different levels of NEs. Our second study aims to fill this gap by including empirical studies that specifically examine the role of NEs in users' music listening behaviours, as well as the evolution of NEs within online platforms. To build our research model, we drew upon existing studies that explore online community participation, social dynamics, and the role of social networks in influencing individuals' music choices. For example, Datta et al. (2017) highlighted how consumers' adoption of online streaming aligns with changes in music consumption and discovery. Oestreicher-Singer and Zalmanson (2013) examined the significance of community participation in the decision to subscribe to a music platform compared to the amount of content consumed. Dewan et al. (2017) explored the impact of online music communities on the songs users listen to, leveraging the theory of social influence. Hagen and Lüders (2016) studied the structure of social networks, including different types of ties (strong, weak, and absent), and their influence on new music discovery within streaming services, while also examining various configurations of social and music homophily derived from social ties.

As an extension, we aimed to explore the impact of the COVID-19 pandemic, a natural event, on online music listening behaviours. The COVID-19 pandemic had far-reaching effects on individuals' lives, impacting not only their physical health but also their mental, social, and spiritual well-being, as evidenced by the implementation of lockdowns and social distancing measures (Ripp et al., 2020; Varshney et al., 2020; Zhang et al., 2020). During these challenging times, music emerged as a crucial tool for reducing loneliness, uplifting mood, and fostering a sense of community (Cabedo et al., 2021; Martín et al., 2021; Ziv & Hollander-Shabtai, 2021). Consequently, there was an expectation that the pandemic would further increase the popularity of streaming services. While existing studies have explored the role of music as a coping strategy and its impact on individuals' well-being during the pandemic, the majority of these studies have relied on self-reported data, which may not capture the intricacies of users' music listening behaviours. By focusing on streaming services, the dominant mode of music consumption (Sim et al., 2022), we sought to gain insights into music consumption patterns by leveraging a vast amount of data from users across different countries.

Furthermore, during the COVID-19 pandemic, the loss of in-person connection prompted individuals to actively engage in online socialisation, leading to a surge in usage of social networking sites worldwide, compared to pre-pandemic times (Asghar et al., 2021; Fink et al., 2021). Within the context of our study, people also turned to social network sites for content consumption, including music, videos, news, and more. Despite this continuing and growing trend, there remains a lack of research investigating the influence of social dynamics and social communication on platform music consumption during the pandemic. The aim of this study was to bridge this research gap by focusing on the significance of social interaction on online music platforms and its role in driving shifts in music consumption behaviour. The study sought to gain valuable insights into the specific changes observed in individual-level music consumption patterns, encompassing factors such as quantity, novelty, variety, and mainstreaminess, during the COVID-19 pandemic. We explored the moderating role of social communication motives, further enhancing our understanding of the relationship between social dynamics and music consumption during this unprecedented time.

The utilisation of Last.fm for data collection and statistical analysis was considered highly appropriate and in line with the research objectives and methodology of the study. Last.fm offers a platform where users can connect and share music as social objects, facilitating easier music discovery among individuals with similar interests and tastes (Hagen & Lüders, 2016). The platform also incorporates a social recommendation system algorithm that leverages users' listening behaviour, preferences, and social networks to provide music recommendations (Henning & Reichelt, 2008). By utilising Last.fm, the study aimed to overcome the limitations associated with collecting NEs data through surveys and questionnaires, which often involve hypothetical questions. Instead, extracting data from online platforms like Last.fm was considered a more accurate way to simulate NEs (van der Aalst et al., 2019). In the following section, a brief overview of the three studies is provided, highlighting their respective research objectives, methods employed, and the process of data collection for each case.

1.2. Thesis Aims and Objectives

This research thesis provides a foundation for a comprehensive exploration and analysis of NEs and users' behaviours on online platforms by considering the social dynamics and social network structure of such platforms. Three distinct and interconnected components collectively form the basis of this thesis, serving as the research objectives.

Objective 1. Advancing the understanding of network effects (NEs) in online platforms

The first study clarifies the limitations of applying the traditional notion of NEs to online platforms and introduces a novel construct for evaluating NEs that goes beyond network size. Given that no prior scale was available to comprehensively measure NEs on online platforms, a theoretical construct was developed, comprising two dimensions: social network structure and users' social actions on online platforms. The development of the scale followed a systematic approach based on the guidelines proposed by MacKenzie et al. (2011). The validity, reliability, and predictive validity of the NEs construct were assessed using data from 200 Last.fm users, including their social network structure and social actions on the platform, using the partial least squares structural equation modelling (PLS-SEM) technique. We are the first researchers to develop theoretical equations that mathematically represent the value of NEs at individual and network levels. The equations presented in this study serve as a reference model, laying the groundwork for future refinement and advancement in understanding NEs on online platforms. The results will be submitted as a paper titled "The Network Effects Construct for Online Platforms: Toward an Integrated Theory, Metrics, and Mathematical Framework" to an A level journal.

Objective 2. Understanding the impact of network effects (NEs) on online music listening behaviours over time

The second study transitions from theoretical measurements of the NEs construct, obtained in the first study, to an empirical examination of the influence of NEs on users' behaviours over time. The study analyses the relationship between NEs, derived from social dynamics and user connections, on music listening behaviours beyond the traditional economic perspective of NEs. Using PLS-SEM with longitudinal data over six months, we investigated the evolution of NEs and their impact on the music listening behaviours of 1,708 Last.fm users, in terms of quantity, novelty, and variety. We further explored the growth, evolution, and persistence of NEs instruments. Incorporating users' demographic and profile information as control variables provided informative insights into understanding online music listening behaviours, aligning with existing research in the field. The results will be submitted as a paper titled "The Impact of Network Effects on Online Music Listening Behaviours: A Longitudinal Study" to an A level journal.

Objective 3. Examining the impact of the COVID-19 pandemic on online music listening behaviours

The third study explores the impact of the COVID-19 pandemic on music listening behaviours, considering changes in quantity, novelty, variety, and mainstreaminess. Aligned with our main objective of the thesis, this study also investigates the social dynamics of music streaming services, and how friendship networks and online communication motives moderated the effect of COVID-19 on music listening behaviours. The causal inference methods, specifically difference in differences (DiD) and two-way fixed effects (TWFE) were employed to analyse the online music listening behaviours and social interactions of 37,328 Last.fm users in 45 countries before and after the initial wave of confinement. The results have been published as a paper titled "The Impact of COVID-19 on Online Music Listening Behaviours in Light of Listeners' Social Interactions" in the Multimedia Tools and Applications Journal.

Figure 1.1 visually illustrates the composition of the thesis, demonstrating the three extended studies that contribute to a comprehensive understanding of the impacts of NEs on online music listening behaviours.

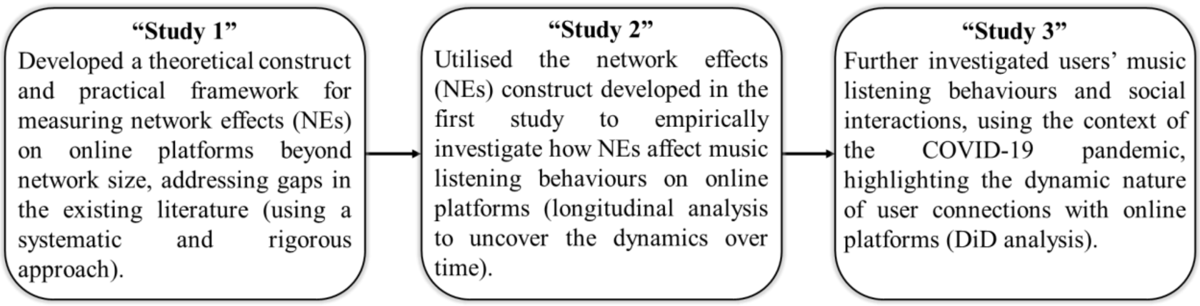


Figure 1.1. Composition of thesis

1.3. Thesis Structure and Outline

The thesis is divided into five chapters, with the current chapter serving as the introduction. In this chapter, the research problem and objectives are presented, providing an overview and setting the stage for the rest of the thesis.

Chapters 2 to 4 consist of self-contained papers that adhere to the standard academic structure, including an abstract, introduction, methodology, results, discussion, conclusion, and future research directions. Each chapter is dedicated to exploring a specific aspect of the research objectives outlined in Section 1.2 and showcases original research conducted by the author.

Chapter 5 of the thesis offers a summary of the research findings and conclusions, providing a comprehensive overview of the study. In addition to the future research directions outlined at the end of Chapters 2 to 4, this chapter provides a consolidated summary of recommendations for further research. The purpose is to emphasise the potential opportunities that arise from this study. Overall, this chapter serves as a valuable resource for researchers and policymakers interested in addressing the limitations of traditional NEs, which primarily focus on network size, on online platforms. It emphasises the importance of considering the social dynamics of these platforms and provides insights for further exploration in this area.

1.4. Ethical Approval

This research does **not** involve the participation of human or animal subjects as it solely relies on secondary data collected through the Last.fm API. However, the researcher has obtained ethical approval for conducting their research from the Waikato Management School Human Research Ethics Committee (Appendix A).

Chapter 2 - The Network Effects Construct for Online Platforms: Toward an Integrated Theory, Metrics, and Mathematical Framework

Mona Ghaffari[a]*, Gohar F. Khan[a], Bruce Ferwerda[b], and Shivendu Pratap Singh[c]

[a]University of Waikato, Digital Business, Hamilton, New Zealand; [b]Jönköping University, Computer Science and Informatics, Jönköping, Sweden; [c]Southern Illinois University Edwardsville, Illinois, USA

*Corresponding author

Publication status: To be submitted to an A level journal.

Abstract

The network effect (NE) has long been recognised as a universal phenomenon whereby new businesses transform into market leaders simply by increasing the number of users. Online platforms enhance this competitive advantage by enabling people to share interests and knowledge and collaborate on content. Researchers have introduced variables to explain the new forms of NEs beyond network size in online platforms; however, a coherent theoretical construct and a practical framework for incorporating these variables are still lacking. Therefore, drawing on social network and social action theories, we developed a novel model for NEs on online platforms as an instrument to measure both individual and network-level NEs. Two subconstructs form the dimensions of this NEs model: (1) social network structure and (2) social action. We applied partial least squares (PLS) modelling to empirical data from Last.fm users (n=200), including their social connections (17,926 nodes and 39,759 edges), combined with an expert focus group to validate the NEs construct. According to our empirical results, the developed NEs model significantly increases users' music listening. We demonstrate how new insights into NEs contribute to interdisciplinary research on information systems (IS) and consumer behaviour studies.

Keywords: Network effect, Online platform, Social network structure, Social action, Consumer behaviour

2.1. Introduction

The network effect (NE) phenomenon stems from communication technologies like telephones and fax machines, where the value of a network depends on its size (Bowling & Hammond, 2008; Farrell & Saloner, 1986). NEs allow users to extract greater value from a product or service as the number of users increases (Katz & Shapiro, 1985). With the growth of the Internet and the proliferation of online platforms, the concept of NEs has extended beyond traditional communication technologies. In addition to telephones and fax machines, NEs now encompass a wide range of networks, including social media and other types of online platforms (Hendler & Golbeck, 2008). Businesses have increasingly benefitted from different types of NEs by providing a place to share content (e.g., YouTube), interests (e.g., Facebook), and expertise (e.g., LinkedIn) (Khan et al., 2019). Traditional NEs have therefore been criticised for failing to capture the new era of collaboration, harmonisation, and interactions evident in recent networks (Knoke, 2014; Thompson, 2003). Researchers have addressed these concerns by introducing possible explanations for the new variations of NEs, considering social network structure and users' social actions within online platforms. Although many attempts have been made, a coherent theoretical construct and a practical framework incorporating these two key categories of variables have not been developed.

Our research priority is to clarify the limitation of applying traditional NEs to online platforms and design a novel construct for calculating NEs beyond network size. The lack of research to unify a NEs model in online platforms stems from the evolving nature of NEs over time and variations in the methodological approaches that scholars have taken in this field. A good theory can help us understand what happens in online platforms as new network industries. Afuah (2013) emphasises the importance of studying NEs through theoretical research as it helps "managers make better decisions in a world in which, increasingly, some of the most complex products and services exhibit NEs" (p. 258). Thus, to provide proper theoretical treatment, we have designed a NEs model based on theories of social network (Arnaboldi et al., 2016; Estrada & Knight, 2015; Liu et al., 2017) and social action (Burt, 1982; Fuhse, 2020).

When exploring NEs in online platforms, numerous studies have examined social network and social action theories from two dimensions: (1) social network structure and (2) social action; however, both dimensions have produced limited results. In most studies, only a few components of the dimensions have been examined, which means other aspects of NEs have been left out. A combination of these two dimensions is also missing. Consequently, the existing literature also lacks a comprehensive analysis of end-user behaviour relating to different NEs values as it is not able to grasp all aspects of NEs. In addition, most previous research has undertaken modelling within an overarching descriptive or conceptual framework, in which the effect of the NEs construct on individual behaviour has not been truly determined. Therefore, our study fills this gap by including the "two pillars" of the NEs construct and argues how they are connected if they represent various aspects of NEs. The study then investigates details of their respective natures. In addition, the study presents a guideline to test novel metrics by applying state-of-the-art statistical tools that measure NEs on a real-world platform. Three objectives arose from this research: (1) identify NEs in online platforms and define them; (2) empirically demonstrate the user participation patterns in forming NEs using data from an online platform, i.e., Last.fm; and (3) develop a mathematical model that integrates new variables of NEs.

The contributions of our work lie in both theory and practice. First, by proposing a novel NEs construct and empirically validating the measures, we believe this research contributes to the existing body of IS research that calls for advancing a new understanding of NEs designed for the next generation of online platforms (e.g., Afuah, 2013; Gregory et al., 2020; Haftor et al., 2021; Khan et al., 2019; McIntyre et al., 2020). In addition, the link between evolving social network analysis and the classic social action perspective enables the study of consumer behaviour on online platforms (e.g., Cousins et al., 2019; Oestreicher-Singer & Zalmanson, 2013). As such, the proposed construct and its measures will be instrumental in identifying influential customers and empowering customer retention strategies on online platforms (such as Last.fm and Netflix). Apart from the benefit of the theoretical contributions, in order to leverage NEs, firms must first understand what drives NEs in their industry rather than accepting them as exogenous forces. This measurement in this study can be applied to online platforms to assess an individual's social network structure and actions to predict how NEs emerge and evolve in users' behaviour (in this instance, music listening).

We used the structured approach developed by MacKenzie et al. (2011) to establish a novel construct for measuring NEs on online platforms. The theoretical construct was conceptualised by considering the definitional properties of the construct and the issues reported in the literature and theory to generate potential items. Combining an expert focus group into the process improved the data richness. A multilevel construct was developed using empirical data from 200 Last.fm users and their social connections (including 17,926 nodes and 39,759 edges). We then modelled and validated the proposed NEs construct and its dimensions using partial least squares (PLS) modelling. We were able to model individual and network-level NEs through our mathematical measurements.

This paper is organised as follows. The following section reviews the literature on NEs definitions and traditional NEs criticism in order to identify the knowledge gap, theories around NEs, and the variables that can be utilised to present a conceptual model. Next, we present the research method, followed by the analysis and findings. This paper concludes by describing the academic and practical implications of the findings, future research directions, and the research limitations.

2.2. Literature Review and Theoretical Development

2.2.1. Traditional Network Effects (NEs)

For over three decades, extensive research has been conducted on NEs in various fields, with the first studies in economics. Early studies coined the term 'network externalities' to describe NEs (Hagiu & Rothman, 2016), and showed that the creation of value through network externalities results from direct connections or multi-sided exchanges between different groups of users (Haftor et al., 2021). Therefore, a network's scale generates network externalities that account for the utility a user derives from that platform (Katz & Shapiro, 1985). This increase in value attracts more users, which leads to even more value (Economides & Himmelberg, 1995; Farrell & Saloner, 1986; Liebowitz & Margolis, 1994).

NEs are classified as direct or indirect. Direct NEs occur when the number of customers using the same product or technology increases the value of the product for each of those customers (Hagiu & Yoffie, 2016); for example, telephone networks are more beneficial to users when more people use them as a communication medium. Several online platforms, such as social media and instant messaging, also benefit from direct NEs. On the other hand, indirect NEs are characterised by the presence of two-sided or multi-sided markets. Indirect NEs occur whenever individuals in one group (e.g., customers on a ride-sharing platform) benefit from the increasing number of members in another group (riders on the same platform) (Hagiu & Wright, 2015; Rochet & Tirole, 2003). These primary classifications are deeply rooted in the size hypothesis (Afuah, 2013).

The basic economic definition of NEs states that the more people use a platform, the more valuable it becomes to each user. The study of NEs by economists (e.g., Katz & Shapiro, 1992; Shapiro et al., 1998) has been followed by strategic studies on how platform providers can improve the number of users by implementing pricing, quality, or entry timing strategies (e.g., Asvanund et al., 2004; Shankar & Bayus, 2003). Scholars of technological management have also focused on the development of platforms and how they influence the generation of NEs through network size (e.g., Boudreau, 2010; Eisenmann et al., 2011; Lee & Mendelson, 2008). It is still the case that researchers continue to focus on strategies for increasing installed bases or determining the impact of the size of an installed base on future platform adoption.

In contrast, little attention has been paid to the emergence of new forms of NEs. Online platforms that enable users to share content with friends and acquaintances and consume content from their social networks create positive network externalities that have an advantage over traditional networks, such as telephones (O'Donovan, 2021). Whenever such behaviours are dynamically reconfigured and more content, comments, likes, tags, and social connections are generated on platforms, NEs will increase the platform’s value to users, regardless of the number of users. Their unique characteristics and the user behaviour they engender mean that online platforms that exhibit NEs differ from those based on traditional communication technologies (such as telephones) or even newer technologies (such as ride-sharing platforms) where NEs are largely determined by the static network size effect (O'Donovan, 2021).

The size hypothesis has been subject to criticism (Afuah, 2013), and more research is being conducted in this field to address the ambiguities surrounding NEs. A new understanding of networks beyond their size is required to deal with questions regarding traditional direct and indirect NEs. Examples of such questions include those asked by Hagiu and Wright (2020): (1) Why are there markets with strong NEs that continue to deteriorate over time? (2) How important is it to users to have many other users purchasing the same product or service? (3) How quickly does the extra value created for users diminish as additional users are added? Consequently, we continue to critique traditional NEs measurements in Section 2.2.2 to highlight the gap that this research aims to fill.

2.2.2. Criticism of Traditional Network Effects (NEs)

According to traditional NEs models, a network's perceived value is primarily determined by the number of users and connections between them (Katz & Shapiro, 1985). The emergence of the Internet has quickly led to the creation of numerous online platforms (e.g., Facebook, Netflix, Amazon) that recognise the power of NEs in accelerating the success and distribution of their businesses (Van Alstyne & Parker, 2017). At the same time, network frameworks have gradually begun to change in parallel with the emergence of the new form of network connections and structures in online platforms (Knoke, 2014). As a result, online platforms have developed several unique characteristics, such as utilising information and communication technologies (ICTs) to enable user interaction, data collection and analysis of user actions, and the creation of NEs (OECD, 2019). As such, network size is too simplistic a measurement to calculate the strengths of NEs in emerging online platforms (Khan et al., 2019). The controversy over traditional NEs and the need to develop a novel construct stem from several issues.

To begin with, the standard definition of NEs states that a higher level of network connectivity can enable the system to "go from a few effects to many or even not die" (Arthur, 2021, p. 140). However, studies have shown that dominant platforms with strong NEs can be outcompeted by new entrants (McIntyre & Srinivasan, 2017). There are well-known histories of online businesses that benefitted from NEs and achieved impressive growth among users but eventually disappeared (Tucker, 2018). Thus, NEs can be beneficial in many ways, but securing a large number of users may not be easy, considering hundreds of similar competitors attempts have failed. An example from the market illustrates how SideCar, a ride-sharing service that existed before Uber, was unable to sustain its operations and ceased. Similarly, the development of NEs that led to the success of Facebook have recently slowed down and other platforms have begun to gain popularity (e.g., TikTok). These cases are incompatible with the logical outgrowth of success and market dominance results based on a traditional view of the number of users on a platform. Consequently, entrepreneurs and founders face a world where traditional NEs appear to be dwindling (Hagiu & Rothman, 2016).

The next problem for traditional NEs is that they are limited to a network's size without considering the social network structure on online platforms. In this vein, networks are assumed to be homogenous: if two networks are equal-sized, consumers see them as perfect substitutes (Katz & Shapiro, 1985). In fact, "consumers are assumed to be heterogeneous in their basic willingness to pay for the product, but homogeneous in their valuations of the network externality" (Katz & Shapiro, 1985, p. 426). Despite this, social networks are not symmetrical since network members do not interact with all platform participants (Suarez, 2005). The transaction between network members identifies each person's position within the network and represents the value each individual gains from or adds to it (Afuah, 2013), challenging the traditional models based on network size.

Additionally, online platforms use a business model that enables users to create social networks and interact with platform features. In addition to the social connections between platform members, social actions such as sharing content, likes, comments, and tags are visible to other users, impacting users' subsequent interaction behaviour. Users observe and respond positively to others' behaviours within their use context, and this interdependent social action creates network externalities by creating the likelihood of further positive reactions (De Vries et al., 2012). For example, on Facebook, the action of a single individual, such as posting a positive comment or liking a page, does not constitute an independent activity (Khan et al., 2019). As positive feedback leads to causal chains of events (Arthur, 1989), the platform should be able to attract more users. If this occurs, the company will continue to generate value through this category of NEs even if it eventually ceases to acquire new customers, in contrast to the size hypothesis.

Moreover, when the size of a network is the only determinant of its value, it is the same as excluding other essential variables, which can lead to biases and inaccurate estimations, cause false conclusions, and potentially mislead researchers and managers (Afuah, 2013). In other words, the key for businesses to employ NEs and achieve long-term success is to relax the size assumption and consider other network characteristics instead of the size hypothesis alone. It has become apparent that NEs are more complex than they once seemed and are no longer concepts to be developed one-dimensionally. Most researchers who challenge traditional NEs believe that businesses cannot incorporate novel variables without understanding their importance (Haftor et al., 2021). In support of this claim, researchers have introduced variables that create (or complete) strong NEs but do not appear in standard metrics or challenge some of the fundamental assumptions of NEs (e.g., Afuah, 2013; O'Donovan, 2021; Suarez, 2005).

Finally, the first studies of NEs were mainly grounded in neoclassical economics (Afuah, 2013); for example, previous platform owners could leverage differential pricing to promote NEs and their adoption (Iyer et al., 2007). However, NEs, as the potent drivers of diffusion in the highly complex and dynamic IT market, cannot be modelled by the standard economic approaches of NEs in other industries (Weitzel et al., 2000). Additionally, NEs strategies relying solely on installed bases are untenable due to technological developments in online platforms. The architecture of online platforms is experiencing rapid growth, and technological advancement is also associated with NEs in new economies (Hagiu & Yoffie, 2016). NEs research must transcend the view that platforms are just markets, and as such, it needs to go beyond the economic aspect of platforms to be effective (Gregory et al., 2020).

To reconsider NEs theory and better understand how NEs operate in the modern IT environment, our study looks at how their technical architecture works – beyond the view of platforms as markets (Gregory et al., 2020). In addition, most of the current literature examines end-users perceived value, while our research follows Suarez's proposition that NEs can also occur upstream in a 'value system' that can encompass both conventional and novel NEs, while the outcome may be positive or negative for its users (Suarez, 2005).

2.2.3. Theories of Social Network and Social Action

Online platforms facilitate social and economic interactions and enable rapid scaling of networks that result in positive NEs (Fenwick et al., 2019). With the presence of social interactions among users of online platforms, the theory of customer behaviour, such as the social action approach (Weber, 1968), provides a way to better understand how social behaviours (e.g., like, comment) that are observable by other users can benefit NEs (Khan et al., 2019). For example, in an examination of social actions in online social communication environments, positive comments or likes that are apparent to other users are considered behaviours within a social context, and this kind of interdependency implies NEs (Khan et al., 2019). Our research is motivated by the classic sociologist Weber (1968) who states that "Action is 'social' insofar as its subjective meaning takes account of the behaviour of others and is thereby oriented in its course" (p. 26). Therefore, social actions such as likes, comments, and mentions are network gains in different disciplines, including business and IS (e.g., Baym, 2013; Lipsman et al., 2012; Otte & Rousseau, 2002).

Furthermore, using social action theory, scholars have conceptualised actions within online networks as intersubjective social activities (Petrič et al., 2011; Renckstorf et al., 1996) in order to bridge communication research and sociology (Krotz, 2009). Four concepts of social action theory emphasise the importance of users' social network structure: (1) the network is an integral part of the context of any given action; (2) actors' position and relationship with others determine their interests and guide behaviour; (3) in turn, these interests motivate a particular action; and (4) individual decisions affect the existing social structure and can reproduce or change network configurations (Fuhse, 2020). We utilised this in-depth understanding of social action and social network theories to build a novel construct for modelling NEs.

On the other hand, according to social network theory, interpersonal relationships play an important role in communicating information, facilitating the transmission of influence of both individuals as well as the media, and improving participants' behavioural and attitude changes (Liu et al., 2017). Social network theory has been formalised and linked to several social action theories, such as Blumer's symbolic interactionism (Blumer, 1986), by researchers including Cordeiro et al. (2018) and De Nooy (2009). This link enables us to expand the classic social action perspective on customer behaviour to include evolving social network analysis (Cordeiro et al., 2018). It is a perspective that enables us to understand concepts of influence within social networks (Boulet & Lebraty, 2018), which diverges substantially from the traditional sociological view that societies are made up of individuals (Williams & Durrance, 2008). The social platform Twitter is the perfect example of how a user can directly influence other Twitter users' reactions by retweeting a message, causing the network structure to be dynamically reconfigured based on such behaviours (Gregory et al., 2020).

With network approaches, nodes in a network cannot be analysed individually; their interconnections define their social contexts (Otte & Rousseau, 2002). Considering that social networks are not symmetrical (Suarez, 2005), the transaction between network members identifies each person's position within the network and represents the value they receive or add to (Afuah, 2013). There is evidence that social network theory emphasises the structure of a user's network to determine the value transferred to or captured by users, as opposed to the number of users (e.g., Afuah, 2013; Gneiser et al., 2012; Suarez, 2005). For example, Afuah (2013) argues that the value transferred from or captured by each user and network provider is determined by the "network's structure (feasibility of transactions, centrality of members, structural holes, network ties, the number of roles each member plays) and its conduction (opportunistic behaviour, reputation signaling [sic], perceptions of trust)" (p. 257). Another example is the economic model of Gneiser et al. (2012), which proposes a valuation of online social networks based on users' interconnectedness.

However, a gap still remains in modelling NEs because recognising the link between classical network measures and social action theory is increasingly essential when connecting NEs with customer behaviour studies on online platforms. The study of (Khan et al., 2019) was one of the first to include the additional exposure associated with social actions within the NEs concept instead of only considering the social network structures. In addition, there is a lack of empirical research on NEs, although network structure and limited social action metrics are used in NEs modelling (e.g., Afuah, 2013; Khan et al., 2019; O'Donovan, 2021; Suarez, 2005). To address and target the knowledge gap, we constructed and evaluated an empirical model to measure NEs in relation to the new generation of online platforms. From the theoretical perspective, this model shows how individuals are socially structured in a network (social network structure), interact (social actions), and create NEs. The social network and social action theories enable us to understand the factors that should be considered when analysing NEs on online platforms. The following section discusses the literature related to the variables of the model.

2.2.4. Research Variables

We examined the NEs variables derived from social network and social action theories before evaluating their contributions to the NEs construct and predicting their effects on online music listening on Last.fm. According to traditional NEs, network growth can provide additional value to existing users while assuming every new member creates a connection with all existing members. However, the value of online networks in the new era does not grow uniformly; it depends on the characteristics of users. As a result, not everyone is equally likely to interact and benefit from a platform's content, services, and products. Traditional NEs ignore the asymmetrical nature of ties in network connections by failing to consider individual-level measurements (Weitzel et al., 2000). Therefore, our research began by examining the structural dimension of individuals' social networks as a general pattern of relationships, namely how individuals communicate with one another.

Social network structure — the arrangement of and relations between different nodes at a given time (Fuhse, 2009).

The graph-like social network structure represents interconnections between nodes and maps nodes into two particular kinds of critical users: hubs and bridges (Nettleton, 2014). The network's hubs are the most critical nodes with many contacts determined by node centralities (Estrada & Knight, 2015); however, the bridges may not necessarily have many contacts but instead occupy a strategic position in the network to derive or create value (Nettleton, 2014). The analysis of centralities identifies central actors – i.e., the nodes situated at key locations within the social network (Hassan, 2009). Beyond a connection possibility, the centrally located nodes are the trigger that increases NEs' level beyond the capacity of regular users (Afuah, 2013). Researchers of NEs evaluate social network structure in terms of the three most common centrality measures (degree, betweenness, and closeness) separately or simultaneously. We used multiple centrality measures simultaneously, as it is considered an appropriate means of reporting the importance and position of a node (Golbeck, 2013).

Degree centrality (DC) — the number of edges that link each node with others shows the node's importance (Boulet & Lebraty, 2018). Degree centrality is restricted to understanding how nodes vary in connecting others or their central position in the whole network (Golbeck, 2013).

Betweenness centrality (BC) — the measure of how often a node appears on the shortest paths between nodes in the network determines users with fewer links but many distant connections (Golbeck, 2013).

Closeness centrality (CC) — the average number of steps to access all other nodes determines the convenience and ease of connection between one node and another network's node (Hansen et al., 2020).

Furthermore, alters connected to the same ego (an ego network refers to an individual as the ego, while their friends are called alters) but not linked to each other create structural holes in information flow (Burt, 1992); thus, bridging structural holes is fundamental to creating a cohesive, information-rich network (Ahuja, 2000). A node's advantages due to its embeddedness in a community are called bonding capital, while its benefits result from its place in the middle of groups and are known as bridging capital. Accordingly, members of a network gain value from bonding, when creates direct and indirect contacts, as well as from bridging, where members serve as intermediaries (Ghaffar & Hurley, 2021; Xu et al., 2019). Therefore, bridging multiple communities is measured as:

Structural holes (SH) — bridging gaps between different regions of a network involves transmitting high volumes of information between these regions (Xu et al., 2019).

The social network analysis method relies on the structural properties of ego networks and tends to concentrate primarily on power while paying little attention to trust (Barbia, 2011). For example, centrality analysis in social networks determines the power derived from relationships and the extent to which certain individuals have a more powerful influence over decisions than others (Barbia, 2011). Nevertheless, online connections are also highly influenced by 'trust' as an indicator of the quality and quantity of communications, decisions, and user interactions (Saeidi, 2020). Social networks' large user bases and ease of use can encourage individuals to build many links with alters. However, many online friends belong to the outer layers, so-called weak-tie friendships, according to Dunbar's circles of acquaintanceship (Dunbar, 2016). Based on Granovetter's (1973) strength of weak ties hypothesis, bridging distant and disconnected parts of a social network must reflect weak ties (Arnaboldi et al., 2016).

Consequently, Dunbar's number theory does not depend on the ego's social network but rather on the degree of trustworthiness of contacts within the ego's network (Barbia, 2011). A highly connected individual is also likely to exert a great deal of influence over their closest friends, which may mean they will have little time to communicate with all of them (Katona et al., 2011). Thus, the ego's network and trust level with alters are organised as a support clique, sympathy group, affinity group, and active ego network (Sutcliffe et al., 2012). Specifically, the ego is more likely to place trust in their alters in the support clique than in those in their active network. Despite the low trust level associated with weak links, they are nevertheless considered valuable due to this group's more significant number of links. The strength of the weak ties hypothesis is thus described as the frequency of communication versus the social intensity of a tie (Mrvar et al., 2018).

Several studies have suggested that trust is a critical factor in influencing the behaviour of online consumers (e.g., Gefen et al., 2003; McKnight et al., 2002). Therefore, consumers are more likely to make decisions based on trusted friends' recommendations than those of strangers (Shokeen & Rana, 2020). The strength of the connections between the nodes can serve as a proxy for reciprocal trust (Arnaboldi et al., 2017). As frequent communication indicates a higher level of trust, the distance from the sub-networks, in which altars are located, to the ego is reversely proportional to the level of communication between the ego and alters (Arnaboldi et al., 2012). Considering the ego network layers, for example, Koroleva and Štimac (2012) found value derived from information in online social networks, while Khan et al. (2019) demonstrated how the degree of trust within the layers of an ego network can be used to determine network externality derived from Facebook likers' networks. Therefore, according to the theory and the researcher's definition, ties strength (the sum of the contact frequencies between the ego and alter) indicates the strength of layers within the ego network (Arnaboldi et al., 2016).

Ties strength (TS) — the number of communications between the ego and alter shows the layers of strength and trust within the network (Dunbar et al., 2015).

For the second dimension of NEs, we used the concept of social actions. Engagement in online platforms can be characterised by various online behaviours, ranging from users who rarely use platforms to skilled and committed users (Bateman et al., 2010). For example, among the many activities available on certain platforms (e.g., on Last.fm: likes, comments, and social networking versus listening to music), some users are limited to consuming products and services daily and monthly. Using this dimension, we distinguished between the ways in which consumers create value through their social actions. However, variables must be customised when conducting empirical research on the feature available for that kind of online platform.

Social action — an interaction through the platform's social features (e.g., like, comment, tag) (Khan et al., 2019).

2.2.5. Conceptual Model

In this model, far more factors are involved than the assumption of traditional NEs based on users' connections (e.g., Farrell & Saloner, 1985; Katz & Shapiro, 1985). Online platforms allow users to connect to many users, information, and services, thereby contributing primarily to the value creation of existing users (O'Donovan, 2021). As shown in Figure 2.1, the conceptual model presents two theoretical roots for creating NEs. On the one hand, based on social network theory, users perceive and create NEs in proportion to the structure of their social networks. On the other hand, online platforms provide users with positive NEs derived from other users' social actions. The actions of individuals contribute to the creation of network externalities through the exposure of other users to the platform and the increase in the positive feedback loop.

Using our conceptual model, we demonstrate that two sets of measures contribute simultaneously to NEs value, filling the gaps in recently developed models that lack comprehensive analysis of these two dimensions. According to social action theory, actors' relationships with others and their positions determine their interests and guide their behaviour. These interests motivate a particular action, and ultimately, individual decisions affect the existing social structure by reproducing or changing network configurations (Fuhse, 2020). Therefore, we borrowed an in-depth understanding of how social actions and social network structures are interconnected in social networks to build a novel construct for modelling NEs. Furthermore, a coherent construct is also required to set strategies that maximise value creation and identify metrics that can limit this ever-increasing value system. The predictive validity of the developed construct was assessed by analysing users' listening behaviour and considering control variables.

Hence, we provide a comprehensive definition of the novel NEs model derived from social network and social action theories as follows:

"The NEs model is derived from the sum of ways in which an individual's social network structure and engagement with a platform create value for users, the platform provider, and the individual themselves".

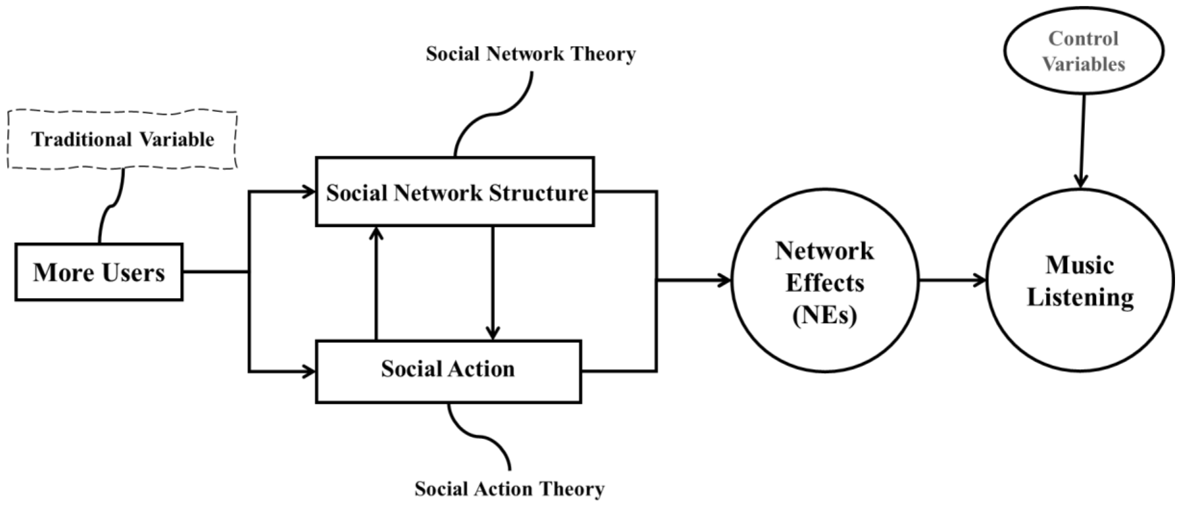


Figure 2.1. Conceptual model of NEs construct and prediction of music listening

2.3. Research Methodology

The process of building a scale according to the structured approach of MacKenzie et al. (2011) is presented as follows: (1) conceptualising the theoretical construct; (2) generating potential items based on the definitional properties of the construct and issues reported in the literature; (3) data measurement: (4) refining and validating the scale with the participation of IS experts and robust statistical analysis; (5) assessing the predictive validity of the construct; and (6) developing a mathematical model.

2.3.1. Item Generation and Construct Conceptualisation

Given that no prior scale was available to measure NEs coherently on online platforms based on conceptualising the social network structure and social actions subconstructs, the first step began with 'item generation'. Theoretical support was provided for the initial item pool from the existing literature. As discussed separately in the literature review, the initial subconstructs list consisted of five items for social network structure and six for social action, as presented in Table 2.1. In this table, we also add a more nuanced description of variables. To conduct predictive validity in our study, we also included music listening behaviour as a dependent variable.

Social network structure — a formative subconstruct that accounts for the overall arrangement of and relations between different nodes at a given time. The social network structure is measured or composed of centralities, structural holes, and ties strength.

Social action — a formative subconstruct that accounts for the level of a user's interaction with the platform's social features (e.g., like, comment).

Table 2.1. Instrument and measurement properties

Subconstruct	Items	Description
Social Network Structure	Degree centrality (DC)	The number of edges that link each node with others shows the node's importance, access, and control over network flow (Afuah, 2013; Bischoff, 2012; Boulet & Lebraty, 2018; Metcalf et al., 2016).
	Betweenness centrality (BC)	The measure of how often a node appears on the shortest paths between nodes in the network determines users with fewer links but many distant connections (Afuah, 2013; Golbeck, 2013; Kane et al., 2014).
	Closeness centrality (CC)	The average number of steps to access all other nodes determines the convenience and ease of connection between one node and another network's node (Afuah, 2013; Kane et al., 2014; Zhang & Luo, 2017).
	Structural hole (SH)	Bridging gaps between different regions of a network involves transmitting high volumes of information between these regions (Afuah, 2013; Kane et al., 2014; Xu et al., 2019).
	Ties strength (TS)	The number of communications between the ego and alters shows the layers of strength and trust within the network (Afuah, 2013; Dunbar et al., 2015; Khan et al., 2019; Suarez, 2005).
Social Action	Like (L)	The number of songs positively rated as loved by a user (Khan et al., 2019).
	Comment (C)	The number of comments posted and replied to by a user (Oestreicher-Singer & Zalmanson, 2013; Shokeen & Rana, 2020).
	Tag (T)	The number of tags assigned to songs, artists, and albums by a user (Oestreicher-Singer & Zalmanson, 2013; Shokeen & Rana, 2020).
	Playlist (P)	The number of songs a user lists to be played together (Oestreicher-Singer & Zalmanson, 2013).
	Event (E)	The number of events a user is interested in or is going to (Oestreicher-Singer & Zalmanson, 2013).
	Obsession (O)	The number of tracks a user assign as obsessions (Oestreicher-Singer & Zalmanson, 2013). Users on Last.fm use the term obsession to describe when they are passionate about a track more than they love it.

2.3.2. Face and Content Validity

In the next step, the content validity of the new scale was affirmed via an online focus group (facilitated through Zoom). We conducted an expert focus group to ensure the validity of the initial item pool for the proposed construct (Morgado et al., 2017) and to exclude the scale's unsuitable items (Mohajan, 2017). The focus group participants (n=24) were purposely selected experts on the development scales or experts on the target construct, as well as potential users of online music platforms from New Zealand, South Korea, Iran, China, and Sri Lanka. Previous studies suggest that having a diverse group of respondents yields better results (Noar, 2003). Table 2.2 provides the participants' demographics.

Table 2.2. Demographic profile of the focus group participant (14 male, 10 female)

Occupation	**Frequency (%)**
Academics	9 (37%)
Business managers	5 (21%)
Graduate students	7 (29%)
Technology experts	3 (13%)
Field of Expertise	**Frequency (%)**
Information systems	9 (37%)
Marketing & Communication	8 (34%)
Business management	5 (21%)
Computer science	2 (8%)
Experience	**Frequency (%)**
1-5 year	6 (25%)
5-10 years	6 (25%)
10-15 years	2 (8%)
15-20 years	5 (21%)
Greater than 20	5 (21%)
Education	**Frequency (%)**
Doctorate	11 (46%)
Masters	7 (29%)
Bachelors	6 (25%)

In the first part of the presentation to participants, the construct was defined and the measurement items related to it were presented. The participants then ranked the items according to how well they fit the variable's definition (content validity), provided written comments concerning the clarity and appropriateness of the wording of the items, and suggested new items (face validity) (Mohajan, 2017). The expert panel suggested adding 'eigenvector centrality' to the social network structure during the ranking process to make the total items 12. Therefore, we included eigenvector centrality (EC) in the social network structure items to measure the importance of the nodes' neighbours (Kane et al., 2014). The experts also suggested changing the term 'shout' used on Last.fm to the term 'comment'. Therefore, we changed the word 'shout' to 'comment', which is more general in the online networks research area. The panel also noted that the number of items on the scale depends on the platform under investigation. For example, 'event' and 'obsession' are social features distinct to Last.fm. Therefore, more specific adaptations are required to apply this model to other platforms (e.g., Spotify or Facebook).

Finally, based on the criteria and guidelines proposed in IS, marketing, and consumer research (MacKenzie et al., 2011; Petter et al., 2007), we conceptualised a novel NEs model as a two-dimensional construct with two first-order formative subconstructs (mode B). The nomological network for construct validity purposes is shown in Figure 2.2.

2.3.3. Data and Measurement

We selected Last.fm for data collection and statistical analysis in this study for four reasons. First, Last.fm users can connect and share music as social objects, which provides easier discovery of music by people with similar interests and tastes (Hagen & Lüders, 2016). Second, this platform has a social recommendation system algorithm that uses individuals' listening behaviour, preferences, and social networks to recommend music (Henning & Reichelt, 2008). Third, through the platform's application programming interface (API), it is possible to access public profiles and collect data about users' social networks and listening behaviours ethically (Pálovics & Benczúr, 2015) [1]. Finally, given the limitations of collecting NEs data through surveys and questionnaires with hypothetical questions, extracting data from digital platforms is recommended as a more accurate way to simulate NEs (van der Aalst et al., 2019).

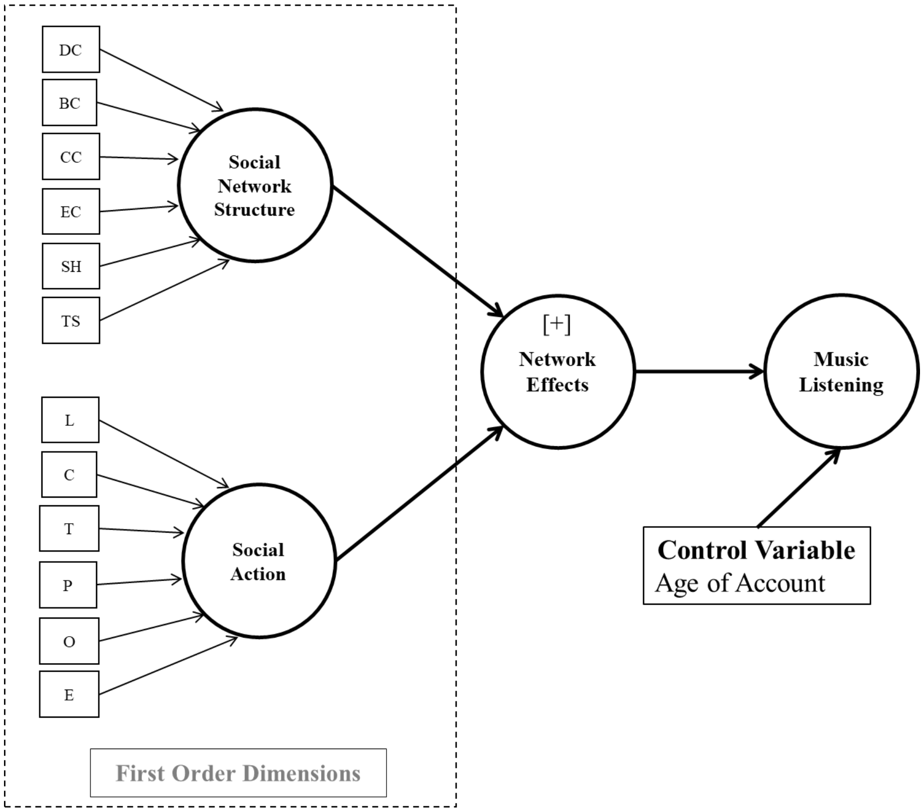


Figure 2.2. The nomological network

Accordingly, we felt that this online service resolved the difficulty of collecting data on NEs measurement and was suited to our reasoning method (i.e., it allowed us to conduct empirical research to analyse NEs leveraging theories of social networks and social action). Below, we describe our sampling method built upon Python (with BeautifulSoup library) for data collection and introduce the equations that were used to measure ties strength (TS). The other variables were directly utilised based on the values calculated by Pajek software (Mrvar & Batagelj, 2018) or derived from Last.fm's API.

[1] Last.fm term of service (https://www.last.fm/api/tos)

Step (1) The data collection included 200 single users who were randomly obtained. We followed several researchers' guides to ensure that the sample size was appropriate: The '10 times' rule (at least 10 times the maximum number of links pointing to any latent variable in the model) is generally used to determine the minimum sample size in the PLS-SEM method (Barclay & Thompson, 1995; Hair et al., 2011). Cohen's power tables are used for power analysis to verify the number of cases obtained from the 10 times rule (Cohen, 1988; Roemer, 2016). Following Cohen's rules of thumb for power analyses for multiple regression models, considering an 80% statistical power at $\alpha = 0.05$, the F test of medium effect size (i.e., $f^2 = 0.15$), with one independent variable, indicates a sample size of at least 67 cases (Cohen, 1992). However, MIS researchers argue that the 10 times rule may only determine the minimum allowable required size to carry out the study (Goodhue et al., 2012), and it may yield a sample size with inadequate statistical power (Garson, 2016). Alternatively, Pituch and Stevens (2016) suggest a sample size of 15 participants per observed variable. Loehlin (2017) argues that researchers should choose at least 100 participants for measurement models with two to four factors. More importantly, it is necessary to decide how small the path coefficients will be to determine the appropriate size. When sample sizes are less than 20, weak path coefficients (e.g., <= 0.2) cannot be determined (Chin & Newsted, 1999). Sample sizes between 150 and 200 are generally required for SEM in this situation (Garson, 2016). A total of 200 users were a safe minimum sample size for our PLS-SEM analysis based on all the above arguments.

Furthermore, we excluded individuals with missing data on key variables, those with a listening history exceeding the 99th percentile, and those with usernames that included radio, music, and genres of music to ensure that data came from actual users, not profiles unrelated to listeners (i.e., radio stations, streaming services, spammers, etc., which also log via Last.fm). As a result, the total sample size was 197 individuals.

Step (2) The sampling was broadened by establishing friends' networks (a directed network of the followings and followers) through API "user.getFriends", including 17,926 nodes and 39,759 edges, to calculate the social network structure measures. With Last.fm, users can follow other users without the other person having to accept their follow. Accordingly, followers are those who follow a user, and following are those who a user follows. We determined the structural properties using the Pajak software (i.e., centralities and structural holes), choosing a directed network as the measurement option (Mrvar & Batagelj, 2018).

Step (3) To calculate the TS in Last.fm, we assumed the Last.fm ego network is similar to Facebook and other social networks. We followed three reasonings for this assumption. First, it has been demonstrated that online communities are similar to offline, face-to-face networks in many ways (Arnaboldi et al., 2017; Dunbar et al., 2015), which is at the heart of designing ego networks for online communities. Second, analysis has already been developed for ego networks such as Facebook, Twitter (Arnaboldi et al., 2017), LinkedIn, XING (Buettner, 2017), as well as in telecommunication services such as call frequency (Carroni & Paolini, 2019). All the results were consistent with "Dunbar's numbers" findings, albeit with some differences. Third, Last.fm is considered a music-based social networking platform (Baym & Ledbetter, 2009), and to this end, we implemented average TS values obtained from two of the field's most widely used social networking sites, i.e., Facebook and Twitter.

To discern between alters at different layers, the parameter to measure the strength of the social relationship is the frequency of contact obtained from online communication logs (Arnaboldi et al., 2016). According to the method, the frequency of contact between two users on Facebook is calculated by the number of interactions between them divided by the estimated duration of their social relationship (Arnaboldi et al., 2016). On Twitter, the frequency of contact is calculated by dividing the number of replies each user sends to the other by the duration of their social interaction (Arnaboldi et al., 2016). Accordingly, Khan et al. (2019)

developed Equation 2.1 to determine TS in the Facebook model, which we extended to account for Twitter (Equation 2.2). Therefore, $TS_{i,t}$ represents the strength of ties among user i and its network at time t.

$$TS_{i,t} = \left(\frac{2}{100}\alpha_1 + \frac{8}{100}\alpha_2 + \frac{23}{100}\alpha_3 + \frac{67}{100}\alpha_4\right) \tag{2.1}$$

(Facebook model)

$$TS_{i,t} = \left(\frac{1}{100}\alpha_1 + \frac{3}{100}\alpha_2 + \frac{9}{100}\alpha_3 + \frac{22}{100}\alpha_4 + \frac{65}{100}\alpha_5\right) \tag{2.2}$$

(Twitter model)

According to Khan et al. (2019), trust amounts are divided among support cliques, sympathy groups, affinity groups, and active networks, respectively, α_1, α_2, α_3, and α_4. To simplify the equation, trust was assumed proportional to the frequency of communication between the alter and the ego in each group. Thus, the normalised values of α_2, α_3, and α_4 concerning α_1 were measured (Equation 2.3). To illustrate this, Table 2.3 provides the normalised values of α_2, α_3, and α_4 relative to α_1 for Facebook and Twitter, respectively, and α_5 for Twitter only (based on the results provided in Table 5 in Arnaboldi et al., 2016). Finally, TS was obtained by substituting the values of Table 2.3 in Equations 2.1 and 2.2 and multiplying it in DC.

$$\alpha_{layer\ i} = \left(\frac{frequency_{\ layer\ i}}{frequency_{layer1}}\right) \quad i = 1,..,4\ for\ Facebook\ and\ i = 1,\dots,5\ for\ Twitter \tag{2.3}$$

Table 2.3. Twitter and Facebook ego network

		Super support clique	**Support clique**	**Sympathy group**	**Affinity group**	**Active network**
Facebook	**Min freq.**	-	5.09	1.95	0.67	0.11
	Trust Size	-	1	0.38	0.13	0.02
	% Alters	-	2%	8%	23%	67%
Twitter	**Min freq.**	20.55	8.91	3.98	1.36	0.18
	Trust Size	1	0.43	0.19	0.07	0.01
	% Alters	1%	3%	9%	22%	65%

Step (4) Using the API "user.getinfo", we accessed the users' social actions (including likes, comments, tags, events, obsessions, and playlists).

Step (5) Through the API "user.getRecentTracks", we accessed the tracks played by users to measure the users' music listening as a dependent variable. The music listening was collected six months later, and the result was then an assessment of predictive validity (Hair et al., 2020). The descriptive statistics are shown in Table 2.4.

Table 2.4. Descriptive statistics of variables

Variable	Mean	SD	Min	Max
Social Network Structure				
Degree centrality	200.45	436.84	1	3,197
Betweenness centrality [0-1]	0.01	0.02	0	0.22
Closeness centrality [0-1]	0.29	0.04	0.19	0.362
Structural hole [0-1]	0.07	0.16	0	1
Ties strength × Degree centrality	15.59	33.90	0.07	248.72
Social Action				
Like	736.53	2320.83	0	24,240
Comment	43.32	130.31	0	1,126
Tag	3.40	8.78	0	50
Playlist	68.04	480.07	0	5,995
Event	3.73	14.69	0	120
Obsession	15.32	40.34	0	425
Dependent Variable				
Number of music listening (for six months)	3,310.10	4,784.91	95.28	30,083.96
Controls				
Age of the account (days)	1,938.15	1,522.86	381	5,644

2.3.4. Partial Least Squares (PLS) for Studying Network Effects

In this section, we provide an introduction to the PLS method, explaining the method and appropriateness of PLS for studying Last.fm Network Effects.

PLS is a powerful statistical method that holds great significance in the field of social sciences and business research (Hair et al., 2016). PLS-SEM is distinct from traditional covariance-based SEM, as it prioritises prediction-focused modelling, making it particularly suitable for complex models with limited sample sizes or non-normal data (Hair et al., 2019). The PLS-SEM method's flexibility and ability to handle formative constructs, reflective constructs, and complex model structures contribute to its widespread adoption in empirical research endeavours (Hair et al., 2016). PLS-SEM involves two core components: the measurement model and the structural model. In the measurement model, latent constructs are formed by multiple observed indicators, and their relationships are estimated using PLS algorithms. The structural model, on the other hand, examines the causal relationships between latent constructs. PLS-SEM offers the advantage of simultaneous assessment of measurement model validity and structural model relationships, making it suitable for exploring intricate pathways within a dataset (Hair et al., 2016; Hair et al., 2019; Henseler et al., 2015).

Methodology Fit: The choice of the PLS method for this research is grounded in its strong alignment with the objectives of studying NEs on the last.fm platform. First, PLS is renowned for its ability to navigate intricate relationships within multivariate datasets, making it an optimal choice for unravelling the intricate dynamics and interconnections inherent in online social networks such as last.fm. In the context of last.fm, the diverse range of variables, including user behaviours, preferences, and social connections, demands an analytical technique that can flexibly accommodate these intricacies. Second, the PLS capacity to handle both observed and latent constructs is crucial for capturing the nuanced nature of NEs, which often stem from underlying factors that might not be directly observable (van der Aalst et al., 2019). Further, the PLS-SEM technique can be used when dealing with several items based on less developed theories and has particular value in predicting and developing new theories (Hair et al., 2011; Hair et al., 2019). In addition, PLS-SEM can be applied without assuming the normality of the data or being constrained by the complexity of the model or other methodological issues (Hair et al., 2016).

Furthermore, PLS is recognised for its robustness in addressing multicollinearity issues—a common challenge in network data analysis due to the interdependencies between variables (Boulet & Lebraty, 2018; Valente et al., 2008). By mitigating multicollinearity, PLS ensures that our analysis provides accurate and meaningful insights into the relationships between social network structure variables, in the complex web of dependencies inherent in the last.fm network. Previous research has demonstrated the efficacy of PLS in capturing latent constructs within network data, as evidenced by its application in studies exploring information diffusion, influence dynamics, and user behaviours within online platforms (e.g., Hair et al., 2012; Pan et al., 2015; Roldán & Sánchez-Franco, 2012). Drawing from this body of work, we can confidently apply the PLS method to provide a comprehensive understanding of the NEs present in the last.fm platform.

2.4. Results

2.4.1. Construct Validity and Reliability

We followed confirmatory composite analysis (CCA) steps using the PLS-SEM technique to confirm the formative construct's measurement model. The CCA method enables constructs to be observed and their interrelationships to be expressed as composites – i.e., linear compounds of subsets of variables (Schuberth et al., 2018). Further, the PLS-SEM technique can be used when dealing with several items based on less developed theories and has particular value in predicting and developing new theories (Hair et al., 2011; Hair et al., 2019). In addition, PLS-SEM can be applied without assuming the normality of the data or being constrained by the complexity of the model or other methodological issues (Hair et al., 2016). We used a repeated indicator approach and inner factor weighting scheme, employing the PLS algorithm to demonstrate the reliability and validity of formative subconstructs (Becker et al., 2012).

Our first step was to test the indicators' multicollinearity. Our statistical analysis, using SmartPLS (Ringle et al., 2015), followed the strict standard of acceptable values for the multicollinearity threshold at variance inflation factor (VIF) <3.3 (Diamantopoulos & Siguaw, 2006). Among all the VIF measures, items BC, DC, and EC in the social network structure category showed high multicollinearity. Studies have shown that correlation in network centrality measures can often be observed (Boulet & Lebraty, 2018; Valente et al., 2008). We used two recommended options to avoid the multicollinearity issue (Petter et al., 2007). The correlated item DC was collapsed into a composite index with item TS. Our method was based on findings in (Khan et al., 2019) that social actions, such as likes on Facebook, can result in positive network externalities depending on how many likes an individual has, their network size (i.e., DC), and four layers of ties strength from strong to weak. According to Khan et al.'s (2019) research, not all friends in an ego network (equivalent to degree centrality) will experience the same level of exposure to the ego's social actions; however, this depends on their location within the ties' strength layers. Khan et al. (2019) adjust degree centrality (the number of edges an ego has), based simply on the level of communication between friends, using the multiplied value of DC with TS in Equations 2.1 and 2.2 as a composite variable, which we used to measure NEs.

Furthermore, to adjust the problem of BC collinearity, we applied a measure called 'corrected betweenness', which is shown by $\widetilde{\mathrm{BC}}$ (Boulet & Lebraty, 2018). In this method, BC is corrected by removing the influence of DC on BC, defined as removing a linear dependence between the centralities. Using this approach, it is possible to detect individuals with high betweenness who do not necessarily possess a high degree centrality. Equation 2.4 demonstrates how $\widetilde{BC}$ is measured (Equation 4 in Boulet & Lebraty, 2018, p. 365).

$$\widetilde{BC} = BC - \frac{S_{BC}}{S_{DC}} \times cor(DC, BC) \times DC \tag{2.4}$$

DC and BC are the degree and betweenness centralities of n individuals in the network. S_{BC} and S_{DC} represent the standard deviations of BC and DC, and cor(DC, BC) indicates the correlation coefficient between BC and DC. This decorrelation method is more effective than relying on the traditional measure of betweenness because it identifies individuals involved in more than one community without necessarily having a large degree of interconnection (i.e., DC) in those communities (Boulet & Lebraty, 2018). Therefore, we continued with corrected betweenness (from now displayed as $\widetilde{\mathrm{BC}}$).

We eliminated EC and found that eliminating this item solved the collinearity problem. We assumed that content validity was not affected because item EC was not popular among scholars. This item was added to the model based on a recommendation from one focus group member. In addition, although the centrality measurements have previously been discussed in the NEs literature (e.g., Afuah, 2013; Suarez, 2005), this is the first attempt to validate the family of centrality indexes in NEs measurement. Then, the inner collinearity statistics between the two subconstructs of social network structure and social action were examined, revealing that the VIF for both was less than 3.3 (VIF = 1.47).

Next, the validity measurements of items provided the following results (subsamples were equalled to 5000 to perform bootstrapping). According to the analysis, it appeared that p-values of outer weights were significant at a level of 5% for all items, except for $\widetilde{BC}$ and SH in social network structure and P in social action, with a p-value of 0.24, 0.19, and 0.58, respectively. In addition to considering other weights, Cenfetelli and Bassellier (2009) suggest assessing the outer loading to determine the absolute contribution due to the low weight of indicators or a nonsignificant weight. The results table for the outer loadings shows that the p-values of $\widetilde{\mathrm{BC}}$ and SH were clearly below 0.05 (with 0.03 and 0.00). Therefore, in the context of this study, the contribution of $\widetilde{BC}$ and SH to social network structure was minor compared to the rest of the indicators; however, they added a substantial amount to social network structure as bivariate indicators. Therefore, we retained them, as previous research and theoretical work have also demonstrated that these indicators can be used to assess NEs given their relevance as indicators of individuals' social network structure (Afuah, 2013; Kane et al., 2014; Xu et al., 2019).

However, it was appropriate to remove P from social action as the outer loading was low (0.26) and nonsignificant (p-value = 0.38). This indicator was not supported by empirical evidence in this situation. It must also be acknowledged that not every formative indicator is statistically significant (Hair et al., 2016); the maximum possible average standardised indicator weight considering four items could be 0.5 ($\frac{1}{\sqrt{4}}$) (Cenfetelli & Bassellier, 2009), which shows how including six items for social action resulted in lower outer weights (value of $\frac{1}{\sqrt{6}} =$ 0.4).

It is also important to note that the outer weight values for $\widetilde{\mathrm{BC}}$, SH, and E were negative, so we followed the prescriptions of (Cenfetelli & Bassellier, 2009). First, we examined the outer loadings to see whether they indicated a negative loading. Because of both negative outer weight and loading, we assessed the bivariate correlations of $\widetilde{BC}$ and SH with other indicators. Since $\widetilde{BC}$ and SH were negatively correlated with other indicators, we found reverse scoring of these two indicators essential, as Cenfetelli and Bassellier (2009) recommend. However, in the case of E, there was a significant negative outer weight along with positive outer loading. According to Cenfetelli and Bassellier (2009) prescription 3, when there is no positive bivariate correlation with social action, it can be concluded that the negative item is potentially measuring something else. Therefore, we found the events that users listed on their profiles occurred outside the platform; due to this, they were not considered social computing elements employed by music streaming services. Because this indicator did not form part of the social actions on the Last.fm platform, we excluded it from the analysis as recommended by Kock (2015). Nonetheless, suppose this indicator was the live streams conducted after COVID-19 within Last.fm. Nonetheless, if this indicator related to Last.fm’s live streams conducted after COVID-19, it could be regarded as the means to facilitate social networking within the streaming platform and account for the resulting network externality (e.g., see Onderdijk et al., 2021).

We retested the validity and reliability measures because we removed items, created a composite variable, and reversed two scores (Lowry & Gaskin, 2014). Table 2.5 presents the final validity statistics. All the remaining items for social network structure and social action were significant. According to the final result as shown in Table 2.5, the modified construct appeared to be the same as initially conceptualised within the social network structure, encompassing centralities, SH, and TS. Social action included various ranges of actions (e.g., like, comment, tag).

Table 2.5. Construct's statistics

Subconstructs	**Outer weights (Outer loadings)**	**T-value**	**P-value**	**VIF**
Social Network Structure				
$\widetilde{BC}$*	0.38 (0.45)	1.41 (2.32)	0.16 (0.02)	1.01
CC	0.38 (0.69)	2.78 (6.82)	0.01 (0.00)	1.63
TS	0.65 (0.84)	4.12 (9.45)	0.00 (0.00)	1.51
SH*	0.05 (0.39)	1.27 (5.71)	0.20 (0.00)	1.38
Social Action				
O	0.21 (0.35)	1.61 (2.1)	0.11 (0.04)	1.03
C	0.80 (0.89)	6.77 (9.81)	0.00 (0.00)	1.49
L	0.24 (0.43)	1.78 (3.23)	0.08 (0.00)	1.12
T	0.25 (0.46)	1.89 (3.51)	0.06 (0.00)	1.14
*The final measurement is based on reversed scores for these two items.				

2.4.2. Test of the Structural Model

We followed the nonparametric bootstrap procedure of PLS-SEM to determine the significance of the path coefficients (Hair et al., 2016). We estimated the path coefficients and the R^2 values to evaluate the structural model. Figure 2.3 demonstrates that first-order subconstructs (social network structure and social action) had significant paths (social network structure, $\beta = 0.37$, $p < 0.10$; social action, $\beta = 0.75$, $p < 0.00$) in the overall NEs construct. Consequently, the path coefficients were significantly different from zero (two-tailed test) with critical t-values above 1.96 and 1.65, respectively. There is a commonly agreed upon significance level of 10% in exploratory studies (Hair et al., 2016). While according to (Hair et al., 2020), "In general, the level of statistical significance required is ≤0.05. But when PLS models are tested using small sample sizes, it may be justifiable to lower the acceptable level of significance to ≤0.10" (p. 106). Our study involving 197 users was considered the minimum sample based on the number of indicators and subconstructs (Cohen, 1992). As an exploratory study, this sample size was appropriate with less stringent rejection criteria, i.e., $p \leq 0.1$ (Cohen, 1992).

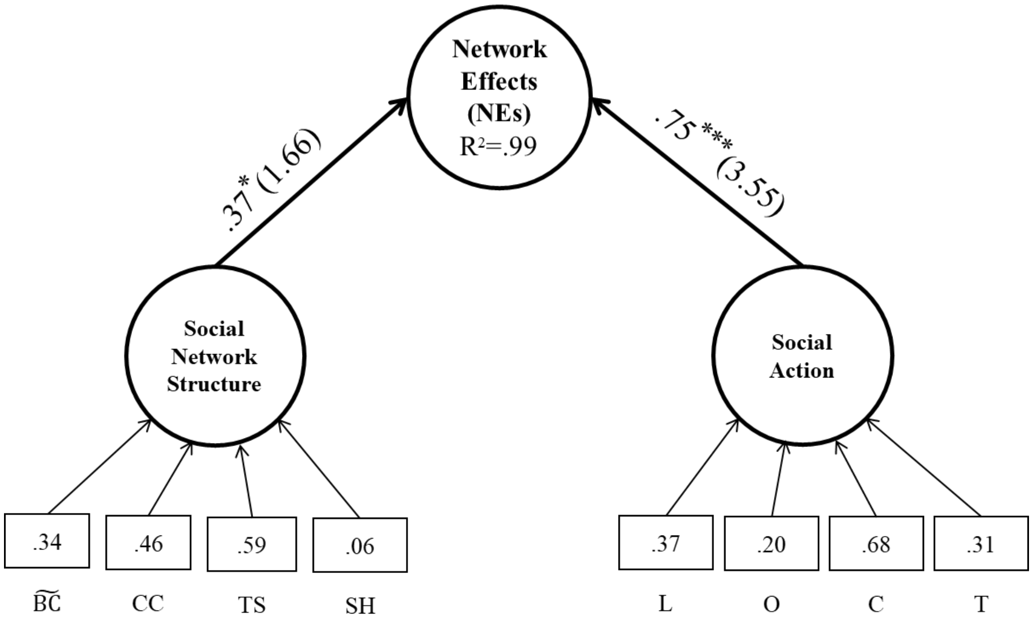


Figure 2.3. Impact of subconstructs on NEs construct. ***$p < 0.00$, *$p < 0.10$, path coefficients with t-values in parentheses

We used a repeated indicator approach for our analysis, specifically formative-formative hierarchical component models, which simultaneously mapped lower-order constructs and a single higher-order construct. Using this approach, the higher-order construct (NEs construct in this study) was almost completely explained by its lower-order constructs, resulting in an R^2 value close to 1.0 (Hair et al., 2017) (see Figure 2.3). As a first step to preventing model-related bias, it is essential to ensure that lower-order constructs have an equal or comparable number of indicators (which was satisfied in this study with the equal number of indicators). The second step is evaluating the measurement models for lower- and higher-order constructs. In the PLS path model, the higher-order construct is not assessed for its indicator variables but instead for its lower-order constructs (Hair et al., 2017). Therefore, the collinearity, significance, and relevance of the relationships between the lower-order constructs were examined, as reported in section 2.4.1 and in the analysis of the structural model in this section.

Specifically, our results support the method of measuring NEs for a formative construct. By examining the items that constitute social network structure and social action, the differences in contribution became evident. Our results showed that social action was the primary driver of NEs when compared to social network structure, as illustrated by the higher path coefficient in our model.

2.4.3. Assess Predictive Validity

Finally, as part of this approach, it was necessary to estimate the predictive power of the scale related to a dependent variable, which was to be determined six months after scale development (Hair et al., 2020). The users' music consumption six months after NEs variables data collection was included as a dependent variable to determine whether our novel model for NEs is a valid predictor of music consumption. Therefore, this paper considered play-count as initial user music listening behaviour measured by the number of songs each user listened to (Datta et al., 2017). As a dependent variable, the number of songs each user listened to in the next six months was predicted based on variables from the period during which the scale was developed. As shown in Figure 2.4, the impact of the NEs construct on music listening was positive and significant ($\beta = 0.30$; $p < 0.01$) with an overall moderate R^2 ($R^2 = 0.28$) (Cohen, 1988). This evidence suggests that the proposed NEs construct provides good predictive validity. The age of the account (the number of days a user was registered to the platform) was used as a control variable in the PLS model. It was demonstrated that the age of the account significantly impacted users' music listening ($\beta = 0.33$; $p < 0.00$).

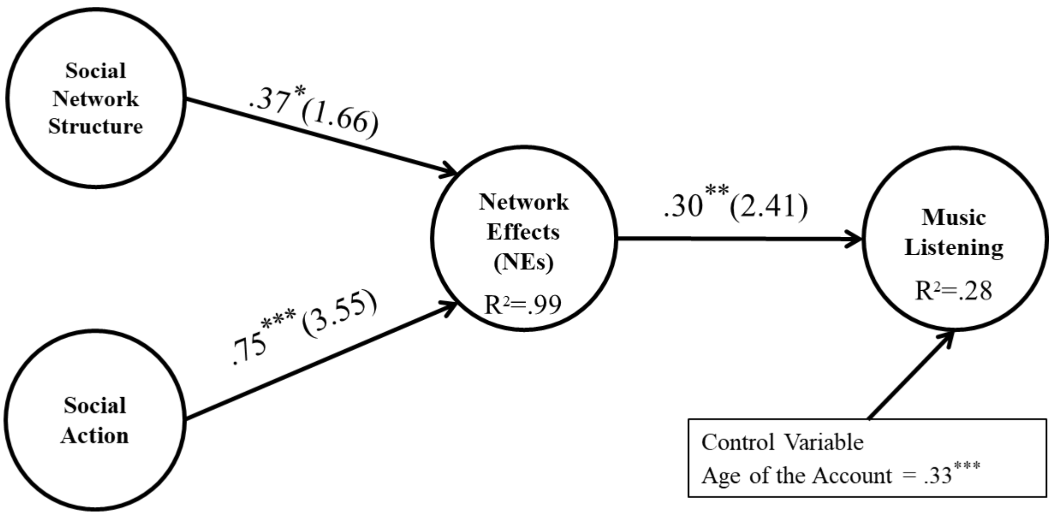


Figure 2.4. Predictive validity of NEs on music listening. ***$p < 0.00$, **$p < 0.01$, *$p < 0.10$, path coefficients with t-values in parentheses

2.4.4. Network Effects Mathematical Modelling

MacKenzie et al. (2011) argue that conceptualising a formative construct is incomplete without explaining how the subconstructs are combined to give the construct its meaning. Multiple subconstructs of the construct must be considered as a whole to determine the focal construct. Therefore, after determining construct validity, reliability, and predictive validity, we developed theoretical equations to mathematically model the proposed NEs construct at individual and network levels. Taking Khan et al.'s NEs model as a starting point, we developed a mathematical model as a reference for online platforms based on two discussed subconstructs (Khan et al., 2019). A noteworthy aspect of this model is that it is considered the fundamental model for further research, which may allow for further refinement in the future.

Khan et al. (2019) modelled NEs mathematically, based on Facebook likers' network but limited to their ties strength and the network size. Khan et al.'s model was adjusted in several ways in our study. Khan et al.'s model is based on the resulting network externality derived from each node's ego network. Taking their model as a starting point, we developed our mathematical model based on transitivity assumptions of the maximum trust in online social networks (Saeidi, 2020). Based on trust transitivity, trust can be generated by sharing and obtaining information from each network node (Buskens, 2020). Liu et al. (2011) illustrated this by arguing that if A trusts B, B trusts C, then C can be trusted by A. As a result, we considered the social network structure of users to demonstrate the possibility of other users building trust among them and receiving information about their social interactions in the network, thus enabling network externality.

Our developed NEs model combines social network structure and this social trust theory (Buskens, 2020; Saeidi, 2020) to fill the gap in NEs research that ignores the trust consideration. Since trust is transitive in social networks, calculating the NEs created by users goes beyond the users' friendship network and includes the trust between users who may not know each other. So, how do we calculate the indirect trust between network users? Katona et al. (2011) demonstrated that variables describing a person's position in a social network are good indicators of influence within the network. We used the aggregate ranking of users derived from their social network structure to represent the location of nodes within the overall network. Users' position can determine whether their nodal spreading capability is more or less than that of users in their following or followers' network. Therefore, the centralities, bridging structural holes, and relationship strength (strong versus weak) provide a more nuanced picture of each user's contribution to the whole network.

The location of nodes in social networks influences their communication efficiency and importance, which is typically assessed based on their centrality measures, such as degree, closeness, betweenness, and K-shell centrality (e.g., Ghanem et al., 2018; Sheikhahmadi & Nematbakhsh, 2016). However, few methods identify important nodes by taking to account structural holes. In contrast to centrality measures, structural holes show an intermediary position between communities and bridging holes (Feng et al., 2018). Thus, structural holes influence and control the formation of social relationships and the dissemination of information (Burt, 1992). Our research aimed to capture both the bonding and bridging importance of nodes to rank nodes based on multiple centrality metrics and structural holes. In this way, the aggregate rankings of each user in the network were computed to assess the subsequent network exposure for other users.

While there are several ranking algorithms to identify spreader users in social networks (e.g., Ghanem et al., 2018; Sheikhahmadi & Nematbakhsh, 2016), as part of our modelling, we used Kemeny-Young's rank aggregation method (Kemeny, 1959; Young & Levenglick, 1978) in a more simplified manner, as Kemeny-Young's approach is an NP-hard model (Dwork et al., 2001). The method aggregates a family of social network structure indices[2] (Boudourides, 2018). We extended Boudourides's work, which uses different centrality indices, and added a structural holes measure to prevent users with greater centrality from necessarily outpacing users with better bridging capabilities (i.e., structural holes measurement). The model was extended to incorporate recent arguments by researchers that centrality measures and structural holes should be merged into one ranking algorithm because nodes that fill structural gaps in the network have an extremely high level of influence (Katona et al., 2011). In response to this, Feng et al. (2018) developed an algorithm for identifying key nodes based on k-shell centrality and structural holes. A method proposed by Zhu et al. (2017) also integrates structural hole theory with node closeness centrality. However, these methods are limited because they do not consider families of centrality indices and assume that nodes with high selected centrality are located at the network's centre. As a result, considering that all centralities and filling the structural hole are equally important, we were able to extend Boudourides's work (Boudourides, 2018). Nevertheless, the inclusion of any other algorithm into the model and the benchmarking of the results could be considered in future research.

[2]This method was derived from work by Boudourides, M. (2018) for the families of centrality indices. We extended it to also consider SH and TS measures.

As the construct validity analysis presented in section 2.4.1 showed, we eliminated EC from calculating social network structure and used the combined value of DC and TS (Equation 2.5).

$$Social\ Network\ Structure_{i,t} = \{\widetilde{BC}_{i,t}, CC_{i,t}, SH_{i,t}, TS_{i,t} \times DC_{i,t}\} \tag{2.5}$$

Following that, every pair of nodes in the network (a combination of 197 nodes) was compared based on their ranking of all variables, regardless of whether nodes were directly connected. Figure 2.5 shows the measurement configuration, with $\widetilde{BC}$, CC, SH, and (TS×DC) respectively in parentheses. The figure is intended only as an illustration. Considering pair (A, B), if all rankings of node B were greater than or equal to the minimum ranking of all four variables for node A, node A was considered to beat node B. In this example, the rankings of node A were [3,1,1,1], and the rankings of node B were [3,2,2,2]. As all rankings of B were greater than the minimum ranking of A, then A beat B. As another example, C's rankings of [3,4,3,3] were greater than the minimum ranking of D of [2,3,2,2], therefore, D beats C. Thus, the rung of user i at time t (R_{it}) demonstrated the number of beats it had in the whole network, representing the spreading power of user i at time t, and the possible indirect trust that was built based on centralities, SH, and TS measures.

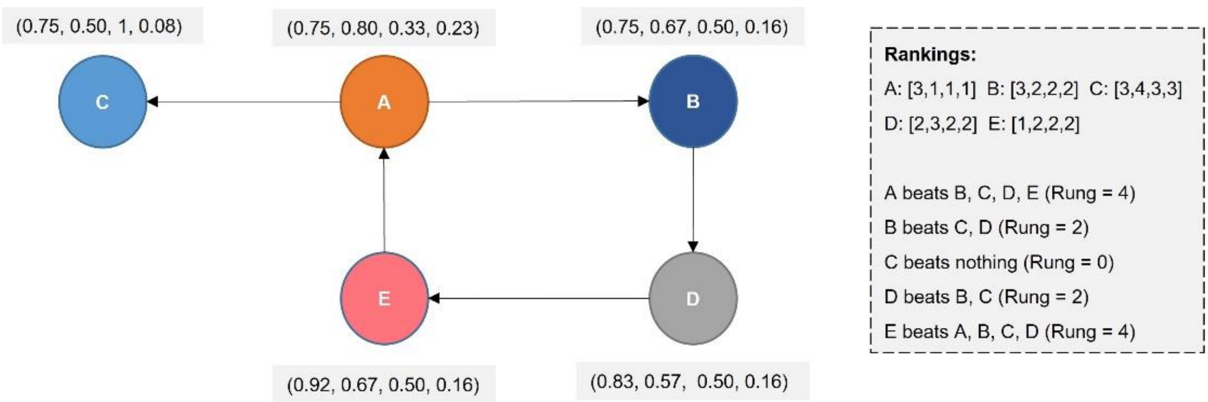


Figure 2.5. Example network for the cumulative ranking model

Further, rather than measuring NEs based only on the effect of likes as a social action, which is only a tiny part of what is possible with social action analysis, in our study, the impacts of other social actions were cumulated for this measurement (cf. Khan et al., 2019). Based on the construct validity analysis in section 2.4.1, we removed P and E from the calculation of social action (Equation 2.6). Finally, we estimated the NEs value through Equation 2.7. We added 1 to R_{it} when calculating NEs since NEs arise from users' engagement and the resulting exposure to the network for other users. Suppose a user does not beat any other user on the network, then the NEs are derived from the interaction between the user and the platform (as for the topic of data NEs). In that case, the user's placement on the network has a negligible effect on other individuals' exposure to the user's interactions (e.g., node C in Figure 2.5). Consequently, with an equal number of social actions, the NEs derived from user A have a higher value than those of user B because the social network structure indicates that the $\widetilde{\mathrm{BC}}$ of both nodes are equal, but node A bridges more SHs, and has a greater CC and TS, increasing higher network exposure for other users.

$$Social\ Action_{i,t} = \left[L_{i,t} + C_{i,t} + T_{i,t} + O_{i,t}\right] \tag{2.6}$$

$$NEs\ (i,t) = (1 + R_{i,t}) \times Social\ Action_{i,t} \tag{2.7}$$

Finally, the resulting NEs at time t, within the integral of all n individuals, was calculated as network-level NEs (Equation 2.8). Beckstrom's law supports our whole network's value. This theory states, "The value of the entire Internet or any network Nj is the summation of the value of that network to all individuals or entities" (Beckstrom, 2009, p. 4).

$$NEs\ (N,t) = \sum_{i=1}^{n} NEs\ (i,t) \tag{2.8}$$

2.4.5. Some Visualisations

Below, we present a series of figures to show how social network structure, social action, and music listening differed among sampled users of the Last.fm online platform. Figure 2.6 shows the visualisation of nodes (users) and the colour ranking of the connections based on the degree centrality. A fraction of the network is magnified to clarify the individuals' position and highlight the most influential users. By referring to this network, it is easier to understand how we attributed value to each user depending on their structural properties, which means their position within the network (in this illustration, their degree centrality), demonstrating the distinct advantage of our model over traditional NEs.

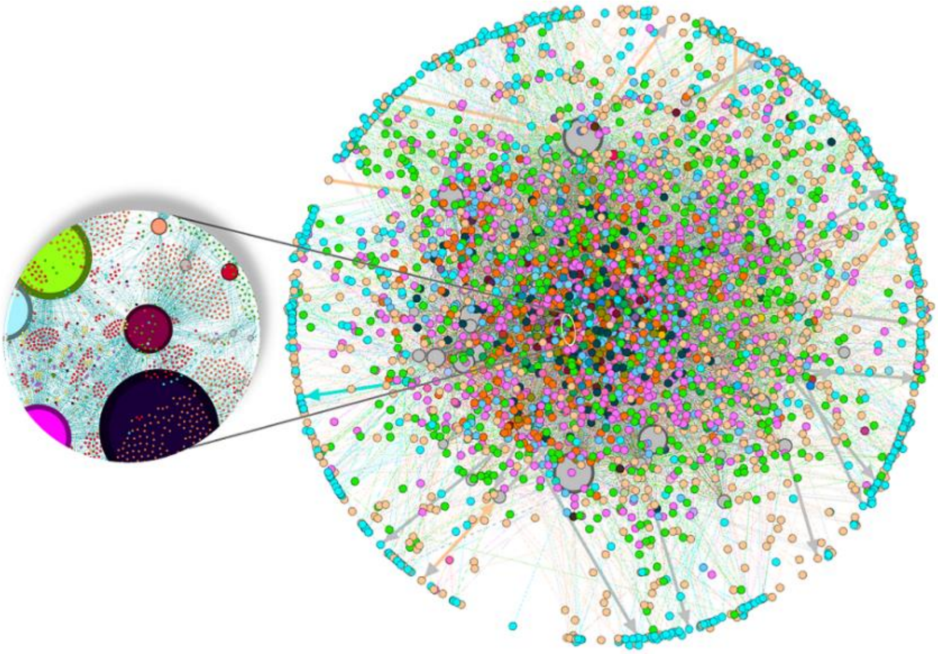


Figure 2.6. Representation of social network on Last.fm

Using the method discussed in section 2.4.4, we calculated the cumulative ranking of individuals based on all items – $\widetilde{\mathrm{BC}}$, CC, SH, and (TS×DC) – to show the differences in social network structure. As shown in the distribution plot (Figure 2.7), 25% of users occupied the critical network position, ranking higher than half of the other users in this study (197 users in total), indicating they affected users' networks more than ordinary users. The comparison was based on the social rung that a person occupied compared to every other node (for more information, refer to section 2.4.4). Next, the social action and music listening distribution plots are delineated in Figures 2.8 and 2.9, respectively. The individual-level analysis shows users who were more likely to be connected with other users sought access to the additional content, products, and services that the business provides and individuals offer to one another.

Accordingly, users with a higher social network structure position were more engaged in social actions and listening to music.

Our finding that the design of the social network structure is a subconstruct that forms NEs is consistent with Afuah’s assertion that centrally located nodes are essential to enhancing the value of a network in the context of creating NEs compared to ordinary users (Afuah, 2013). On average, 80% of NEs subconstructs were derived from 25% of the study population, and about 50% of individuals contributed to only 5% of the values. Therefore, platform providers and decision-makers can use NEs modelling in this study at the individual level to identify contributors who invest significantly more NEs, a strategy known as “marquee” (Parker et al., 2016, p. 94). This study shows that among all social actions, users were considerably engaged in liking, commenting, and highlighting their obsession, indicating their interest in sharing ideas regarding listening behaviour.

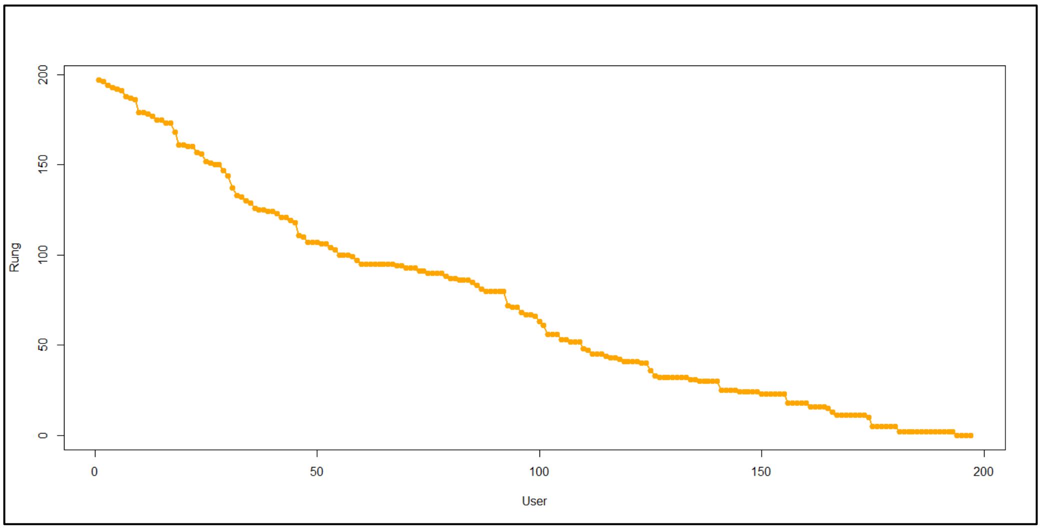


Figure 2.7. Individuals' social network structure distribution graph

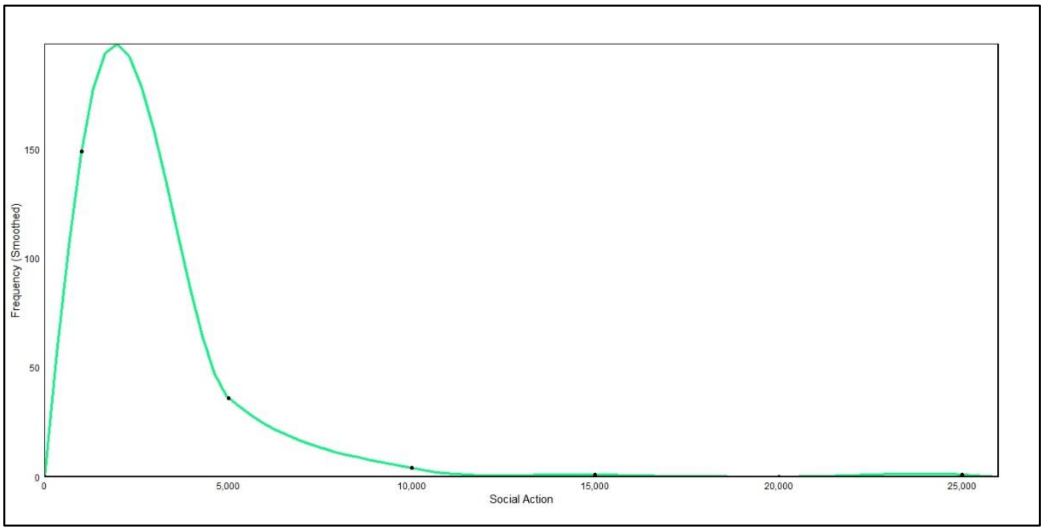


Figure 2.8. Individuals' social action distribution graph

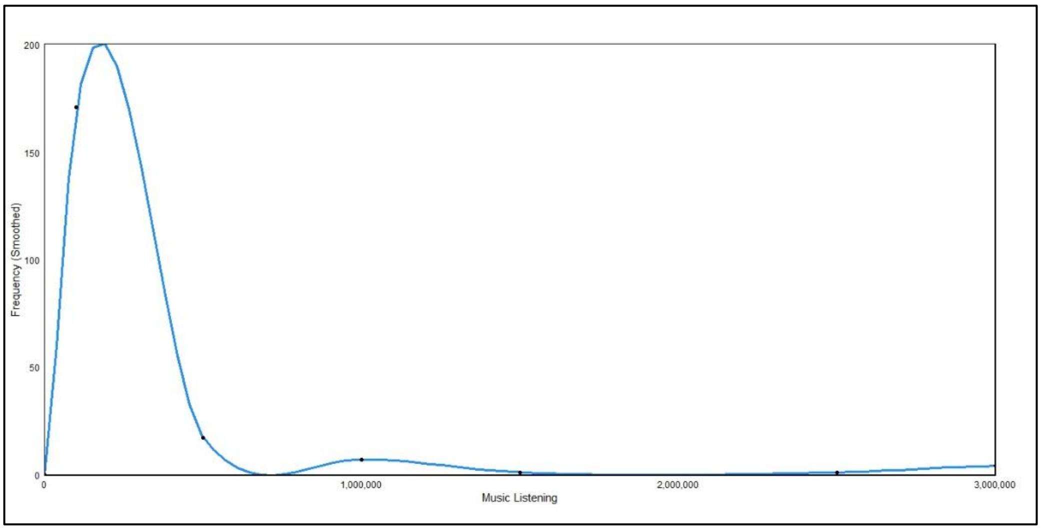


Figure 2.9. Individuals' music listening distribution graph

2.5. Discussion and Conclusion

According to traditional NEs studies, firms gain dominance over competitors once a critical mass is reached (Clough & Wu, 2020). By contrast, the business models of online platforms such as Last.fm employ novel value creation, which we incorporated in our NEs construct. We developed a comprehensive NEs construct based on two subconstructs in order to create and maintain the types of variables required for NEs to flourish and survive. We used exploratory factor analysis as a novel method to develop a scale measuring NEs in online platforms through variables beyond the network's size. With the help of social network and social action theories, we constructed a new scale for measuring NEs on online platforms.

To the best of our knowledge, this is the first research that provides valuable benchmarking that enables online business platforms to mathematically calculate NEs. We used a theoretical model and empirical analysis to develop measurements based on real-time market information (i.e., Last.fm). Our research findings conclude that focusing on the platform's features, such as making friends and sharing interests, can significantly increase NEs and music consumption. In the following, we discuss several theoretical and practical implications, focusing on the contributions of our model compared with the extant literature and how business decision-makers might intervene to ensure a high level of value is delivered to users.

2.5.1. Implications for Academia

Numerous studies have shown that dominant platforms with strong NEs can be outcompeted by new entrants, which is contrary to the standard definition of NEs (McIntyre & Srinivasan, 2017). As a result, dominance in the market does not necessarily translate into a more significant number of users; instead, it requires the specification of particular variables appropriate for today's business environment. Entrepreneurs and founders must understand how NEs evolve throughout a business as well as over time if they are to navigate the newly reshaped path of online platforms (Hagiu & Rothman, 2016). Due to this necessity, the first strength of our contribution stems from a novel approach to measuring NEs in online platforms through variables beyond network size. We employed an approach that dynamically models NEs taking into consideration the technological structure of online platforms and variables beyond network size that have been identified as crucial for the formulation of NEs on online platforms with complex and time-varying network structures.

Online platforms are often described as complex network structures since various types of connections are formed and evolve throughout their usage, for instance, friendship connections and networks of co-likers. There is increasing evidence that the structure of social networks can play a crucial role in interpreting NEs, contrary to traditional NEs that assume network values are static and equal over a fixed network size (Afuah, 2013). Among the researchers who have highlighted the structure of connections as the driver of NEs, the social network structure variables have been explored separately or collectively within an overarching descriptive or conceptual framework of NEs (Afuah, 2013; Kane et al., 2014; Katona et al., 2011; Suarez, 2005), while an aggregated analysis in an empirical study is an innovative approach. In this study, a comprehensive social network analysis was included conservatively, using all variables simultaneously and testing them empirically on an online platform (i.e., Last.fm) for the first time.

Studying NEs at the individual level became possible due to the study of social network structure, which examines the structural properties of each individual. Our model, however, distinguishes itself from models relying only on structural variables by pinpointing the second set of variables significantly associated with NEs on online platforms as far as individuals' contributions are concerned. The results of this study suggest that having a large number of friends does not in itself result in an increase in NEs. Using social features that are integrated into online platforms and that are used by users of those platforms may allow online platforms to generate NEs through the use of their services. According to our theoretical and empirical findings, variables that describe individuals' positions within a social network are good indicators of NEs. Yet, the importance of the structure of the social network in creating NEs is, on average, lower than the importance of the social actions of users.

Furthermore, for the first time since (Khan et al., 2019), this study examined the mathematical measurement of NEs based on the two categories of social network structure and social action with the comprehensive use of theoretical equations. We developed a model that combines social network structure and social trust theory (Buskens, 2020; Saeidi, 2020) to fill the gap in NEs research that ignores the trust component. Because trust in social networks is transitive, we calculated NEs by considering the trust between users, regardless of whether they are friends. A mathematical model of NEs was created by aggregating the ranking of users in order to determine the location of nodes in the overall network based on the social network structure of each user. In this research, the development of a mathematical model for measuring NEs at individual and network levels contributes to the development of NEs theory as well as allowing the empirical application of the NEs model in various fields (e.g., customer behaviour studies and new tech economy).

Our choice of variables for the proposed NEs construct was based on social network and social action theories, whereas previous research has only focused on the structural properties of individuals' social networks. In this regard, it is not clear from the extant literature how individuals who are connected to many users or, importantly, positions within a network may make a more significant contribution to NEs. This study addressed the question by analysing users' social actions on the platform. We argue that the interconnection between users allows them to directly influence other users' reactions by providing additional information about products and services via likes, comments, tags, and events, thereby increasing NEs. This research empirically supports social network structure and social actions as subconstructs of

NEs. Interestingly, social action appears to be the primary driver of NEs rather than social network structure, since it had a higher path coefficient in our empirical study.

Digital technologies and platformisation have revolutionised business models over the past decade, and the NEs model has evolved due to these changes. In the proposed NEs model, higher NEs value results from users' position as influential actors and their higher levels of engagement with platform social features. Although the proposed model discusses the need to examine these two types of contributions simultaneously, it distinguishes their measurement, allowing platform providers to plan their own strategies for developing NEs. These factors can contribute to the platform's dominance within the industry. The study of user behaviour on Last.fm in this research showed that users who exhibited a better social network structure (based on centralities, bridging structural holes, and ties strength) were more engaged in social actions such as comments, likes, and tags than ordinary users, which led to an increase in music consumption. Therefore, online platforms are encouraged to provide socialising functions, such as enabling people to become friends and share interests, in order to increase the probability of successful consumption even for new users.

Moreover, this study found that NEs value derived from social network structure and social actions positively impacted listening to music. Yet a significant percentage of users (27%) did not use social networking features, including those who listened to thousands of songs per month. Therefore, music consumers saw social connections as an added value to their music consumption rather than intrinsically connected (Oestreicher-Singer & Zalmanson, 2013). Considering these results, we believe that a comprehensive list of music and a suitable recommendation system is necessary to create value for customers; however, platform providers may also consider strategies to encourage social interaction and connection between users to increase users' music listening. For example, Spotify's "social listening" feature lets friends control music together and considers social listening behaviour as socialising. Apple

Music also allows users to see what their friends listen to. These characteristics demonstrate the significance of social components as an integral part of core business activities aimed at boosting NEs.

Online platforms play an increasingly important role in almost all industries, and they are also becoming more prevalent in the literature on IS (De Reuver et al., 2018). However, it is important to note that the NEs construct is often misused in the field of IS research, where it is incorrectly assumed that an increase in the number of users will automatically lead to improved performance. The development of a more detailed NEs construct in the field of IS seems to be timely in light of increasing platformisation and the role played by online communities. Due to the varying business models used on online platforms, NEs derive from a variety of sources and evolve differently. It follows that NEs can vary from business to business and develop and mature in various ways over time. It is imperative to carefully examine the nature of online platforms and their specific social features while also considering their differences and their technology. In Table 2.6, we present two levels of social networking and minimal social networking and two levels of social action and minimal social action within online platforms. Using this table, we can generalise the proposed NEs model by identifying the locations of various online platforms, and extend it by studying additional dimensions.

Table 2.6. Social networking and social action on online platforms

Social Networking	**Social Action**
Creating and maintaining a social network of friends and acquaintances through connecting with all people, e.g., following and sending requests.	Sharing and experiencing with others, e.g., content sharing, posts, likes, comments, tags, events, games.
Minimal Social Networking	**Minimal Social Action**
Keeping up relationships within one's own network, e.g., private communication, direct messages.	Using knowledge for its own benefit, e.g., making a profile, views, clicks, acquiring information about products such as opinions and comments, downloading content.

Social networking and social action are both employed by a number of businesses. An excellent example is Facebook, where users' friendship networks and social actions such as liking, commenting, and tagging produce value for the existing user base by providing users with additional content and connections to enjoy and potentially attract new users. A similar dynamic can be observed in the business models of LinkedIn and music platforms such as Last.fm, both of which rely heavily on the online community. In contrast to social networks, where friendship networks and actions are highly valued, e-commerce platforms ignore social networks and do little to address social actions such as reviews and likes. The purpose of this study is to highlight the importance of these two dimensions when developing a NEs model. Incorporating these dimensions into a NEs model can provide valuable insights for platform providers seeking to enhance their performance by leveraging these factors. In Table 2.6, following a similar approach to O'Donovan (2021), we illustrate how online platforms adopt diverse ranges of these dimensions, moving beyond a narrow focus on a business model limited to these dimensions.

In addition to theoretical improvement in NEs studies, the proposed NEs model can be applied to research in IS. Our research makes it possible for future user behaviour studies to measure the impact of NEs on user choices, for example, willingness to pay (e.g., Oestreicher-Singer & Zalmanson, 2013), the success of software projects (e.g., Ghapanchi & Tavana, 2015), and information technology diffusion (e.g., Li et al., 2014), or apply its factors to the value system of cryptocurrencies (e.g., Cousins et al., 2019). Further, we believe the NEs construct to be an adequate theoretical foundation for researchers who argue that the perceived value and economic efficiency of empirical IS research call for new conceptualisations to replace traditional ones. An example includes the long-term success of marketing and management programmes, such as calculating social media's returns on investment (ROI) (e.g., Gilfoil & Jobs, 2012; Khan et al., 2019), and the resource-based view (RBV) of online social businesses (e.g., Afuah, 2013; Wade & Hulland, 2004).

Technology management studies can use our proposed method to measure the impact of the user-centric design of platform functionalities as a contributor to NEs, rather than focusing on network size only, as is the case in previous studies (e.g., Boudreau, 2010; Eisenmann et al., 2011; Lee & Mendelson, 2008). Ultimately, the user-centric design of the platforms (the type, nature, and positioning of components) can enhance users' engagement and satisfaction (Zhou et al., 2009) and act as a moderator for NEs (Gregory et al., 2020; Khan et al., 2019). In this way, companies that offer their products and services through apps as part of customer engagement strategies may benefit from more NEs (Kim et al., 2013). Studying the differences between an app and a website would be beneficial in enhancing NEs and in identifying the advantages and disadvantages of offering business apps. Nonetheless, as far as we know, no detailed analysis has yet addressed the difference between NEs levels derived from apps and websites on a specific platform.

As a methodological conclusion, consistent with previous research that has used the Last.fm API as a suitable academic research tool (Hagen & Lüders, 2016; Schedl, 2017), we also believe researchers could derive digital user behaviour from this API. Last.fm does not limit access to the scale of data, and researchers can find and focus on key ideas with thousands of users instead of solely focusing on small-scale users. Accordingly, we believe that this online service resolves the difficulty of collecting data on NEs measurement (van der Aalst et al., 2019) and was suited to our reasoning method (i.e., it allowed us to conduct empirical research to analyse NEs leverage of social network and social action theories). However, items belonging to the social network structure (i.e., eigenvector centrality) and social action (i.e., event and playlist) did not make it through our strict statistical criteria. Still, we assume that the ability of the variables to measure scale depends on the platform being evaluated. As the researchers and experts both suggest, other studies could examine the proposed NE model by keeping these eliminated items and including more variables.

2.5.2. Implication for Practice

The lack of knowledge about NEs prevents founders from establishing NEs from the start. The ability to monitor and predict the evolution of NEs is of great importance to competing industries influenced by NEs. Accordingly, online platform businesses can estimate their NEs at the individual and network level using the results of this study with novel metrics tailored to the characteristics of their online platforms. We applied a novel model for measuring NEs in a music streaming platform. The benchmarks are available for different platforms: (1) to predict the growth of value over time, (2) to analyse the demographic gaps in NEs caused by individual differences, such as gender and age, (3) to compare the value of NEs with competing platforms, and (4) to examine online platform economics in the context of NEs.

In addition, platform providers such as Last.fm may want to create a situation where members play more than one role in the network and thus contribute more value. Research has shown that networks are more valuable if each member performs multiple roles (Afuah, 2013). YouTube is an excellent example of this point where users can both watch and create content, allowing them to play multiple roles and actively participate in the online community. We suggest platform providers engage their consumers more effectively through apps to maximise their value. They can then compare the effectiveness of apps and websites based on NEs levels generated by users of both apps and websites.

The NEs model introduced in this paper can be calculated using total and average daily interactions. Our approach was to determine the nature of the platform and then choose between the total and average measurements. We divided the platforms' nature into "long-term interaction" and "short-term interaction" based on how frequently users interacted. While long-term interactions could explain the users' preferences entirely, short-term interactions were likely to have captured only a fraction of users' activity due to higher repetition (Davidson et al., 2010). As a method of identifying the nature of a platform, we considered the frequency of interaction on the platform. Our analysis showed that music listening was a short-term interaction, with an average of 0.85 out of [0-1] in our empirical findings (based on the proportion of active days listening to music); therefore, Last.fm is a platform for which the average value of interactions is better suited. Consequently, for our NEs model, we recommend using average daily numbers for platforms like music streaming that has short-term interactions. Platforms with fewer activities and engagement levels but long-term interactions can measure NEs by calculating the total number of interactions (e.g., online e-commerce sites like Amazon or movie streaming sites like Netflix).

2.5.3. Limitations

Our work provides the foundation for expanding the NEs equation beyond network size. Nevertheless, our study has some limitations. First, it was tested only on Last.fm, a music streaming platform, and it would be worthwhile to investigate other platforms. Second, we noticed additional features that could not be accessed via the Last.fm API, such as "scrobbling now" (i.e., listening to music now). The proposed NEs model may be better completed by combining such live features. For this reason, platform providers may consider adding another category of metrics (e.g., Live metrics) to the model.

Moreover, we used the average value of sub-networks and trust values for Facebook and Twitter since no studies have been undertaken on Last.fm's ego networks. There is a need to study the number of sub-networks and trust values in Last.fm, validate the Dunbar theory in Last.fm, and compare it with Facebook and Twitter. There is a need for research to find the weights of different social actions in social networks and apply them to our NEs model. Next, the literature review associated with consumer behaviour and IS research revealed the nature of perceived value: functional or utilitarian, emotional or hedonistic, monetary or value-formoney, and social. Therefore, it is essential to understand the nature of perceived value from NEs. Finally, the proposed NEs model should be studied in both a positive and negative context in the future, similar to previous studies that have examined the positive and negative effects of direct and indirect NEs (Parker et al., 2016).

2.5.4. Future Research Directions

We present a summary of the background and the research directions and opportunities derived from this research in Table 2.7. Then in Figure 2.10, we connect each research direction to our research phases as the standard scale development steps.

Table 2.7. Future research directions concerning NEs on online platforms

Research Area	**Background**	**Potential Research Questions**
1. Examining the impact of other variables	Additional factors will complement and enhance our study, including the user-centric design of platform functionalities (Gregory et al., 2020; Khan et al., 2019), playing multiple roles (Afuah, 2013), push notifications, and messages (Kim et al., 2013). In addition, this study is the basis for further empirical studies of the interaction between the proposed NEs model and data NEs in the data-driven economy, even though several researchers have described this conceptualisation in an explanatory analysis (e.g., Gregory et al., 2020; Haftor et al., 2021; O'Donovan, 2021). An individual-level study of NEs allows for the study of demographic variables that can be used to identify the individual contributors.	Q1. What other variables are used to measure, moderate, or mediate NEs? Q2. How do online platforms expose their users to NEs via technical features? Q3. What are the combinations of other NEs (e.g., data NEs) with the proposed model? Q4. What is the variation of NEs based on demographic variables?
2. Examining the NEs' value system	This study makes possible a study on different types of perceived value, both positive and negative, similar to other studies that have distinguished positive and negative effects or direct and indirect NEs (Parker et al., 2016). A conceptualisation that differs from traditional ones is required to account for perceived value and economic efficiency in empirical IS research. Therefore, the	Q5. What is the nature of perceived value in the proposed NEs model? Q6. What are the implications of the NEs model for the economic efficiency of empirical IS research?

Research Area	Background	Potential Research Questions
	proposed NEs model in this study constitutes a theoretical approach to research on calculating returns on investment (ROI) of social media (Gilfoil & Jobs, 2012; Khan et al., 2019) and resource-based views (RBVs) of online social businesses (Afuah, 2013; Wade & Hulland, 2004).	
3. Applying NEs model across a wide range of contexts	The application of NEs to IS research can also be used to study user behaviour and business development, such as software project success (Ghapanchi & Tavana, 2015), technology diffusion (Li et al., 2014), the value system of cryptocurrencies (Cousins et al., 2019), whether friends like the same music (Aiello et al., 2012), and how sharing interests is considered to be a form of ties (Baym & Ledbetter, 2009). The study of strategic planning processes to determine organisations' applied network value is limited to the social structure, for example, in examining group performance (Rulke & Galaskiewicz, 2000), diversification strategies (Ozkan-Canbolat, 2014), and the value of organisations' network (Niemczyk et al., 2021). Therefore, applying the comprehensive NEs model would be an important endeavour.	Q7. What are the effects of NEs on other variables in IS research? Q8. What is the impact of NEs on user behaviour study?
4. Improving the methodology	Our study employs a novel approach to measure NEs on online platforms through variables beyond network size. The indicators under each subconstruct may vary based on the evaluated platform. It might be worthwhile to compare two competing platforms or compare other platforms with Last.fm.	Q9. What is the variation of the proposed NEs model on different platforms? Q10. How do the dimensions of the proposed NEs model differ across different platforms?

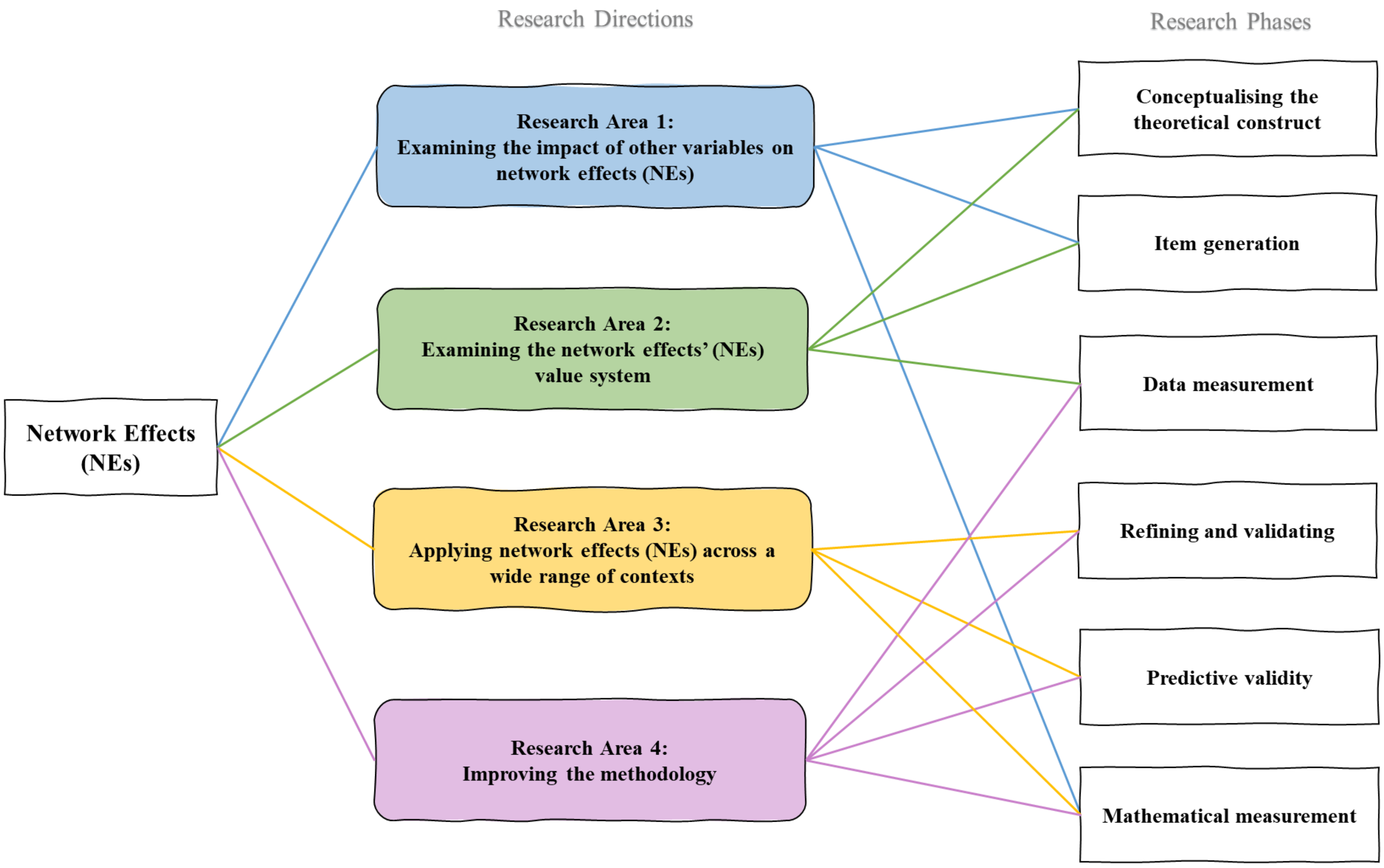


Figure 2.10. Research directions and connection with research phases

Acknowledgments

All authors certify that they have no affiliations with or involvement in any organisation or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Chapter 3 - The Impact of Network Effects on Online Music Listening Behaviours: A Longitudinal Study

Mona Ghaffari[a]*, Gohar F. Khan[a], Bruce Ferwerda[b], and Shivendu Pratap Singh[c]

[a]University of Waikato, Digital Business, Hamilton, New Zealand; [b]Jönköping University, Computer Science and Informatics, Jönköping, Sweden; [c]Southern Illinois University Edwardsville, Illinois, USA

*Corresponding author

Publication status: To be submitted to an A level journal.

Abstract

The evolution of online platforms has given rise to new forms of network effects (NEs), which offer possibilities for growth and expansion that go beyond mere network size. With the increasing popularity of digital media platforms, investigating how NEs impact users' behaviours has become an intriguing but still developing area of research. Thus, this study aims to develop a comprehensive understanding of NEs by examining users' social network structure and actions on an online music platform to uncover their impacts on music listening behaviours. Employing partial least square structural equation modelling (PLS-SEM) and analysing longitudinal data, we delve into users' music listening behaviours, examining changes in the quantity, novelty, and variety of music consumption. The panel data was obtained from Last.fm users at two points in time (N = 1,708 users, including 113,158 nodes and 252,747 edges in January 2022, and 122,495 nodes and 364,158 edges in July 2022). The research findings represent a novel contribution to the study of NEs, moving beyond network size, and provide empirical evidence of the impact of NEs on users' music listening behaviours. The insights presented in this paper are instrumental in understanding the role of NEs on online platforms and in predicting user behaviours across various digital media domains, such as music, movies, and games.

Keywords: Network effects, Online music platform, Social dynamics, Music listening behaviours, Social network structure, Social action

3.1. Introduction

In recent years, online platforms have received considerable attention from both academics and industry practitioners, especially for their implications when analysing user behaviour. With the help of these platforms, the music industry has experienced profound changes, providing listeners with the opportunity to create their own profiles, communicate with fellow listeners, express preferences, provide feedback on artists and songs, and access additional online services (Lee et al., 2016; Liu, 2007). This rapid advancement of technology has also facilitated the growth of network effects (NEs) across digital media platforms, driving user expansion, fostering interactions, facilitating content generation, and exerting a substantial market influence (McIntyre & Srinivasan, 2017). Thus, NEs studies take a complementary approach by focusing on the dynamics between platforms and users rather than using the traditional economic reasoning associated with the network size hypothesis (Afuah, 2013). Despite these significant changes, to the best of the authors' knowledge no study has empirically analysed the evolution of NEs over time in the context of online music platforms and their impact on users' behaviours.

First, our research builds upon studies conducted by scholars who have examined the significance of online community participation and social dynamics in enhancing music experiences on online platforms. For example, Oestreicher-Singer and Zalmanson (2013) delved into the relationship between community engagement and users' willingness to pay for premium services, shedding light on the financial aspect of these platforms. Further research examined the effects of adopting online streaming services on music consumption and discovery (Datta et al., 2017). Another key area of research has revolved around the role of social networks and online music communities in influencing individuals' song choices (Dewan et al., 2017). Additionally, Hagen and Lüders (2016) contributed to the understanding of music discovery on streaming services by examining the impact of social features and types of social ties, considering both social and music homophily.

Furthermore, we expand on the study of users' music listening behaviours within the context of NEs, building upon a robust foundation of existing theoretical studies that emphasise the importance of social network structure when examining NEs on online platforms (Afuah, 2013; Gregory et al., 2020; Suarez, 2005). While traditionally, the total number of users is associated with the value of a product or service, when evaluating the intensity of NEs, it is essential to consider the network's structure and the strength of connections among adopters (Mcintyre & Subramaniam, 2009). Measures such as ties among network users, density, trust, and user network topology impact the benefits derived from the installed base of users (Afuah, 2013; Weitzel et al., 2000). Examining NEs through the lens of network theory also emphasises that their positive effects are not static but instead vary over time, continuously manifesting and evolving within the social network structure of users, even when the number of users on the platform remains constant (Khan et al., 2019).

In selecting the variables to measure users' music listening behaviours and to determine how NEs impact these variables, we carefully reviewed the music consumption patterns on streaming platforms as identified in the existing literature (Datta et al., 2017; Johansson et al., 2018; Kaminskas & Bridge, 2016; Kjus, 2016; Morris & Powers, 2015; Schedl et al., 2018; Zhang, 2013). Furthermore, we considered the findings of studies that explore the influence of music recommendation systems on users' listening behaviours (Castells et al., 2015; Hurley & Zhang, 2011; Kaminskas & Bridge, 2016; Morris & Powers, 2015; Schedl & Hauger, 2015; Vargas, 2011; Wang et al., 2021). According to these studies, recommendation systems contain a popularity bias despite the anticipated advantages of advanced search and recommendation tools that aim to personalise content delivery in digital media platforms so that it is tailored to individual preferences (Hesmondhalgh et al., 2023). Building upon these insights, our study specifically focused on the variables of quantity, novelty, and variety in music listening as critical factors when analysing users' behaviours on music platforms. By examining these variables, our objective is to contribute to a deeper understanding of the informed strategies that can be employed to revitalise and enhance music listening behaviours.

In the analysis of the outcomes, we studied three distinct effects. First, the **synchronous effect** to examine the immediate association between NEs levels and quantity, novelty, and variety in music listening at the same point in time. Second, the **carryover effect** to investigate the development and emergence of NEs over time, considering cumulative resources and predicting NEs at later points while controlling for baseline NEs levels. Last, the **time-varying effect** to explore variations in the relationships between NEs and online music listening behaviours across different time periods. Therefore, we investigated the following research questions:

RQ1. What is the synchronous effect of NEs levels on the quantity, novelty, and variety of music listening at a specific moment?

RQ2. What is the carryover effect of NEs on the development and emergence of NEs over time?

RQ3. What is the time-varying effect of NEs on online music listening behaviours across different time periods?

Our study adopted a longitudinal research design using the partial least squares structural equation modelling (PLS-SEM) method (Roemer, 2016) on data from Last.fm users (N = 1,708; age: M = 27.09 years, SD = 11.33; gender: 1,252 men, 456 women) to investigate the factors driving NEs over time and their impact on online music listening behaviours. Our findings revealed that NEs are strongly associated with the enhancement of users' music listening and encourage the exploration of unfamiliar music options. The presence of NEs also increases the inclination to explore and listen to various artists, thus expanding users' music libraries. Importantly, these influences of NEs on music listening behaviours exhibit a significant and consistent strengthening effect over time, emphasising their long-term impact on shaping users' preferences and behaviours. Gender differences were observed, with males consuming more music and seeking more novelty and variety than females. The role of age in relation to novelty and variety in music listening is complex and warrants further investigation. Additionally, our study highlights that subscribers and individuals with longer account durations tend to engage in more extensive music listening with greater novelty and variety.

This study contributes to two pivotal domains: First, it enhances the understanding of user behaviours on digital media platforms within the context of NEs. Second, it illuminates the transformative nature of NEs on these platforms to drive changes and success. We measured NEs beyond traditional network size notions and established a theoretical and practical framework to study NEs as catalysts for sustainable growth that are able to enhance users' music listening. NEs are no longer seen as external and uncontrollable forces but as strategic tools for success, actively shaping users' musical preferences, promoting diversity, and igniting novelty. Drawing on insights from social network and social action theories, this study delved into the intricate interplay of social network structures and dynamics, illuminating the mechanisms through which NEs are formed. A longitudinal study design provided greater insight into two elements—NEs instruments and their carryover effect. In the ever-changing digital area, this study has implications for platform design and management, providing valuable guidance to platform owners who wish to invest in growth opportunities and strategically harness NEs to achieve sustainable success.

The remaining sections of this paper are structured as follows. In Section 3.2, we review the relevant literature on NEs theory and music listening and present our hypotheses regarding the impact of NEs on online music listening behaviours. Section 3.3 describes the empirical methodology employed in this study. We present the data analysis results in Section 3.4. We discuss the implications for academia and practice in Section 3.5. Section 3.6 concludes the paper and outlines potential avenues for future research.

3.2. Research Background

Our research background is grounded in two main areas of research: (1) NEs and online platforms and (2) the field of online music listening behaviours. Drawing from the research background, we developed a theoretical model that served as the framework for our empirical study. The current knowledge in the field informed this model and guided our hypothesis formulation for the data analysis.

3.2.1. Network Effects (NEs) and Online Platforms

Researchers have extensively studied the NEs phenomenon over the past three decades based on a traditional definition that the value of a product or service increases with the growth of its user base (Economides & Himmelberg, 1995; Katz & Shapiro, 1985; Shapiro et al., 1998). The exploration of NEs in the early neoclassical economic studies primarily revolved around determining their occurrence based on the network size (Afuah, 2013). Therefore, the network size was considered the significant driver of NEs for a long time (Vieira et al., 2021). For example, as the number of users adopting telephones and fax machines increased, the value of these devices grew through NEs, leading to enhanced communication capabilities, expanded reach, and increased opportunities for collaboration and exchange of information (Economides & Himmelberg, 1995; Shapiro et al., 1998).

The advent of the Internet and technological advancements have further expanded NEs across a wide range of digital media platforms, including software, video, video games, music, and social media (McIntyre & Srinivasan, 2017). NEs have become integral to the platform economy, playing a vital role in increasing insights into consumer behaviours and dynamics (Parker et al., 2016; Reillier & Reillier, 2017). Various successful companies, including

Amazon, Netflix, Microsoft, Facebook, Uber, and Airbnb, have recognised NEs as catalysts for business growth—the platform business model these companies adopt fosters NEs and contributes to their profitability (Gregory et al., 2020). However, applying existing economic theory to platforms does not adequately address the needs of platform owners who face challenges related to harnessing and leveraging NEs when seeking to increase the growth and success of their platforms (Salminen et al., 2018).

Accordingly, a new area of research called the theory of positive NEs has emerged, focusing on the social dynamics of platforms (Weitzel et al., 2000). Researchers have begun to realise that relying solely on gross network size is not a sufficient indicator of the presence of NEs on online platforms. The value of a product or service can be largely associated with the overall size of its user base if the intensity of NEs is determined by its fundamental design. One example is online video platforms, whose success is attributed to implementing innovative services that enhance NEs by attracting more users and increasing user retention (Rong et al., 2019). However, when NEs are driven by social connections, relying solely on the total number of adopters may not accurately represent the network's value. Instead, it becomes crucial to consider the network's structure and the strength of connections among adopters when evaluating its intensity value (Mcintyre & Subramaniam, 2009). Other social network structure measures, such as ties among network partners and the density and topology of the user network, contribute to the benefits derived from an installed user base (Afuah, 2013; Suarez, 2005; Weitzel et al., 2000).

In addition, digital media platforms commonly revolve around specific interests, allowing users to create profiles and connect with like-minded individuals (Liu, 2007). For example, adding online capabilities to a music platform can attract a broader community of online participants and enhance music listening experiences (Lee et al., 2016). This incorporation of online capabilities broadens the range of functionalities offered by the platform, enabling users to participate in various activities such as interacting with other listeners, expressing preferences for songs, providing feedback on artists' pages, and accessing supplementary online content or services. While, users can choose to what extent they will engage with and socially interact on platforms (Mechant & Evens, 2011), numerous studies have demonstrated that consumers can be influenced by social interactions with others, regardless of their familiarity with or knowledge of each other's consumption intentions or identities (Dewan et al., 2017).

After thoroughly critiquing the economic theory of NEs based on the network size, a pivotal question arises that demands rigorous scholarly investigation and due consideration (Weitzel et al., 2000): what are the critical components for developing an interdisciplinary theory of NEs that can seamlessly integrate and comprehensively elucidate the intricate interplay between users as actors and the social dynamics of online platforms? This inquiry stemmed from the recognition that the economic perspective alone may not provide a comprehensive understanding of the multifaceted dynamics at play in a contemporary online platform that relies on NEs. By embracing an interdisciplinary approach, we were able to delve deeper into the mechanisms underlying NEs, uncovering the factors, mechanisms, and conditions that foster online platforms' growth, influence, and overall success in today's digital era (Weitzel et al., 2000). The detailed development of the interdisciplinary NEs construct is extensively discussed in Chapter 2. Chapter 2 comprehensively explores the theoretical foundations, conceptual framework, and empirical methodologies employed to develop and refine the NEs construct. Section 3.2.3 of this chapter provides a concise definition and overview of social network and social action theories that give rise to our developed NEs construct and studying the users music listening behaviours within this context.

3.2.2. Online Music Listening Behaviours

The online music platform has revolutionised how people access and listen to music in numerous ways. This technological advancement and open accessibility to music have given users the flexibility to listen to music on the go and create new opportunities to discover and access novel music (Karatay, 2022). The transformative impact of online music platforms on music consumption and listening behaviours has been extensively explored, with studies investigating how these platforms have revolutionised the accessibility and discovery of music and increased individuals' engagement (Datta et al., 2017; Karatay, 2022). More recently, studies have taken a nuanced approach to studying users' music listening behaviours on online platforms. In our research context, we targeted the literature that helps us to understand music listening behaviours on online platforms, specifically focusing on the influence of NEs while also examining the impact of relevant control variables.

The body of research on online music listening behaviours has been enriched by including social dynamics and interactive functionalities as areas of focus in order to determine the ways in which they facilitate music consumption and interaction (Salminen et al., 2018). In order to develop insights into these behaviours, there is now a widespread acceptance of the importance of exploring how users establish connections with others, engage in music-related communities, and contribute to a platform's content. For example, Dewan et al. (2017) examined the impact of individuals' social network friends and the experiences of an online music community as a whole on the songs individuals listen to, leveraging the theory of social influence. Hagen and Lüders (2016) provided detailed insights into the influence of social features and various types of ties (strong, weak, and absent ties) on individuals' discovery of new music on streaming services. Specifically, their study focused on ties characterised by different configurations of social and music homophily.

Studies examining music listening behaviour on streaming platforms have highlighted the significance of discovery and diversity as crucial variables in understanding music listening behaviours (Kjus, 2016; Morris & Powers, 2015). Specifically, this area of research has grown in response to the increasing importance of measures such as novelty, serendipity, and diversity, which address concerns related to music recommendation algorithms (Castells et al., 2015; Hurley & Zhang, 2011; Kaminskas & Bridge, 2016). The introduction of advanced search and recommendation tools was initially expected to enable listeners to explore niche music that aligns with their preferences (Levy & Bosteels, 2010). However, researchers in the music recommendation field have extensively examined popularity bias, which refers to the tendency of recommendation systems to favour popular items in their predictions, potentially resulting in reduced exploration of new music and homogenised taste (Hesmondhalgh et al., 2023).

Through their recommendation systems, music streaming platforms subtly encourage users to primarily engage with familiar music, thus impeding the exploration and enhancement of users' musical experiences (Hesmondhalgh et al., 2023). A research by Spotify further supports the notion that recommendation systems contribute to a decrease in diversity in music consumption; in contrast, user exploration outside these recommendations increases musical diversity (Anderson et al., 2020). Consequently, in recent years, there has been an increased focus on exploring novelty and variety in online music listening behaviours as researchers seek to understand and address the potential impact of providing only popular items on streaming platforms rather than introducing users to novelty and diversity (Sunitha et al., 2022). The improvement of music recommendation algorithms in academic computer science, accompanied by research on user behaviour, is helping to address issues by providing a comprehensive understanding of the multifaceted nature of music listening behaviours, including the number of songs played and the novelty and variety of user preferences (e.g., Datta et al., 2017).

In this study, the analysis of online music listening behaviours used key metrics that provide valuable insights into users' exploration, discovery, and diversity in music consumption. One such metric is 'novelty', the ratio of unique new artists listened to by a user to the total number of artists listened to overall. This ratio reflects the user's willingness to venture beyond familiar artists and indicates their openness to novel musical experiences (Zhang, 2013). An additional complementary metric calculates the total time or number of times users listen to the songs of new artists and divides this number by users' overall music consumption, thus helping to determine the extent to which users prioritise the discovery of fresh and unfamiliar content (Datta et al., 2017).

Another metric used to measure listeners' music listening behaviours on Last.fm music platform is 'diversity'. The distinct number of unique artists listened to by a user provides insights into the diversity and breadth of the user's musical taste, indicating their desire to explore a wide range of styles and genres (Datta et al., 2017; Schedl & Hauger, 2015). A further metric is the average frequency a user listens to each artist in their music collection (Schedl & Hauger, 2015). This metric helps in understanding users' affinity towards certain artists and highlights their music preferences and tastes.

Finally, incorporating user demographic and profile information has long been recognised as significant in helping to better understand users' music listening behaviours. In the field of music recommendation systems, listeners' demographic and profiling characteristics are user-side features that can be used to improve the recommendation model (Ferwerda et al., 2017; Langmeyer et al., 2012; Muhlenbach et al., 2017; Rentfrow & Gosling, 2003; Vigliensoni & Fujinaga, 2016). Vigliensoni and Fujinaga (2016) found that the accuracy of music recommendation models significantly improved when listeners' self-declared age, country, and gender were incorporated as profiling features. Therefore, we took into account the significance of individual characteristics in understanding online music listening behaviours, including age and gender (Berkers, 2012; Putzke et al., 2014). We also included account related variables, such as the age of the account and subscriber status (Anderson et al., 2020; Datta et al., 2017), as control variables.

3.2.3. Theoretical Development

The advent of online platforms has ushered in a new era of user engagement and social interaction, giving rise to powerful NEs that go beyond traditional notions of network size and greatly enhance the value of these platforms. While streaming platforms like Last.fm that include social networking features may not fit the conventional definition of social network sites, they exhibit distinct characteristics of NEs within their social dynamics. For example, the value of an online music platform increases as more users share their music preferences, create playlists, connect with others, and engage in activities such as commenting and tagging songs. These social connections and interactions have the potential to attract additional users to the platform, leading to a virtuous cycle of growth and value creation. As the network expands and evolves, users' behaviours are significantly influenced by the perceived value derived from NEs. The interplay between user-generated content, social interactions, and the platform's features creates a dynamic ecosystem that drives user engagement and enhances the overall user experience.

Figure 3.1 illustrates the theoretical model we developed to guide our research on the Last.fm music platform. First, researchers of NEs have proposed a strong relationship between users' social network structure and their derived value from the network, as well as their contributions to it (Afuah, 2013; Boulet & Lebraty, 2018; Suarez, 2005; Zhang & Luo, 2017). By delving into social connections, we can better understand how NEs shape users' behaviours, preferences, and interactions on a platform. As an illustration, User A is characterised by a mere 10 connections and has no or minimal communication. In this scenario, User A can be identified as an isolated node within the network, where the overall size and activity of the network have negligible influence on their experience. Conversely, User B, boasting a substantial network with hundreds of connections and active communication, assumes the role of bridging structural holes, linking distant nodes, and making significant contributions to the network's dynamics. Ultimately, occupying a critical position within the network empowers users to make valuable contributions, enhances their perceived value, and positively influences their consumption behaviours.

Second, the established theoretical framework underscores the significance of social action theory (Weber, 1968) in understanding NEs and their effects on users' behaviours on online platforms. Researchers in the field of 'uses and gratifications' theory acknowledge the significant role of the social interaction motive in driving users' engagement with the social dynamics of the platform. For example, Khan (2017) found that social interactions motivate users to actively engage through commenting and uploading content on YouTube. However, the motive for seeking relaxing entertainment strongly predicts users' engagement in video viewing, suggesting that users are motivated to watch videos on the platform to unwind and enjoy leisure time. Our study emphasises the importance of adopting the alternative social action perspective, which considers media use as a social relationship among individuals who interact and attribute meaning to their actions (Petrič et al., 2011). By recognising media use as a social relation, our research aimed to gain a deeper understanding of how social interactions on the platform contribute to music consumption behaviours. Users can engage with comments, tags, likes, and follow/following features to gain insights, receive recommendations, and participate in discussions related to the music they consume. The social action perspective enables researchers to capture the underlying social dynamics that occur within these interactions, providing insights into how social interactions shape patterns of music consumption.

This perspective emphasises the role and significance of social interactions in shaping users' perceptions and extracting value from the platform (Khan et al., 2019; Petrič et al., 2011). This means that a user's actions indirectly contribute to the value experienced by other users and the user themselves. For example, when a user leaves a positive comment or clicks the "like" button on a song or artist's profile, it is not merely an isolated individual action but an interdependent social action where users take note of others' behaviour and create network externalities (Khan et al., 2019). Consequently, the virtual network formed on a music platform through interactions among music listeners, such as the network of likers and commenters, becomes receptive to network externalities. Ultimately, this amplification effect benefits both the contributing user and enhances the overall value of NEs on the music platform.

We developed a novel construct for modelling NEs by considering the interconnections between social network structure and social actions on online platforms. Chapter 2 provides further details of our proposed approach. A longitudinal analysis uniquely positioned us to understand how NEs drivers influence and grow music listening behaviours over time on the Last.fm music platform. The analysis involved tracking the same individuals through two points in time to observe changes in their behaviours and the NEs that drove those changes. Our prior predictions are formally stated as hypotheses below (also see Figure 3.1). Therefore, we proposed the following hypotheses, taking into account five dependent variables: quantity and two metrics each for measuring novelty and variety.

First, the model was used cross-sectionally to assess the impact of the proposed NEs construct on online music listening behaviours, leveraging from social network and social action theories (**synchronous effect**).

H1: NEs will positively affect music listening quantity at time t_1.

H2: NEs will positively affect music listening quantity at time t_2.

H3: NEs will positively affect music listening novelty at time t_1.

H4: NEs will positively affect music listening novelty at time t_2.

H5: NEs will positively affect music listening variety at time t_1.

H6: NEs will positively affect music listening variety at time t_2.

Second, we expected that NEs would become stronger over the course of time when users were exposed to NEs from the previous time window (**carryover effect**).

H7: The NEs construct at one point in time will affect the same construct in a subsequent point in time.

Third, we expected the direct impacts of NEs on music listening behaviours to increase over time (**time-varying effect**).

H8: The impact of NEs on music listening quantity will strengthen over time.

H9: The impact of NEs on music listening novelty will strengthen over time.

H10: The impact of NEs on music listening variety will strengthen over time.

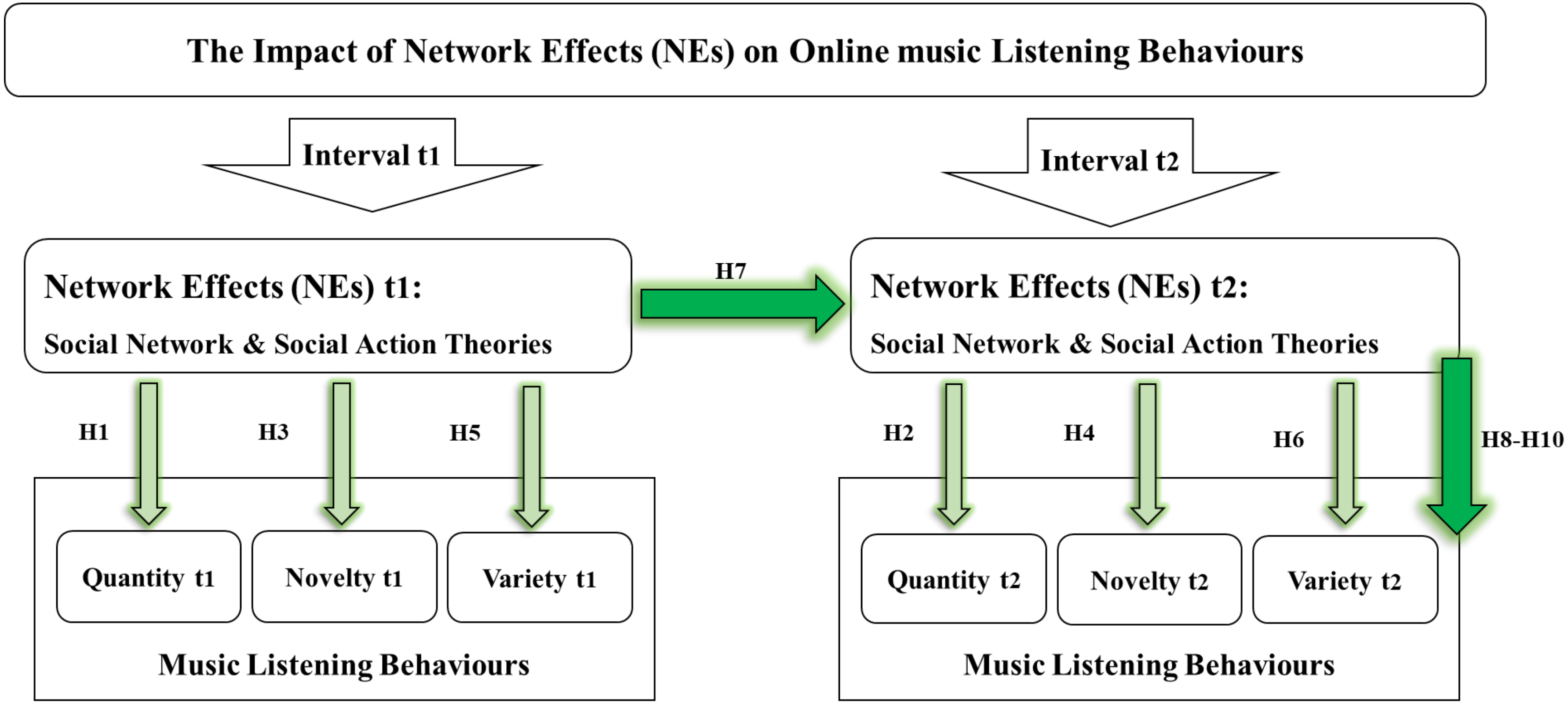


Figure 3.1. Research model

3.3. Research Methodology

3.3.1. Longitudinal PLS Path Modelling

We employed the PLS-SEM approach to examine the relationship between NEs and online music listening behaviours, encompassing cross-sectional and longitudinal analyses. This study is one of only a few to use this method in longitudinal research, despite the increasing interest and growing application of PLS-SEM in recent years (Doleck et al., 2019; Hair et al., 2016). The use of PLS-SEM in this research had several advantages. First, this technique is well-suited for predictive research models, especially in the initial phases of theory development, and enables the analysis of unobservable and intricate variables, such as NEs in the context of this study (Roemer, 2016; Shea & Howell, 2000). Therefore, the PLS-SEM approach allowed us to predict the dependent variables based on the theoretical construct developed in this study to measure NEs (Hair et al., 2011; Henseler et al., 2009). Second, it is well-suited for dealing with the complexity of longitudinal studies, which involve examining development and change across a significant number of measured constructs at different time points and measuring their effects (Fornell & Cha, 1994; Roemer, 2016). Finally, PLS-SEM is a flexible method for analysing different types of data since it does not assume any specific data or residual distribution (Chin & Newsted, 1999; Jacobs et al., 2011).

Within the realm of causal analysis techniques, PLS stands as a prominent method in the context of our study. As articulated by Pearl (2009, pp. 26-27), the distinctions among these various techniques can sometimes be quite nuanced, to the point where exhaustive debate might not be entirely warranted. The pivotal factor here revolves around the specific inquiries that researchers pose when constructing their analytical diagrams. If your research question aligns with understanding 'What factors determine the value of this variable?' then it typically leads to the construction of a structural equation model. This nuanced choice in method underscores the importance of aligning the chosen analytical approach with the precise research questions at hand, ensuring the method's appropriateness and effectiveness in addressing the research objectives.

Although, to our knowledge, there is limited or non-existent research on NEs in a longitudinal model, specifically beyond network size, we adopted a well-known guideline for PLS-SEM longitudinal modelling (Roemer, 2016). This approach was supported by previous studies using established theories, such as the theory of reasoned action (TRA) of Fishbein and Ajzen (1975), the technology acceptance model (TAM) of Davis et al. (1989), and the diffusion of innovation (DOI) theory of Rogers (1995). In particular, these theories have been applied in user behaviour studies employing the longitudinal PLS model (e.g., Jacobs et al., 2011; Johnson et al., 2006; Roemer & Henseler, 2022), which inspired our research methodology.

3.3.2. Instrument Development

The first methodological step involved creating or adapting measurement instruments to effectively operationalise the NEs construct as depicted in the conceptual model. These measurement instruments were used to assess social network structure and social actions. The process first entails establishing the face and content validity of the measurement instrument items, ensuring their appropriateness and relevance for measuring the intended constructs. In the current study, the instruments items' face and content were initially validated in Chapter 2 (see Chapter 2, Sections 2.3.1 and 2.3.2 for more details), on which this chapter builds by utilising the measurement instruments to measure NEs on online platforms. The measurement instruments in this study were evaluated as formative constructs, with items (introduced in detail in Chapter 2) collected at two intervals (t_1 and t_2), following the approach recommended by Roemer (2016). The items of the measurement instruments and their corresponding definitions are presented in Table 3.1.

The music listening behaviours examined in our study are widely recognised as crucial aspects of music consumption research (Lozano Murciego et al., 2021). As such, our dependent variables focused on two key dimensions: (1) the number of songs listened to by users and (2) the dynamics of music consumption in terms of novelty and variety in artists' preferences. These variables captured the core aspects of individuals' music listening behaviours and provided valuable insights into their engagement and exploratory tendencies within the realm of music. Table 3.2 presents an overview of the dependent variables, outlining the measures to assess users' music listening behaviours. In addition, our study considered several individual characteristics as control variables. These variables are recognised as significant factors influencing users' music listening behaviours, including age, gender (Berkers, 2012; Putzke et

Table 3.1. NEs measurement instruments and their items

Items	Description
Social Network Structure	
Degree centrality (DC)	The number of edges connecting each node to others serves as a measure of the node's significance, accessibility, and influence on the flow of the network (Afuah, 2013; Bischoff, 2012; Boulet & Lebraty, 2018; Metcalf et al., 2016).
Eigenvector centrality (EC)	This measure refers to the importance of the nodes' neighbours (Kane et al., 2014).
Betweenness centrality (BC)	Measuring how frequently a node appears on the shortest paths between other nodes in the network helps identify users who have fewer direct connections but are connected to many nodes at greater distances (Afuah, 2013; Golbeck, 2013; Kane et al., 2014).
Closeness centrality (CC)	The average number of steps required to reach all other nodes in the network indicates the convenience and ease of connectivity between a given node and other nodes in the network (Afuah, 2013; Kane et al., 2014; Zhang & Luo, 2017).
Structural hole (SH)	Bridging structural holes plays a vital role in facilitating the transmission of substantial information between different network regions, effectively bridging gaps and enhancing overall connectivity (Afuah, 2013; Kane et al., 2014; Xu et al., 2019).
Ties strength (TS)	The frequency of communications between the ego and alter reflects the levels of strength and trust within the network layers (Afuah, 2013; Dunbar et al., 2015; Khan et al., 2019; Suarez, 2005).
Social Action	

Like (L)	The measure refers to the number of songs that have been positively marked as loved by a user, indicating their strong preference (Khan et al., 2019).
Comment (C)	The measure refers to the number of comments a user has actively posted and engaged in by providing responses and interaction with other users (Oestreicher-Singer & Zalmanson, 2013; Shokeen & Rana, 2020).
Tag (T)	The number of tags a user assigns to songs, artists, and albums (Oestreicher-Singer & Zalmanson, 2013; Shokeen & Rana, 2020).
Playlist (P)	The number of songs a user lists to be played in conjunction. This behaviour signifies the user's interest in creating playlists or curated collections of songs with a specific theme, mood, or purpose (Oestreicher-Singer & Zalmanson, 2013).
Event (E)	The measure represents the number of events a user expresses interest in or plans to attend (Oestreicher-Singer & Zalmanson, 2013).
Obsession (O)	The number of tracks designated as "obsessions" by a user reflects their intense passion and interest in those specific songs (Oestreicher-Singer & Zalmanson, 2013).

al., 2014), age of the account, and subscriber status (Anderson et al., 2020; Datta et al., 2017). By accounting for these factors, we aimed to isolate the effects of the NEs construct on music listening behaviours while controlling for potential control variables.

Table 3.2. Music listening behaviours variables and definitions

Variable	Definition
Quantity	The total number of songs listened to by a user during each interval serves as a quantity measure of their music consumption (Datta et al., 2017).
Novelty1	The ratio of the number of unique new artists listened to by a user for the first time to the total number of unique artists listened to in each interval reflects the user's exploration and discovery of new music (Datta et al., 2017).
Novelty2	The value of the discoveries is obtained by dividing the amount of listening to new artists by the total consumption. This calculation allows us to assess the proportion of a user's music consumption dedicated to the discovered new artists (Datta et al., 2017).
Variety1	The distinct number of unique artists a user listens to within a specific interval provides insights into the diversity and breadth of the user's musical taste and preferences (Datta et al., 2017; Schedl & Hauger, 2015).
Variety2	The average frequency at which a user listens to each artist in their music collection during each interval provides a measure of their engagement and preference for specific artists (Schedl & Hauger, 2015).

Finally, the nomological network for the research model, which encompasses the defined research variables and adheres to Roemer's guideline, is presented in Figure 3.2. This network visually represents the interconnections and relationships between the variables, providing a comprehensive overview of the theoretical framework and the proposed associations among the constructs.

3.3.3. Data and Measurement

This study extracted secondary data from Last.fm, including users' music listening history, friendships, digital profiles, and demographic information (age and gender). Last.fm serves as a valuable data collection and analysis platform and has been utilised in previous research studies. This interactive platform allows users to connect with others and share music interests, facilitating the exchange of music recommendations, discussions, and collaborative exploration. By leveraging the social networking features of the platform, we conducted

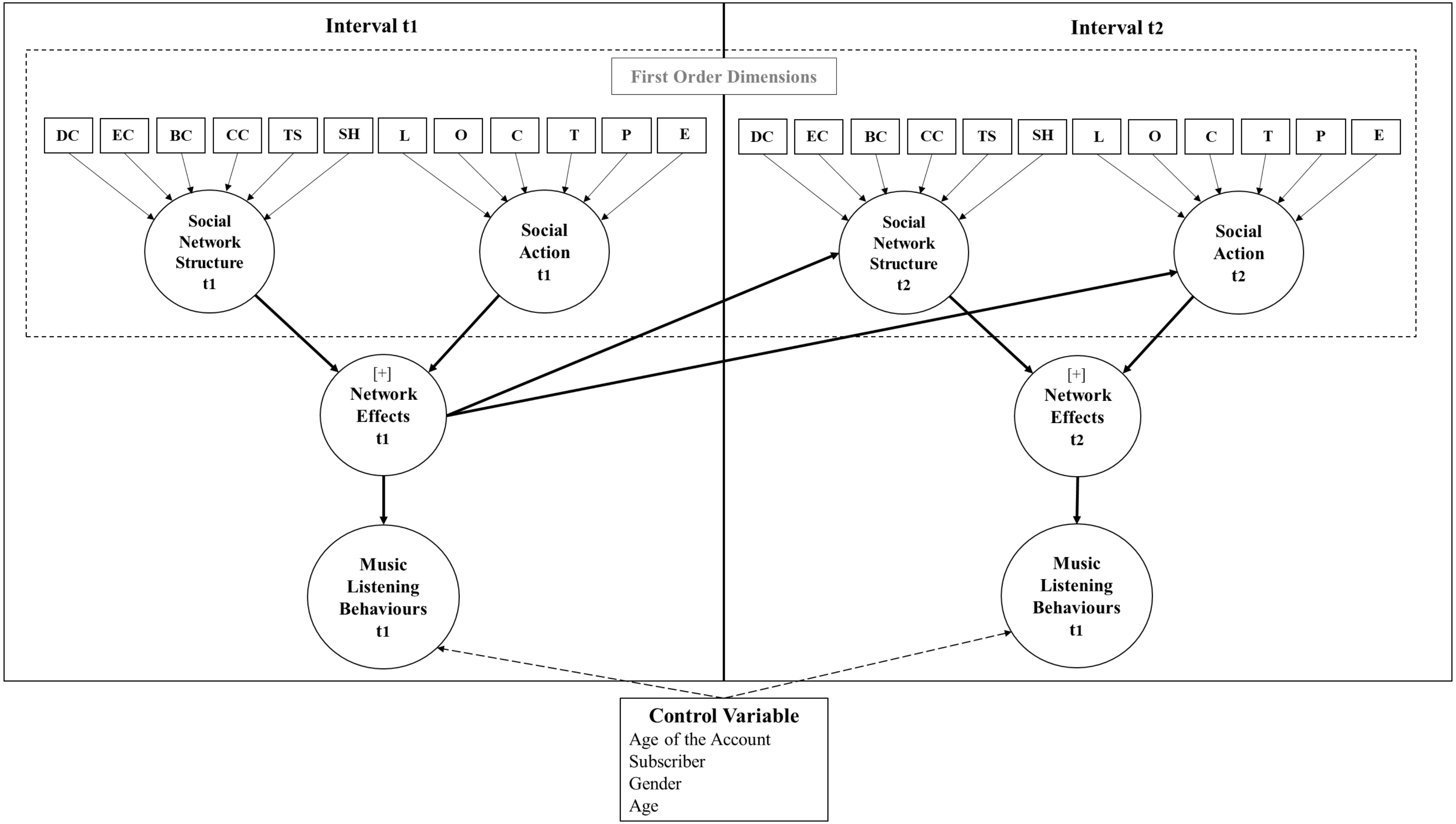


Figure 3.2. The nomological model

empirical research to examine users' social connections and interactions, thereby gaining insights into their overall music listening behaviours. The data collection was conducted within six months at two points in time between January 2022 and July 2022. This panel data allowed us to understand how NEs can dynamically shape and influence music listening behaviours as we explored their evolution and changes from one interval to the next.

We collected data from the same set of Last.fm users (1,708 single users) at two time points, referred to as t_1 and t_2. The data included: (1) tracks played, (2) loved tracks, (3) tags, (4) comments, (5) events, (6) obsessions, (7) playlists, and (8) the list of followers and followings. Additionally, metadata information for each track (i.e., artists) was collected to calculate the novelty and variety in music listening using an algorithm introduced by Datta et al. (2017) to identify unique artists and songs. Music listening history, following and followers, social actions, and demographic and account-related variables were obtained directly from the Last.fm application programming interface (API), while social network structure variables were calculated using Pajek (Mrvar & Batagelj, 2018). The data collection process and sampling method are described below.

Step 1) We initiated the data collection by randomly selecting 2,000 Last.fm single users from the dataset introduced by Melchiorre et al. (2021) and recorded information on the age and gender of the individuals. This sample was chosen with the aim of collecting data on their music listening behaviours and friendship connections. Our sample size exceeded the recommended minimum sample size requirements for conducting this research, as determined by various methods for estimating the minimum sample size in PLS-SEM. For example, we considered the '10 times' rule (Hair et al., 2011), which suggests a sample size of at least 10 times the number of observed variables, as well as guidelines such as having 15 participants per observed variable (Pituch & Stevens, 2016) and a minimum of 100 participants for measurement models with two to four factors (Loehlin, 2017). Initially, our total sample size was 2,000, but we encountered unavailable data for the remaining 292 users due to changes in privacy settings or account cancellations during the observation period. Consequently, the final sample size for analysis consisted of 1,708 single users.

Step 2) Utilising the Last.fm API function "user.getRecentTracks", we collected the information on the tracks played by each user, enabling us to capture the nuances of their music listening behaviours.

Step 3) We expanded the data collection by establishing friends' networks through the Last.fm API function "user.getFriends". In interval t_1, the network consisted of 113,158 nodes and 252,747 edges, while in interval t_2, it comprised 122,495 nodes and 364,158 edges. These networks were used to calculate the social network structure of individuals. It is important to note that the friendship network in Last.fm is directed, allowing for both followers and followings. Followers represent users who follow a particular user, while followings are those a user follows. We used the Pajak software to determine the social network structural properties (Mrvar & Batagelj, 2018), specifically focusing on centralities and structural holes. The measurement option chosen for this analysis was a directed network.

Step 4) We then utilised the Last.fm API function "user.getinfo" to access users' social actions, such as likes, comments, tags, events, obsessions, and playlists, as well as their subscriber status and the age of their accounts.

The descriptive statistics can be found in Table 3.3.

3.4. Data Analysis and Results

The research model of this study encompasses both cross-sectional and longitudinal relationships, which were validated using PLS-SEM. Following the guideline provided by Roemer (2016, p. 1904), we constructed a single PLS model with constructs measured at two points in time. The statistical analysis was conducted using the SmartPLS software (Ringle et al., 2015). PLS-SEM longitudinal data analysis, similar to the cross-sectional model, requires measurement and structural models to be validated separately (Götz et al., 2009). In the subsequent sections, we present a detailed account of the data analysis process and report the obtained results.

Table 3.3. Descriptive analysis of variables (1,708 observations)

Variable	Mean	SD	Min	Max
Social Network Structure				
Degree centrality t1	92.54	471.99	0	13,293
Degree centrality t2	185.64	646.17	0	13,281
Betweenness centrality t1 [0-1]	0.05	0.09	0	1
Betweenness centrality t2 [0-1]	0.04	0.08	0	1
Closeness centrality t1 [0-1]	0.07	0.18	0	1
Closeness centrality t2 [0-1]	0.10	0.21	0	1
Structural hole t1 [0-1]	0.78	0.32	0	1
Structural hole t2 [0-1]	0.46	0.08	0	0.5
Ties strength × Degree centrality t1	7.2	36.72	0	134.20
Ties strength × Degree centrality t2	14.44	50.27	0	138.26
Social Action				
Like t1	71.01	281	0	5,466
Like t2	221.39	557	0	7,165
Comment t1	17.46	57.68	0	830
Comment t2	60.05	306	0	1,896
Tag t1	10.03	17.79	0	100
Tag t2	15.16	24.77	0	150
Playlist t1	47.52	373.69	0	1,461
Playlist t2	55.74	392.39	0	1,761
Event t1	6.89	34.86	0	391
Event t2	7.26	37.51	0	422
Obsession t1	10.26	35.44	0	755
Obsession t2	30.33	73.27	0	1,110
Dependent Variables				
Quantity t1	2,095.81	3067.39	39	32,952
Quantity t2	2,327.53	3,285.40	72	33,913
Novelty1 t1 [0-1]	0.07	0.10	0	1
Novelty1 t2 [0-1]	0.24	0.35	0	0.71
Novelty2 t1 [0-1]	0.28	0.18	0	0.36
Novelty2 t2 [0-1]	0.14	0.36	0	0.96
Variety1 t1	15.38	47.62	4.13	50.99
Variety1 t2	20.98	52.05	13.88	56
Variety2 t1	211.57	419.79	1.51	196.33
Variety2 t2	397.22	525.55	8.91	295.89
Controls				
Age	27.09	11.33	12	70
Gender (male=1)	0.73	0.44	0	1

Subscriber (paid=1)	0.07	0.25	0	1
Age of the account (weeks)	343.10	256.80	5	935.29

3.4.1. Measurement Model

The first step of model validation involved assessing the measurement models of the NEs construct, which comprised two subconstructs: social network structure and social action. The measurement models were evaluated as formative constructs based on indicators collected at intervals t1 and t2. To assess the reliability and validity of the formative subconstructs, we employed a repeated indicator approach and an inner factor weighting scheme, utilising the PLS algorithm (Becker et al., 2012). Although the measurement model of the proposed NEs construct was initially validated in Chapter 2, we re-evaluated its validity and reliability in the current study to ensure its consistency with the longitudinal model. For further details, please refer to Section 2.4.1 in Chapter 2.

We examined the multicollinearity of the items utilised in the measurement models. Upon analysis, we found no issues of collinearity among the measures of the constructs, as indicated by a variance inflation factor (VIF) of less than 3.3 (Diamantopoulos & Siguaw, 2006), except for items BC, DC, and EC in the social network structure. Our findings are consistent with previous studies that have highlighted the presence of correlations in network centrality measures (Boulet & Lebraty, 2018). Two recommended approaches to mitigate the issue of multicollinearity were followed (Petter et al., 2007). We combined the correlated item DC with item TS to form a composite item based on the adjustment to degree centrality proposed by Khan et al. (2019) and the four layers of tie strength (Dunbar et al., 2015). The issue of collinearity in BC was solved by implementing the "corrected betweenness" measure, denoted as $\widetilde{\mathrm{BC}}$ in Equation 3.1 (Equation 4 in Boulet & Lebraty, 2018, p. 365).

$$\widetilde{BC} = BC - \frac{S_{BC}}{S_{DC}} \times cor(DC, BC) \times DC \tag{3.1}$$

DC and BC are measures of degree and betweenness centralities for n individuals in a network. The standard deviations of BC and DC are denoted as S_{BC} and S_{DC}, respectively, and cor(DC, BC) represents the correlation coefficient between these two measures. Section 2.4.1 in Chapter 2 contains additional information regarding these two corrections.

The second approach to resolve the collinearity issue was eliminating item EC from the model as it was not widely used in the literature. The centrality measures that remained as social network structure indicators are well established in the NEs literature. After these adjustments in the measurement model, the inner VIF values for the social network structure and social action subconstructs were examined. Both were below 3.3 (VIF = 1.02 for t_1 and VIF=1.07 for t_2), indicating no issues with multicollinearity.

The validity measurements of items (with subsamples of 5000 for bootstrapping) produced the following results. We found that outer weights for all items except for $\widetilde{BC}$ and SH in social network structure and P in social action were significant at $p < 0.05$. Therefore, to determine their absolute contribution, we assessed the outer loading of indicators (Cenfetelli & Bassellier, 2009). It was deemed appropriate to remove item P from the social action category due to its low outer loading and nonsignificant *p*-value, but the outer loadings of $\widetilde{BC}$ and SH were significant at $p < 0.05$. Therefore, we retained $\widetilde{BC}$ and SH and eliminated P, as previous research and theoretical work have demonstrated their usefulness in assessing NEs through their relevance as items of social network structure (Afuah, 2013; Kane et al., 2014; Xu et al., 2019). While their contribution to social network structure is minor compared to other indicators, they add a substantial amount as bivariate indicators. Based on the results, it can be concluded that the use of the playlist (P) was not supported by empirical evidence in the current study (for further details, see Section 2.4.1 in Chapter 2).

Finally, E showed a negative outer weight and a positive outer loading. According to prescription 3, negative items lacking a positive correlation with social action could measure a different construct (Cenfetelli & Bassellier, 2009, p. 697). Hence, the events listed by users on their profiles took place outside the platform and were not regarded as social dynamics employed by Last.fm and we excluded E from the analysis (for more information, see Kock, 2015). After removing items and creating a composite variable, the final validity statistics were retested (presented in Table 3.4), indicating that all remaining items for social network structure and social action were significant. Running the measurement models with all available items for each interval resulted in consistent findings across two intervals, which strongly supported the validity and reliability of the measurement model in this longitudinal study. Chapter 2 provides more details on this data analysis.

Table 3.4. Measurement model statistics

Subconstructs	Outer weights (Outer loadings)	T-value	P-value	VIF
Social Network Structure (Interval t1)				
$\widetilde{BC}$	0.17 (0.22)	2.67 (3.10)	0.00 (0.00)	1.04
CC	0.22 (0.38)	3.00 (5.29)	0.00 (0.00)	1.05
TS	0.84 (0.64)	15.86 (9.19)	0.00 (0.00)	1.05
SH	0.25 (0.43)	3.39 (6.11)	0.00 (0.00)	1.09
Social Action (Interval t1)				
O	0.16 (0.23)	2.01 (2.74)	0.00 (0.00)	1.00
C	0.40 (0.54)	4.04 (5.98)	0.00 (0.00)	1.03
L	0.46 (0.61)	8.00 (11.79)	0.00 (0.00)	1.04
T	0.60 (0.75)	6.59 (9.96)	0.00 (0.00)	1.05
Social Network Structure (Interval t2)				
$\widetilde{\mathrm{BC}}$	0.26 (0.74)	1.99 (12.75)	0.00 (0.00)	1.63
CC	0.18 (0.27)	3.16 (4.29)	0.00 (0.00)	1.01
TS	0.67 (0.88)	5.25 (17.41)	0.00 (0.00)	1.59
SH	0.32 (0.48)	4.69 (7.19)	0.00 (0.00)	1.05
Social Action (Interval t2)				
O	0.25 (0.28)	2.62 (3.33)	0.00 (0.00)	1.03
C	0.51 (0.58)	5.50 (6.51)	0.00 (0.00)	1.01
L	0.29 (0.54)	4.79 (8.78)	0.00 (0.00)	1.12
T	0.60 (0.54)	6.45 (8.80)	0.00 (0.00)	1.11
Note: The analysis of outer weights and outer loadings shows that all results are significant at $p < 0.05$.				

3.4.2. Test of the Structural Models

The structural model was evaluated using the nonparametric bootstrap approach of PLS-SEM with 5,000 subsamples to establish the significance of the path coefficients and R^2 values (Hair et al., 2016). In the first part of the evaluation, we examined the path coefficients of the subconstructs, namely social network structure and social action, within the NEs construct over two intervals. These coefficients were evaluated to assess these subconstructs' strength, direction, and contribution to forming the NEs construct. The analysis involved running five individual models for the five dependent variables (quantity, two novelty metrics, and two variety metrics) to achieve this (see Table 3.5). The results indicated that social network structure and social action contributed to the formation of the NEs construct, as shown by the respective path coefficients and their significant levels (this result consistently confirms the findings from the study conducted in Chapter 2).

Table 3.5. Test of the path coefficients for NEs subconstructs

Structural Model	**Time**	**Effect**	Path Coefficient	*t*-values	*p*-values	Significance
Quantity	t1	SNSt1→NEst1	0.52***	4.96	*p* <0.001	Yes
		SAt1→ NEst1	0.76***	8.34	*p* <0.001	Yes
	t2	SNSt2→NEst2	0.76***	13.42	*p* <0.001	Yes
		SAt2→ NEst2	0.44***	5.87	*p* <0.001	Yes
Novelty1	t1	SNSt1→NEst1	0.52***	4.91	*p* <0.001	Yes
		SAt1→ NEst1	0.76***	8.20	*p* <0.001	Yes
	t2	SNSt2→NEst2	0.75***	12.98	*p* <0.001	Yes
		SAt2→ NEst2	0.46***	6.31	*p* <0.001	Yes
Novelty2	t1	SNSt1→NEst1	0.49***	3.81	*p* <0.001	Yes
		SAt1→ NEst1	0.78***	7.13	*p* <0.001	Yes
	t2	SNSt2→NEst2	0.61***	6.52	*p* <0.001	Yes
		SAt2→ NEst2	0.61***	6.56	*p* <0.001	Yes
Variety1	t1	SNSt1→NEst1	0.49***	4.13	*p* <0.001	Yes
		SAt1→ NEst1	0.79***	7.59	*p* <0.001	Yes
	t2	SNSt2→NEst2	0.76***	13.55	*p* <0.001	Yes
		SAt2→ NEst2	0.44***	5.95	*p* <0.001	Yes
Variety2	t1	SNSt1→NEst1	0.49***	3.59	*p* <0.001	Yes
		SAt1→ NEst1	0.78***	6.65	*p* <0.001	Yes
	t2	SNSt2→NEst2	0.74***	7.76	*p* <0.001	Yes
		SAt2→ NEst2	0.46***	3.74	*p* <0.001	Yes

In addition, a comparison was made between the strength of the path coefficients of the social network structure and social action subconstructs in the model. Considering the structural model of the quantity analysis in Table 3.5, the path coefficients for social network structure and social action in time t_1 (0.52 and 0.76, respectively) indicate that social action has a more significant influence on shaping NEs compared to social network structure. However, this relationship was observed to change over time, and the path coefficient of social network structure became stronger than social action in time t_2, with values of 0.76 and 0.44, respectively. This suggests that while social action is important in initially shaping NEs, social network structure becomes a more dominant factor over time. The results were repeated in the models of novelty and variety, as depicted in Table 3.5.

We then followed by testing the study's main hypotheses, presented below. First, the cross-sectional hypotheses were tested to explore the direct relationships between the proposed NEs construct and online music listening behaviours (quantity, novelty, and variety) in each time interval. The longitudinal hypotheses were then examined to investigate the impact of NEs at one time on the subsequent time and to determine whether the direct effects of the NEs construct on online music listening behaviours strengthened over time. Figures 3.3 to 3.5 summarise the hypotheses, paths, and path coefficients for each point in time.

3.4.2.1. Test of the Structural Model—Quantity

Cross-sectional Design:

H1: NEs will positively affect music listening quantity at time t_1.

H2: NEs will positively affect music listening quantity at time t_2.

The number of songs each user listened to (quantity) was predicted as a dependent variable at times t_1 and t_2 (Figure 3.3). The analysis revealed that the path coefficient from the NEs construct to quantity was positive and statistically significant ($\beta = 0.22$ and $\beta = 0.30$, $p < 0.001$, at times t_1 and t_2, respectively), indicating a positive relationship between NEs and the number of songs users listened to. The overall model fit was moderate, with an R^2 of 0.25 and 0.26 at times t_1 and t_2 (Cohen, 1988). The results for quantity showed the robustness of our results, supporting H1 and H2. Specifically, the findings suggested that for every 100% increase in NEs experienced by a user, we could expect a corresponding increase of 22% and 30% in the number of songs listened to over time periods t_1 and t_2, respectively.

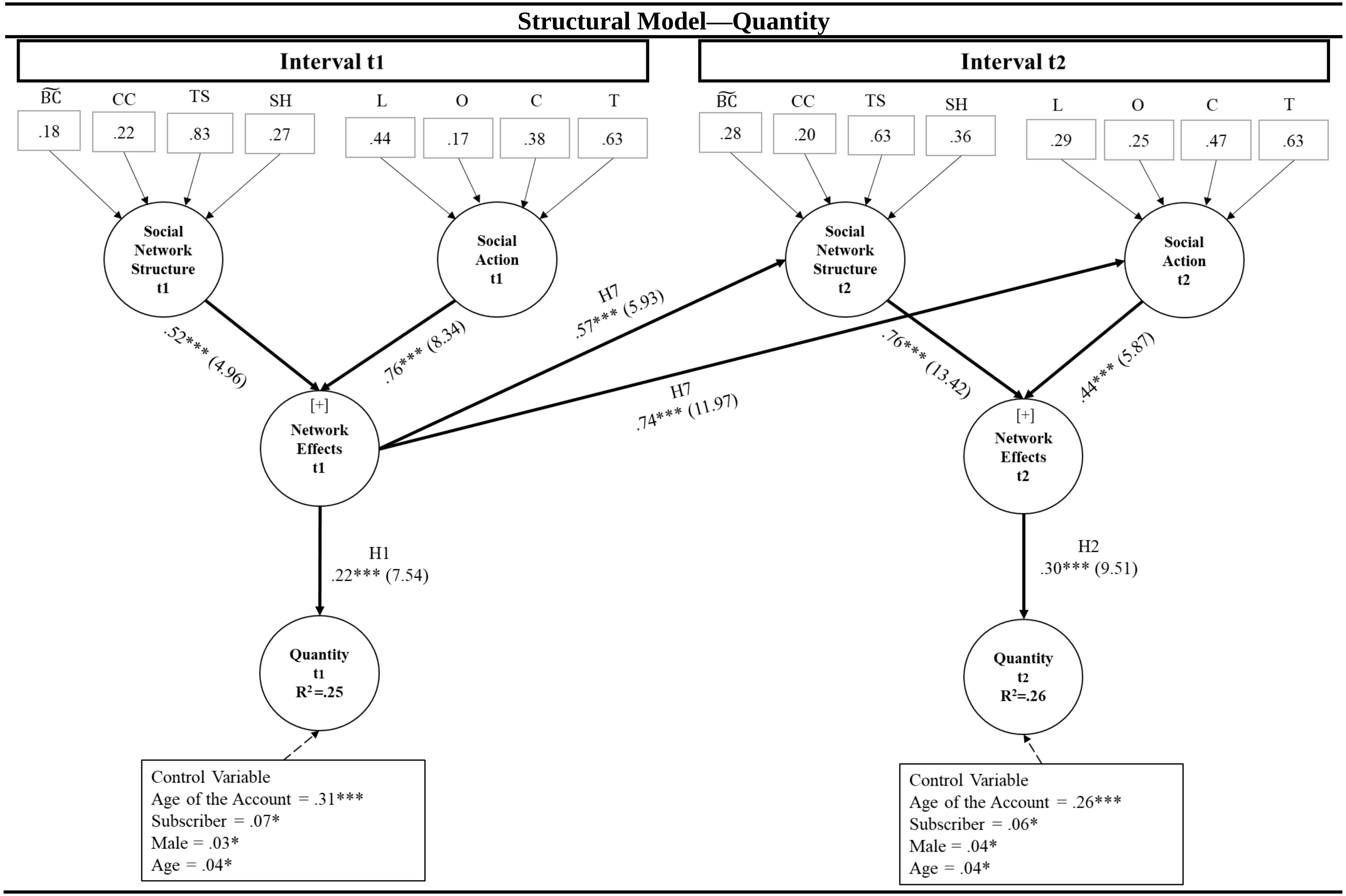


Figure 3.3. Structural model of quantity (path coefficients with t-values in parentheses)
****p* <0.001, ***p* <0.05, **p* <0.10.

3.4.2.2. Test of the Structural Model—Novelty

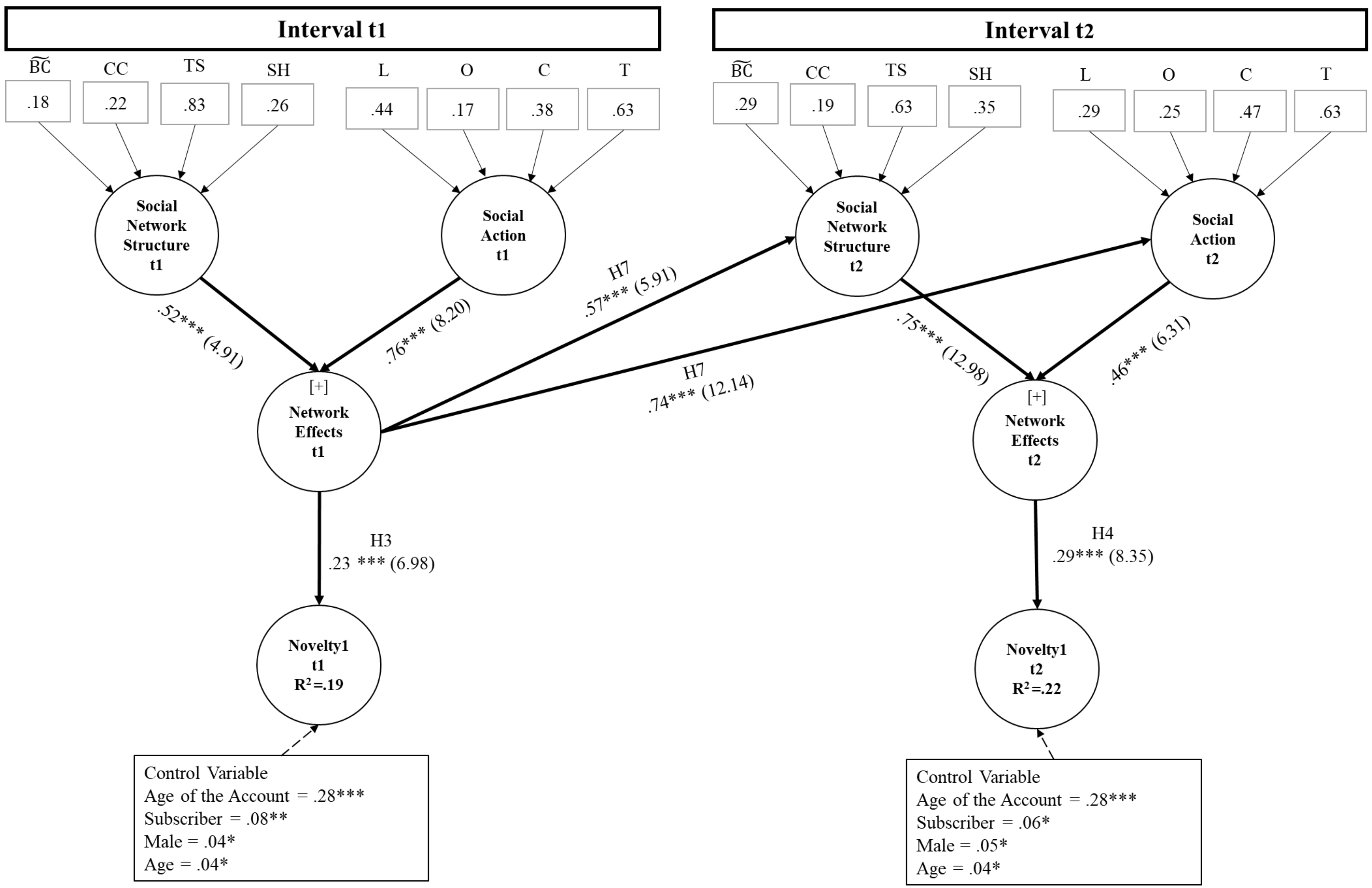
<u>Cross-sectional Design:</u>

H3: NEs will positively affect music listening novelty at time t_1.

H4: NEs will positively affect music listening novelty at time t_2.

The dependent variable of novelty was studied using two metrics in each interval: novelty1 was obtained by dividing the number of unique new artists a user listened to for the first time by the number of unique artists listened to, and novelty2 as the value of the discoveries was obtained by dividing the amount of listening to new artists by total consumption. As shown in Figure 3.4, the impact of the NEs construct on novelty1 was positive and significant ($\beta = 0.23$, $\beta = 0.29$; $p < 0.001$, at times t_1 and t_2, respectively) with a moderate R^2 of 0.19 and 0.22 at times t_1 and t_2. Similarly, the impact of the NEs construct on novelty2 as positive and significant ($\beta = 0.09$, $\beta = 0.21$; $p < 0.001$, at times t_1 and t_2, respectively) with a moderate R^2 of 0.16 and 0.18 at times t_1 and t_2. The results for novelty1 and novelty2 both showed the robustness of our results, supporting H3 and H4. Specifically, the findings suggested that for every one unit increase in NEs experienced by a user, we could expect a corresponding increase of 0.23 and 0.29 in novelty1 and an increase of 0.09 and 0.21 in novelty2 over time periods t_1 and t_2, respectively.

Structural Model—Novelty1



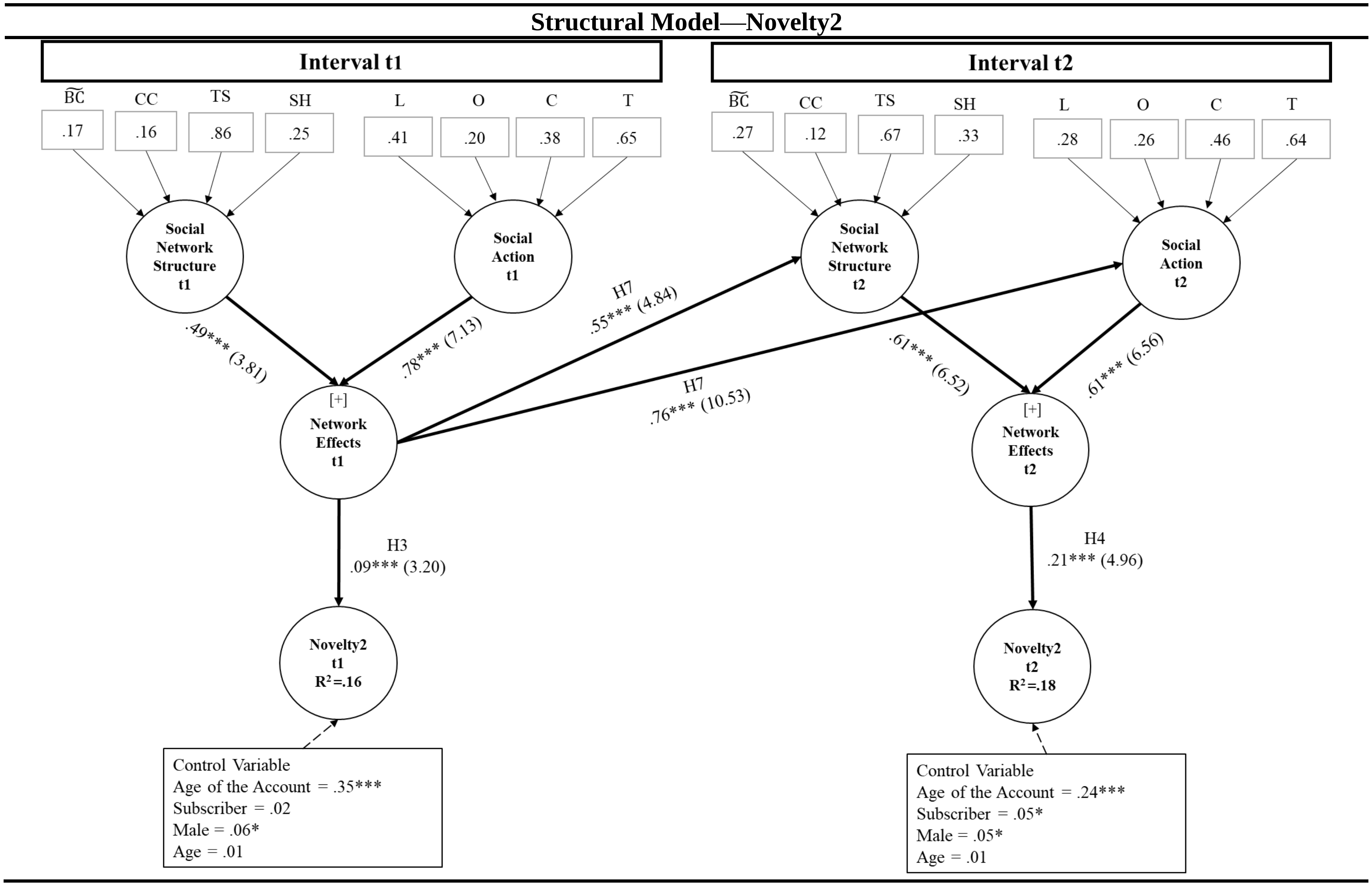


Figure 3.4. Structural model of novelty (path coefficients with t-values in parentheses)

****p* <0.001, ***p* <0.05, **p* <0.10.

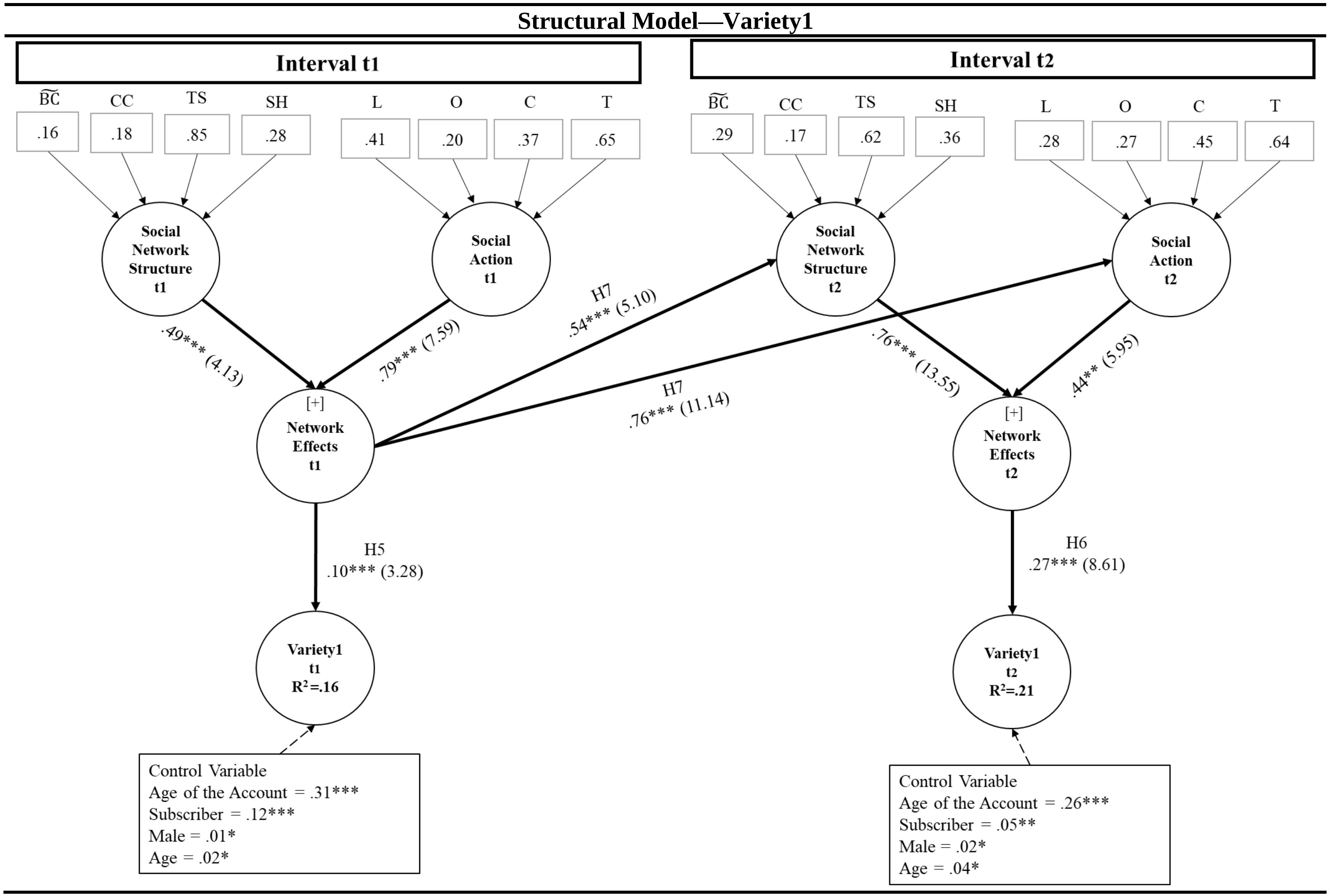
3.4.2.3. Test of the Structural Model—Variety

Cross-sectional Design:

H5: NEs will positively affect music listening variety at time t_1.

H6: NEs will positively affect music listening variety at time t_2.

The impact of the NEs construct on the variety of music listened to is shown in Figure 3.5. The results showed that NEs significantly and positively impacted the number of artists in a user's listening history (variety1) in both intervals ($\beta = 0.10$, $\beta = 0.27$; $p < 0.001$, at times t_1 and t_2, respectively), with a moderate R^2 of 0.16 and 0.21 at times t_1 and t_2. Moreover, the impact of NEs on the average amount of listening to each artist (variety2) was positive and significant in both intervals ($\beta = 0.06$, $\beta = 0.14$; $p < 0.001$, at times t_1 and t_2, respectively), with a moderate R^2 of 0.16 and 0.20 in t_1 and t_2. The results for variety1 and variety2 both showed the robustness of our results, supporting H5 and H6. Specifically, the findings suggested that for every 100% increase in NEs experienced by a user, we could expect a corresponding increase of 10% and 27% in the number of artists in a user's listening history and an increase of 6% and 14% in the average amount of listening to each artist over time periods t_1 and t_2, respectively.



Structural Model—Variety1
Interval t1
Interval t2
BC
CC
TS
SH
L
O
C
T
.16
.18
.85
.28
.41
.20
.37
.65
.29
.17
.62
.36
.28
.27
.45
.64
Social Network Structure t1
Social Action t1
Social Network Structure t2
Social Action t2
.49*** (4.13)
.79*** (7.59)
H7
.54*** (5.10)
H7
.76*** (11.14)
.76*** (13.55)
.44** (5.95)
[+]
Network Effects t1
[+]
Network Effects t2
H5
.10*** (3.28)
H6
.27*** (8.61)
Variety1 t1 R²=.16
Variety1 t2 R²=.21
Control Variable
Age of the Account = .31***
Subscriber = .12***
Male = .01*
Age = .02*
Control Variable
Age of the Account = .26***
Subscriber = .05**
Male = .02*
Age = .04*

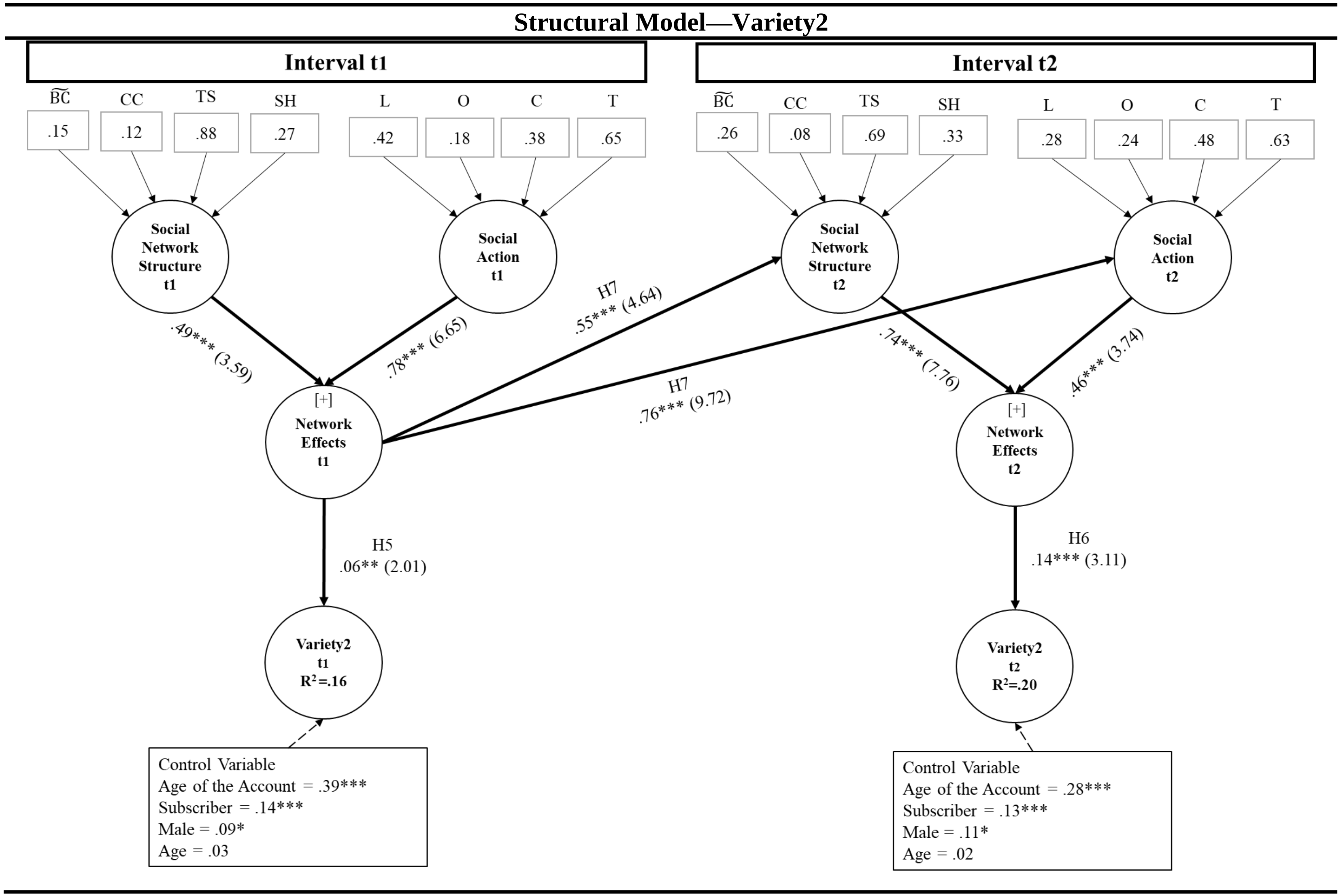


Figure 3.5. Structural model of variety (path coefficients with t-values in parentheses)

****p* <0.001, ***p* <0.05, **p* <0.10.

3.4.3. Test of the Carryover Effects

<u>Longitudinal Design:</u>

H7: The NEs construct at one point in time will affect the same construct in a subsequent point in time.

We conducted additional tests to investigate whether the NEs construct established during interval t1 would continue to influence the same construct at subsequent interval t2 (carryover effects). To achieve this, the model analysis involved measuring the impact of the NEs construct on the subconstructs at the second point in time rather than directly on the NEs construct itself (as outlined in Hair et al., 2016). This hypothesis is essential in comprehending the impact of NEs on lower-order constructs over time and detecting any changes in these effects across periods. The graphical representations of the carryover effect can be seen in Figures 3.3, 3.4, and 3.5, while a summary of the results is provided in Table 3.6.

Table 3.6. Test of the carryover effects

Structural Model	**Effect**	Path Coefficient	*t*-values	*p*-values	Significance
Quantity	NEst1→SNSt2 NEst1→SAt2	0.57 0.74	5.93 11.97	p <0.001 p <0.001	Yes Yes
Novelty1	NEst1→SNSt2 NEst1→SAt2	0.57 0.74	5.91 12.14	p <0.001 p <0.001	Yes Yes
Novelty2	NEst1→SNSt2 NEst1→SAt2	0.55 0.76	4.84 10.53	p <0.001 p <0.001	Yes Yes
Variety1	NEst1→SNSt2 NEst1→SAt2	0.54 0.76	5.10 11.14	p <0.001 p <0.001	Yes Yes
Variety2	NEst1→SNSt2 NEst1→SAt2	0.55 0.76	4.64 9.72	p <0.001 p <0.001	Yes Yes

We observed the positive carryover effect in all five models, underscoring the evolutionary nature of NEs on online platforms and revealing their potential long-term consequences stemming from users' social actions and social networking. The phenomenon was further explored by conducting a multigroup analysis to investigate whether the impact of NEs on online music listening behaviours intensifies over time. This analysis allowed us to assess any variations or changes in the influence of NEs across different periods, providing valuable insights into the dynamic nature of NEs.

3.4.4. Test of the Time-Varying Effects

H8: The impact of NEs on music listening quantity will strengthen over time.

H9: The impact of NEs on music listening novelty will strengthen over time.

H10: The impact of NEs on music listening variety will strengthen over time.

To fully understand the impact of the NEs construct on music listening behaviours, it is necessary to first examine the significance of paths at each time interval (t_1 and t_2) and subsequently test the changes in the path coefficients over time. The term "multigroup analysis" in the PLS literature describes these types of analyses (Henseler et al., 2009; Sarstedt et al., 2011). For the multigroup analysis, we adhered to the steps outlined in Roemer's (2016) guideline to compare the path coefficients:

Step 1) Calculate confidence intervals (CI) by selecting the "bias-corrected and accelerated (BCa)" method during PLS path modelling bootstrapping.

Step 2) Check the path coefficients and their CI for effects between time intervals. If the path coefficient at time t falls outside the CI of the path coefficient at time t+1, there is a significant difference between them.

Table 3.7 presents the path coefficients, bias-corrected CI, comparisons for each effect, and the significance of changes between time periods. The results showed that the effects of NEs on quantity, novelty, and variety became significantly stronger over time, as shown by the mean differences and paired samples t-test (p<0.001), supporting hypotheses H8, H9, and H10. These findings emphasise the dynamic nature of the relationships between NEs and online music listening behaviours over time, underscoring the significance of conducting longitudinal studies on NEs.

Table 3.7. Test of the changes in path coefficients (multigroup analysis)

Time	**Effect**	Path coefficient	Size of the change	Bias corrected CI	Comparison of path coefficient t+1 with CI t and path coefficient t with CI t+1	Path coefficient t+1 inside CI t? Path coefficient t inside CI t+1?	Significant change?
t1 t2	NEst1→Quantityt1 NEst2→Quantityt2	0.22 0.30	0.08	(0.16; 0.28) (0.23; 0.33)	0.22<0.23 0.28<0.30	No	Yes
t1 t2	NEst1→Novelty1t1 NEst2→Novelty1t2	0.23 0.29	0.06	(0.16; 0.28) (0.24; 0.35)	0.23<0.24 0.29>0.28	No	Yes
t1 t2	NEst1→Novelty2t1 NEst2→Novelty2t2	0.09 0.21	0.12	(0.04; 0.14) (0.12; 0.28)	0.12>0.09 0.21>0.14	No	Yes
t1 t2	NEst1→Variety1t1 NEst2→Variety1t2	0.10 0.27	0.17	(0.04, 0.17) (0.21, 0.33)	0.10<0.21 0.27>0.17	No	Yes
t1 t2	NEst1→Variety2t1 NEst2→Variety2t2	0.06 0.14	0.08	(0.01; 0.13) (0.07; 0.22)	0.06<0.07 0.14>0.13	No	Yes

3.4.5. Test of Control Variables

Controlling for potential variables is an important aspect of any empirical research. Therefore, in addition to studying the impact of the NEs construct on the dependent variables in the model, we also analysed several control variables to account for their potential influence on music listening behaviours. These control variables included the age of the account, subscription, age, and gender. We examined the significance of their paths and effect sizes, with the results presented in Figures 3.3 to 3.5.

Across all five structural models, we found that the age of the account was the most significant variable in predicting online music listening behaviours. This result indicated that with the absence of NEs, the number of days a user was registered on the platform significantly impacted their music listening. This variable positively influenced music listening behaviours, as evidenced by path coefficients of 0.31 and 0.26 for quantity, 0.28 for novelty1, 0.35 and 0.24 for novelty2, 0.31 and 0.26 for variety1, and 0.39 and 0.28 for variety2, at times t_1 and t_2, respectively (p-values presented in Figures 3.3 to 3.5). This finding implied a positive relationship between the duration of a user's registration on the platform and their music listening behaviours, which may be explained by their increased familiarity with the platform and its music offerings.

The next most significant variable in our analysis was gender. On average, males listened to significantly more music than females and tended to explore a more diverse and novel range of music artists. This variable exerted a positive influence on online music listening behaviours, as indicated by the path coefficients of 0.03 and 0.04 for quantity, 0.04 and 0.05 for novelty1, 0.06 and 0.05 for novelty2, 0.01 and 0.02 for variety1, and 0.09 and 0.11 for variety2 (p-values presented in Figures 3.3 to 3.5), at times t_1 and t_2, respectively.

Furthermore, we observed that being a paying subscriber to Last.fm significantly influenced a user's music consumption patterns compared to their non-paying peers. Specifically, the coefficients were 0.07 and 0.06 for quantity, 0.08 and 0.06 for novelty1, 0.02 and 0.05 for novelty2, 0.12 and 0.05 for variety1, and 0.14 and 0.13 for variety2, at times t_1 and t_2, respectively (p-values presented in Figures 3.3 to 3.5). This finding suggested that being a subscriber to Last.fm was associated with a more active and engaged approach to music exploration and a greater variety of music listened to.

Additionally, we found that the users' age significantly impacted the amount of music they listened to. However, this level was not as significant for novelty and variety. To obtain a more accurate understanding of how age influences individuals' music listening behaviours, researchers are advised to analyse the age groups of the listeners instead of treating age as a single variable. For more discussion on the difference between these four individual characteristics of music listeners and the study's dependent variables, refer to the more in-depth discussion in Chapter 4, Section 4.4.4.

3.5. Discussion

The following sections will delve into our study's theoretical and practical implications. The study's findings on the impact of NEs on online music listening behaviours have implications for NEs, online platforms, and user behaviour research areas, as well as for decision-makers in the digital media industry. Maintaining long-term success in the rapidly changing digital environment, empowered by NEs, requires platform owners to intervene with new design strategies to leverage NEs and maintain a competitive and effective edge.

3.5.1. Implications for Academia

The findings of our study have significant implications for academia in two main areas: music listening behaviours and the characteristics of NEs within online platforms.

Music listening behaviours:

First, as users actively interact with NEs instruments, there is a significant and noticeable surge in the quantity of music consumed, underscoring the profound impact of these instruments on shaping users' music consumption. Second, the NEs instruments are strongly associated with enhanced novelty in users' music listening choices, ultimately leading them to explore a broader range of unfamiliar music options. Third, the presence of NEs significantly enhances users' inclination to explore and listen to various artists, consequently expanding their music library and broadening their musical horizons. The last and most crucial point is that all three influences of NEs mentioned above exhibit a substantial and consistent strengthening effect as time progresses. This finding underscores the notion that the positive impact of NEs on music listening behaviours is not serendipitous but rather a significant determinant in shaping users' long-term music listening behaviours.

Our research findings indicate that the factors influencing novelty and variety in users' music listening are more complex than those affecting the quantity of music consumed. Specifically, our analysis reveals that the NEs construct has a lower predictive validity (indicated by the R^2 value) for novelty and variety compared to the quantity of music consumed. This suggests the presence of additional variables or factors contributing to users' preferences for novel and diverse songs (Castells et al., 2015). Future studies can explore additional variables to gain a deeper understanding, allowing for robust analysis and a more comprehensive examination of the evolution of novelty and variety in music listening. Open lines of research in this field include the user's emotional state, situation, and intention as contextual factors (Lozano Murciego et al., 2021). Incorporating insights from the contextual reasoning behind the inclination to listen to novel and diverse songs can inform the inclusion of additional variables in the model, potentially improving its overall fit and predictive power.

According to our research, as users gain experience and actively engage with Last.fm's associated social features, the impact of NEs on their music listening behaviours progressively increases over time. This finding aligns with researchers' emphasis on the need to focus on online community participation, social influence, and the social dynamics of online music platforms to encourage user adoption and enhance their music listening experiences (Datta et al., 2017; Dewan et al., 2017; Hagen & Lüders, 2016; Oestreicher-Singer & Zalmanson, 2013). While the fact that online communities and social dynamics are important elements in understanding user behaviour on online platforms is widely acknowledged, it is crucial also to consider the underlying social network structure. To address this gap, we integrated the social network structures with social features while extending the work conducted by Oestreicher-Singer and Zalmanson (2013) and Datta et al. (2017). Our study investigated music listening behaviours, taking into consideration the social network structure of users' connections and overall social interactions. By integrating these two aspects, we are now in a stronger position to make meaningful contributions to the existing theoretical research on NEs that emphasises the importance of social network structure in analysing NEs on online platforms (Afuah, 2013; Gregory et al., 2020; Khan et al., 2019; Suarez, 2005).

The findings from analysing individual characteristics as control variables align with previous research on music listening behaviours. We found that males tend to listen to a greater quantity of music and seek out more novelty and variety than females. This finding is supported by existing literature, which indicates differences in music preferences between males and females (Berkers, 2012; Rentfrow & Gosling, 2003). Females generally show an appreciation for mainstream genres such as pop, folk, and classical music (Colley, 2008; Roe, 1985; Wel et al., 2008). While our study did not delve into the underlying reasons for these gender differences, previous research suggests that socialisation and cultural factors may play a role. Males often use music to establish group affiliation and impress others, leading them towards non-mainstream genres (North et al., 2000; Ter Bogt et al., 2017). In contrast, females approach music instrumentally and socially, conforming to social norms and preferring more mainstream and sociable genres (Berkers, 2012; Colley, 2008).

The statistical analysis revealed that age had no significant impact on two variables of music listening behaviours: novelty (measured as the amount of listening to new artists divided by the total consumption) and variety (measured as the average frequency of listening to each artist), although there was a minimal effect on the amount of music listened to ($p < 0.10$). Understanding the relationship between age and music preferences based on novelty and variety is complex and requires careful consideration. Comparing preferences across different age groups can be challenging due to differences in familiarity with new music styles (Rentfrow et al., 2011). Further research should incorporate various genres, employ different analytical techniques, and include a diverse age range in the sample (Hargreaves & North, 1999). Musical tastes evolve over time, with new genres capturing the attention of younger generations and defining their sound. While the popularity of specific genres may fluctuate and new forms of music emerge, the music themes that resonated with each generation in their formative years retain a special place in their preferences (Smith, 1994).

Our study findings indicate that subscribers to music streaming platforms exhibit higher levels of music consumption and have more novel and varied music preferences. This finding is consistent with prior research, suggesting that subscribers are more inclined to explore a greater variety of music than non-subscribers (Arditi, 2018; Dimont, 2017). Furthermore, research by Hagen (2015) revealed that subscribers actively engage with a music platform’s social and interactive features, such as playlist creation and sharing, resulting in increased overall listening time. Another notable finding of our study is that individuals with longer account durations on Last.fm (as indicated by the age of the account) tend to engage in more extensive music listening and seek more novelty and variety. Previous research has indicated the positive impact of registration time on music listening behaviours (Datta et al., 2017; Schedl

& Hauger, 2015), which can be accounted for by the gradual evolution of music preferences over time.

Network Effects (NEs):

Our decision to incorporate social network and social action theories in our study was justified, as our findings not only confirm but also expand upon the theory of NEs, highlighting the positive cycle of value creation and its impact on user behaviour. Consistent with social network theory (Fuhse, 2020; Liu et al., 2017), our examination of social network structure underscores the importance of interpersonal relationships and their role in influencing behaviour among key individuals within the network. Additionally, including social elements in music streaming services like Spotify and Last.fm allows users to connect and engage with music as a social entity (Hagen & Lüders, 2016). Drawing from social action theory (Krotz, 2009; Renckstorf et al., 1996), our study consistently demonstrates that active participation in Last.fm's social features, characterised by interpersonal social activities, significantly contributes to increased music listening, novelty, and variety.

Moreover, the study's findings suggest that NEs have a carryover effect, resulting in a cumulative impact on the measurement instruments of NEs over time. This effect is crucial to understanding user behaviour on online platforms, as it emphasises the importance of considering the longitudinal nature of NEs in shaping user experiences and behaviours. The findings of our study suggest that managing NEs in the short term may not be sufficient, as a more long-term approach is necessary to sustain user engagement and behaviour on online platforms. This aligns with previous research that has emphasised the gradual process of building familiarity with a platform and its features, highlighting the importance for platform owners to exercise patience in cultivating users' engagement practices (Oestreicher-Singer & Zalmanson, 2013).

The decision to incorporate both the measures of the social network structure and social interaction simultaneously and longitudinally in this study enhances the value and contribution of the study to the existing NEs literature. Our study demonstrates that social action, specifically user interactions and engagement on the platform, plays a significant role in shaping NEs during the initial stages. However, as time passes, the social network structure, which refers to the underlying connections and relationships between users, becomes more influential in shaping NEs, surpassing the initial impact of social action on the platform. This shift suggests that the structural characteristics of the social network, such as the density of connections and the centrality of certain users, play a significant role in driving NEs. Being exploratory, our research paves the way for future studies to delve deeper into the generalisability and robustness of the findings regarding social network structure and social action roles in NEs.

3.5.2. Implication for Practice

The findings of our study highlight the crucial role played by the social features of Last.fm in fostering NEs and positively impacting users' music listening behaviours. This underscores the importance for practitioners to reconsider the role of the social dynamics on their online platforms and recognise how modifications or the introduction of new features can serve as opportunities to shape user behaviour. However, it is worth noting that the key to success for platforms that are under pressure to grow and are experiencing competition is not necessarily to include more features, but to offer the best user experience in their key area of focus. By doing so, they can attract and retain users who value that specific function or feature (Spilker & Colbjørnsen, 2020). For example, in the case of our study, we found that certain features, such as playlists and events, did not meet the strict statistical criteria for contributing to NEs. This finding has important implications for design science, as it highlights the need for a theory-driven methodology, such as the information systems design theory (Walls et al., 1992), to guide the design of platforms.

It is widely argued by researchers that when an ecosystem stops evolving and becomes static, the platform becomes susceptible to being overtaken (Tiwana, 2015). This phenomenon is evident in the cases of Myspace compared with Facebook in the social media industry, as well as Napster compared with Spotify in the music industry (Smedlund et al., 2018). For instance, if a dominant platform experiences a decline in value over time due to changes in NEs, this can be detected early on, potentially before new entrants or alternative platforms emerge. Ultimately, researchers and practitioners are required to devise strategies and interventions that optimise the positive effects of NEs and enhance the overall user experience. By incorporating a theoretical construct and utilising SEM, this study helps platform owners better understand consumer behaviour and offers insights into how individuals engage with and respond to these technologies, leading to a deeper understanding of NEs and their impact on consumer behaviour.

Insights provided by this study encompass areas such as technology acceptance, technology diffusion, premium registration, and product/service consumption. Furthermore, this research emphasises the importance of analysing the value created by NEs in shaping users' behaviours across diverse platform markets in our economy. The influence of NEs is not limited to technology sectors like video games, music, and software but can be extended to traditional industries such as health and real estate (Bowman et al., 2022; Eisenmann et al., 2006; Mcintyre & Subramaniam, 2009; Vieira et al., 2021).

3.6. Conclusion and Future Research Directions

3.6.1. Conclusion

Online music platforms have profoundly impacted the music industry, ultimately transforming how people access and listen to music. At the same time, as music platforms continue to evolve, there has been a notable shift towards platforms that embrace a more social nature, fostering social dynamics that aim to actively engage users in social interactions and shape their connections to the platform. These social features and mechanisms create an environment where individuals are encouraged to interact, share their musical experiences, and establish social connections with other users, thereby enhancing the platform’s overall social experience and influence. As a result, the platform also becomes a hub for social interactions and a catalyst for building social connections based on shared musical interests, ultimately shaping users’ sense of belonging and loyalty to the platform. Consequently, there is an increasing need to understand and analyse the behaviours of individuals engaging with music online. In parallel, the formation of social networks within platforms’ online communities has garnered substantial academic interest, prompting researchers to examine the social connections and influences that permeate these networks.

In an effort to illuminate the intricate nature of these relationships, this study incorporated social network and social action theories to extend the existing model of NEs, unravel the underlying mechanisms that drive user behaviours, and elucidate how these factors shape users’ music consumption patterns. The distinctive advantage of our study is the incorporation of a theoretical construct and the employment of a longitudinal SEM, which empowered us to examine, characterise, and advance the understanding of NEs and their impact on music listening behaviours over time. We conducted an empirical study using data collected from 1,708 Last.fm users over two distinct time intervals spanning six months. Our findings reveal the positive influence of NEs on music listening quantity, novelty, and variety, and we observed that these effects grow more robust as time progresses. Moreover, we identified that NEs from previous periods significantly contribute as instruments for NEs in subsequent periods, indicating the cumulative nature of their impact.

Furthermore, in our study, we harnessed user profile information and demographic data to gain deeper insights into variations in users' music listening behaviours. Exploring user profile information, including age, gender, subscriber status, and age of the account, we observed that, within the scope of this study, male users exhibited higher levels of music consumption than female users, demonstrating increased novelty and variety in their listening. However, we did not identify a statistically significant relationship between users' age and music listening behaviours. Additionally, subscriber status and account age positively influenced the quality, novelty, and variety of users' music listening. By delving into these aspects, researchers can uncover the specific mechanisms through which user characteristics interact with NEs, paving the way for more targeted strategies in platform design, content recommendation, and personalised user experiences.

3.6.2. Future Research Directions

In Table 3.8, we outline potential future research directions that may interest researchers seeking to delve further into the subject. These directions offer avenues for exploring and expanding knowledge in the field, inviting researchers to investigate new areas and contribute to the existing body of research.

Table 3.8. Summary of research opportunities and directions

<table>
<tr><td>Research Opportunity</td><td>Assessing the generalisability of the findings</td></tr>
<tr><td colspan="2">Research Directions
• Examine the impact of NEs on user behaviour in different digital media platforms, such as movies, social media, and games.
• Validate/compare the NEs’ influence on platforms other than Last.fm
• Review any changes in the results from different platform domains, for example, NEs instruments used on marketplace platforms and service-oriented platforms (for more ideas on studying the differences between platforms, see Spilker & Colbjørnsen, 2020).</td></tr>
<tr><td>Research Opportunity</td><td>Additional factors that can act as mediators and moderators</td></tr>
<tr><td colspan="2">Research Directions
• Explore additional factors beyond those considered in this study, both as control variables and as moderators/mediators, to identify the relationship between NEs and music listening behaviours.
• Including data NEs into the NEs construct developed in this study (look at the article on data NE, Gregory et al., 2020)
• Investigate how demographic values affect personal NEs perceptions (for more ideas, see Katona et al., 2011; Maicas et al., 2009; Voigt & Hinz, 2015)</td></tr>
<tr><td>Research Opportunity</td><td>User behaviour, experience, and satisfaction</td></tr>
<tr><td colspan="2">Research Directions
• Examine the influence of NEs on user behaviour, experience, and satisfaction other than music listening (as an example of this type of study, look at Hagen & Lüders, 2016).
• Integrating the study’s NEs construct with other research areas focusing on the social dynamics of new technologies, for example health in the study by Bowman et al. (2022).</td></tr>
<tr><td>Research Opportunity</td><td>Developing methods and data collection techniques</td></tr>
<tr><td colspan="2">Research Directions
• Users can write reviews, comment, and tag content on Last.fm. In addition to providing valuable insight into users’ opinions and preferences, these user-generated contents can also provide insight into the experiences of others on the platform and contribute to the study of NEs on online platforms.
• Develop a longitudinal study based on different approaches than SEM in this study, strengthening the empirical analysis and providing a more robust platform for drawing meaningful conclusions and implications.
• Conduct a longitudinal study of user behaviour spanning over a year and/or with multiple data collection points. We believe that investigating NEs in a long-term study necessitates data collection for at least a year to accurately observe changes in NEs levels and their resulting outcomes.</td></tr>
</table>

Chapter 4 - The Impact of COVID-19 on Online Music Listening Behaviours in Light of Listeners' Social Interactions

Mona Ghaffari[a]*, Gohar F. Khan[a], Shivendu Pratap Singh[b], and Bruce Ferwerda[c]

[a]University of Waikato, Digital Business, Hamilton, New Zealand; [b]Southern Illinois University Edwardsville, Illinois, USA; [c]Jönköping University, Computer Science and Informatics, Jönköping, Sweden

*Corresponding author

Publication status: Published in the Multimedia Tools and Applications Journal. https://doi.org/10.1007/s11042-023-16079-1

Abstract

This study investigated the global changes in online music listening behaviours in response to COVID-19 and its restrictions (such as quarantine, school and workplace closures, and travel restrictions). In addition, the research included an examination of how friendship networks and online communication motives have moderated the effect of COVID-19 on music listening behaviours. The robust causal inference methods: difference in differences (DiD) and two-way fixed effects (TWFE), were conducted to analyse the online music listening behaviours and social interactions of 37,328 Last.fm users in 45 countries before and after the first wave of confinement. It was found that in response to COVID-19, the quantity, variety, and novelty of music consumption decreased, shifting toward mainstream artists, whereas individuals with more online social connections and communications showed the reverse behaviour. Our research shows that online social interactions and community development significantly impact listeners' behaviours and can be used as a guide to develop new design strategies for digital media, such as music, movies, and games.

Keywords: COVID-19 pandemic, Mental health, Music listening, Online platform, Social dynamics

4.1. Introduction

The COVID-19 pandemic has affected many people across the globe since its debut, with accompanying high mortality and infection rates. In an effort to cope with COVID-19 health consequences, many countries have enacted social distancing regulations, lockdown restrictions, or cancelled large gatherings and events at different times, measures that have varied in scope, duration, and rigidity (Ziv & Hollander-Shabtai, 2021). Although these measures have reduced public health risks, the social and economic consequences may have long-term effects on people's minds and emotions (Fink et al., 2021). It has been known for a long time that music benefits mental health. During the COVID-19 pandemic, researchers have studied its role in reducing loneliness, raising mood, helping people cope with difficult situations, and creating a sense of community (e.g., Cabedo et al., 2021; Martín et al., 2021; Ziv & Hollander-Shabtai, 2021). Therefore, in the wake of the COVID-19 impact on people's lives, a new stream of research is being developed to better understand how music listening behaviours have changed.

Results of studies using self-reported data show that people have increasingly used music as a coping strategy during the challenging times of the COVID-19 pandemic (Cabedo et al., 2021; Fink et al., 2021; Kiernan et al., 2021). As a result, there has been an expectation that the pandemic could boost the popularity of streaming services. However, the findings from streaming platform statistics indicate a decrease in music listening during lockdowns, which contradicts the results of direct questionnaires (Howlin & Hansen, 2022). Nevertheless, we found the current literature does not examine changes in other aspects of music listening behaviours at the individual level, such as novelty, variety, and mainstreaminess in music consumption.

At the same time, people who lacked face-to-face interaction during the initial lockdowns resorted to online social communication and building online friendships to alleviate feelings of social isolation (Fink et al., 2021). Ultimately, this motivated us to examine the social dynamics of music streaming services (in this case, Last.fm), which are also considered social network sites, to understand better how social networking and communication motives intersect with music streaming. As far as ascertained, no study has reconsidered the social dynamics of music streaming platforms during the COVID-19 crisis. We drew upon the current controversy regarding the demand for online music listening and the lack of research on fundamental musical listening behaviours – variety, novelty, and mainstreaminess – during the COVID-19 pandemic to discuss how individuals' choices of songs have changed. We aimed to determine the degree to which COVID-19 related variables influence online music listening behaviours based on theories about social contexts and functional goals that determine music selection behaviours (Greb et al., 2019; Schäfer & Sedlmeier, 2009). In addition, based on the social dynamics theory of online platforms (Hagen & Lüders, 2016; Salminen et al., 2018), we questioned the moderating roles of social networks and the communication motives of listeners.

As a result, we proposed the following research questions with reference to the independent variables (IV) and dependent variables (DV) of our study:

RQ1. What is the effect of the COVID-19 pandemic (IV) on the quantity, novelty, variety, and mainstreaminess of music consumption (DVs)?

RQ2. What is the effect of the number of new COVID-19 cases (IV) on the quantity, novelty, variety, and mainstreaminess of music consumption (DVs)?

RQ3: What is the effect of COVID-19 restrictions (IV) on the quantity, novelty, variety, and mainstreaminess of music consumption (DVs)?

RQ4: Do online social connection and communication (moderators) have a different effect on the impact of COVID-19 restrictions (IV) in terms of the quantity, novelty, and variety of music consumption (DVs)?

This study sought to address the research gap by using demographically representative samples of Last.fm users (N = 37,328; age: M = 26 years, SD = 10; gender: 27,125 men, 10,203 women) from 45 countries. Our study examined the unanticipated outbreak of COVID-19 as a real-world event to investigate outcome variables using the difference in differences (DiD) method, a widely used causal inference approach. In the second part of the study, which examined the effects of new COVID-19 cases and restriction policies on the behaviours under investigation, the fixed effects (FEs) method was used to analyse the results. We furthered our investigation through the lens of the online community provided by Last.fm that enables social connections and communication with other people.

Our results showed a decrease of 15% in online music listening due to the COVID-19 pandemic. In addition to this decline in online music consumption, the novelty and variety of tastes decreased and shifted toward mainstream artists. We additionally found that with the increase of weekly COVID-19 cases and strengthening lockdown policies, music listeners' choices became more mainstream with less variety and novelty. In contrast, due to COVID-19 restrictions, listeners who had more social ties and more communication with friends demonstrated distinct changes in behaviour: they consumed more music, discovered more music, and had a wider variety of tastes. Our study of Last.fm users, based on their individual characteristics, revealed that it was not the virus infection (as measured by new cases of COVID-19), but instead major changes caused by the initial lockdowns (measured by the stringency index) that changed the demand for online music listening.

The findings of our study make several significant contributions. First, shifts in mood caused by an event can drive changes in music listening behaviours. Thus, we addressed whether users changed their music listening habits due to the COVID-19 pandemic and the initial lockdowns. The results of this study work for a wide range of music recommendation systems, such as Last.fm and Spotify, by identifying the causality of context and its impact on novelty and variety, thus highlighting the need to have a real-time musical response in a similar context. The results of our study show that online social interaction can be essential to the analysis of music listening behaviour, which aids the development of further consumer behaviour research and marketing strategies for other digital media, such as movies and software. Our findings suggest that the meaning of user connections within a platform may change if the context changes (in this case, the COVID-19 pandemic). Online music communities that foster communication and social ties can improve music consumption on online music platforms through this awareness. Therefore, we contribute to improving the design of digital platforms such as music, movies, and games by infusing design-oriented research into our research goals.

The rest of the paper is organised as follows. The following section examines the literature on online music listening and the social dynamics of streaming platforms to present a conceptual model. In Section 4.3, we discuss the research method. The analysis and findings are presented in Section 4.4. We discuss the academic and practical implications in Section 4.5. We conclude our research and outline the future research directions in Section 4.6.

4.2. Research Background

Our research background is centred on (1) listening to music within the context of the COVID-19 pandemic and (2) the social dynamics of streaming platforms.

4.2.1. Listening to Music within the Context of COVID-19

Since the start of the COVID-19 pandemic, people worldwide have faced several challenges. Many countries have implemented different lockdowns and social distancing strategies to keep the disease under control, but this has adversely affected all citizens' mental, social, and spiritual well-being (Poudel & Subedi, 2020; Ripp et al., 2020; Varshney et al., 2020; Zhang et al., 2020). Researchers have increasingly examined the possible benefits of musical activities for people who have experienced different mental health issues and a sense of uncertainty due to COVID-19 (Wang et al., 2020). In particular, music has been found to alleviate social health concerns, such as loneliness and social isolation (Ziv & Hollander-Shabtai, 2021), and create positive and regulating emotions (González Corona et al., 2020). Therefore, having identified the COVID-19 pandemic as a significant threat, research across many disciplines has focused on music listening habits during the COVID-19 crisis.

A rich literature has emerged about music's role in providing social connection, comfort, and humour to cope with negative emotions (e.g., Cabedo et al., 2021; Fink et al., 2021; Ramesh, 2020; Ziv & Hollander-Shabtai, 2021). During the initial stages of the COVID-19 pandemic, one of the initiatives people chose to alleviate stress was participating in music-related activities, whether on balconies, streets, or online, to strengthen their relationships, empower themselves, and build connections with others (Frei-Landau, 2020; Imber-Black, 2020). Singing on balconies, clapping for healthcare workers, whistling, and using kitchen utensils as musical instruments appeared on social media videos, showing how music serves as a social tool (Hansen et al., 2021). These music-related activities further confirm that the current COVID-19 pandemic has increased musical contact among people (Ramesh, 2020). Music has kept people connected even when physically separated.

Studies using self-reported data suggest that over half of the surveyed population used music as a coping strategy during challenging times of the COVID-19 pandemic (Cabedo et al., 2021; Fink et al., 2021; Kiernan et al., 2021). Additionally, studies focused on how music affects people based on age, familiarity with music, and the significance of music in their everyday lives (Fink et al., 2021; Granot et al., 2021). Mas-Herrero et al. (2020) found that music was preferred over reading or watching TV for coping with COVID-19 psychological distress Researchers have also studied the role of music-related activities in mental health; for example, Cabedo et al. (2021) studied the impact of musical activities on individuals' perceived well-being and following a broad literature review. Ramesh (2020) linked music-making and music-playing to therapeutic interventions during the COVID-19 pandemic. However, the design of this type of research has generally relied on the role music has played in the past or self-reported data at the single-country level from a limited sample size (e.g., Henry et al., 2021; Martínez-Castilla et al., 2021; Pinto, 2021; Ziv & Hollander-Shabtai, 2021). Further, a gap remains in exploring online music listening behaviours where the behavioural traits are not limited to a dichotomous variable (e.g., listening or not listening).

On the other hand, the findings from streaming platform statistics contradict the results of direct questionnaires, which indicate a decrease in music listening during lockdowns (Howlin & Hansen, 2022). Among a few researchers, Sim et al. (2022) found that the consumption of visual entertainment (e.g., live video on demand) increased while audio consumption decreased during COVID-19 lockdowns. However, further studies on changes in music listening behaviours are missing from the current literature, such as studies on novelty, variety, and mainstreaminess at the individual level. These are the leading variables in studying online music listening behaviours (Bauer & Schedl, 2019; Datta et al., 2017; Schedl & Hauger, 2015), as different kinds of music can reflect users' musical preferences and desires for variety (Datta et al., 2017). However, it has also been found that individuals often choose only one or two styles of music from their favourite playlist in a specific context (Knees & Schedl, 2013).

Users' music listening behaviours are increasingly being tracked in music recommendation systems considering additional taxonomies, such as mood and activity (Ferwerda et al., 2019). For example, during the COVID-19 pandemic, researchers have formulated a better way to recommend music based on users' emotions by reading users' facial expressions or obtaining direct input from them (Ulleri et al., 2021). Studies have also shown that emotion-aware algorithms can utilise the information provided by COVID-19 cases and outperform baseline algorithms (Wang et al., 2021). Typically, context-aware music recommendation systems are concerned with studying users' musical listening behaviours in the context of the real-world and utilising that information as input for the system. It is not a new topic in music recommendation systems to relate users' music listening to the context of events or situations (Elliott et al., 2011) and the consequent emotions (Yousefian Jazi et al., 2021). Music recommendation systems incorporate user emotion into the operation to enrich the user experience of music streaming services (Yang et al., 2016). Therefore, researchers emphasise the importance of considering situational or contextual aspects and their association with user emotions that shape users' musical tastes and affect their consumption behaviours (Schedl, Zamani, et al., 2018). For example, Spotify reported that listeners' musical habits have significantly altered since the start of the COVID-19 pandemic: people listen to music more often during the weekend, and music taste is becoming increasingly focused on being relaxed and calm (Lanzoni, 2020).

Therefore, our study aimed to examine the impact of the COVID-19 pandemic and the accompanying restrictions on individuals' music listening behaviours by using empirical data from Last.fm and studying individual-level music listening behaviours.

4.2.2. Social Dynamics of Streaming Platforms

During the most restrictive periods of the COVID-19 pandemic, businesses that could stream content directly to their customers saw the most success (Guren et al., 2021). However, during these periods of isolation and social separation, listening to music through streaming services declined (Sim et al., 2022). We looked for reasons in the literature from the perspective of the social dynamics of streaming platforms. In recent years, streaming has become the most popular method of listening to music (Aguiar & Waldfogel, 2018), and online music services have made the music experience more personal (Stewart et al., 2018). Digital platforms have changed how people listen to music, turning music listening into a more individual activity (Karatay, 2022). However, during the initial COVID-19 isolation periods, people turned toward activities with a stronger sense of community, belonging, and social elements (Grigoriadou, 2021). Music streaming lacks this feature. During the time of this pandemic, researchers have observed a change in music consumption patterns, with an increasing number of users transitioning from audio-based streaming services to video-based platforms like YouTube. This shift can be attributed to the enhanced interactive features and active engagement opportunities provided by YouTube, distinguishing it from platforms such as Spotify and Pandora (Howlin & Hansen, 2022).

Following the first wave of the COVID-19 pandemic, many countries implemented restrictions and limited social interaction at different levels; however, people still found creative ways to participate in activities and keep in touch with each other (Tuck & Thompson, 2021; Ziv & Hollander-Shabtai, 2021). Because of the loss of in-person connection, people actively socialised online and built online friendships to alleviate feelings of social isolation (Fink et al., 2021). For this reason, social network sites' usage has encountered an upward trend worldwide compared to before the pandemic (Asghar et al., 2021), and people use this platform for content (e.g., news, videos, music, etc.) consumption as well. However, despite the variety of ways people communicate online in social network sites, streaming services do not appear to prominently facilitate social interaction in their technological design or substitute the social network sites (Stewart et al., 2018).

The desire to communicate and interact with others also moves individuals toward streaming platforms. The user communities provided by content providers show that consumer communities have become one of the most active online communities (Salminen et al., 2018). An important characteristic of social network sites is that the nodes in the community have a greater number of internal connections than external ones (Furht, 2010), which can help bring people together in times of social isolation. In this sense, the role of social networking tools in music streaming platforms is akin to Ray Oldenburg's concept of a "third place" in creating a sense of community since they support communication and interaction between members (Mechant & Evens, 2011). Social and community motivations have a stronger hold on users when they join live music streaming channels than similar channels in mass media (Hilvert-Bruce et al., 2018). Likewise, the decision to subscribe to online music platforms can also be significantly influenced by participation in the community rather than by the amount of content consumed (Oestreicher-Singer & Zalmanson, 2013).

Last.fm enables members to create a social network and socially interact using a personal profile, where they can follow and be followed by other users and communicate through private chat and shouts[3]. Considering the above discussion, we aimed to measure whether increased online social interaction during the COVID-19 pandemic has moderated the effect of COVID-19 on online music listening. As far as can be ascertained, the social dynamics linked to online music platforms is missing from researchers' analysis of the impact of COVID-19 on online music behaviour.

4.2.3. Conceptual Model

Figure 4.1 represents our conceptual model that offers a multifaceted framework for understanding the influence of three theoretical pillars on individuals' online music listening behaviours during the initial COVID-19 lockdown period. These pillars are social contexts and functional goals, the causal inference of COVID-19, and the social dynamics of music streaming platforms, which play an essential role in influencing online music listening behaviours and consumption patterns but have not been studied in an integrated manner to the best of our knowledge. Our model provides researchers and practitioners with a comprehensive understanding of analysing these factors and making more accurate predictions about their impacts on music listening behaviours during a pandemic or other contexts.

[3] Shouts in Last.fm work in a similar manner to posts and replies in SNSs such as Twitter and Facebook.

Social contexts and functional goals: the first pillar refer to the social norms, reasons, and motivations behind an individual's music listening behaviours. While people generally enjoy variety in the music they listen to, they tend to select specific genres based on their listening context. For instance, an individual may listen to music to relax after a long workday or choose to listen to a particular genre or artist to feel a sense of connection with others who share similar musical preferences. Thus, the proposed model suggests that social contexts and functional goals play a significant role in shaping individuals' music listening behaviours, particularly in the specific context of the COVID-19 pandemic, which is the focus of our study.

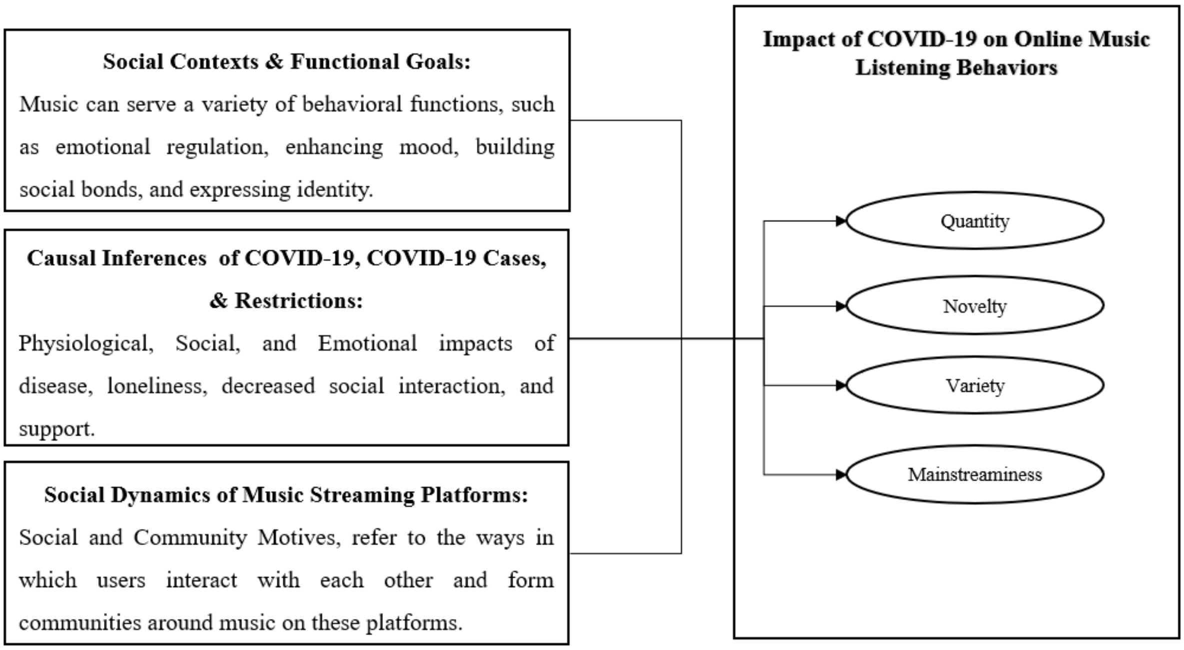


Figure 4.1. Conceptual model

The causal inference of COVID-19: the second pillar is the causal inference of COVID-19 as a natural event, highlighting the potential impact of the pandemic on online music listening behaviours. The closure of music venues, cancellation of live music events, and the implementation of lockdowns and social distancing may have resulted in changes to online music listening. Specifically, the model proposes that during times of heightened uncertainty and instability caused by the COVID-19 pandemic, individuals might gravitate toward familiar music and avoid seeking novelty and variety in music. These behaviours might happen, for example, due to individuals might stick to music that relieves the stress and loneliness caused by the uncertainty and hardships during the pandemic. At the same time, preserving a sense of belonging and emotional connection to happier times before the pandemic.

The social dynamics of music streaming platforms: a third pillar of the model represents the possibility that people have increasingly turned to online platforms for social interaction; as a result, music streaming platforms such as Last.fm have become more than just a means of accessing music but also a context for socialising and connecting with others. This social aspect of music streaming platforms can provide a sense of belonging and emotional support, particularly for those experiencing loneliness or isolation due to lockdowns and social distancing. In addition to accessing music, users can also engage in social interactions such as sharing playlists, commenting on music preferences, and following other users. So social interaction, measuring the social network size and communication through an online platform such as Last.fm could moderate the impact of COVID-19 on online music listening behaviours.

The present study focuses on the actual music listening behaviours rather than the quantity of music listening or self-reported data, which can only provide information on whether individuals listen to music more or less. To achieve this goal, the proposed conceptual model includes ovals representing various dimensions of music listening behaviours at the individual level. These include the amount of music listened to (quantity), the extent to which individuals sought out new music (novelty), the range of different artists that they listened to (variety), and the extent to which they listened to popular or mainstream music (mainstreaminess).

4.3. Research Methodology

In this section, we first describe the variables and data we used for the analysis and then explain the methods by which we conducted the analysis.

4.3.1. Definition of Variables

In this study, we chose to employ DiD and FEs analysis to gauge the causal impact of the: (1) COVID-19 intervention as a natural event, alongside two independent variables, namely the (2) new COVID-19 cases, and (3) stringency index, on the dependent variables. In addition, to encompass the entirety of research on users' music listening behaviours, in addition to the dependent variable of (1) quantity of music listening, we included (2) novelty, (3) variety, and (4) mainstreaminess. These variables are established measures of music listening behaviours and are widely utilised in the literature (Datta et al., 2017; Dewan et al., 2017; Schedl & Hauger, 2015; Schedl, Wiechert, et al., 2018). Our choice to incorporate these variables in our study was to provide a comprehensive understanding of how COVID-19 impacted music listening behaviours. As a result, we conducted three separate data analysis for each independent variable and each time on one of the dependent variables.

The first dependent variable is quantity, which measured the number of songs that user i listened to in a specific week t (Datta et al., 2017). Furthermore, we estimated the results by measuring novelty and variety within two different formulas to test the robustness of our analysis. Considering two indexes for variety and novelty analysis, we built two models to test the robustness of our results as suggested and used in the literature (e.g., Datta et al., 2017; Schedl & Hauger, 2015). The dependent variable of variety in consumption consists of two indexes. The variable variety1 determines the number of unique artists that user i listened to in a specific week t (Datta et al., 2017; Schedl & Hauger, 2015). Variety2 is the average amount of listening to each artist by user i in a specific week t (Schedl & Hauger, 2015).

Similarly, the dependent variable of novelty in consumption includes two indexes. We collected a history of music listening one month before our official data analysis time period for each user as the baseline time to operationalise the novelty measurement (i.e., from 1st-31st October 2019). Therefore, we measured novelty for each user based on their music history. For week t, if an artist that user i listened to was new within the baseline period or the weeks before each week, it was considered new. The variable novelty1 is defined as the number of unique new artists that user i listened to for the first time divided by the total number of unique artists in a specific week t (Datta et al., 2017). The variable novelty2 is the value of the discoveries measured by the number of consumptions of new artists divided by the total number of consumptions for user i in a specific week t (Datta et al., 2017).

We then defined listening preferences toward mainstream artists by the dependent variable of the mainstreaminess (Bauer & Schedl, 2019; Madison & Schiölde, 2017; Schedl & Hauger, 2015). The popularity of songs, albums, or artists on music streaming services is commonly determined by the number of times they have been played (Bauer & Schedl, 2019). Another way to assess the popularity of artists is to count their total number of listeners (Schedl & Tkalčič, 2014). Similar to novelty and variety explained according to the song artists, we measured users' mainstreaminess regarding the artists they listened to. Accordingly, we first determined the number of listening in total from all listeners and the number of listeners to particular artists to select the top 20 public artists during the baseline period and the weeks before each week. Considering the method introduced by Bauer and Schedl (2019) and based on these two artist popularity measures, user mainstreaminess is defined as the number of consumptions matching the top 20 public artists divided by the total consumptions for user i in a specific week t.

We also found it worthwhile to explore the role of social interactions as moderators and the importance of individual characteristics as control variables in our study. Last.fm also allows members to build social networks and conduct social communications using their personal profiles. Based on the social dynamics of Last.fm, (1) social network connections and (2) social communication constituted the moderator variables analysed for their ability to affect the variables of interest. In addition, for causal inferences to be drawn from the study context, it was essential to control for variables relevant to music listening behaviours (Schedl, Zamani, et al., 2018). We used several control variables in our study, which are characteristics commonly found in individual-level studies on music listening. Thus, we analysed the differences in music listening among individuals as determined by their (1) age, (2) gender (Berkers, 2012; Putzke et al., 2014), (3) age of the account, and (4) subscriber status (Anderson et al., 2020; Datta et al., 2017).

Social network size was calculated by the total number of followings and followers of user i. However, we were interested in obtaining the panel data on building social networks through the platform during the study period, data relating to the following and follower dates were not available to us. Thus, as in previous research, we used the total number of social networks to measure this variable in our study (e.g., Dewan et al., 2017). To assess the social communication effect in our study, the number of comments and replies posted on the user i profile showed the amount of communication for that user over a specific week t (Chan-Olmsted et al., 2019; Katsma & Spil, 2010). Social communication did not include private messages through inboxes, as these were unavailable data and did not fall under the scope of this study.

We present our research model in Figure 4.2. Table 4.1 summarises the study variables and their definitions.

4.3.2. Data and Measurement

Our dataset was constructed using Last.fm, including a panel on individuals' music consumption and social interactions. The advantage of research using a music-focused social network site, such as Last.fm is that real observational data can be collected from users concerning their social connections while their music listening behaviours are also evident (Dewan et al., 2017). We collected the music listening data of 37,328 users from 1st November 2019 to 27th March 2020 (dividing our research into 21 weeks). This timeline represents the

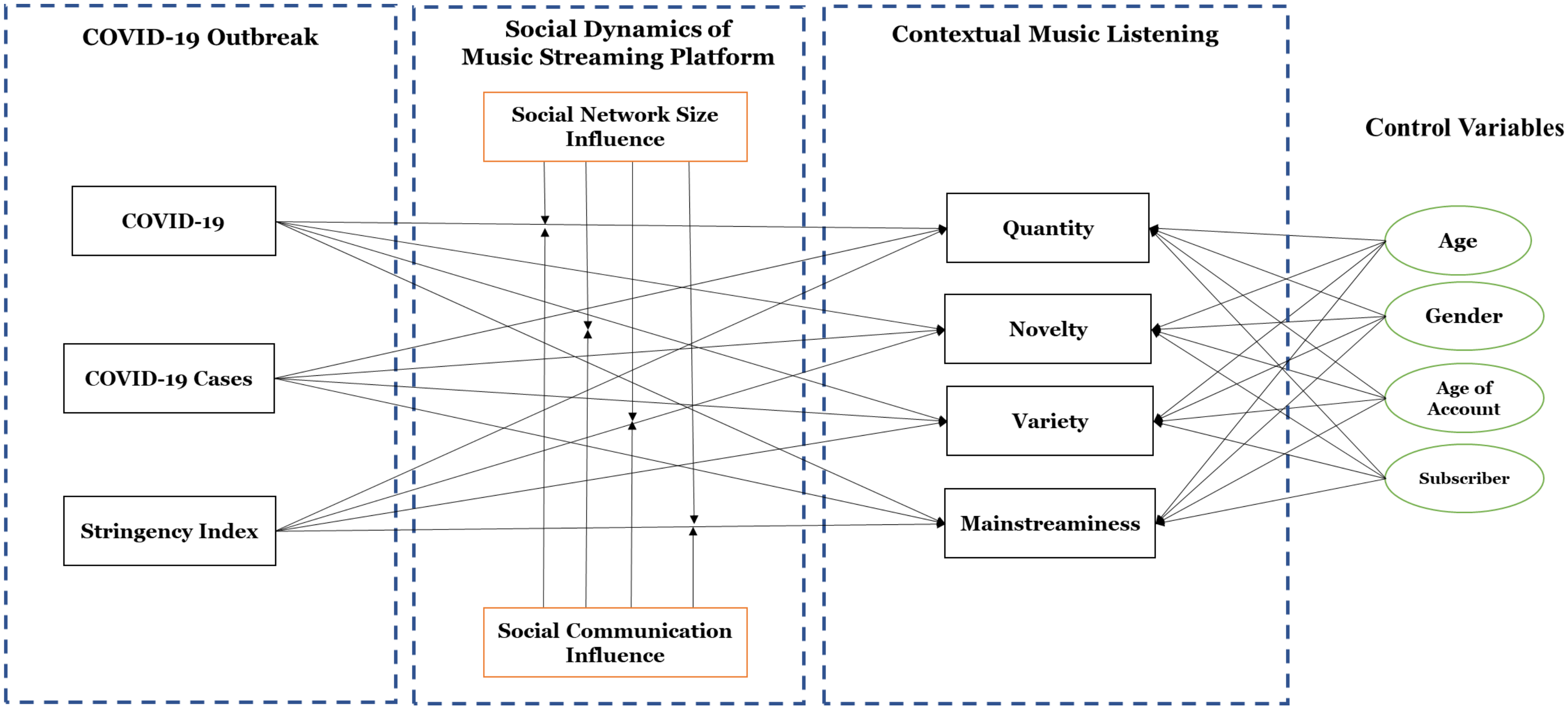


Figure 4.2. Research model

Table 4.1. Definition of research variables

Variable	Definition
Independent Variables	
COVID-19	A binary variable in which unaffected countries in a specific week are represented by 0 and affected countries are defined by 1 following the COVID-19 outbreak (Liu et al., 2020).
New COVID-19 Cases	The sum of confirmed new COVID-19 cases for a specific week (Liu et al., 2020).
COVID-19 Stringency Index	Enforced social distancing by governments drawn from OxCGRT for a specific week (Hale et al., 2021).
Dependent Variables	
Quantity	The total number of songs a user listened to in a specific week (Datta et al., 2017).
Novelty1	The number of unique new artists a user listened to for the first time is divided by the number of unique artists in a specific week (Datta et al., 2017).
Novelty2	The amount of listening to new artists is divided by the total consumption for a user in a specific week (Datta et al., 2017).
Variety1	The number of unique artists a user listened to in a specific week (Datta et al., 2017; Schedl & Hauger, 2015).
Variety2	The average number of a user's listening to artists in a specific week (Schedl & Hauger, 2015)
User Mainstreaminess	The number of listenings that match up to the top 20 public artists is divided by the total number of listenings for a user in a specific week (Bauer & Schedl, 2019).
Moderator Variables	
Social Communication	The total number of comments and replies on a user's profile in a specific week (Chan-Olmsted et al., 2019).
Social Network Size	The total number of a user's followings and followers (Dewan et al., 2017).
Control Variables	
Age	A user's age at the time of the investigation (Berkers, 2012; Putzke et al., 2014).
Gender	Gender of a user (Berkers, 2012; Putzke et al., 2014).
Age of the account	The number of weeks passed since a user's registration on Last.fm (Anderson et al., 2020; Datta et al., 2017).
Subscriber	The subscription status was 1 for a paid member and 0 otherwise (Datta et al., 2017).

first COVID-19 cases confirmed in countries based on international studies (Liu et al., 2020; Sim et al., 2022). Although the outbreak has continued in many places since this period, we can refer to this period as the first wave of the COVID-19 pandemic. The following steps were involved in data collection:

Step 1) The sample consisted of randomly selected single users from different geographical areas (45 countries) using the dataset introduced by Melchiorre et al. (2021). We excluded individuals with missing data on key variables, those who registered on Last.fm after the investigation started, and those with a listening exceeding the 99th percentile. As a result, the total sample size was 37,328 individuals.

Step 2) We recorded the individuals' age, gender, and country. Then, users were divided into four age groups: adolescence (12-19): n =1387 young adulthood (20-39): n =32,664, middle adulthood (40-65): n =2,999, and above 65: n=278 according to the primary life stages (Erikson, 1993). Individuals' resident country was used to collect data in step 5.

Step 3) We obtained the songs users listened to using the service's application protocol interface (API), "user.getRecentTracks", built on Python (with BeautifulSoup library). We were able to identify unique artists based on the name of the artists associated with each song using an algorithm to gain a unique artist list (for more details, see Datta et al., 2017)

Step 4) We then broadened the sample by identifying friends' networks (a directed network of the followings and followers) using API "user.getFriends", with a result of 2,647,578 following and follower relationships.

Step 5) Additionally, we accessed a separate data set containing a time-stamped log of users' comments and replies and used this to determine users' social communication.

Step 6) The COVID-19 variables for every country, including the COVID-19 start week and weekly new cases, were derived from the "Our World in Data website" [4] along with the stringency index derived from the OxCGRT dataset (Hale et al., 2021). The descriptive statistics of the dataset are presented in Table 4.2.

[4] https://ourworldindata.org/covid-cases

Table 4.2. Summary statistics of variables

Variable	Mean	SD	Min	Max
Independent variables (weekly)				
COVID-19 (start week from 1 to 21)	14.89	2.33	10	20
New COVID-19 cases	1,402	7,883	0	73,030
Stringency index (%)	11.06	19	0	100
Dependent variables (weekly)				
Quantity	48.52	158.17	0	6,979
Variety1	1.57	12.24	0	2,852
Variety2	14.38	44.59	0	3,962
Novelty1 [0-1]	0.14	0.28	0	1
Novelty2 [0-1]	0.18	0.34	0	1
User mainstreaminess [0-1]	0.94	0.14	0	1
Moderators				
Follower	37.37	116.46	0	7,433
Following	34.79	119.92	0	7,534
Social communication (weekly)	0.02	0.14	0	44
Controls				
Gender (female=1)	0.27	0.44	0	1
Age	25.42	9.33	12	115
Hofstede cultural value [0-1]	0.56	0.05	0.38	0.71
Age of the account (weeks)	543	109	24	883
Subscriber (paid =1)	0.007	0.08	0	1

4.3.3. DiD and Fixed Effects Analysis

DiD analysis is a quasi-experimental method well-suited for analysing natural experiments (Angrist & Pischke, 2008), such as the COVID-19 pandemic as an exogenous event. Using DiD analysis to compare online music listening behaviours between treatment groups exposed to COVID-19 and control groups not exposed can estimate the causal effect of COVID-19 on online music listening while controlling for other potential influencing factors. In addition, quasi-experimental designs are often favoured when the randomized assignment of participants is challenging or unfeasible, as such conditions commonly occur in real-world research settings (Price et al., 2015). In situations where random assignment is not feasible or ethically justifiable, such as in our study where we have no control over the spread of COVID-19 in different countries, FEs analysis can also be employed as a viable alternative (Stock & Watson, 2003).

Moreover, DiD and FEs analysis can both control for time-invariant confounders that may affect the treatment (COVID-19) and the outcome variables (online music listening behaviours), such as individual-level characteristics or unobserved heterogeneity (Angrist & Pischke, 2008; Imai & Kim, 2019). This is crucial in studying online music listening behaviours (Aguiar, 2017), where individual-level factors could influence both COVID-19 exposure and online music listening behaviours. Controlling for these time-invariant confounders can minimise omitted variable bias, and the actual causal effect of COVID-19 on online music listening behaviours can be estimated accurately. Furthermore, FEs analysis can also be used to explore the moderation effect of social interactions on the relationship between COVID-19 and online music listening behaviours by incorporating an interaction term between the treatment (COVID-19) and social interaction variables, as well as the within-person changes in social interaction variables over time (Allison, 2009).

Our study relies on using archival data obtained from Last.fm music platform. It employs a competing outcome framework within a quasi-experiment setting to measure the causal impact of COVID-19 on music listening behaviours. However, as with any analysis of archival data, there may be validity and exploratory concerns that require more than one method to address them, as discussed on page 69, paragraph 2 in (Wooldridge, 2021). We chose these methods as they are commonly utilised in the literature and have a reputation for their reliability in measuring intervention effects (e.g., Bhattacharya et al., 2019; Callaway & Sant'Anna, 2021; Datta et al., 2017; Dewan et al., 2017; Greb et al., 2019; Huang et al., 2016; Liu et al., 2020; Shmargad & Watts, 2016; Wooldridge, 2021). In addition, using multiple equations allows us to account for a wide range of variables that may impact music listening behaviours during the COVID-19 pandemic. As a result, we have employed multiple methods and included multiple equations to mitigate the risks of omitted variable bias, confounding effects, time-varying covariates, fixed effects, unobserved heterogeneity, and reverse causality.

4.3.3.1. DiD Analysis for the Causal Effect of COVID-19

Researchers increasingly employ the DiD method to estimate treatment effects on treated groups (i.e., the causal effect of policy interventions) (Callaway & Sant'Anna, 2021). In online music listening research, the DiD method with two periods and groups is used to examine the impact of events or new design options on music listening behaviours (e.g., Datta et al., 2017; Dewan et al., 2017; Liu et al., 2020). We applied the DiD method to analyse the causal effect of COVID-19 on music listening behaviours during our research period. The most common regression approach researchers utilise to identify the DiD effect is two-way fixed effect (TWFE) regressions (Callaway, 2022) as in the Equation 4.1:

$$Y_{it} = \alpha_i + \upsilon_t + \theta D_{it} + \epsilon_{it} \tag{4.1}$$

According to Equation 4.1, D_{it} is a binary variable that shows participation in the treatment for unit i at time t. The unit FEs (α_i), and the time FEs (υ_t) are included as well as idiosyncratic, time-varying unobservables (ϵ_{it}). Assuming the homogeneity of the treatment effect and that the parallel trends assumption is valid, θ in the TWFE regression represents the effect of taking part in the treatment (Callaway, 2022). However, in our study, it was necessary to apply a multi-time period DiD approach to investigate the effect of COVID-19 on music listening behaviours since the intervention period varied across individuals from different countries.

Compared to single-treatment design, there are several theoretical advantages to applying multi-time DiD design, also known as staggered DiD. First, when only one treatment period is used, there is a possibility that confounding variables undermine the exposure of interest (i.e., treatment), which violates the parallel trends assumption (Baker et al., 2022). Also, recent econometric theory studies challenge the validity and robustness of TWFE estimates when more than two treatment groups or periods are included or when treatment timing varies (Baker et al., 2022). Additionally, the observational data may also be subject to interactive fixed effects that contradict the parallel trends assumption compared to the experimental data. Therefore, in this study, we used a novel approach built to handle staggered treatment adoption designs (i.e., Callaway & Sant'Anna, 2021). This method of estimating the average treatment effects on treated (ATT) is based on the variation in the timing of the treatments, with the parallel trends assumption conditional on observed covariates.

In this DiD analysis, the control group included users in countries before the confirmation of the first COVID-19 case who became part of the treatment group after the start of the COVID-19 outbreak in those countries. In particular, we identified the date of the first confirmed COVID-19 case in each country and defined it as when the COVID-19 pandemic started. In addition, as the "never-treated" group of units was not available in our dataset, we favoured the "not yet treated" group of units as a control group, making it possible to employ more comparison units to enhance inference procedures potentially (Callaway & Sant'Anna, 2021). As far as we know, this is the first study to analyse the impact of COVID-19 on music listening behaviours using the staggered DiD method, which is well suited to real-world situations.

The COVID-19 effect might differ between treatment groups g at time t, with group g including the time users were first treated (e.g., individuals in countries where the COVID-19 pandemic began in week 12 have a separate group from individuals in countries where it started in week 13). In terms of treatment groups, there were different causal parameters of interest, ATT(g, t), called the "group-time average treatment effect". The ATT(g, t) was used in the estimation procedure that incorporated the clustered bootstrapped standard error of the data, thereby accounting for autocorrelation and clustering (Callaway & Sant'Anna, 2021). A generalised propensity score was estimated as part of this doubly robust estimation procedure, thereby allowing a logit model to be constructed that considers each individual characteristic (Callaway & Sant'Anna, 2021). As explained above, the conditional parallel trends assumption was that the observed covariates were considered.

While the interpretation of ATT(g, t) can be difficult when there are many groups and periods, Callaway and Sant'Anna (2021) present a family of causal effect parameters in staggered DiD setups to estimate the overall effects of participation in the treatments: simple aggregation (a weighted average according to the group size of all ATT(g, t)), event studies (average effects of treatment at different exposure durations), group-specific effects (average effects within each group), and calendar time effects (aggregations across different time periods). A group-specific effect is the analysis of treatment effects across all groups where the ATT will be interpreted the same way as there are exactly two time periods and two groups of individuals (Callaway & Sant'Anna, 2021). We used a tool in the R programming language, the "did package" introduced by Callaway and Sant'Anna (2020), to implement the method.

4.3.3.2. Fixed Effects Analysis.

FEs regression was used to analyse the impact of other characteristics of the COVID-19 outbreak (i.e., new COVID-19 cases and the stringency index) on music listening behaviours. Using FEs analysis in our panel data allowed us to control unobserved heterogeneity and eliminate potential biases (Bu et al., 2020). We also reviewed different research areas to examine the FEs method's ability to estimate time-variant variables in the study of music listening behaviours (e.g., Bhattacharya et al., 2019; Datta et al., 2017; Greb et al., 2019; Huang et al., 2016; Liu et al., 2020; Shmargad & Watts, 2016). Equation 4.2 illustrates the FEs model used in this study.

$$\begin{aligned} \mathrm{Y_{it}} = \alpha_\mathrm{i} + \upsilon_\mathrm{t} + \beta_1 \mathrm{X_{it}} + \beta_2 \mathrm{Gender_i} + \beta_3 \mathrm{Age_i} + \beta_4 \mathrm{Subscriber_i} + \\ \beta_5 \mathrm{Age\ of\ account_i} + \epsilon_\mathrm{it} \end{aligned} \tag{4.2}$$

In Equation 4.2, Y_{it} are the dependent variables, and X_{it} are the independent variables for individual i at week t. Furthermore, FEs variables and control variables are also included in the equation. α_i is a country-level FEs, υ_t is a week-level FEs, and ϵ_{it} is the error term. In the case of too many entities, the individual FEs may only explain minimal variations in our dependent variables. Individual-level EFs are recommended to be placed in several meaningful categories to prevent type II errors – for example, citizenships or ethnicities (Park, 2011). Thus, we used country-level FEs to deal with the large number of individuals we included in our analysis. Country-level FEs are reliable indicators of time-invariant characteristics and circumstances that differ among countries (e.g., population, population density, GDP per capita, life expectancy, and the human development index in different countries). Week-level FEs accounted for common time patterns throughout the weekly variation. Finally, we controlled for individuals' age, gender, age of the account, and subscriber. As a result, the coefficient of the independent variable represented the average impact of the independent variables on music listening quantity, variety, novelty, and user mainstreaminess in this study.

4.4. Analysis and Findings

In this section, we present our findings using a staggered DiD method to examine COVID-19's impact on the dependent variables of our study. Then, the results of the TWFE are depicted relating to the effects of new COVID-19 cases and the stringency index on dependent variables. Finally, we present the results of the interaction between independent variables and the model's moderators, including social connection size and social communication.

4.4.1. The Causal Effect of COVID-19 on Music Listening Behaviours

We chose to analyse data from 1st November 2019 to 27th March 2020 (21 weeks), the time of the first wave of the COVID-19 pandemic and two months prior to that. We defined treatment groups based on the period when a country first became infected by COVID-19, while those living in countries not yet affected by COVID-19 represented the untreated group. With multiple groups and time periods, the overall ATT based on a family of causal effect parameters became easier to interpret, as discussed in Section 4.3.3.1. Summary statistics for staggered DiD under the assumption of unconditional parallel trends are provided in Table 4.3

with the overall ATT in column ATT, followed by bootstrapped standard errors in column SE, and a 95% confidence interval in the next column.

Table 4.3. Estimates of aggregated COVID-19 effect (unconditional parallel trends)

Panel (a) Quantity				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
log Quantity	Simple weighted average	-0.2067	0.0295	[-0.2896, -0.1237] **
	Group-specific effects	-0.1907	0.0245	[-0.2593, -0.1220] **
	Event study	-0.1696	0.0371	[-0.2737, -0.0654] **
	Calendar time effects	-0.1546	0.0205	[-0.2121, -0.0971] **
Panel (b) Novelty				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
Novelty1	Simple weighted average	-0.0319	0.0040	[-0.0398, -0.0240] **
	Group-specific effects	-0.0278	0.0036	[-0.0348, -0.0207] **
	Event study	-0.0274	0.0060	[-0.0392, -0.0157] **
	Calendar time effects	-0.0242	0.0029	[-0.0298, -0.0186] **
Novelty2	Simple weighted average	-0.0376	0.0050	[-0.0474, -0.0279] **
	Group-specific effects	-0.0337	0.0043	[-0.0421, -0.0253] **
	Event study	-0.0317	0.0063	[-0.0440, -0.0194] **
	Calendar time effects	-0.0283	0.0037	[-0.0356, -0.0210] **
Panel (c) Variety				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
log Variety1	Simple weighted average	-0.0863	0.0119	[-0.1096, -0.0631] **
	Group-specific effects	-0.076	0.0098	[-0.0952, -0.0568] **
	Event study	-0.074	0.0178	[-0.1089, -0.0391] **
	Calendar time effects	-0.0663	0.0083	[-0.0825, -0.0501] **
log Variety2	Simple weighted average	-0.1515	0.0213	[-0.1932, -0.1098] **
	Group-specific effects	-0.1397	0.0189	[-0.1767, -0.1026] **
	Event study	-0.1235	0.0236	[-0.1698, -0.0772] **
	Calendar time effects	-0.1129	0.0153	[-0.1430, -0.0829] **
Panel (d) Mainstreaminess				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
Mainstreaminess	Simple weighted average	0.01	0.0029	[0.0032, 0.0144] **
	Group-specific effects	0.01	0.0023	[0.0021, 0.0111] **
	Event study	0.01	0.0038	[0.0003, 0.0128] *
	Calendar time effects	0.01	0.002	[0.0036, 0.0115] **

Note: The unconditional parallel trends assumption is used in the DiD method. Variables of interest include novelty, mainstreaminess, and the natural logarithm of quantity and variety.
$*p < 0.10$; $**p < 0.05$

The first set of results based on the unconditional parallel trends assumption shows that the COVID-19 pandemic significantly decreased all six dependent variables compared to a no-pandemic scenario. The quantity of online music listening was associated with a 21% reduction caused by the COVID-19 pandemic when using a simple average effect, and close to 19%, 17%, and 15% less quantity when using group-specific, event studies, and calendar-time aggregation methods, respectively (Panel (a) of Table 4.3). The results showed that the novelty in consumption – that is, the number of unique new artists divided by the total number of unique artists (novelty1) – decreased compared to a no-pandemic scenario by around 3%, measuring simple average, group-specific, event studies, and calendar time effect, respectively (Panel (b) of Table 4.3). Also, the COVID-19 pandemic significantly decreased the value of the discoveries (novelty2), by about 3% to 4%, measuring a simple average, group-specific, event studies, and calendar time effect, respectively (Panel (b) of Table 4.3).

In terms of the variety in music consumption, COVID-19 caused a decrease in the number of unique artists (variety1) users listened to by about 7% to 8%, measuring a simple average, group specific, event studies, and calendar time effect, respectively (Panel (c) of Table 4.3). Further, the COVID-19 pandemic significantly decreased the average listening of users to each artist (variety2) compared to a no-pandemic scenario, with 15%, 14%, 12%, and 11%, measuring a simple average, group-specific, event studies, and calendar-time effect, respectively (Panel (c) of Table 4.3). There was a small increase in the user mainstreaminess percentage for listening to the top 20 artists using all four aggregation methods (Panel (d) of Table 4.3). Therefore, music consumption did not decline based on a shift to niche music since novelty and variety declined while mainstream music listening increased slightly.

The first extension in our DiD method is that the parallel trends assumption could only be confirmed by considering covariates. We furthered the conditional parallel trend assumption to prove the negative effect of the COVID-19 pandemic on music listening behaviours. Therefore, the second set of results was based on the assumption that individuals with the same characteristics would similarly listen to music if no treatment had been initiated (Table 4.4).

The individual characteristics that we used are age and gender. The analysis showed small changes between unconditional and conditional parallel trend assumptions when considering quantity (Panel (a) of Table 4.4). However, the results were almost the same following novelty, variety, and mainstreaminess analysis (Panels (b), (c), and (d) of Table 4.4). Overall, we can conclude a decreasing trend in online music listening behaviours during the initial stages of the COVID-19 pandemic, as shown in Table 4.4. As the results of our research reveal, it is not surprising that the COVID-19 pandemic reduced online music listening quantity (see the literature review in Section 4.2.1); however, as far as we know, no previous studies have looked at novelty, variety, and mainstreaminess concerning COVID-19, meaning this research was exploratory in nature.

The second extension in our DiD method is that the parallel trends assumption was violated despite including covariates. We supplemented our DiD approach with an additive time-invariant covariate whose effect on untreated outcomes might vary over time (Callaway & Karami, 2022). To use this method, we had to obtain a never-treated group. Researchers suggest that when at some point, all units have been treated, the available periods should be reduced so that at least one never-treated group remains throughout the investigation. Notably, the resulting data loss is not an issue for time periods with no comparison groups since DiD cannot be utilised to determine treatment effect parameters (Callaway, 2022). In our data set, we eliminated weeks 19, 20, and 21 and continued with 18 weeks. Using this method, an interactive FEs structure, also referred to as a factor structure, was used to model untreated potential outcomes. A time-invariant unobservable can have different effects over time if such a structure is used. The interactive FEs model for untreated potential outcomes is as Equation 4.3:

$$Y_{it}(0) = \upsilon_t + \alpha_i + \lambda_i F_t + \epsilon_{it} \tag{4.3}$$

Table 4.4. Estimates of aggregated COVID-19 effect (conditional parallel trends)

Outcome	Estimand	ATT	SE	[95% Conf. Int.]
Panel (a) Quantity				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
log Quantity	Simple weighted average	-0.2181	0.0327	[-0.2821, -0.1541] **
	Group-specific effects	-0.2008	0.0311	[-0.2617, -0.1399] **
	Event study	-0.1824	0.0352	[-0.2515, -0.1134] **
	Calendar time effects	-0.1606	0.0235	[-0.2067, -0.1145] **
Panel (b) Novelty				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
Novelty1	Simple weighted average	-0.0334	0.0046	[-0.0423, -0.0244] **
	Group-specific effects	-0.0292	0.004	[-0.0370, -0.0214] **
	Event study	-0.0285	0.0057	[-0.0397, -0.0173] **
	Calendar time effects	-0.0252	0.0035	[-0.0321, -0.0183] **
Novelty2	Simple weighted average	-0.0396	0.0055	[-0.0503, -0.0288] **
	Group-specific effects	-0.0354	0.0049	[-0.0450, -0.0259] **
	Event study	-0.0335	0.0067	[-0.0466, -0.0203] **
	Calendar time effects	-0.0295	0.004	[-0.0374, -0.0216] **
Panel (c) Variety				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
log Variety1	Simple weighted average	-0.0874	0.0122	[-0.1113, -0.0634] **
	Group-specific effects	-0.0771	0.0114	[-0.0995, -0.0547] **
	Event study	-0.0748	0.0169	[-0.1079, -0.0417] **
	Calendar time effects	-0.0666	0.0087	[-0.0837, -0.0494] **
log Variety2	Simple weighted average	-0.1623	0.0241	[-0.2094, -0.1152] **
	Group-specific effects	-0.1491	0.0219	[-0.1920, -0.1062] **
	Event study	-0.1355	0.0264	[-0.1872, -0.0838] **
	Calendar time effects	-0.1191	0.018	[-0.1544, -0.0838] **
Panel (d) Mainstreaminess				
Outcome	**Estimand**	**ATT**	**SE**	**[95% Conf. Int.]**
Mainstreaminess	Simple weighted average	0.01	0.0017	[0.0022, 0.0088] **
	Group-specific effects	0.01	0.0014	[0.0014, 0.0069] **
	Event study	0.01	0.0023	[0.0004, 0.0086] *
	Calendar time effects	0.01	0.0013	[0.0022, 0.0072] **

Note: The conditional parallel trend assumption based on age and gender is used in the DiD method. Variables of interest include novelty, mainstreaminess, and the natural logarithm of quantity and variety.
$*p < 0.10$; $**p < 0.05$

As shown in Equation 4.3, $Y_{it}(0)$ represents the potential outcome for an untreated individual in time period t, along with unit FEs (α_i), time FEs (υ_t), the unobserved, and time-invariant covariates (λ_i), whereas F_t represents the time-varying effect of these individual characteristics. For a special case of the model where $F_t = t$, a linear trend model can be used to solve the model (Heckman & Hotz, 1989; Mora & Reggio, 2019; Wooldridge, 2005). Equation 4.4 presents a linear trend model.

$$Y_{it}(0) = \upsilon_t + \alpha_i + \lambda_i t + \epsilon_{it} \quad (4.4)$$

Therefore, our study sought results based on age, gender, and cultural values of time-invariant covariates. We added Hofstede cultural dimensions (Hofstede et al., 2005), computed based on a user's country of origin, as additional covariates for determining cultural preferences (Ferwerda et al., 2016; Schedl, 2017; Skowron et al., 2017). The ATT results are represented in Table 4.5. The results of the linear trends model were similar to those obtained through the previous method.

Table 4.5. Aggregated COVID-19 effect estimates (linear trends model)

Panel (a) Quantity				
Outcome	**Estimand**	**ATT**	**SE**	**[90% Conf. Int.]**
log Quantity	Linear trend	-0.15	0.0235	[-0.2760, -0.0284] *
Panel (b) Novelty				
Outcome	**Estimand**	**ATT**	**SE**	**[90% Conf. Int.]**
Novelty1	Linear trend	-0.02	0.0177	[-0.0399, 0.0183]
Novelty2	Linear trend	-0.02	0.0171	[-0.0443, 0.0120]
Panel (c) Variety				
Outcome	**Estimand**	**ATT**	**SE**	**[90% Conf. Int.]**
log Variety1	Linear trend	-0.07	0.0436	[-0.1443, -0.0008] *
log Variety2	Linear trend	-0.11	0.0665	[-0.2172, -0.0001] *
Panel (d) Mainstreaminess				
Outcome	**Estimand**	**ATT**	**SE**	**[90% Conf. Int.]**
Mainstreaminess	Linear trend	0.02	0.0112	[0.0059, 0.0429] *
Note: The confidence interval is at the 90%* level. The covariates included in the model are age, gender, and cultural values. Variables of interest include novelty, mainstreaminess, and the natural logarithm of quantity and variety. The results of the novelty are not significant at the 90% confidence interval.				

4.4.2. The Impact of New COVID-19 Cases and Restrictions on Music Listening Behaviours

This section presents our findings on whether new COVID-19 cases and the stringency index led to changes in online music listening behaviours considering quantity, novelty, variety, and user mainstreaminess. We report our first set of results examining the impact of the logarithm of new COVID-19 cases on quantity, novelty, and variety (see Table 4.6). Overall, we found a causal relationship between the prevalence of new COVID-19 cases and decreases in all outcome variables. According to the coefficient for the dependent variable, the logarithm of quantity (Table 4.6, column 1), a 1% increase in new cases of COVID-19 in a week would cause users' total listening to decrease by approximately 1% (exp (-0.007)-1) at $p<0.01$. The average weekly music listening of individuals following the start of the COVID-19 pandemic was 46 songs, so a 10% increase in COVID-19 cases reduced the weekly listening by almost five songs. As a result, COVID-19 cases had an economic impact in addition to their statistical significance.

The negative impact of new COVID-19 cases was evident in novelty: a 1% increase in weekly new COVID-19 cases caused the novelty of listening to music to decrease by 0.001 (Table 4.6, columns 2 and 3). However, the effect of new COVID-19 cases on novelty was not economically and statistically significant for novelty1. Then, we found a significant and economic decrease in two variety measures of listening to music (Table 4.6, columns 4 and 5). Based on variety1 and variety2, a 1% increase in new COVID-19 cases in a week resulted in a reduction of 0.2% in the number of artists in a user's listening history in a week and a reduction of 0.6% in the average listening to each artist.

The second set of results examined the stringency index of lockdown levels. The data were collected during the early stages of the COVID-19 outbreak, when governments worldwide responded differently to the pandemic, as determined by the University of Oxford on a scale of 0 to 100. This presented an opportunity to look at the impact of the stringency index on our studied variables. For example, the average stringency index in all 45 countries reached 76% during week 21 of the study (week beginning on 20th March 2020), while some countries experienced no stringency until week 18. Overall, with the increase in the stringency index of lockdown levels, we observed the presence of negative and decreasing coefficients (Table 4.7).

Table 4.6. New COVID-19 cases effect estimates

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log COVID-19 cases	-0.007***	-0.001	-0.001**	-0.002*	-0.006***
	(0.003)	(0.0004)	(0.0004)	(0.001)	(0.002)
20<age≤39	-0.212***	-0.024***	-0.034***	-0.061***	-0.169***
	(0.013)	(0.002)	(0.002)	(0.005)	(0.010)
39<age≤65	-0.362***	-0.046***	-0.062***	-0.117***	-0.275***
	(0.015)	(0.003)	(0.003)	(0.006)	(0.012)
65<age	-0.492***	-0.062***	-0.082***	-0.155***	-0.355***
	(0.030)	(0.005)	(0.005)	(0.011)	(0.023)
Gender (m)	0.420***	0.058***	0.070***	0.151***	0.294***
	(0.005)	(0.001)	(0.001)	(0.002)	(0.004)
Age of the account	0.003***	0.001***	0.001***	0.001***	0.003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Subscriber (1)	3.091***	0.356***	0.456***	1.006***	2.271***
	(0.026)	(0.004)	(0.004)	(0.010)	(0.020)
R^2	0.12	0.12	0.12	0.10	0.11
Users	37,304	37,304	37,304	37,304	37,304
Observations	723,467	723,467	723,467	723,467	723,467

Note: All models include country FEs and week FEs; control variables are reported in the table. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.
∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01.

Column 1 of Table 4.7 shows that with a 1% increase in the stringency index in a week, the music listening dropped by 0.1% (exp (-0.001)-1) at *p*<0.01. We ran the same model for the impact of the stringency index on novelty and variety (Table 4.7, columns 2 to 5). Results strongly pointed to a decrease in novelty and variety due to the increased stringency index. In Table 4.7, columns 2 and 3, the coefficient for the effect of the stringency index on novelty1 and novelty2 was significant at *p*<0.01, and the impact of the stringency index on the novelties showed a decreasing result. Similar to the impact of new COVID-19 cases, the stringency index had a greater effect on the variety variables compared to the novelty variables. With a 1% increase in the stringency index in a week, the number of unique artists (variety1) and average listening to each artist (variety2) decreased by 1% and 3%, respectively, at *p*<0.01 (Table 4.7, columns 4 and 5). Thus, the stringency index clearly impacted users' music listening behaviours compared with no government restrictions.

Table 4.7. Stringency index effect estimates

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log Stringency index	-0.04*** (0.005)	-0.003*** (0.001)	-0.005*** (0.001)	-0.011*** (0.0001)	-0.034*** (0.0003)
20<age≤39	-0.212*** (0.013)	-0.019*** (0.001)	-0.024*** (0.002)	-0.061*** (0.005)	-0.169*** (0.010)
39<age≤65	-0.362*** (0.015)	-0.035*** (0.002)	-0.044*** (0.002)	-0.117*** (0.006)	-0.275*** (0.012)
65<age	-0.492*** (0.030)	-0.047*** (0.003)	-0.059*** (0.004)	-0.155*** (0.011)	-0.355*** (0.023)
Gender (m)	0.420*** (0.005)	0.043*** (0.001)	0.050*** (0.001)	0.151*** (0.002)	0.294*** (0.004)
Age of the account	0.003*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.003*** (0.000)
Subscriber (1)	3.091*** (0.026)	0.356*** (0.004)	0.456*** (0.004)	1.006*** (0.010)	2.271*** (0.020)
R^2	0.12	0.12	0.12	0.10	0.11
Users	37,304	37,304	37,304	37,304	37,304
Observations	723,467	723,467	723,467	723,467	723,467

Note: All models include country FEs and week FEs; control variables are reported in the table. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty, and the natural logarithm of quantity and variety.
∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01.

Given that the quantity and variety of music consumption declined with the increase of both new COVID-19 cases and the stringency index, we looked at mainstream consumption to measure the share of unique varieties (Datta et al., 2017). The trend of users' play counts for the top 20 mainstream artists (superstars) showed the user mainstreaminess value based on two definitions of popular artists, as discussed in detail in Section 4.3.1. Table 4.8 shows the impact of new COVID-19 cases and the stringency index on user mainstreaminess. A doubling increase in the COVID-19 cases in a week caused users to listen to 10% more mainstream music at $p<0.05$ (Table 4.8, column 1). There was a consistent impact of COVID-19 on users' mainstreaminess when considering the stringency index, indicating that it had a considerable effect. In column 2 of Table 4.8, the stringency index is shown as having increased mainstream listening among individuals by 0.2% at $p < 0.01$, indicating that, for example, when there were governmental restrictions of 50%, users listened to 10% more mainstream music (mainstreaminess of 0.653) than when there were no governmental restrictions (mainstreaminess of 0.594).

Table 4.8. The effect of the stringency index and new COVID-19 cases on user mainstreaminess

Model	log Mainstreaminess	log Mainstreaminess
log COVID-19 cases	0.001** (0.001)	
log Stringency index		0.002*** (0.000)
20<age≤39	0.007*** (0.001)	0.012*** (0.001)
39<age≤65	0.014*** (0.001)	0.025*** (0.001)
65<age	0.015*** (0.001)	0.028*** (0.002)
factor(gender) m	-0.011*** (0.001)	-0.019*** (0.001)
Age of the account	-0.0002*** (0.000)	-0.0002*** (0.000)
Subscriber (1)	-0.125*** (0.002)	-0.125*** (0.002)
R^2	0.07	0.07
Users	37,304	37,304
Observations	723,467	723,467

Note: All models include country FEs and week FEs; control variables are reported in the table. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include user mainstreaminess.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

We performed this last step to ensure our analysis was reliable and valid. In the first step, we conducted diagnostic tests appropriate for the FEs model (Rahman et al., 2022), including the following three tests in R. For heteroscedasticity, the Breusch-Pagan test was conducted using the bptest() function. Afterward, we tested autocorrelation using the function pbgtest(). We ran the third test for cross-sectional independence using the Breusch-Pagan LM test of independence using the pcdtest() function. According to the results of the tests, heteroscedasticity, autocorrelation, and cross-sectional dependency were present, which may invalidate the standard error in the original model.

Consequently, we used the panel-corrected standard error (PCSE) estimator as an advantage in panel data analysis because it addresses the problems of heteroscedasticity, autocorrelation, and cross-sectional dependency (Bailey & Katz, 2011; Rahman et al., 2022). The PCSE estimator proposed by Beck and Katz (1995) can be computed using the function vcovBK() when applied to panel models estimated by the plm package in R (Bailey & Katz, 2011). As shown in Table 4.9, the results of the PCSE model are consistent with the estimations from the original model. Using the PCSE estimator and the original estimator, we were able to ensure the robustness of our analysis and that the results could be interpreted with confidence.

Table 4.9. Panel corrected standard error (PCSE) model results

Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**	**Log Mainstreaminess**
Original Model						
log COVID-19 cases	-0.007*** (0.003)	-0.001 (0.0004)	-0.001** (0.0004)	-0.002* (0.001)	-0.006*** (0.002)	0.001** (0.001)
Log Stringency index	-0.040*** (0.005)	0.003*** (0.001)	-0.005*** (0.001)	-0.011*** (0.0001)	-0.034*** (0.0003)	0.002*** (0.000)
PCSE Model						
log COVID-19 cases	-0.007*** (0.003)	-0.001 (0.0004)	-0.001*** (0.0004)	-0.002** (0.001)	-0.006*** (0.002)	0.001*** (0.0002)
Log Stringency index	-0.040*** (0.005)	0.004*** (0.001)	-0.006*** (0.001)	-0.011*** (0.002)	-0.034*** (0.004)	0.002*** (0.000)

Note: All models include country FEs and week FEs; control variables are age, gender, age of the account, and subscriber. The panel-corrected standard errors of the PCSE model and the robust standard errors clustered at the individual level of the original model are reported in parentheses.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

4.4.3. Social Network Size and Social Communication

As part of our research, we also explored how socialising features offered by streaming platforms such as Last.fm can be leveraged to counteract the negative effects of the COVID-19 pandemic on the music streaming industry. Among the standard features associated with streaming platforms and social network sites, we placed special emphasis on individuals' social communication and social network size since they are significant features of the built-in interactive capabilities of social network sites (Chan-Olmsted et al., 2019; Katsma & Spil, 2010; Mechant & Evens, 2011). Among the listed features in Last.fm, social communication was the only variable available in the Last.fm service that could be exploited through time series. Due to this limitation, we could only access data about daily communications (including time and date), based on users' profiles to provide a perspective of users' social communications. We then used the total number of users' social networks as a second variable that measures social network size.

We hypothesised that utilising social communication through Last.fm coupled with the social network size, led to a greater music play count, the discovery of new music, and a variety in music consumption, even though COVID-19 negatively impacted these variables (based on our findings presented in Sections 4.4.1 and 4.4.2). Therefore, we empirically evaluated the following regression equation:

$$Y_{it} = \alpha_i + \upsilon_t + \beta_1 X_{it} + \beta_2 (X_{it} \times Communication_{it}) + \beta_3 (X_{it} \times Social\ network\ size_{it}) + \beta_4 Gender_i + \beta_5 Age_i + \beta_6 Subscriber_i + \beta_7 Age\ of\ account_i + \epsilon_{it} \quad (4.5)$$

In Equation 4.5, Y_{it} are the dependent variables and X_{it} are the independent variables for individual i at week t. Furthermore, FEs variables are also included in the equation: α_i is a country FE, υ_t is a week FE, and ϵ_{it} is the error term. The moderator variable for individual i at week t is social communication and the social network size within Last.fm. Similar to previous equations, we controlled for age, gender, subscriber, and age of account when conducting our analysis. Considering the COVID-19 lockdown conditions associated with increased online social interaction, among the independent variables in this study, the stringency index accurately reflected the lockdown conditions (Hale et al., 2021). Therefore, we measured the moderating effect of social communication and social network size at various levels of the stringency index (0, 25%, 50%, 75%, and 100%).

The results are reported in Table 4.10. As in Section 4.4.2 (Table 4.7), we determined the negative effects of the stringency index on quantity, novelty, and variety, and we will not repeat them in this section. The main impact of social communication was 0.38 at p<0.01, indicating that an increase in social communication by one unit resulted in a rise of 46% (exp (0.38)-1) in music play counts when the stringency index equalled zero. Similarly, we observed the positive main effect of social communication on novelty1 (0.05), novelty2 (0.06), variety1 (0.21), and variety2 (0.18) at $p<0.01$. Therefore, in cases where the stringency index was zero, social communication through the platform substantially impacted how music was consumed in terms of quantity, novelty, and variety.

Table 4.10. Stringency index interaction with social communication

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
Social communication	0.377*** (0.020)	0.053*** (0.003)	0.059*** (0.003)	0.207*** (0.007)	0.183*** (0.015)
0< stringency≤25 × communication	0.057 (0.039)	0.006 (0.005)	0.010 (0.007)	0.037*** (0.014)	0.020 (0.030)
25< stringency≤50× communication	0.188* (0.080)	0.036*** (0.011)	0.037*** (0.013)	0.084*** (0.029)	0.129** (0.061)
50< stringency≤75× communication	0.518*** (0.126)	0.068*** (0.017)	0.082*** (0.021)	0.130*** (0.046)	0.417*** (0.097)
75< stringency≤100× communication	0.97*** (0.213)	0.164*** (0.029)	0.182*** (0.036)	0.317*** (0.078)	0.683*** (0.164)
R^2	0.12	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

Note: All models include country FEs and week FEs, and control variables are age, gender, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty, and the natural logarithm of quantity and variety.
∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01.

The key variable of interest was the interaction term stringency index × social communication, representing the average effect of the stringency index on music listening quantity, novelty, and variety when considering the social communication of listeners. This interaction term was estimated to be positive, with varying degrees of coefficient in the five columns (Table 4.10). According to the interaction measures, the effect of the stringency index on quantity, novelty, and variety was positive for users who took part in social communication. The relationship between this increment and the stringency index was intriguing. When there was an interaction of the stringency index of 25% in social communication, there was an increase of 6% in quantity. There was also 19% more music listening when the stringency index was between 25% to 50%, and 52% more music listening when the stringency index was between 50% and 75%. Finally, there was 97% more music listening when the stringency index went above 75% (Table 4.10, column 1). Similarly, interactions of the stringency index with novelty and variety were also significantly positive, supporting the moderating effect of social communication (Table 4.10, columns 2 to 5).

Using the moderating effect of social communication, we found that the negative impact of the COVID-19 stringency index on music listening behaviours tended to be more pronounced among those who did not use Last.fm as a social network site to interact with the community. In contrast, the stringency index that governments utilised during the COVID-19 pandemic had less impact on socially active listeners. To fully understand the interaction effects, we used the interact plot as the most suitable method of interpretation (Aiken et al., 1991). We note in Figure 4.3 that socially active users listened to more music and that there was also a positive relationship between the stringency index and the amount of music they listened to. As a result, we conclude that social communication moderated the negative impact of the stringency index on music listening quantity, which may have been due to the effects of social distancing or the shock to music streaming services caused by the COVID-19 crisis. The interaction plots of novelty and variety values are presented in Figures 4.4 and 4.5 respectively, which exhibited a similar trend.

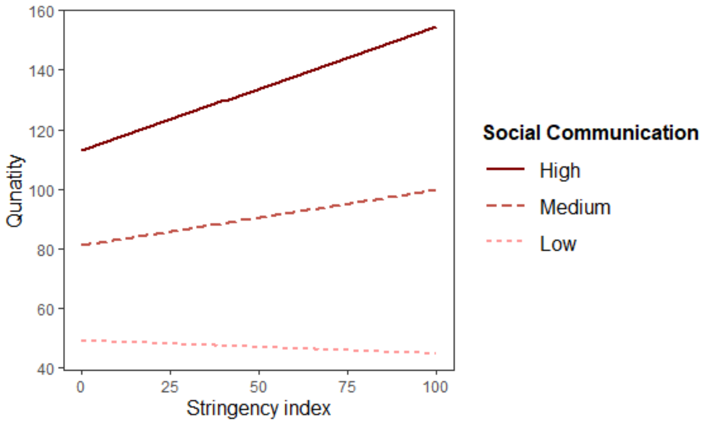


Figure 4.3. Interaction plot of the stringency index and social communication (related to the quantity)

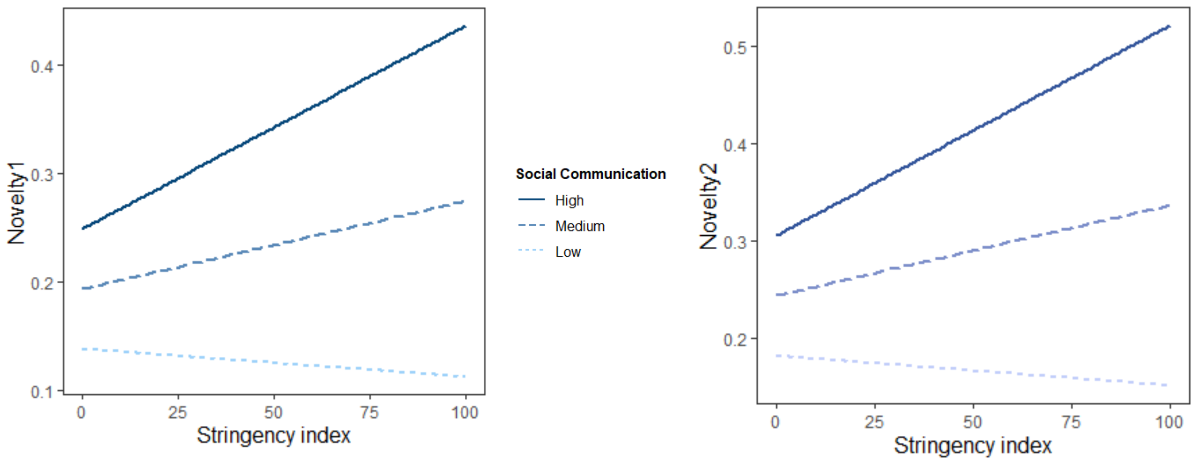


Figure 4.4. Interaction plot of the stringency index and social communication (related to novelty)

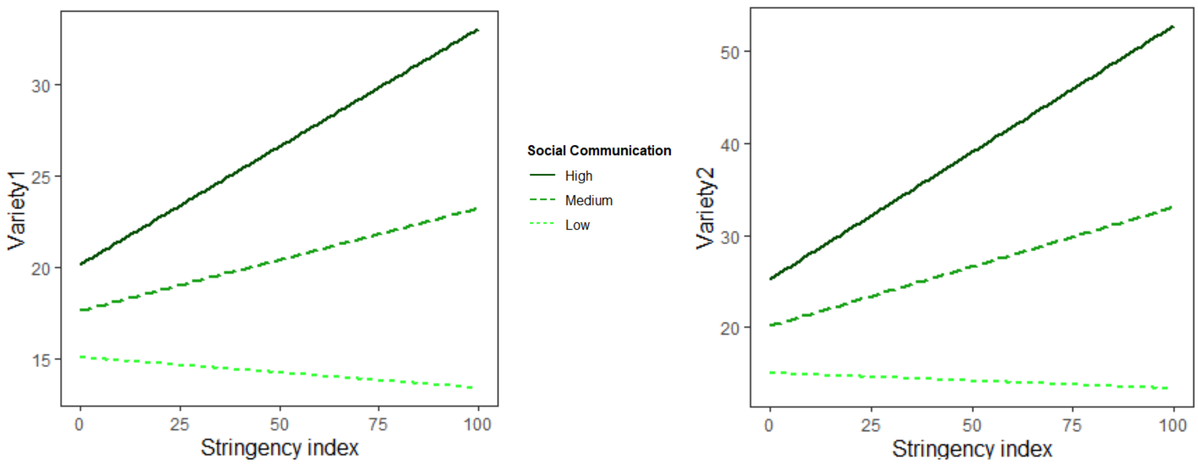


Figure 4.5. Interaction plot of stringency index and social communication (related to variety)

Next, we examined the users' total social network size as a moderator, which significantly explained the relationship between the stringency index and studied variables, including quantity, novelty, and variety (Table 4.11). The main impact of social network size was 0.35 at p<0.01, indicating that a 1% increase in social network size resulted in a rise of 42% (exp (0.35)-1) in music listening when the stringency index equalled zero (Table 4.11, column 1). Similarly, we observed the positive and significant main effect of social network size on novelty1 (0.05), novelty2 (0.06), variety1 (0.12), and variety2 (0.26) at p<0.01 (Table 4.11, columns 2 to 5). Therefore, in cases where the stringency index was zero, the social network size of the users within the platform substantially impacted how music was consumed in terms of quantity, novelty, and variety.

Table 4.11. Stringency index interaction with social network size

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log Network size	0.354*** (0.002)	0.046*** (0.001)	0.059*** (0.001)	0.121*** (0.001)	0.261*** (0.001)
0< stringency≤25 × log network size	-0.003 (0.003)	-0.001*** (0.001)	-0.001* (0.001)	-0.001 (0.001)	-0.003 (0.002)
25< stringency≤50 × log network size	-0.015** (0.006)	-0.002*** (0.001)	-0.002** (0.001)	-0.004 (0.002)	-0.012** (0.005)
50< stringency≤75 × log network size	-0.022*** (0.005)	-0.003*** (0.001)	-0.003*** (0.001)	-0.006*** (0.002)	-0.016*** (0.004)
75< stringency≤100 × log network size	0.031*** (0.008)	0.003*** (0.001)	0.005*** (0.001)	0.011*** (0.003)	0.024*** (0.007)
R^2	0.18	0.18	0.18	0.16	0.16
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

Note: All models include country FEs and week FEs; control variables are age, gender, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

The key variable of interest was the interaction term of stringency index × social network size, representing the average effect of the stringency index on quantity, novelty, and variety of music consumption when considering the listeners' social network size. The magnitude of the interaction term showed that when considering the size of the social networks, the negative impact of the stringency index on all studied variables was smaller for users with more friends. Further, when the stringency index exceeded 75%, the interaction term of the stringency index and social network size demonstrated a positive coefficient. Comparing Tables 10 and 11 indicates that the effect of network size was not as prominent as social communication. However, the results of this study are not necessarily conclusive that social communication is more effective than a social network size since our analysis was not based on panel data on weekly social network size.

4.4.4. Individual Characteristics of Music Listeners

Finally, the analysis of individual characteristics related to the outcome variables indicates that the negative impact of new COVID-19 cases was not significant in females' music listening behaviours; however, the effect of the stringency index on music listening was significant for males and females (Tables 4.12 and 4.13). Although males listened to significantly more music than females, with more novelty and variety, the negative impact of COVID-19 on males' music listening behaviours was more than on females. During the investigation, increasing restrictions and social distancing policies resulted in a greater reduction in music listening among males than females (Table 4.13). The variety and novelty analysis also showed that restriction policies affected males more than females (Table 4.13, columns 2 to 5).

Furthermore, the results showed that when new COVID-19 cases and the stringency index increased, young adults (20-39) listened to more music than adolescents (under 20); however, older adults over 65 listened to significantly less music than adolescents (Table 4.14). In addition, the impact of the COVID-19 pandemic on novelty and variety in music consumption among all age groups did not significantly differ, except for those over 65, for whom the effect of COVID-19 was more negative than it was for adolescents.

Table 4.12. New COVID-19 cases interaction with gender

Panel (a) Female					
Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**
log COVID-19 cases	-0.005 (0.004)	-0.0002 (0.001)	-0.0003 (0.001)	-0.0004 (0.002)	-0.005 (0.003)
R^2	0.10	0.10	0.10	0.09	0.10
Users	10,198	10,198	10,198	10,198	10,198
Observations	195,902	195,902	195,902	195,902	195,902
Panel (b) Male					
log COVID-19 cases	-0.008** (0.003)	-0.001 (0.0004)	-0.001** (0.001)	-0.002* (0.001)	-0.007*** (0.002)
R^2	0.11	0.10	0.11	0.10	0.10
Users	27,106	27,106	27,106	27,106	27,106
Observations	527,565	527,565	527,565	527,565	527,565

Note: All models include country FEs and week FEs; control variables are age, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Table 4.13. Stringency index interaction with gender

Panel (a) Female					
Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**
log Stringency index	-0.035*** (0.009)	-0.004*** (0.001)	-0.005*** (0.002)	-0.010*** (0.003)	-0.029*** (0.007)
R^2	0.10	0.10	0.10	0.09	0.10
Users	10,198	10,198	10,198	10,198	10,198
Observations	195,902	195,902	195,902	195,902	195,902
Panel (b) Male					
log Stringency index	-0.042*** (0.007)	-0.004*** (0.001)	-0.006*** (0.001)	-0.011*** (0.002)	-0.035*** (0.005)
R^2	0.11	0.10	0.11	0.10	0.10
Users	27,106	27,106	27,106	27,106	27,106
Observations	527,565	527,565	527,565	527,565	527,565

Note: All models include country FEs and week FEs; control variables are age, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.
$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Table 4.14. New COVID-19 cases and stringency index interactions with age

Panel (a)					
Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**
log COVID-19 cases ×					
20≤age≤39	0.008*	0.001	0.001	0.002	0.005
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)
39<age≤65	0.003	0.0004	0.0003	0.0005	0.002
	(0.005)	(0.001)	(0.001)	(0.002)	(0.004)
65<age	-0.001	-0.001	-0.001	-0.005	-0.0001
	(0.010)	(0.001)	(0.002)	(0.004)	(0.007)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
Panel (b)					
Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**
log Stringency index ×					
20≤age≤39	0.014*	0.002	0.002	0.004	0.011*
	(0.008)	(0.001)	(0.001)	(0.003)	(0.006)
39<age≤65	0.005	0.001	0.001	0.001	0.004
	(0.010)	(0.001)	(0.002)	(0.003)	(0.007)
65<age	-0.034*	-0.005**	-0.007**	-0.018**	-0.016
	(0.019)	(0.003)	(0.003)	(0.007)	(0.015)
R^2	0.12	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

Note: All models include country FEs and week FEs; control variables are gender, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01.

The impact of the new COVID-19 cases and stringency index on subscribers was positive (Table 4.15, panels (a) and (b)). With the increase in the stringency index, subscribers listened to more music with more novelty and variety than non-subscribers. The impact of the stringency index was significantly and economically greater than the new COVID-19 cases' impact. However, considering the age of the account, the coefficient of the impact of new COVID-19 cases and the stringency index of all dependent variables were close to zero (Table 4.16).

Table 4.15. New COVID-19 cases and stringency index interactions with subscribers

Panel (a)					
Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**
log COVID-19 cases × Subscriber	0.015* (0.009)	0.001 (0.001)	0.003* (0.001)	0.005* (0.003)	0.007 (0.007)
R^2	0.12	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
Panel (b)					
log Stringency index × Subscriber	0.070*** (0.017)	0.008*** (0.002)	0.012*** (0.003)	0.029*** (0.006)	0.038*** (0.013)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
Note: All models include country FEs and week FEs; control variables are gender, age, and age of the account. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01.					

Table 4.16. New COVID-19 cases and stringency index interactions with age of account

Panel (a)					
Model	**log Quantity**	**Novelty1**	**Novelty2**	**log Variety1**	**log Variety2**
log COVID-19 cases × Age of account	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
Panel (b)					
log Stringency Index × Age of account	0.0000** (0.0000)	0.000*** (0.0000)	0.000*** (0.0000)	0.000*** (0.0000)	0.000 (0.0000)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
Note: All models include country FEs and week FEs; control variables are gender, age, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01.					

Our analysis pointed to how platform providers can target their marketing efforts to those who contribute to the system. For example, the impact of the first wave of the COVID-19 pandemic had a more negative impact on the amount of music listened to by males. In addition, subscribers remain the most significant contributor to the Last.fm platform's value, even after the big shock of the COVID-19 pandemic. Since Last.fm's most loyal customers are its subscribers, when it suffers a crisis like the COVID-19 pandemic, it could benefit from developing special plans or policies to increase subscribers or target this specific group. The policy of Spotify to offer a three-month free subscription relates directly to our results, aside from the subscription fee.

Furthermore, as we examine the user characteristics reported in this section, we also observe variations in the effects of new COVID-19 cases and the stringency index on online music listening behaviours, including quantity, novelty, variety, and mainstreaminess. Our study revealed that it was not the virus infection (as measured by new cases of COVID-19) but instead major changes caused by the initial lockdowns (measured by the stringency index) that changed the demand for online music listening. Therefore, new COVID-19 cases might not be a robust estimator of changes in COVID-19 level in a study of online music listening, in contrast to the stringency index, a measure of the extent of COVID-related lockdowns, school closures, and social distancing.

4.4.5. Summary of Analysis

- We used the DiD method (Equation 4.1) to estimate the average treatment effect on individuals affected by COVID-19. DiD is a standard method of investigating and estimating effects in quasi-experiment settings (Callaway, 2022).
- While the DiD method is one of the most appropriate ways to estimate the average treatment effect, it cannot be used to explore heterogeneity in treatment effect based on other confounding variables (Wooldridge, 2021). To address this issue, we estimated the FEs analysis represented by Equation 4.2.
- In real-life scenarios testing and supporting assumptions for DiD estimation is challenging, especially when the treatment is staggered. To address this issue, newer methods like staggered DiD, with more flexible assumptions, provide a

robust framework to estimate the average treatment effect in staggered adoption scenarios (Equation 4.3). Equation 4.4 is an extension of Equation 4.3, accommodating the linear trend model.

- Equation 4.5 investigates the moderating effect of social network size and social communication on music listening behaviours.

4.5. Discussion

In the following, we discuss several theoretical and practical implications regarding the impact of the COVID-19 pandemic on online music listening behaviours and how digital media decision-makers may need to intervene with the new design strategies to ensure that they remain effective under COVID-19 and other future circumstances.

4.5.1. Implications for Academia

4.5.1.1. Online Music Listening Behaviours

The first strength of our contribution stems from analysing online music listening behaviours through the context of the COVID-19 pandemic. Employing specific real-world events or daily experiences is an alternative method to predict users' behaviours. A growing body of music recommendation research includes information about time, sessions (morning, evening, night), feedback, and location to formulate users' contextual behaviours (Katarya & Verma, 2018). The previous literature has also discussed various possibilities for determining users' emotional music selection based on real-world events. For example, researchers have exploited individuals' music listening behaviours in the context of past and future real-world events (Schedl, Wiechert, et al., 2018), determined the mood of public sentiment (Liu et al., 2020), and discussed the best way to benefit listeners' psychological wellbeing (Ziv & Hollander-Shabtai, 2021). Our research increases current knowledge of online music listening behaviours by analysing the causal relationship between the COVID-19 pandemic and the consequent changes in quantity, novelty, variety, and mainstreaminess in consumption on a global scale that has not been studied previously.

According to our research, music listening behaviours have been affected by three components of the COVID-19 pandemic: the outbreak as a real-world event, the weekly new COVID-19 cases, and the stringency of lockdowns. The results of our study provide evidence that in its early stages, the COVID-19 pandemic negatively affected online music listening and that individuals' music listening decreased by approximately 15% compared with pre-pandemic time. Unlike the common belief that there was an increase in music streaming, we found that music listening continued to decline with the rise of weekly COVID-19 cases and strengthening lockdown policies following the beginning of the COVID-19 pandemic. In addition, the rising number of COVID-19 cases and restrictions resulted in less variety and novelty and more mainstream listening among music listeners.

By utilising the staggered DiD method, we were able to present Box plots that depict the distribution of data before the onset of COVID-19 and for various groups affected by COVID-19 during different weeks. This type of visualisation is beneficial for identifying changes in the data's central tendency, variability, and skewness. The use of never treated data made it possible to make these comparisons, as discussed in Section 4.4.1. We encourage readers to refer to the Box plots for all dependent variables (Figure 4.6). Overall, the Box plots demonstrate that the users' music listening quantity decreased due to the impact of COVID-19 and turned to less novelty and variety in music consumption. Furthermore, the music listening to mainstream artists also increased.

We believe, our research opens up the possibility that a range of music recommendation systems, such as Last.fm and Spotify, will be able to take advantage of these causalities to determine the impact of COVID-19 on music preferences and make better recommendations.

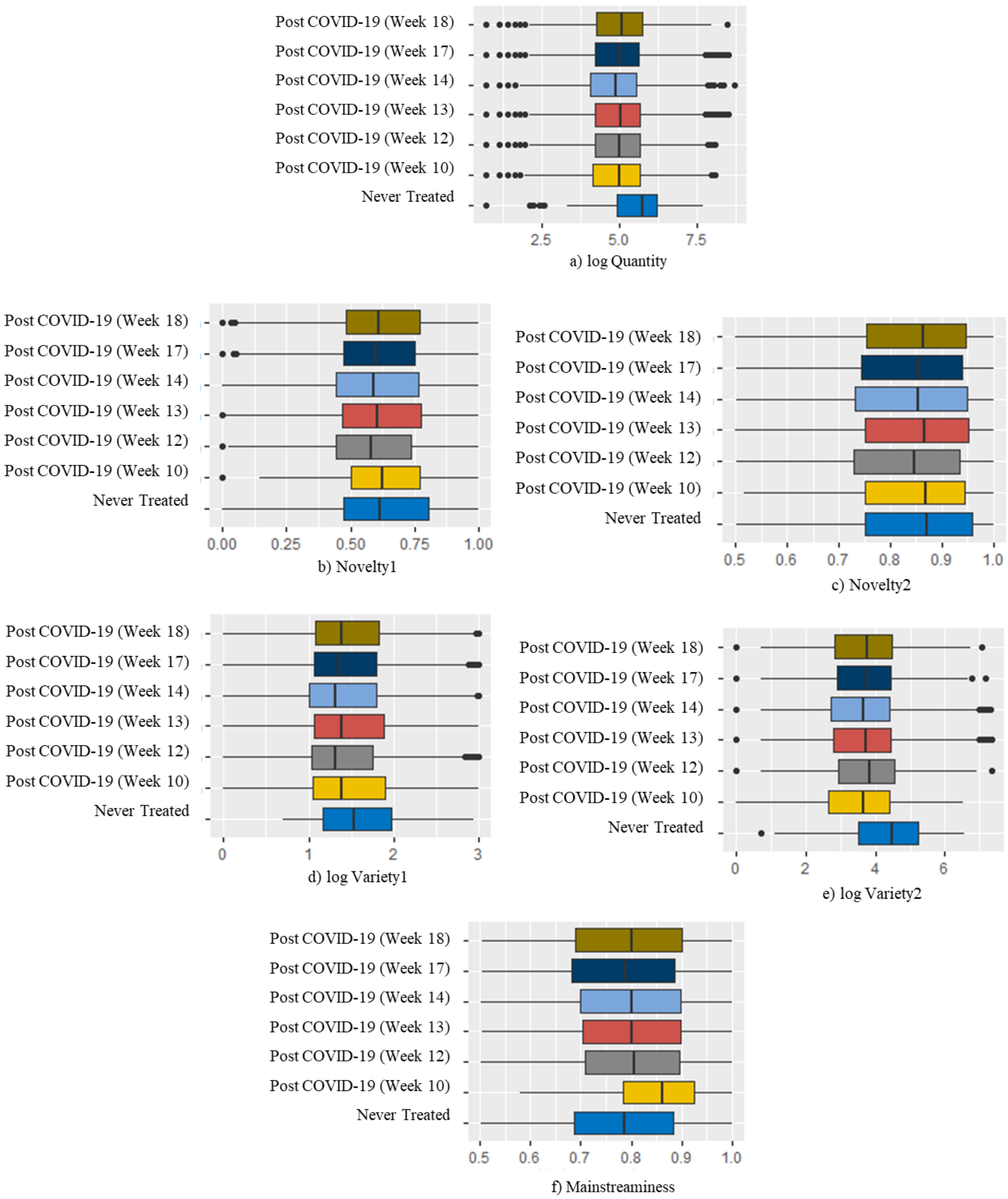


Figure 4.6. Box plot of music listening behaviours among the never-treated group and groups week 10-18

One possible explanation for the decline in music streaming is that music is generally consumed as part of a combined activity instead of a standalone activity (Sim et al., 2022). Statistics cited in (Sim et al., 2022) indicate that nearly 29% of all music consumption occurs in the car, 30% occurs at work or while performing routine tasks, and 54% of consumers listen to music while commuting to work. In addition, reduced participation in events suitable for music listening, such as outdoor activities, parties, and galleries due to the COVID-19 pandemic, may be responsible for decreased music consumption. The analysis of the stringency index in our study, which indicates the level of government restrictions in various countries, such as closing schools and workplaces and imposing travel restrictions, also confirms the negative impact of COVID-19 on the quantity, novelty, and variety of music consumption.

An important feature of online music consumption is that services have made the music experience more personal (Hagen & Lüders, 2016; Stewart et al., 2018). In fact, digital platforms have changed the way people listen to music and turned music listening into a more individual activity (Karatay, 2022). However, in response to the initial COVID-19 restrictions and isolation requirements, people have since turned to activities that engender a stronger sense of socialisation and community (Grigoriadou, 2021). Researchers have also observed a "migration of music consumers from audio-based to video-based streaming services" since platforms like YouTube permit more active participation than audio-based platforms like Spotify and Pandora (Howlin & Hansen, 2022, p. 4). During the initial stages of the COVID-19 pandemic, various music clips were created to supplement pre-existing music as a response to the crisis (Ziv & Hollander-Shabtai, 2021). Aside from the novelty and significance of "coronamusic" during the lockdowns of 2020, much of this music pertained to music videos (Hansen et al., 2021). Consequently, "to fulfil emotional coping goals, engagement with music may have become more attentive, immersive, multimodal, and active", independent of significant reductions in measurable listening time (Howlin & Hansen, 2022, p. 3).

Online music listening trends cannot be attributed to a shift to more niche markets due to the decline of novelty and variety and the increased preference for mainstream artists found in our research. Likewise, the demand for nostalgia consumption showed a positive increase in response to the COVID-19 lockdowns (Yeung, 2020). Our study on novelty and variety consistently showed that during our research period in the early phases of the pandemic, COVID-19 significantly and negatively affected the desire for unusual or novel items, and users preferred to stick to their previous preferences and mainstream artists. Consumers generally love variety and different kinds of music can reflect users' musical preferences (Datta et al., 2017). However, individuals often choose only one or two styles of music from their favourite playlist in specific situations (Knees & Schedl, 2013). A recent Spotify report indicates that listeners' musical habits turned to relaxing and calming music at the start of COVID-19 pandemic (Lanzoni, 2020).

It is widely agreed that user behaviour research is essential during the current pandemic and for potential future crises (Bu et al., 2020; Howlin & Hansen, 2022; Sim et al., 2022). The behaviour of users during a global crisis that has massive influences requires re-examination, for example, to develop health guidelines for people who are isolated from their communities due to quarantine (Bu et al., 2020). Music is nominated as the second most common method humans use to control their emotions (Parkinson & Totterdell, 1999). However, we found that users did not turn to streaming services to listen to or discover music during the first wave of the COVID-19 pandemic to the level they had in the past. As an alternative, researchers who worked on video games during the pandemic discovered that individuals enjoyed playing video games both to escape the gloomy nature of their daily lives and maintain a sense of uncertainty within the game environment (Boldi et al., 2022).

In response to the stress and isolation caused by the early stages of COVID-19 pandemic, music had the opportunity to provide a positive and therapeutic experience based on an individual's needs (Ramesh, 2020). While our study emphasises that the COVID-19 pandemic adversely affected online listening behaviours during our research period, future research could explore the factors affecting music consumption within the COVID-19 context, such as lack of genre and listener knowledge and unsuitable recommendations. Using the experience of the

COVID-19 pandemic, context-aware music recommendations could offer users more significant opportunities in certain places, times, and according to their COVID-19 preferences (e.g., see Ulleri et al., 2021; Wang et al., 2021). This also relies on artists' partnerships with academics for effective music intervention in disaster situations (Street, 2004). More radically, "academics could join musicians in activism and even direct action on health and other matters" (Andrews et al., 2011, p. 192).

Our study's examination of individual characteristics aligns with previous research investigating the impact of gender and age variables on music listening behaviours. Specifically, our findings indicate that males tend to listen to more music than females, seeking out a greater level of novelty and variety. Previous research supports these results, highlighting differences in music preferences between males and females (Rentfrow & Gosling, 2003). Evidence suggests that males prefer less mainstream music genres, while females favour melodic and popular genres (Berkers, 2012). Specifically, females tend to exhibit a preference for mainstream music genres such as pop (Christenson & Peterson, 1988; Colley, 2008), folk (Hargreaves et al., 1995; Roe, 1985), and classical music (Christenson & Roberts, 1998; Wel et al., 2008). A more detailed discussion can be found in (Christenson & Peterson, 1988; Christenson & Roberts, 1998; North & Hargreaves, 2007).

Although the present study does not delve into the underlying reasons for these gender differences, previous research has suggested that socialisation and cultural factors may be at play. Specifically, males often use music to establish their group affiliation and identity, and to impress others, which may explain their tendency towards non-mainstream music (Colley, 2008; North et al., 2000; Ter Bogt et al., 2017). The desire to impress others is a social motivation that can demonstrate their knowledge and appreciation of more obscure or niche music genres. Females, however, conform to social norms and are more likely to approach music more instrumentally and socially, as opposed to using it for identity construction or impressing others, which is the case with males. Therefore, females prefer more mainstream and sociable music genres (Berkers, 2012; Christenson & Peterson, 1988; Colley, 2008).

Our analyses also yielded several other noteworthy results. While the impact of COVID-19 was negative on three aspects of music listening, quantity, novelty, and variety, this impact was more significant on males than females. This finding could be due to various reasons, such as differences in gender-specific roles and responsibilities at home during the pandemic, variations in the types of music preferred by males and females, or discrepancies in the amount of leisure time available to males and females. For example, females prefer listening to music over playing computer games, while males prefer playing computer games (North et al., 2000). The differences in male and female adolescents' leisure behaviours may be due to gender stereotyping and may be explained by differences in socialisation practices (Gibbons et al., 1997). Considerable research cites in (Martínez-Castilla et al., 2021) indicates women listen to music more often than men to get enjoyment, pleasure, relief from emotional stress, or to lessen loneliness (e.g., Chamorro-Premuzic et al., 2012; Lonsdale & North, 2011; Ter Bogt et al., 2017). In contrast, males were more likely to use music to support their social identity (Lonsdale & North, 2011; Ter Bogt et al., 2011). However, other studies have inconsistently demonstrated that the psychological benefits of singing and listening to music do not appear to be affected by gender (Livesey et al., 2012). The COVID-19 pandemic provides the opportunity to re-examine the music listening behaviours associated with the personal characteristics of the listeners.

Considering the age of the listeners, we could not find any specific differences in the impact of new COVID-19 cases and music listening. However, with the increase in the stringency index, including school closures, working from home, and many other restrictions, older adults showed a more considerable decline in music consumption than younger listeners. We examined specific age groups to understand this effect better. With the increase in the stringency index, young adults (20-39) listened to more music than adolescents (under 20); however, users over 65 years old listened to significantly less music. Among the benefits of music listening, young adults seek to regulate their mood and connect with others, whereas older individuals listen to music to maintain personal growth (Groarke & Hogan, 2016; Lonsdale & North, 2011). Our finding that the negative effect of the stringency index on online music listening was greater among older adults is supported by the study of (Martínez-Castilla et al., 2021), in which retirees reported the lowest impact of music on their wellbeing during the COVID-19. Because earlier COVID-19 challenges caused more social dissociation and isolation in older people than in other age groups, their emotional health was negatively affected, and music was no longer as beneficial as it once was (Cabedo et al., 2021).

Our study indicates that subscribers in music streaming platforms tend to a higher degree of music consumption and possess more diverse and novel music preferences. Previous research has similarly suggested that subscribers are more inclined to listen to more music and explore novel music than non-subscribers (Arditi, 2018; Dimont, 2017). Furthermore, research by Hagen (2015) indicates that subscribers utilise the platform's social and interactive features, such as creating and sharing playlists, increasing their overall listening time. Consequently, subscribers are more likely to use the platform's unique experience to discover new and diverse music and as a way to share music with others. In addition, our study on the impacts of COVID-19 on music streaming platform subscribers, for the first time, reveals that as the stringency index increases, subscribers listen to music with more novelty and variety than non-subscribers. The strategy of focusing on subscribers may have saved music streaming platforms during the COVID-19 shock in the industry.

Another notable finding of our research is that individuals who have been using Last.fm for an extended period tend to listen to more music and have more diverse and novel music listening behaviours, as indicated by the age of their account. This can be attributed to the gradual evolution of their music preferences over time. Research has suggested that registration time could positively affect music listening behaviours (e.g., Anderson et al., 2020; Datta et al., 2017). Nonetheless, it is worth noting that the impact of registration time on music listening behaviours may differ in the COVID-19 context. Therefore, further investigation is necessary to comprehend this association during the COVID-19 pandemic, as our analysis did not reveal any moderating effect of this variable.

4.5.1.2. Social Network Size and Social Community Motives

One of the key observations of our research is that there were significant differences in individuals' inclinations towards using Last.fm as a social network site during the early stages of the COVID-19 pandemic. We found that individuals' social activities moderated their online music listening behaviours during the start of the COVID-19 pandemic – those with social network connections listened to more music than those without connections. Additionally, users who utilised Last.fm as a way to join a community and interact with other users listened to more music with more novelty and variety, not only in general but also during lockdown times. It is likely that social communication and network motivations encourage users to utilise music streaming platforms more frequently than those who use them only to listen to music. During the early stages of the COVID-19 pandemic, social networking and community motives influenced how people listened to music or chose the theme for their emotional feelings. Despite our focus on music listening, the topic of social networking opens up a whole new area for future research.

To our knowledge, existing research has not considered social networking activities alongside online music listening behaviours within the context of COVID-19. Our research connects the limitations of face-to-face socialising and the increased tendency to use social network sites during the COVID-19 pandemic with music listeners' motives to use Last.fm's socialising features. This methodology helped us distinguish socially active users of Last.fm during the COVID-19 pandemic and study their music listening behaviours more nuancedly. We found that during the research period, the negative effects of COVID-19 on online music listening were more pronounced for those who did not use Last.fm as a social networking tool to communicate with the Last.fm community. In contrast, as an indicator of governments' lockdown policies during the outbreak of the COVID-19 pandemic, the stringency index had a significant and positive effect on online music listening when it interacted with social communication. Streaming platforms that rethink the design of their services can benefit from integrating social networking features, much like Last.fm positioning itself as a social music platform.

Since the start of the COVID-19 pandemic, various industries have been affected both positively and negatively. The positive implications are clear in some industries, such as IT and software; however, the online music industry was reversely impacted (Seetharaman, 2020). The majority of COVID-19 response strategies were developed in conjunction with the transformation of traditional business models (Khlystova et al., 2022). Specifically, technology transformation has also been examined in the human-computer interaction community (Boldi et al., 2022). The significant impact of digital and technology transformation is due to the innovative design of products and services that enhance users' experiences. For example, the live streams conducted during the early stages of the COVID-19 pandemic increased feelings of physical and social presence (Onderdijk et al., 2021). Based on the perception of Last.fm as a social network site centred around music listening, we suggest that online streaming platform business models focus on how users discover, share, and discuss music. We propose that social communities can be utilised as effective business models to boost the performance of online music platforms throughout the remainder of the COVID-19 pandemic. The design of music streaming platforms such as Spotify and Apple Music could be examined as a future research topic to see how social dynamics might affect them (Stewart et al., 2018).

In recent years, the expansion of social networks has led to several significant changes in the music streaming industry to fill the gap in online communication (Dewan et al., 2017). Over time, features of online streaming services have developed to resemble those of social network sites (e.g., Facebook, Twitter). Users can listen to songs and follow users, watch their favourite songs, post, and reply. While some social features are designed to promote the online music community, for example, the “friend feed” feature provided by Spotify, Kirk et al. (2016) found that participants in their study on music listening behaviours were not interested in using this feature to stay in touch and listen to music; rather, they listened to music with their friends only when co-located. These results suggest there may be more design gaps in the social elements of online music platforms than a lack of interest in socialising behaviours, for example, co-listening (Stewart et al., 2018). In spite of the widespread use of social networking sites that revolve around shared interests, social networking is generally not seen as dependent on online music listening, meaning its vast benefit to online music services is underrated.

Although social networking could provide many advantages for the music streaming industry, these platforms still have gaps. For example, to ensure that a website is design-oriented and in compliance with different marketing strategies, service providers need to foster social connections on their sites to encourage social interaction and consumer consumption simultaneously (Dewan et al., 2017). Emerging music streaming services enable users to connect and share ideas rather than merely listen to music. Some prominent examples of this service are Wavy.fm[5], Hype[6], and Localify[7]. Our research suggests that, as the music streaming industry aims to monetise music consumption, social networking components can effectively regain market share through new revenue streams.

[5] https://wavy.fm
[6] https://hypem.com
[7] https://localify.org/

Our research provides us with the opportunity to re-examine the design of content streaming services in two ways: (1) by including social features in streaming services and (2) by integrating social technologies (such as ICTs) into streaming services. In the first instance, it is plausible that our results can be generalised to other experience products, such as online videos, books, software, and other digital content. Furthermore, it would be helpful to study user behaviour regarding social connections and communication motives in services other than music in greater detail, such as online gaming communities (e.g., Xbox Live Communities), online book communities (e.g., LibraryThing), e-sports streaming platforms (e.g., Twitch), and online fitness communities (e.g., ikePlus.com). In the second instance, mainstream social network sites such as Facebook and Twitter are increasingly used to consume content, including listening to music and viewing videos. The interconnectivity between social network sites and streaming services is undervalued because neither is a dependent technology.

4.5.2. Implication for Practice

Based on our findings, we present the following practical implications. By emphasising the social dynamics of online platforms, music streaming services and other digital platforms, such as video hosting services and software solutions, can respond to the current pandemic and future crises. In addition, owners of digital platforms seeking to increase consumption should consider the implications of social media strategies. It may be beneficial to take advantage of listeners' social and community motivations to encourage digital media consumption and engagement, resulting in more website revenue. We found that during the initial stages of the COVID-19 pandemic, people's online music listening habits varied depending on the characteristics of individual listeners. Platform providers are encouraged to adopt recommendation strategies based on the type of user and the type of music produced in a particular context (in our case, the COVID-19 pandemic).

To fully align with the social dynamics of social network sites, digital platforms need to create more features such as live chats, live streaming, and multi-streaming to use the most of social dynamics. While the social characteristics of platforms are essential to increase the quantity of music listening, they are even more important in promoting novelty, variety, and listening to music outside of mainstream artists. In the design of a digital streaming platform, there could be more socialising features common to social network sites, such as indicating a friend online, tags in a comment or post, and sharing a co-experience (e.g., attending events in Last.fm). In terms of applications, it may be easier to achieve this goal if platforms offer more innovative features, such as displaying the number of listeners present or notifying the user when a friend selects to co-listen (Stewart et al., 2018).

The artificial intelligence (AI) and machine learning advances on NEs within social media platforms opens an intriguing realm of research. These technological advancements are poised to reshape online platforms significantly. First, AI-driven recommendation systems have transformed content discovery by tailoring content to users' preferences, strengthening positive NEs. Secondly, AI can uncover latent connections and interests among users, broadening the network's scope and intensifying NEs. Moreover, AI streamlines content creation and sharing, encouraging more frequent user interactions. Additionally, predictive analytics in AI can optimise user acquisition strategies, accelerating network growth. Real-time engagement, facilitated by AI sentiment analysis, ensures platform relevance, and aligns with user needs, reinforcing NEs. Last but not least, AI extracts valuable insights from user data, fuelling iterative platform improvements, and creating a virtuous cycle of enhanced features, attracting more users, and amplifying NEs. This fascinating area of research explores how AI and machine learning redefine the intricacies of NEs in online platforms, promising exciting possibilities for platform providers and researchers to combine the data NEs (see Gregory et al., 2020).

4.6. Conclusion and Future Research Directions

4.6.1. Conclusion

In this research, we utilised the unanticipated outbreak of COVID-19 as a real-world event to investigate the causal association between the pandemic and individuals' music consumption and discoveries. Shifts in mood caused by an event can drive changes in music listening behaviours. Therefore, context-aware music recommendation systems can boost recommendation results by capturing and representing contextual information compared to conventional recommendation systems. The emotional aspect of music relates to wellbeing theories. Thus, we addressed the need to determine whether users changed their song choices during the early phases of the pandemic. However, our results showed a decrease in online music listening by 15% due to the COVID-19 pandemic. With this in mind, we utilised the DiD method to study the causal impact of the COVID-19 pandemic on variety, novelty, and mainstreaminess. We additionally found that with the increase of weekly COVID-19 cases and strengthening lockdown policies during the first wave of the COVID-19 pandemic, the choices of music listeners became more mainstream with less variety and novelty. However, the results showed that even when the stringency index was extremely high, such as above 80%, individuals with social networks or those who used the Last.fm platform to communicate with others listened to more music with significantly more novelty and variety. As a final point, we discussed the implications of our research for academics and practitioners.

4.6.2. Future Research Directions

In Table 4.17, we present a summary of the contributions of this research and future research directions based on the opportunities the research provides. Potential research questions support each research direction.

Table 4.17. Future research directions

Research Area	Contribution	Potential Research Questions
1. Impact of COVID-19 on online music listening behaviours	We identified the contextual online music listening behaviours in response to the first wave of the COVID-19 pandemic from a set of variables much broader than used in previous studies. In addition, the social dynamics of the streaming platforms were discussed as the moderator of the impact of COVID-19 on music listening.	Q1. What other variables measure, moderate, or mediate online music listening behaviours? Q2. How did the Last.fm users' listening patterns during the COVID-19 pandemic differ from those on other platforms?
2. Factors affecting music listening behaviours within the COVID-19 context	While our study emphasised that the first wave of the COVID-19 pandemic adversely affected online music listening behaviours, future research could explore the factors affecting music consumption within the Covid-19 context, such as lack of genre, listeners' knowledge, and unsuitable recommendations.	Q3. What is the reason behind the changes in online music listening behaviours?
3. Social dynamics of online platforms	There is a potential for future research to examine the socialising features of online platforms similar to social networking sites and how those features can be translated into opportunities for streaming platforms in different ways.	Q4. What role does design initiative play in influencing user behaviours on streaming platforms? Q5. How can platform owners develop more proactive approaches when responding to issues instead of simply accepting them as exogenous forces?
4. Insights from sentiment analysis	When conducting our research, we noted opportunities to review changes in music sentiments, such as in the lyrics, comments, tags. These matches noted changes in song titles that replicate the sentiments of the society during a real-world event (Liu et al., 2020). The qualitative aspects of shouts on Last.fm indicate that the communication features of Last.fm primarily facilitates discussions about music (Mechant & Evens, 2011). As a promising direction for future research, we also suggest analysing listeners' comments on Last.fm during the Covid-19	Q6. What are the changes in the sentiment of song lyrics consumed within the context of the Covid-19 pandemic? Q7. What are the changes in the sentiment of communications within the music community after the COVID-19 pandemic?

Research Area	Contribution	Potential Research Questions
	pandemic and examining the ensuing changes.	
5. Methodological improvements	We conducted a study on Last.fm; generally, the development of streaming as a phenomenon and its evolution requires more research across various industries and disciplines. Furthermore, it would be helpful to study user behaviours in services other than music in greater detail, such as online gaming communities, online book communities, e-sports streaming platforms, and online fitness communities.	Q8. How did the COVID-19 pandemic impact other user behaviours, such as gaming and video streaming? Q9. How can the results of this study be generalised to different music platforms?

Data Availability Statements

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Chapter 5 - Summary, Conclusions, and Recommendations

5.1. Summary and Conclusions

This thesis aimed to enhance the understanding of network effects (NEs) on online platforms by introducing a comprehensive theoretical construct and practical framework that surpasses the limitations of network size, thereby opening up fresh perspectives and insights into the dynamic nature of NEs. Through an extensive longitudinal empirical analysis, this study demonstrated the practical application of the developed NEs construct in investigating user behaviour, specifically focusing on unravelling the intricate dynamics of users' music listening. Furthermore, this research illuminated the importance of contextual factors in understanding user behaviour on online platforms, emphasising how context influences a user's motivation to connect to a platform, as demonstrated by the study of the COVID-19 pandemic.

Figure 5.1 summarises the main findings and conclusions from three chapters and illustrates how they align with the thesis objectives.

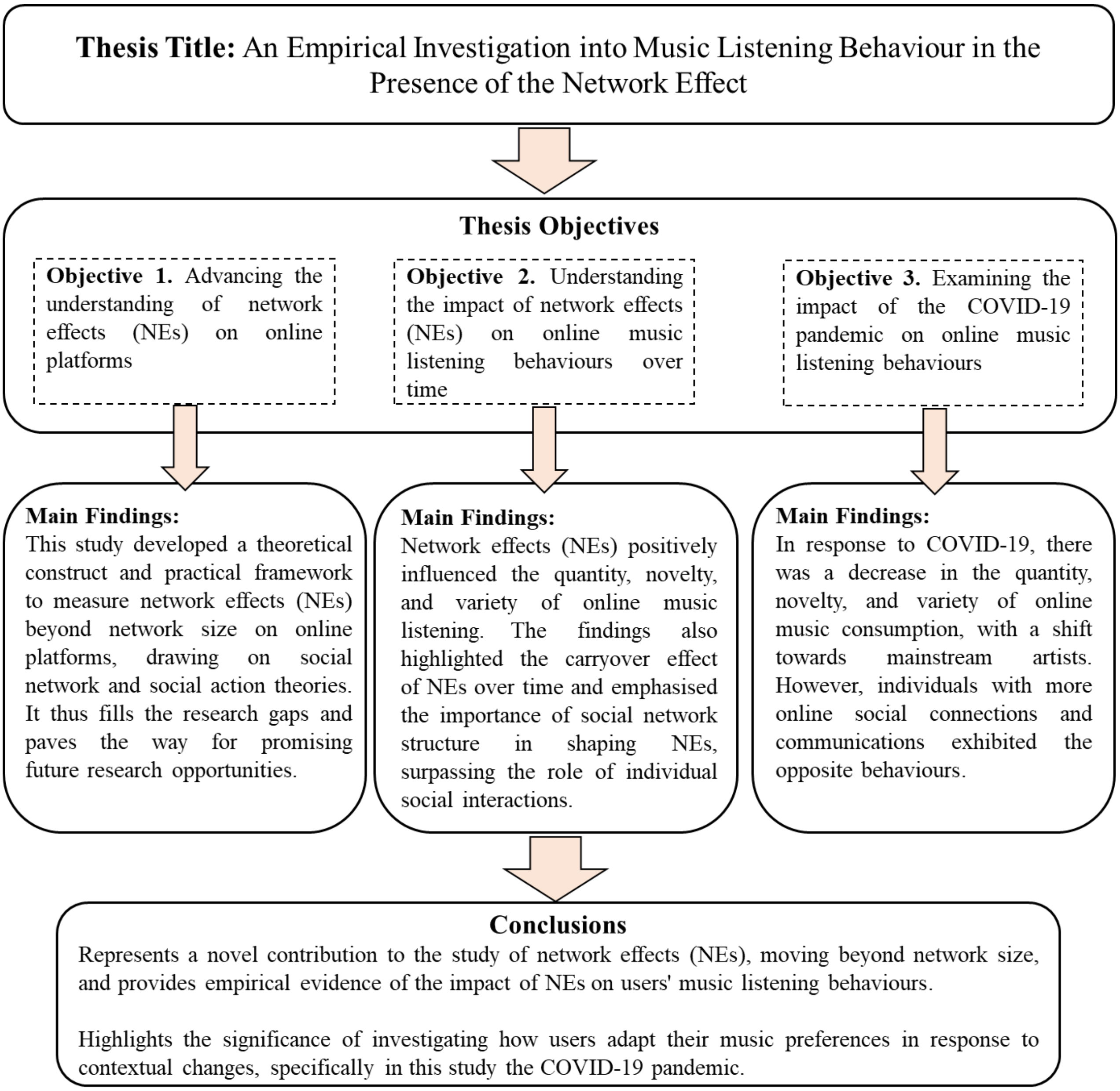


Figure 5.1. PhD thesis overview

5.1.1. Advancing the Understanding of Network Effects (NEs) in Online Platforms

In the first study of the thesis, we aimed to highlight the limitations of traditional NEs when applied to online platforms and develop a novel construct that goes beyond the concept of network size. We found that the NEs literature introduce variables derived from social network and social action theories. However, these studies have yielded limited results as they have focused on only a few components of these dimensions from either one of these two theories at a time, disregarding other crucial aspects of NEs. Additionally, the studies lack a practical framework supported by empirical foundations. Consequently, this study identified that despite the continuous development of NEs research and variations in methodological approaches, there remains a lack of a unified NEs model.

To bridge the research gaps, this first study moved away from a merely theoretical or conceptual base toward an empirical foundation. The study followed a structured approach to establish the NEs construct, considering the theoretical indicators reported in the literature of the research area, and conducted a focus group to ensure the face and content validity of the construct indicators. Empirical data from 200 Last.fm users and their social connections (including 17,926 nodes and 39,759 edges) were utilised to develop and validate the NEs construct using partial least squares modelling (PLS). This research further provided mathematical measurements of NEs at both the individual and network levels, marking a groundbreaking achievement.

This first study of the thesis offers several key contributions. First, it adds value to the existing body of information systems (IS) research by emphasising the importance of proposing a novel NEs construct that fits within the social dynamics of online platforms or which can be applied to a specific research project. This study advances the understanding of NEs in the context of online platforms and highlights the level of misinterpretation and misuse of NEs in the IS field. Second, the proposed NEs model holds significant potential for application in diverse research areas, such as user behaviour, technology acceptance, information diffusion, and the value system of online platforms, providing a foundation for future empirical studies. Next, by understanding the interplay between users' positions in the social network and the social interactions within online platforms, this study shows how managers and decision-makers can devise strategies to enhance NEs, increase user satisfaction, and improve business performance in industries that are influenced by NEs.

5.1.2. Understanding the Impact of Network Effects (NEs) on Online Music Listening Behaviours Over Time

In the second study of the thesis, we focused on empirically examining the implications of the proposed NEs construct, building on the measures and significance discussed earlier in our research. Our analysis investigated three distinct effects: (1) the synchronous effect, which explored the immediate association between higher NEs levels and increased quantity, novelty, and variety in music listening at the same point in time; (2) the carryover effect, which investigated the development and emergence of NEs over time, accounting for cumulative resources and predicting NEs at later points while controlling for baseline NEs levels; and (3) the time-varying effect, which explored variations in the relationships between NEs and online music listening behaviours across different time periods. Using a longitudinal design and employing partial least squares structural equation modelling (PLS-SEM), we analysed data from 1,708 Last.fm users in two intervals: January 2022 with 113,158 nodes and 252,747 edges, and July 2022 with 122,495 nodes and 364,158 edges. Our findings highlight that NEs have a significant positive impact on enhancing users' music listening experiences, promoting exploration of unfamiliar music, and increasing the variety and novelty of artists listened to. Additionally, the study identified individual differences in music consumption patterns by incorporating them as control variables.

This second study of the thesis makes significant contributions to two areas: music listening behaviours and the characteristics of NEs in online platforms. It highlights the substantial impact of NEs on users' desire to explore and listen to various artists, thereby expanding their music library and broadening their musical horizons. The findings underscore the long-term influence of NEs on music listening behaviours, emphasising that NEs are not random occurrences but rather strategic determinants in shaping users' long-term music preferences. By recognising NEs as strategic tools rather than external forces, this research provides valuable insights for platform design and management, guiding the use of NEs for sustainable growth and enriched user behaviours. The longitudinal design of the study enhances our understanding of NEs, revealing that while social action initially plays a significant role in shaping NEs through user interactions and engagement, the structural characteristics of a social network, such as connection centrality and structural holes, gain more influence over time, surpassing the impact of social action in driving NEs.

Furthermore, the theoretical and practical framework developed in this study can be extended beyond online music platforms to other digital media, including movies, games, and software. Platform owners and practitioners can benefit from recognising the importance of social dynamics in fostering NEs and influencing users' behaviours, leading to strategic modifications and the introduction of new features to enhance the overall user experience. By embracing the transformative potential of NEs, they can effectively drive user engagement, foster community-building, and facilitate growth. Further, the impact of NEs extends beyond technology sectors, permeating traditional industries including health and real estate, enabling practitioners to influence user behaviours and make informed decisions through the advancement of NEs.

5.1.3. Examining the Impact of the COVID-19 Pandemic on Online Music Listening Behaviours

In the third study of the thesis, we focused on the impact of the global COVID-19 pandemic on music listening behaviours. The positive effects of music on mental health and its potential to alleviate feelings of loneliness, uplift mood, and foster a sense of community during this time have been recognised by a number of scholars (Cabedo et al., 2021; Martín et al., 2021; Ziv & Hollander-Shabtai, 2021). However, we found a lack of comprehensive investigation on how the crisis affected music listening behaviours, particularly in terms of variety, novelty, and mainstreaminess. Therefore, this third study examined how individuals' song preferences changed during the first wave of the pandemic, using COVID-19 variables and theories emphasising social contexts and functional goals in studies of music listening behaviours (Greb et al., 2019; Schäfer & Sedlmeier, 2009). Considering the social dynamics theory of online platforms (Hagen & Lüders, 2016; Salminen et al., 2018), the study also explored the moderating roles of social networks and communication motives in the context of music streaming platforms. The study utilised a large demographically representative sample of Last.fm users, consisting of 37,328 participants from 45 countries. The analysis of the outcomes included both the difference-in-differences (DiD) method, a widely used causal inference approach, to examine the impact of the unexpected COVID-19 outbreak as a real-world event, and the fixed effects (FEs) method to analyse the effects of new COVID-19 cases and restriction policies on the behaviours under investigation.

The findings of the study indicated a significant decrease of 15% in online music listening due to the COVID-19 pandemic. Alongside this decline in online music consumption, there was a noticeable decrease in the novelty and variety of musical tastes, with a shift towards more mainstream artists. However, an interesting observation emerged regarding listeners who had more social ties and engaged in greater communication with friends. These individuals demonstrated distinct changes in behaviour during the pandemic, consuming more music, discovering a wider range of music, and displaying a greater variety of tastes.

The findings of the third study make several significant contributions. First, we show that shifts in mood resulting from an event, such as the COVID-19 pandemic, can lead to changes in music listening behaviours. This highlights the importance of examining how users adapt their music preferences in response to contextual changes. Second, our research identifies the causal relationship between context and its impact on novelty and variety in music consumption, offering valuable insights for music recommendation systems like Last.fm and Spotify. Additionally, our study highlights the significance of online social interaction in analysing music listening behaviours, thereby facilitating the development of consumer behaviour research for a broader range of digital media platforms, including movies and games. In light of our study's findings, it is recommended that online platforms shift their focus from solely emphasising product features to placing greater emphasis on the social aspects of their platforms. By integrating design-oriented research into this study, including the information systems design theory (Walls et al., 1992), platform developers and designers can actively improve the design of digital platforms.

5.2. Future Research Directions

Here, we offer an overview of each chapter's discussion on future research directions, enabling future researchers to delve deeper into the subject matter. We categorise the opportunities derived from this research thesis into three areas: (1) assessing the generalisability of the findings, (2) examining the impact of other variables, and (3) developing methods and data collection techniques. The summary of the thesis opportunities and future research directions are outlined in Table 5.1.

Table 5.1. Summary of thesis opportunities and research directions (3 studies)

<table>
<tr><td>Research Opportunity</td><td>Assessing the generalisability of the findings</td></tr>
<tr><td colspan="2">Research Directions
• Conducting a comparative analysis between Last.fm and other competing or alternative platforms, focusing on the NEs construct and its impact on users' behaviours, would yield valuable insights and further enrich the findings of this research thesis.
• Comparing the listening patterns of Last.fm users during the COVID-19 pandemic or in general with other platforms could provide insights into distinct social dynamics and behaviours across online platforms.
• Future research could expand on the findings of our study, which highlights the adverse effects of the initial wave of the COVID-19 pandemic on online music listening behaviours. This could involve investigating the specific factors that contributed to changes in users' music listening behaviours, such as the availability of appropriate genres, listeners' knowledge, and the suitability of music recommendations.</td></tr>
<tr><td>Research Opportunity</td><td>Examining the impact of other variables</td></tr>
<tr><td colspan="2">Research Directions
• In order to enhance and reinforce the NEs model, integrating additional factors from the platform's standpoint is advantageous. These factors include elements such as platform governance and policies, users' multiple roles, platform interface and user experience, as well as privacy and trust considerations.
• The study also underscores the potential for further refinement of the model by exploring the interaction between the proposed NEs model and data NEs in the data-driven economy, as discussed by Gregory et al. (2020).
• To gain a more comprehensive understanding of the level of NEs, it is advisable to conduct individual-level studies focusing on the relationship between demographic factors and NEs. This research approach would provide deeper insights into how demographic variables influence the level of NEs (e.g., see Katona et al., 2011; Maicas et al., 2009; Voigt & Hinz, 2015).
• To further explore the relationship between NEs and music listening behaviours, it is important to consider additional factors that were not included in this study. These factors can serve as control variables and also act as moderators or mediators, providing a more comprehensive understanding of the dynamics between NEs and music listening behaviours.</td></tr>
<tr><td>Research Opportunity</td><td>Developing methods and data collection techniques</td></tr>
<tr><td colspan="2">Research Directions
• While this research primarily focused on the theory of positive NEs (Weitzel et al., 2000), it is recommended that future studies differentiate between positive and negative effects or direct and indirect NEs (as discussed in Parker et al., 2016) to provide a more nuanced understanding.
• The inclusion of user-generated content, such as comments and tags, could provide valuable insights into the experiences of platform users within the context of NEs and COVID-19 studies.
• Conducting a longitudinal study with multiple data collection points over more than one year is crucial for accurately capturing changes in NEs levels and their corresponding outcomes.</td></tr>
</table>

Master Reference List

Afuah, A. (2013). Are network effects really all about size? The role of structure and conduct. *Strategic Management Journal*, *34*(3), 257-273. https://doi.org/10.1002/smj.2013

Aguiar, L. (2017). Let the music play? Free streaming and its effects on digital music consumption. *Information Economics and Policy*, *41*, 1-14. https://doi.org/10.1016/j.infoecopol.2017.06.002

Aguiar, L., & Waldfogel, J. (2018). As streaming reaches flood stage, does it stimulate or depress music sales? *International Journal of Industrial Organization*, *57*, 278-307. https://doi.org/10.1016/j.ijindorg.2017.06.004

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly*, *45*(3), 425-455. https://doi.org/10.2307/2667105

Aiello, L. M., Barrat, A., Schifanella, R., Cattuto, C., Markines, B., & Menczer, F. (2012). Friendship prediction and homophily in social media. *ACM Transactions on the Web (TWEB)*, *6*(2), 1-33. https://doi.org/10.1145/2180861.2180866

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

Allison, P. D. (2009). *Fixed effects regression methods for longitudinal data using SAS*. SAS Institute Inc.

Anderson, A., Maystre, L., Anderson, I., Mehrotra, R., & Lalmas, M. (2020). Algorithmic Effects on the Diversity of Consumption on Spotify. Proceedings of The Web Conference 2020, 2155–2165. https://doi.org/10.1145/3366423.3380281

Andrews, G. J., Kearns, R. A., Kingsbury, P., & Carr, E. R. (2011). Cool aid? Health, wellbeing and place in the work of Bono and U2. *Health & Place*, *17*(1), 185-194. https://doi.org/10.1016/j.healthplace.2010.09.008

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion* (1st ed.). Princeton University Press.

Arditi, D. (2018). Digital subscriptions: The unending consumption of music in the digital era. *Popular Music and Society*, *41*(3), 302-318. https://doi.org/http://dx.doi.org/10.1080/03007766.2016.1264101

Arnaboldi, V., Conti, M., La Gala, M., Passarella, A., & Pezzoni, F. (2016). Ego network structure in online social networks and its impact on information diffusion. *Computer Communications*, *76*, 26-41. https://doi.org/10.1016/j.comcom.2015.09.028

Arnaboldi, V., Conti, M., Passarella, A., & Dunbar, R. I. M. (2017). Online social networks and information diffusion: The role of ego networks. *Online Social Networks and Media*, *1*, 44-55. https://doi.org/10.1016/j.osnem.2017.04.001

Arnaboldi, V., Conti, M., Passarella, A., & Pezzoni, F. (2012 September 03-05). *Analysis of ego network structure in online social networks* [Paper presentation]. International Conference on Privacy, Security, Risk and Trust and 2012 International Confernece on Social Computing, Amsterdam, Netherlands, 31-40. https://doi.org/10.1109/SocialCom-PASSAT.2012.41

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, *99*(394), 116-131.

Arthur, W. B. (2021). Foundations of complexity economics. *Nature Reviews Physics*, *3*(2), 136-145. https://doi.org/10.1038/s42254-020-00273-3

Asghar, M. Z., Iqbal, A., Seitamaa-Hakkarainen, P., & Barbera, E. (2021). Breaching learners' social distancing through social media during the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, *18*(21), 11012. https://doi.org/10.3390/ijerph182111012

Asvanund, A., Clay, K., Krishnan, R., & Smith, M. D. (2004). An empirical analysis of network externalities in peer-to-peer music-sharing networks. *Information Systems Research*, *15*(2), 155-174. https://doi.org/10.1287/isre.1040.0020

Bailey, D., & Katz, J. N. (2011). Implementing panel-corrected standard errors in R: The pcse package. *Journal of Statistical Software*, *42*, 1-11. https://doi.org/10.18637/jss.v042.c01

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370-395. https://doi.org/10.1016/j.jfineco.2022.01.004

Barbia, G. (2011, Septemeber 12-14). *Trust centrality in online social networks* [Paper presentation]. European Intelligence and Security Informatics Conference, Athens, Greece, 372–377. https://doi.org/10.1109/EISIC.2011.17

Barclay, D., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies*, *2*, 285-309.

Bateman, P. J., Gray, P., & Butler, B. (2010). The impact of community commitment on participation in online communities. *Information Systems Research*, *22*(4), 841-854. https://doi.org/10.1287/isre.1090.0265

Bauer, C., & Schedl, M. (2019). Global and country-specific mainstreaminess measures: Definitions, analysis, and usage for improving personalized music recommendation systems. *PloS One*, *14*(6), e0217389.

https://doi.org/10.1371/journal.pone.0217389

Baym, N. K. (2013). Data not seen: The uses and shortcomings of social media metrics. *First Monday*, *18*(10). https://doi.org/10.5210/fm.v18i10.4873

Baym, N. K., & Ledbetter, A. (2009). Tunes that bind? *Information, Communication & Society*, *12*(3), 408-427. https://doi.org/10.1080/13691180802635430

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science review*, *89*(3), 634-647. https://doi.org/10.2307/2082979

Becker, J.-M., Klein, K., & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models. *Long Range Planning*, *45*(5-6), 359-394. https://doi.org/10.1016/j.lrp.2012.10.001

Beckstrom, R. (2009). *A new model for network valuation* [Research paper]. National Cybersecurity Center.

Berkers, P. (2012). Gendered scrobbling: Listening behaviour of young adults on Last.fm. *Interactions: Studies in Communication & Culture*, *2*(3), 279-296. https://doi.org/10.1386/iscc.2.3.279_1

Bhattacharya, P., Phan, T. Q., Bai, X., & Airoldi, E. M. (2019). A coevolution model of network structure and user behavior: The case of content generation in online social networks. *Information Systems Research*, *30*(1), 117-132. https://doi.org/10.1287/isre.2018.0790

Bischoff, K. (2012). We love rock'n'roll: Analyzing and predicting friendship links in Last.fm. Proceedings of the 4th Annual ACM Web Science Conference, Evanston, Illinois, 47–56. https://doi.org/10.1145/2380718.2380725

Boldi, A., Rapp, A., & Tirassa, M. (2022). Playing during a crisis: The impact of commercial video games on the reconfiguration of people's life during the COVID-19 pandemic. *Human–Computer Interaction* (ahead-of-print), 1-42. https://doi.org/10.1080/07370024.2022.2050725

Boudourides, M. (2018). *Cumulative rank aggregation of a family of network centrality indices*. Medium. https://medium.com/@mosabou/cumulative-rank-aggregation-of-a-family-of-network-centrality-indices-e625a76bf7e4

Boudreau, K. (2010). Open platform strategies and innovation: Granting access vs. devolving control. *Management Science*, *56*(10), 1849-1872. https://doi.org/10.1287/mnsc.1100.1215

Boulet, R., & Lebraty, J. F. (2018). A new influence measure based on graph centralities and social network behavior applied to Twitter data. *Communications of the Association for Information Systems*, *43*(1), 360 – 377. https://doi.org/10.17705/1CAIS.04321

Bowling, N. A., & Hammond, G. D. (2008). A meta-analytic examination of the construct validity of the Michigan Organizational Assessment Questionnaire job satisfaction subscale. *Journal of Vocational Behavior*, *73*(1), 63-77. https://doi.org/10.1016/j.jvb.2008.01.004

Bowman, N. D., Rieger, D., & Tammy Lin, J.-H. (2022). Social video gaming and well-being. *Current Opinion in Psychology*, *45*, 101316. https://doi.org/10.1016/j.copsyc.2022.101316

Bu, F., Steptoe, A., Mak, H. W., & Fancourt, D. (2020). Time-use and mental health during the COVID-19 pandemic: A panel analysis of 55,204 adults followed across 11 weeks of lockdown in the UK. *MedRxiv*. https://doi.org/10.1101/2020.08.18.20177345

Buettner, R. (2017). Getting a job via career-oriented social networking markets. *Electronic Markets*, *27*(4), 371-385. https://doi.org/10.1007/s12525-017-0248-3

Burt, R. S. (1982). *Toward a structural theory of action: Network models of social structure, perception, and action*. Academic Press. https://doi.org/10.1016/C2009-0-21953-2

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Harvard University Press.

Buskens, V. (2020). Spreading information and developing trust in social networks to accelerate diffusion of innovations. *Trends in Food Science & Technology*, *106*, 485-488. https://doi.org/10.1016/j.tifs.2020.10.040

Cabedo, A., Arriaga, C., & Moliner, L. (2021). Uses and perceptions of music in times of COVID-19: A Spanish population survey. *Frontiers in Psychology*, *11*, 1-13. https://doi.org/10.3389/fpsyg.2020.606180

Callaway, B. (2022). Difference-in-differences for policy evaluation. *arXiv.org:2203.15646*. https://doi.org/10.48550/arXiv.2203.15646

Callaway, B., & Karami, S. (2022). Treatment effects in interactive fixed effects models with a small number of time periods. *Journal of Econometrics*, *233*(1), 184-208. https://doi.org/10.1016/j.jeconom.2022.02.001

Callaway, B., & Sant'Anna, P. (2020). *Getting started with the did package*. GitHub. https://bcallaway11.github.io/did/articles/did-basics.html

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200-230. https://doi.org/10.1016/j.jeconom.2020.12.001

Carroni, E., & Paolini, D. (2019). *The business model of a streaming platform* [Working paper]. Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

Castells, P., Hurley, N. J., & Vargas, S. (2015). Novelty and diversity in recommender systems. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender systems handbook* (pp. 881-918). Springer. https://doi.org/10.1007/978-1-4899-7637-6_26

Cenfetelli, R. T., & Bassellier, G. (2009). Interpretation of formative measurement in information systems research. *MIS Quarterly*, *33*(4), 689-707. https://doi.org/10.2307/20650323

Chamorro-Premuzic, T., Swami, V., & Cermakova, B. (2012). Individual differences in music consumption are predicted by uses of music and age rather than emotional intelligence, neuroticism, extraversion or openness. *Psychology of Music*, *40*(3), 285-300. https://doi.org/10.1177%2F0305735610381591

Chan-Olmsted, S., Wang, R., & Hwang, K.-H. (2019). Substitutability and complementarity of broadcast radio and music streaming services: The millennial perspective. *Mobile Media & Communication*, *8*(2), 209-228. https://doi.org/10.1177%2F2050157919856647

Chin, W., & Newsted, P. (1999). Structural equation modeling analysis with small samples using partial least square. *Statistical Strategies for Small Sample Research*, *1*(1), 307-341.

Christenson, P. G., & Peterson, J. B. (1988). Genre and gender in the structure of music preferences. *Communication Research*, *15*(3), 282-301. https://doi.org/10.1177/009365088015003004

Christenson, P. G., & Roberts, D. F. (1998). It's not only rock & roll: Popular music in the lives of adolescents. *Journal of Communication*, *49*(4), 212-229. https://doi.org/10.1111/j.1460-2466.1999.tb02829.x

Clough, D. R., & Wu, A. (2020). Artificial intelligence, data-driven learning, and the decentralized structure of platform ecosystems. *Academy of Management Review*, *47*(1), 184–189. https://doi.org/10.5465/amr.2020.0222

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159. https://doi.org/10.1037/0033-2909.112.1.155

Colley, A. (2008). Young people's musical taste: Relationship with gender and gender-related traits. *Journal of Applied Social Psychology*, *38*(8), 2039-2055. https://doi.org/10.1111/j.1559-1816.2008.00379.x

Cordeiro, M., Sarmento, R. P., Brazdil, P., & Gama, J. (2018). Evolving networks and social network analysis methods and techniques. In J. Višňovský & J. Radošinská (Eds.), *Social media and journalism-trends, connections, implications* (pp. 101-134). IntechOpen.

Cousins, K., Subramanian, H., & Esmaeilzadeh, P. (2019). A value-sensitive design perspective of cryptocurrencies: A research agenda. *Communications of the Association for Information Systems*, *45*(1), 511-547. https://doi.org/10.17705/1CAIS.04527

Datta, H., Knox, G., & Bronnenberg, B. J. (2017). Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery. *Marketing Science*, *37*(1), 5-21. https://doi.org/10.1287/mksc.2017.1051

Davidson, J., Liebald, B., Liu, J., Nandy, P., Vleet, T. V., Gargi, U., Gupta, S., He, Y., Lambert, M., Livingston, B., & Sampath, D. (2010). The YouTube video recommendation system. Proceedings of the fourth ACM conference on Recommender systems, 293–296. https://doi.org/10.1145/1864708.1864770.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

De Nooy, W. (2009). Formalizing symbolic interactionism. *Methodological Innovations Online*, *4*(1), 39-51. https://doi.org/10.1177/205979910900400105

De Reuver, M., Sørensen, C., & Basole, R. C. (2018). The digital platform: A research agenda. *Journal of Information Technology*, *33*(2), 124-135. https://doi.org/10.1057/s41265-016-0033-3;

De Vries, L., Gensler, S., & Leeflang, P. S. H. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing*, *26*(2), 83-91. https://doi.org/10.1016/j.intmar.2012.01.003

Dewan, S., Ho, Y.-J., & Ramaprasad, J. (2017). Popularity or proximity: Characterizing the nature of social influence in an online music community. *Information Systems Research*, *28*(1), 117-136. https://doi.org/10.1287/isre.2016.0654

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management*, *17*(4), 263-282. https://doi.org/10.1111/j.1467-8551.2006.00500.x

Dimont, J. (2017). Royalty inequity: Why music streaming services should switch to a per-subscriber model. *Hastings Law Journal*, *69*(2), 675-700.

Doleck, T., Lajoie, S. P., & Bazelais, P. (2019). Social networking and academic performance: A longitudinal perspective. *Education and Information Technologies*, *24*(2), 1545-1561. https://doi.org/10.1007/s10639-018-9843-y

Dunbar, R. I. M. (2016). Do online social media cut through the constraints that limit the size of offline social networks? *Royal Society Open Science*, *3*(1), 150292.

https://doi.org/10.1098/rsos.150292

Dunbar, R. I. M., Arnaboldi, V., Conti, M., & Passarella, A. (2015). The structure of online social networks mirrors those in the offline world. *Social Networks*, *43*, 39-47. https://doi.org/10.1016/j.socnet.2015.04.005

Dwork, C., Kumar, R., Naor, M., & Sivakumar, D. (2001). Rank aggregation methods for the web. Proceedings of the 10th international conference on World Wide Web, 613–622. https://doi.org/10.1145/371920.372165

Economides, N., & Himmelberg, C. P. (1995). Critical mass and network size with application to the US fax market. *NYU Stern School of Business EC-95-11*. https://doi.org/https://dx.doi.org/10.2139/ssrn.6858

Eisenmann, T., Parker, G., & Van Alstyne, M. (2011). Platform envelopment. *Strategic Management Journal*, *32*(12), 1270-1285. https://doi.org/10.1002/smj.935

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two sided markets. *Harvard Business Review*, *84*(10), 92-101.

Elliott, D., Polman, R., & McGregor, R. (2011). Relaxing music for anxiety control. *Journal of Music Therapy*, *48*(3), 264-288. https://doi.org/10.1093/jmt/48.3.264

Erikson, E. H. (1993). *Childhood and society*. WW Norton & Company.

Estrada, E., & Knight, P. A. (2015). *A first course in network theory*. Oxford University Press.

Farrell, J., & Saloner, G. (1985). Standardization, compatibility, and innovation. *RAND Journal of Economics*, *16*(1), 70-83. https://doi.org/10.2307/2555589

Farrell, J., & Saloner, G. (1986). Installed base and compatibility: Innovation, product preannouncements, and predation. *The American Economic Review*, *76*(5), 940-955.

Feng, J., Shi, D., & Luo, X. (2018). An identification method for important nodes based on k-shell and structural hole. *Journal of Complex Networks*, *6*(3), 342-352. https://doi.org/ https://doi.org/10.1093/comnet/cnx035

Fenwick, M., McCahery, J. A., & Vermeulen, E. P. M. (2019). The end of 'Corporate' governance: Hello 'Platform' governance. *European Business Organization Law Review*, *20*(1), 171-199. https://doi.org/10.1007/s40804-019-00137-z

Ferwerda, B., Tkalcic, M., & Schedl, M. (2017). Personality traits and music genre preferences: How music taste varies over age groups. Proceedings of the 1st Workshop on Temporal Reasoning in Recommender Systems (RecTemp) at the 11th ACM Conference on Recommender Systems, 16-20.

Ferwerda, B., Vall, A., Tkalcic, M., & Schedl, M. (2016). Exploring music diversity needs across countries. Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization, 287–288. https://doi.org/10.1145/2930238.2930262.

Ferwerda, B., Yang, E., Schedl, M., & Tkalcic, M. (2019). Personality and taxonomy preferences, and the influence of category choice on the user experience for music streaming services. *Multimedia Tools and Applications*, *78*(14), 20157-20190. https://doi.org/10.1007/s11042-019-7336-7

Fink, L. K., Warrenburg, L. A., Howlin, C., Randall, W. M., Hansen, N. C., & Wald-Fuhrmann, M. (2021). Viral tunes: Changes in musical behaviours and interest in coronamusic predict socio-emotional coping during COVID-19 lockdown. *Humanities and Social Sciences Communications*, *8*(1), 1-11. https://doi.org/10.1057/s41599-021-00858-y

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Addison-Wesley.

Fornell, C., & Cha, J. (1994). Partial least squares. In R. Bagozzi (Ed.), *Advanced marketing research* (pp. 52-78). Blackwell.

Frei-Landau, R. (2020). "When the going gets tough, the tough get—Creative": Israeli Jewish religious leaders find religiously innovative ways to preserve community members' sense of belonging and resilience during the COVID-19 pandemic. *Psychological Trauma: Theory, Research, Practice, and Policy*, *12*(S1), S258. https://doi.org/https://psycnet.apa.org/doi/10.1037/tra0000822

Fuhse, J. A. (2009). The meaning structure of social networks. *Sociological Theory*, *27*(1), 51-73. https://doi.org/10.1111/j.1467-9558.2009.00338.x

Fuhse, J. A. (2020). Theories of social networks. In R. Light & J. Moody (Eds.), *The Oxford handbook of social networks* (pp. 34-49). Oxford University Press.

Furht, B. (2010). *Handbook of social network technologies and applications*. Springer.

Garson, G. D. (2016). *Partial least squares: Regression and structural equation models*. Statistical Associates.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51-90. https://doi.org/10.2307/30036519

Ghaffar, F., & Hurley, N. (2021). Modelling social capital: The structural hole connections game. Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, 9–13. https://doi.org/10.1145/3487351.3488365

Ghanem, M., Magnien, C., & Tarissan, F. (2018). Centrality metrics in dynamic networks: a comparison study. *IEEE Transactions on Network Science Engineering*, *6*(4), 940-951. https://doi.org/10.1109/TNSE.2018.2880344

Ghapanchi, A. H., & Tavana, M. (2015). A longitudinal study of the impact of open source software project characteristics on positive outcomes. *Information Systems Management*, *32*(4), 285-298. https://doi.org/10.1080/10580530.2015.1079999

Gibbons, J. L., Lynn, M., & Stiles, D. A. (1997). Cross-national gender differences in adolescents' preferences for free-time activities. *Cross-Cultural Research*, *31*(1), 55-69. https://doi.org/10.1177%2F106939719703100104

Gilfoil, D. M., & Jobs, C. (2012). Return on investment for social media: A proposed framework for understanding, implementing, and measuring the return. *Journal of Business and Economics Research*, *10*(11), 637-650. https://doi.org/10.19030/jber.v10i11.7363

Gneiser, M., Heidemann, J., Klier, M., Landherr, A., & Probst, F. (2012). Valuation of online social networks taking into account users' interconnectedness. *Information Systems and e-Business Management*, *10*(1), 61-84. https://doi.org/10.1007/s10257-010-0153-1

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., & Verlegh, P. (2005). The firm's management of social interactions. *Marketing Letters*, *16*(3/4), 415-428. https://doi.org/10.1007/s11002-005-5902-4

Golbeck, J. (2013). *Analyzing the social web*. Elsevier. https://doi.org/10.1016/B978-0-12-405531-5.00003-1

González Corona, F., Estaún Ferrer, S., & Cladellas Pros, R. (2020). Música como reductor de ansiedad: Un estudio piloto. *Ansiedad y Estrés*, *26*(1), 46-51. https://doi.org/10.1016/j.anyes.2020.02.001

Goodhue, D. L., Lewis, W., & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS Quarterly*, *36*(3), 981-1001. https://doi.org/10.2307/41703490

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2009). Evaluation of structural equation models using the partial least squares (PLS) approach. In *Handbook of partial least squares: Concepts, methods and applications* (pp. 691-711). Springer.

Granot, R., Spitz, D. H., Cherki, B. R., Loui, P., Timmers, R., Schaefer, R. S., Vuoskoski, J. K., Cárdenas-Soler, R.-N., Soares-Quadros Jr, J. F., & Li, S. (2021). "Help! I need somebody": Music as a global resource for obtaining wellbeing goals in times of crisis. *Frontiers in Psychology*, *12*, 1038. https://doi.org/10.3389/fpsyg.2021.648013

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360-1380. https://doi.org/10.1086/225469

Greb, F., Steffens, J., & Schlotz, W. (2019). Modeling music-selection behavior in everyday life: A multilevel statistical learning approach and mediation analysis of experience sampling data. *Frontiers in Psychology*, *10*, 390. https://doi.org/10.3389/fpsyg.2019.00390

Gregory, R., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2020). The role of artificial intelligence and data network effect for creating user value. *Academy of Management Review*, *46*, 534–551. https://doi.org/10.5465/amr.2019.0178

Grigoriadou, E. T. (2021). The urban balcony as the new public space for well-being in times of social distancing. *Cities & Health*, *5*(S1), S208-S211. https://doi.org/10.1080/23748834.2020.1795405

Groarke, J. M., & Hogan, M. J. (2016). Enhancing wellbeing: An emerging model of the adaptive functions of music listening. *Psychology of Music*, *44*(4), 769-791. https://doi.org/10.1177%2F0305735615591844

Guren, C., McIlroy, T., & Sieck, S. (2021). COVID-19 and book publishing: Impacts and insights for 2021. *Publishing Research Quarterly*, *37*(1), 1-14. https://doi.org/10.1007/s12109-021-09791-z

Haftor, D. M., Costa Climent, R., & Lundström, J. E. (2021). How machine learning activates data network effects in business models: Theory advancement through an industrial case of promoting ecological sustainability. *Journal of Business Research*, *131*, 196-205. https://doi.org/10.1016/j.jbusres.2021.04.015

Hagen, A. N. (2015). The playlist experience: Personal playlists in music streaming services. *Popular Music and Society*, *38*(5), 625-645. https://doi.org/10.1080/03007766.2015.1021174

Hagen, A. N., & Lüders, M. (2016). Social streaming? Navigating music as personal and social. *The International Journal of Research into New Media Technologies*, *23*(6), 643-659. https://doi.org/10.1177/1354856516673298

Hagiu, A., & Rothman, S. (2016). Network effects aren't enough. *Harvard Business Review*, *94*(4), 17.

Hagiu, A., & Wright, J. (2015). Multi-sided platforms. *International Journal of Industrial Organization*, *43*, 162-174. https://doi.org/10.1016/j.ijindorg.2015.03.003

Hagiu, A., & Wright, J. (2020). When data creates competitive advantage. *Harvard Business Review*, *98*(1), 94-101.

Hagiu, A., & Yoffie, D. B. (2016). Network effects. In *The palgrave encyclopedia of strategic management* (pp. 1-5). Springer.

Hair, J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3). https://doi.org/10.1108/IMDS-04-2016-0130

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*, 101-110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529-538. https://doi.org/10.1038/s41562-021-01079-8

Hansen, D. L., Shneiderman, B., Smith, M. A., & Himelboim, I. (2020). *Analyzing social media networks with NodeXL* (2nd ed.). Elsevier. https://doi.org/10.1016/B978-0-12-817756-3.00006-6

Hansen, N. C., Treider, J. M. G., Swarbrick, D., Bamford, J. S., Wilson, J., & Vuoskoski, J. K. (2021). A crowd-sourced database of coronamusic: documenting online making and sharing of music during the COVID-19 pandemic. *Frontiers in Psychology*, *12*, 2377. https://doi.org/10.3389/fpsyg.2021.684083

Hargreaves, D. J., Comber, C., & Colley, A. (1995). Effects of age, gender, and training on musical preferences of British secondary school students. *Journal of Research in Music Education*, *43*(3), 242-250. https://doi.org/10.2307/3345639

Hargreaves, D. J., & North, A. C. (1999). Developing concepts of musical style. *Musicae Scientiae*, *3*(2), 193-216. https://doi.org/10.1177/102986499900300203

Hassan, N. R. (2009). Using social network analysis to measure IT-enabled business process performance. *Information Systems Management*, *26*(1), 61-76.

https://doi.org/10.1080/10580530802557762

Heckman, J. J., & Hotz, V. J. (1989). Choosing among alternative nonexperimental methods for estimating the impact of social programs: The case of manpower training. *Journal of the American Statistical Association*, *84*(408), 862-874.

Hendler, J., & Golbeck, J. (2008). Metcalfe's law, Web 2.0, and the semantic Web. *Journal of Web Semantics*, *6*(1), 14-20. https://doi.org/10.1016/j.websem.2007.11.008

Henning, V., & Reichelt, J. (2008, December 07-12). *Mendeley - A Last.fm for research?* [Paper preserntation]. Fourth IEEE International Conference on eScience, Indianapolis, IN, 327–328. https://doi.org/10.1109/eScience.2008.128

Henry, N., Kayser, D., & Egermann, H. (2021). Music in mood regulation and coping orientations in response to COVID-19 lockdown measures within the United Kingdom. *Frontiers in Psychology*, *12*, 1796. https://doi.org/10.3389/fpsyg.2021.647879

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics & P. N. Ghauri (Eds.), *New challenges to international marketing* (pp. 277-319). Emerald. https://doi.org/10.1108/S1474-7979(2009)0000020014

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hesmondhalgh, D., Campos Valverde, R., Kaye, D., & Li, Z. (2023). The impact of algorithmically driven recommendation systems on music consumption and production: A literature review. *UK Centre for Data Ethics and Innovation Reports*.

Hilvert-Bruce, Z., Neill, J. T., Sjöblom, M., & Hamari, J. (2018). Social motivations of live-streaming viewer engagement on Twitch. *Computers in Human Behavior*, *84*, 58-67. https://doi.org/10.1016/j.chb.2018.02.013

Hofstede, G., Hofstede, G. J., & Minkov, M. (2005). *Cultures and organizations: Software of the mind*. McGraw Hill.

Howlin, C., & Hansen, N. C. (2022). Music in times of COVID-19. In G. Kreutz & G. Bernatzky (Eds.), *Music and medicine* (2nd ed.). Springer.

Huang, N., Hong, Y., & Burtch, G. (2016). Social network integration and user content generation: Evidence from natural experiments. *MIS Quarterly*, 17-001.

Hurley, N., & Zhang, M. (2011). Novelty and diversity in top-n recommendation--analysis and evaluation. *ACM Transactions on Internet Technology*, *10*(4), 1-30. https://doi.org/10.1145/1944339.1944341

Imai, K., & Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? *American Journal of Political Science*, *63*(2), 467-490. https://doi.org/10.1111/ajps.12417

Imber‐Black, E. (2020). Rituals in the time of COVID-19: Imagination, responsiveness, and the human spirit. *Family Process*, *59*(3), 912-921. https://doi.org/10.1111/famp.12581

Iyer, B., Lee, C.-H., Venkatramen, N., & Vesset, D. (2007). Monitoring platform emergence: Guidelines from software networks. *Communications of the Association for Information Systems*, *19*(1), 1. https://doi.org/10.17705/1CAIS.01901

Jacobs, N., Hagger, M. S., Streukens, S., De Bourdeaudhuij, I., & Claes, N. (2011). Testing an integrated model of the theory of planned behaviour and self-determination theory for different energy balance-related behaviours and intervention intensities. *British Journal of Health Psychology*, *16*(1), 113-134.

https://doi.org/10.1348/135910710X519305

Johansson, S., Werner, A., Åker, P., & Goldenzwaig, G. (2018). *Streaming music: Practices, media, cultures*. Routledge. https://doi.org/10.4324/9781315207889

Johnson, M. D., Herrmann, A., & Huber, F. (2006). The evolution of loyalty intentions. *Journal of Marketing*, *70*(2), 122-132. https://doi.org/10.1509/jmkg.70.2.122

Kaminskas, M., & Bridge, D. (2016). Diversity, serendipity, novelty, and coverage: A survey and empirical analysis of beyond-accuracy objectives in recommender systems. *ACM Transactions on Interactive Intelligent Systems*, *7*(1), 1-42. https://doi.org/10.1145/2926720

Kane, G. C., Alavi, M., Labianca, G., & Borgatti, S. (2014). What's different about social media networks? A framework and research agenda. *MIS Quarterly*, *38*(1), 275-304.

Karatay, S. (2022). Oline music listening practices and user motivations. *Yeni Yüzyılda İletişim Çalışmaları Dergisi*, *3*(4), 77-95.

Katarya, R., & Verma, O. P. (2018). Efficient music recommender system using context graph and particle swarm. *Multimedia Tools and Applications*, *77*(2), 2673-2687. https://doi.org/10.1007/s11042-017-4447-x

Katona, Z., Zubcsek, P. P., & Sarvary, M. (2011). Network effects and personal influences: The diffusion of an online social network. *Journal of Marketing Research*, *48*(3), 425-443. https://doi.org/10.1509/jmkr.48.3.425

Katsma, C., & Spil, T. (2010, August 12-15). A taxonomy of digital music services. Proceedings of the 16th Americas Conference in Information Systems, Lima, Peru.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, *75*(3), 424-440.

Katz, M. L., & Shapiro, C. (1992). Product introduction with network externalities. *Journal of Industrial Economics*, *40*(1), 55-83. https://doi.org/10.2307/2950627

Kemeny, J. G. (1959). Mathematics without numbers. *Daedalus*, *88*(4), 577-591.

Khan, G. F., Mohaisen, M., & Trier, M. (2019). The network ROI: Concept, metrics, and measurement of social media returns (a Facebook experiment). *Internet Research: Electronic Networking Applications and Policy*, *30*(2), 631-652. https://doi.org/10.1108/INTR-07-2018-0346

Khan, M. L. (2017). Social media engagement: What motivates user participation and consumption on YouTube? *Computers in Human Behavior*, *66*, 236-247. https://doi.org/https://doi.org/10.1016/j.chb.2016.09.024

Khlystova, O., Kalyuzhnova, Y., & Belitski, M. (2022). The impact of the COVID-19 pandemic on the creative industries: A literature review and future research agenda. *Journal of Business Research*, *139*, 1192-1210. https://doi.org/10.1016/j.jbusres.2021.09.062

Kiernan, F., Chmiel, A., Garrido, S., Hickey, M., & Davidson, J. W. (2021). The role of artistic creative activities in navigating the COVID-19 pandemic in Australia. *Frontiers in Psychology*, *12*, 696202. https://doi.org/10.3389%2Ffpsyg.2021.696202

Kim, E., Lin, J.-S., & Sung, Y. (2013). To app or not to app: Engaging consumers via branded mobile apps. *Journal of Interactive Advertising*, *13*(1), 53-65. https://doi.org/10.1080/15252019.2013.782780

Kirk, D. S., Durrant, A., Wood, G., Leong, T. W., & Wright, P. (2016). Understanding the sociality of experience in mobile music listening with Pocketsong. Proceedings of the 2016 ACM Conference on Designing Interactive Systems, 50–61. https://doi.org/10.1145/2901790.2901874

Kjus, Y. (2016). Musical exploration via streaming services: The Norwegian experience. *Popular Communication*, *14*(3), 127-136. https://doi.org/10.1080/15405702.2016.1193183

Knees, P., & Schedl, M. (2013). A survey of music similarity and recommendation from music context data. *ACM Transactions on Multimedia Computing, Communications, Applications*, *10*(1), 1-21. https://doi.org/10.1145/2542205.2542206

Knoke, D. (2014). *Economic networks*. John Wiley & Sons.

Kock, N. (2015). PLS-based SEM algorithms: The good neighbor assumption, collinearity, and nonlinearity. *Information Management and Business Review*, *7*(2), 113-130. https://doi.org/10.22610/imbr.v7i2.1146

Koroleva, K., & Štimac, V. (2012, December 16-19). *Tie strength vs. Network overlap: Why information from lovers is more valuable than from close friends on social network sites?* [Paper presentation]. 33rd International Conference on Information Systems (ICIS), Florida, USA.

Krotz, F. (2009). Bridging the gap between sociology and communication science: communication as social action. In R. P. Konig, P. W. Nelissen, & F. J. Huysmans (Eds.), *Meaningful media: communication research on the social construction of reality; to honour Karsten Renckstorf's academic career* (pp. 21-36). Tandem Felix.

Langmeyer, A., Guglhör-Rudan, A., & Tarnai, C. (2012). What do music preferences reveal about personality? *Journal of Individual Differences*, *33*(2), 119-130. https://doi.org/10.1027/1614-0001/a000082

Lanzoni, L. (2020). *Music industry in the digital era: A pendulum swinging between dematerialization and new shapes* [Master's Degree Thesis, LuissThesis]. Luiss Guido Carli. http://tesi.luiss.it/29255/

Lee, D., & Mendelson, H. (2008). Divide and conquer: Competing with free technology under network effects. *Production and Operations Management*, *17*(1), 12-28. https://doi.org/10.3401/poms.1070.0005

Lee, J., Wishkoski, R., Aase, L., Meas, P., & Hubbles, C. (2016). Understanding users of cloud music services: Selection factors, management and access behavior, and perceptions. *Journal of the Association for Information Science and Technology*, *68*. https://doi.org/10.1002/asi.23754

Levy, M., & Bosteels, K. (2010). Music recommendation and the long tail. Proceedings of the Workshop on Music Recommendation and Discovery (WOMRAD), 55-58.

Li, X., Kauffman, R. J., Yu, F., & Zhang, Y. (2014). Externalities, incentives and strategic complementarities: Understanding herd behavior in IT adoption. *Information Systems and e-Business Management*, *12*(3), 443-464. https://doi.org/10.1007/s10257-013-0231-2

Liebowitz, S. J., & Margolis, S. E. (1994). Network Externality: An uncommon tragedy. *Journal of Economic Perspectives*, *8*(2), 133-150. https://doi.org/10.1257/jep.8.2.133

Lipsman, A., Mudd, G., Rich, M., & Bruich, S. (2012). The power of "like": How brands reach (and influence) fans through social-media marketing. *Journal of Advertising research*, *52*(1), 40-52. https://doi.org/10.2501/JAR-52-1-040-052

Liu, G., Wang, Y., & Orgun, M. A. (2011). Trust transitivity in complex social networks. Proceedings of the AAAI Conference on Artificial Intelligence, 25(1), 1222-1229. https://doi.org/10.1609/aaai.v25i1.8087

Liu, H. (2007). Social network profiles as taste performances. *Journal of Computer-Mediated Communication*, *13*(1), 252-275. https://doi.org/10.1111/j.1083-6101.2007.00395.x

Liu, M., Zangerle, E., Hu, X., Melchiorre, A., & Schedl, M. (2020). Pandemics, music, and collective sentiment: Evidence from the outbreak of COVID-19. Proceedings of the 21st International Society for Music Information Retrieval Conference (ISMIR), 157-165. http://dx.doi.org/10.5281%2Fzenodo.4245394

Liu, W., Sidhu, A., Beacom, A. M., & Valente, T. W. (2017). Social network theory. *The International Encyclopedia of Media Effects*, 1-12. https://doi.org/10.1002/9781118783764.wbieme0092

Livesey, L., Morrison, I., Clift, S., & Camic, P. (2012). Benefits of choral singing for social and mental wellbeing: Qualitative findings from a cross‐national survey of choir members. *Journal of Public Mental Health*, *11*(1), 10-26. https://doi.org/10.1108/17465721211207275

Loehlin, J. C. (2017). *Latent variable models: An introduction to factor, path, and structural equation analysis* (5th ed.). Taylor & Francis. https://doi.org/10.4324/9781315643199

Lonsdale, A. J., & North, A. C. (2011). Why do we listen to music? A uses and gratifications analysis. *British Journal of Psychology*, *102*(1), 108-134. https://doi.org/10.1348/000712610X506831

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication*, *57*(2), 123-146. https://doi.org/10.1109/TPC.2014.2312452

Lozano Murciego, Á., Jiménez-Bravo, D. M., Valera Román, A., De Paz Santana, J. F., & Moreno-García, M. N. (2021). Context-aware recommender systems in the music domain: A systematic literature review. *Electronics*, *10*(13), 1555. https://doi.org/10.3390/electronics10131555

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, *35*(2), 293-334. https://doi.org/10.2307/23044045

Madison, G., & Schiölde, G. (2017). Repeated listening increases the liking for music regardless of its complexity: Implications for the appreciation and aesthetics of music. *Frontiers in neuroscience*, *11*, 147. https://doi.org/10.3389/fnins.2017.00147

Maicas, J. P., Polo, Y., & Sese, F. J. (2009). The role of (personal) network effects and switching costs in determining mobile users' choice. *Journal of Information Technology*, *24*(2), 160-171. https://doi.org/10.1057/jit.2008.35

Mandl, C. E. (2019). Limits to growth: Network effect and attractiveness principle. In *Managing complexity in social systems* (pp. 121-128). Springer. https://doi.org/10.1007/978-3-030-01645-6_13

Martín, J. C., Ortega-Sánchez, D., Miguel, I. N., & Gil Martín, G. M. (2021). Music as a factor associated with emotional self-regulation: A study on its relationship to age during COVID-19 lockdown in Spain. *Heliyon*, *7*(2), e06274. https://doi.org/10.1016/j.heliyon.2021.e06274

Martínez-Castilla, P., Gutiérrez-Blasco, I. M., Spitz, D. H., & Granot, R. (2021). The efficacy of music for emotional wellbeing during the COVID-19 lockdown in Spain: an analysis of personal and context-related variables. *Frontiers in Psychology*, *12*, 1193. https://doi.org/10.3389/fpsyg.2021.647837

Mas-Herrero, E., Singer, N., Ferreri, L., McPhee, M., Zatorre, R., & Ripolles, P. (2020). Rock'n'roll but not sex or drugs: Music is negatively correlated to depressive symptoms during the COVID-19 pandemic via reward-related mechanisms. *PsyArXiv*. https://doi.org/10.31234/osf.io/x5upn

McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, *38*(1), 141-160. https://doi.org/10.1002/smj.2596

McIntyre, D. P., Srinivasan, A., Afuah, A., Gawer, A., & Kretschmer, T. (2020). Multi-sided platforms as new organizational forms: A dynamic perspective on strategy, scope and business models. *Academy of Management Perspectives*, *35*(4), 566-583. https://doi.org/10.5465/amp.2018.0018

Mcintyre, D. P., & Subramaniam, M. (2009). Strategy in network industries: A review and research agenda. *Journal of Management*, *35*(6), 1494-1517. https://doi.org/https://doi-org.ezproxy.waikato.ac.nz/10.1177%2F0149206309346734

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81

Mechant, P., & Evens, T. (2011). Interaction in web-based communities: a case study of Last. fm. *International Journal of Web Based Communities*, *7*(2), 234-249. https://doi.org/10.1504/IJWBC.2011.039513

Melchiorre, A. B., Rekabsaz, N., Parada-Cabaleiro, E., Brandl, S., Lesota, O., & Schedl, M. (2021). Investigating gender fairness of recommendation algorithms in the music domain. *Information Processing & Management*, *58*(5), 102666. https://doi.org/10.1016/j.ipm.2021.102666

Metcalf, J., Keller, E. F., & Boyd, D. (2016). *Perspectives on big data, ethics, and society*. Council for Big Data, Ethics. https://bdes.datasociety.net/council-output/perspectives-on-big-data-ethics-and-society/

Mitomo, H. (2017 July 30th - August 2nd). *Data network effects: implications for data business* [Paper presentation]. 28th European Regional Conference of the International Telecommunications Society (ITS), Passau, Germany.

Mohajan, H. K. (2017). Two criteria for good measurements in research: Validity and reliability. *Annals of Spiru Haret University. Economic Series*, *17*(4), 59-82.

Mora, R., & Reggio, I. (2019). Alternative diff-in-diffs estimators with several pretreatment periods. *Econometric Reviews*, *38*(5), 465-486. https://doi.org/10.1080/07474938.2017.1348683

Morgado, F. F., Meireles, J. F., Neves, C. M., Amaral, A., & Ferreira, M. E. (2017). Scale development: Ten main limitations and recommendations to improve future research practices. *Psicologia, Reflexão e Crítica*, *30*(3), 1-20. https://doi.org/10.1186/s41155-016-0057-1

Morris, J. W., & Powers, D. (2015). Control, curation and musical experience in streaming music services. *Creative Industries Journal*, *8*(2), 106-122. https://doi.org/10.1080/17510694.2015.1090222

Mrvar, A., & Batagelj, V. (2018). *Programs for analysis and visualization of very large networks reference manual*. http://mrvar2.fdv.si/pajek%20/pajekman.pdf.

Mrvar, A., Batagelj, V., & De Nooy, W. (2018). Brokers and bridges. In *Exploratory social network analysis with Pajek: Revised and expanded edition for updated software* (3rd ed., pp. 170-196). Cambridge University Press. https://doi.org/DOI: 10.1017/9781108565691.013

Muhlenbach, F., Largeron, C., & Stan, J. (2017). Recommender systems using social network analysis: Challenges and future trends. In R. Alhajj & J. Rokne (Eds.), *Encyclopedia of social network analysis and mining* (pp. 1-14). Springer. https://doi.org/10.1007/978-1-4614-7163-9_35-1

Nettleton, D. (2014). *Commercial data mining*. Elsevier. https://doi.org/10.1016/B978-0-12-416602-8.00016-9

Niemczyk, J., Trzaska, R., Wilczyński, M., & Borowski, K. (2021). Business models 4.0 using network effects: Case study of the Cyfrowy Polsat Group. *Sustainability*, *13*(21), 11570. https://doi.org/10.3390/su132111570

Noar, S. M. (2003). The role of structural equation modeling in scale development. *Structural equation modeling*, *10*(4), 622-647. https://doi.org/10.1207/S15328007SEM1004_8

North, A. C., & Hargreaves, D. J. (2007). Lifestyle correlates of musical preference: 1. Relationships, living arrangements, beliefs, and crime. *Psychology of Music*, *35*(1), 58-87. https://doi.org/10.1177/0305735607068888

North, A. C., Hargreaves, D. J., & O'Neill, S. A. (2000). The importance of music to adolescents. *British Journal of Educational Psychology*, *70*(2), 255-272. https://doi.org/10.1348/000709900158083

O'Donovan, N. (2021). Personal data and collective value: Data-driven personalisation as network effect. In Eisler and Kohl (Ed.), F*orthcoming in data-driven personalisation in markets, politics and law* (pp. 74-92). Cambridge University Press.

OECD. (2019). *An introduction to online platforms and their role in the digital transformation*. OECD.

Oestreicher-Singer, G., & Zalmanson, L. (2013). Content or community? A digital business strategy for content providers in the social age. *MIS Quarterly*, *37*(2), 591-616. https://doi.org/10.25300/MISQ/2013/37.2.12

Onderdijk, K. E., Swarbrick, D., Van Kerrebroeck, B., Mantei, M., Vuoskoski, J. K., Maes, P.-J., & Leman, M. (2021). Livestream experiments: The role of COVID-19, agency, presence, and social context in facilitating social connectedness. *Frontiers in Psychology*, *12*, 1741. https://doi.org/10.3389/fpsyg.2021.647929

Otte, E., & Rousseau, R. (2002). Social network analysis: A powerful strategy, also for the information sciences. *Journal of Information Science*, *28*(6), 441-453. https://doi.org/10.1177/016555150202800601

Ozkan-Canbolat, E. (2014). Organizational network effect on diversification strategies. *Strategic Management Quarterly*, *2*(2), 27-48.

Pálovics, R., & Benczúr, A. (2015). Temporal influence over the Last. fm social network. Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, 486–493. https://doi.org/10.1145/2492517.2492532

Pan, V.-Q., Chew, P.-Q., Cheah, A. S.-G., Wong, C.-H., & Tan, G. W.-H. (2015). Mobile marketing in the 21st century: a partial least squares structural equation modelling approach. *International Journal of Modelling in Operations Management*, *5*(2), 83-99. https://doi.org/10.1504/IJMOM.2015.072669

Park, H. M. (2011). Practical guides to panel data modeling: a step-by-step analysis using stata. *Public Management & Policy Analysis Program, Graduate School of International Relations, International University of Japan*, *12*, 1-52.

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. WW Norton & Co.

Parkinson, B., & Totterdell, P. (1999). Classifying affect-regulation strategies. *Cognition and Emotion*, *13*(3), 277-303. https://doi.org/10.1080/026999399379285

Pearl, J. (2009). *Causality*. Cambridge university press.

Petrič, G., Petrovčič, A., & Vehovar, V. (2011). Social uses of interpersonal communication technologies in a complex media environment. *European Journal of Communication*, *26*(2), 116-132. https://doi.org/10.1177/0267323111402654

Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly*, *31*(4), 623-656. https://doi.org/10.2307/25148814

Pinto, M. P. (2021). *Managing the impact of the pandemic in the music industry* [Master's Degree Thesis, Instituto Universitario de Lisboa]. ProQuest One Academic.

https://www.proquest.com/docview/2675222916?pq-origsite=gscholar&fromopenview=true

Pituch, K. A., & Stevens, J. P. (2016). *Applied multivariate statistics for the social sciences* (6th ed.). Routledge.

Poudel, K., & Subedi, P. (2020). Impact of COVID-19 pandemic on socioeconomic and mental health aspects in Nepal. *International Journal of Social Psychiatry*, *66*(8), 748-755. https://doi.org/10.1177%2F0020764020942247

Price, P. C., Jhangiani, R., & Chiang, I.-C. A. (2015). Nonexperimental research. In *research methods in psychology* (2nd Canadian ed.). Victoria, B.C: BCcampus.

Putzke, J., Fischbach, K., Schoder, D., & Gloor, P. A. (2014). Cross-cultural gender differences in the adoption and usage of social media platforms – An exploratory study of Last.FM. *Computer Networks*, *75*, 519-530. https://doi.org/10.1016/j.comnet.2014.08.027

Qiang, C. Z. W., Pitt, A., & Ayers, S. (2004). *Contribution of information and communication technologies to growth*. World Bank.

Rahman, M. M., Alam, K., & Khanam, R. (2022). Socio-economic factors affecting high infant and child mortality rates in selected African countries: Does globalisation play any role? *Globalization and Health*, *18*(1), 69. https://doi.org/10.1186/s12992-022-00855-z

Ramesh, B. (2020). Influence of music as a coping strategy during COVID-19. *SBV Journal of Basic, Clinial and Applied Health Science*, *3*(3), 128-130.

Reillier, L. C., & Reillier, B. (2017). *Platform strategy: How to unlock the power of communities and networks to grow your business* (1st ed.). Routledge.

Renckstorf, K., McQuail, D., & Jankowski, N. W. (1996). *Media use as social action: A European approach to audience studies*. John Libbey London.

Rentfrow, P. J., Goldberg, L. R., & Levitin, D. J. (2011). The structure of musical preferences: A five-factor model. *Journal of Personality and Social Psychology*, *100*(6), 1139-1157. https://doi.org/10.1037/a0022406

Rentfrow, P. J., & Gosling, S. D. (2003). The Do Re Mi's of everyday life: The structure and personality correlates of music preferences. *Journal of Personality and Social Psychology*, *84*(6), 1236-1256. https://doi.org/10.1037/0022-3514.84.6.1236

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. http://www.smartpls.com/

Ripp, J., Peccoralo, L., & Charney, D. (2020). Attending to the emotional well-being of the health care workforce in a New York City health system during the COVID-19 pandemic. *Academic Medicine*, *95*(8), 1136–1139. https://doi.org/10.1097%2FACM.0000000000003414

Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990-1029. https://doi.org/10.1162/154247603322493212

Roe, K. (1985). Swedish youth and music: Listening patterns and motivations. *Communication Research*, *12*(3), 353-362. https://doi.org/10.1177/009365085012003007

Roemer, E. (2016). A tutorial on the use of PLS path modeling in longitudinal studies. *Industrial Management & Data Systems*, *116*(9), 1901-1921. https://doi.org/10.1108/IMDS-07-2015-0317

Roemer, E., & Henseler, J. (2022). The dynamics of electric vehicle acceptance in corporate fleets: Evidence from Germany. *Technology in Society*, *68*, 101938. https://doi.org/10.1016/j.techsoc.2022.101938

Rogers, E. M. (1995). *Diffusion of innovations*. Free Press.

Roldán, J. L., & Sánchez-Franco, M. J. (2012). Variance-based structural equation modeling: Guidelines for using partial least squares in information systems research. In *Research* *methodologies, innovations and philosophies in software systems engineering and information systems* (pp. 193-221). IGI global.

Rong, K., Xiao, F., Zhang, X., & Wang, J. (2019). Platform strategies and user stickiness in the online video industry. *Technological Forecasting and Social Change*, *143*, 249-259. https://doi.org/10.1016/j.techfore.2019.01.023

Rulke, D. L., & Galaskiewicz, J. (2000). Distribution of knowledge, group network structure, and group performance. *Management Science*, *46*(5), 612-625. https://doi.org/10.1287/mnsc.46.5.612.12052

Saeidi, S. (2020). A new model for calculating the maximum trust in online social networks and solving by Artificial Bee Colony algorithm. *Computational Social Networks*, *7*(1), 1-21. https://doi.org/10.1186/s40649-020-00077-6

Salminen, J., Gach, N., & Kaartemo, V. (2018). Platform as a social contract: An analytical framework for studying social dynamics in online platforms. In A. Smedlund, A. Lindblom, & L. Mitronen (Eds.), *Collaborative value co-creation in the platform economy* (pp. 41-64). Springer.

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. In *Measurement and research methods in international marketing* (Vol. 22, pp. 195-218). Emerald Group Publishing Limited.

Schäfer, T., & Sedlmeier, P. (2009). From the functions of music to music preference. *Psychology of Music*, *37*(3), 279-300. https://doi.org/10.1177%2F0305735608097247

Schedl, M. (2017). Investigating country-specific music preferences and music recommendation algorithms with the LFM-1b dataset. *International Journal of Multimedia Information Retrieval*, *6.*(1), 71-84.

https://doi.org/10.1007/s13735-017-0118-y

Schedl, M., & Hauger, D. (2015). Tailoring music recommendations to users by considering diversity, mainstreaminess, and novelty. Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information, 947–950. https://doi.org/10.1145/2766462.2767763

Schedl, M., & Tkalčič, M. (2014). Genre-based analysis of social media data on music listening behavior: are fans of classical music really averse to social media? Proceedings of the First International Workshop on Internet-Scale Multimedia Management, 9–13. https://doi.org/10.1145/2661714.2661717

Schedl, M., Wiechert, E., & Bauer, C. (2018). The effects of real-world events on music listening behavior: An intervention time series analysis. Proceedings of the The Web Conference 2018, 75–76. https://doi.org/10.1145/3184558.3186936

Schedl, M., Zamani, H., Chen, C.-W., Deldjoo, Y., & Elahi, M. (2018). Current challenges and visions in music recommender systems research. *International Journal of Multimedia Information Retrieval*, *7*(2), 95-116. https://doi.org/10.1007/s13735-018-0154-2

Schuberth, F., Henseler, J., & Dijkstra, T. K. (2018). Confirmatory composite analysis. *Frontiers in Psychology*, *9*, 2541. https://doi.org/10.3389/fpsyg.2018.02541

Seetharaman, P. (2020). Business models shifts: Impact of Covid-19. *International Journal of Information Management*, *54*, 102173. https://doi.org/10.1016/j.ijinfomgt.2020.102173

Shankar, V., & Bayus, B. L. (2003). Network effects and competition: An empirical analysis of the home video game industry. *Strategic Management Journal*, *24*(4), 375-384. https://doi.org/10.1002/smj.296

Shapiro, C., Carl, S., & Varian, H. R. (1998). *Information rules: A strategic guide to the network economy*. Harvard Business Press.

Shea, C. M., & Howell, J. M. (2000). Efficacy-performance spirals: An empirical test. *Journal of Management*, *26*(4), 791-812. https://doi.org/10.1177/014920630002600409

Sheikhahmadi, A., & Nematbakhsh, M. A. (2016). Identification of multi-spreader users in social networks for viral marketing. *Journal of Information Science*, *43*(3), 412-423. https://doi.org/10.1177/0165551516644171

Shmargad, Y., & Watts, J. K. M. (2016). When online visibility deters social interaction: The case of digital gifts. *Journal of Interactive Marketing*, *36*, 1-14. https://doi.org/10.1016/j.intmar.2016.01.004

Shokeen, J., & Rana, C. (2020). Social recommender systems: techniques, domains, metrics, datasets and future scope. *Journal of Intelligent Information Systems*, *54*(3), 633-667. https://doi.org/10.1007/s10844-019-00578-5

Sim, J., Cho, D., Hwang, Y., & Telang, R. (2022). Frontiers: Virus shook the streaming star: Estimating the COVID-19 impact on music consumption. *Marketing Science*, *41*(1), 19-32. https://doi.org/10.1287/mksc.2021.1321

Skowron, M., Lemmerich, F., Ferwerda, B., & Schedl, M. (2017). Predicting genre preferences from cultural and socio-economic factors for music retrieval. In J. M. Jose, C. Hauff, I. S. Altıngovde, D. Song, D. Albakour, S. Watt, & J. Tait (Eds.), *Advances in information retrieval* (Vol. 10193, pp. 561-567). Springer. https://doi.org/10.1007/978-3-319-56608-5_49

Smedlund, A., Faghankhani, H., Ikävalko, H., & Turkama, P. (2018). Platform ecosystem orchestration for efficiency, development, and innovation. In A. Smedlund, A.

Lindblom, & L. Mitronen (Eds.), *Collaborative value co-creation in the platform economy* (pp. 29-40). Springer. https://doi.org/10.1007/978-981-10-8956-5_2

Smith, T. W. (1994). Generational differences in musical preferences. *Popular Music and Society*, *18*(2), 43-59.

Spilker, H. S., & Colbjørnsen, T. (2020). The dimensions of streaming: toward a typology of an evolving concept. *Media, Culture & Society*, *42*(7-8), 1210-1225. https://doi.org/10.1177/0163443720904587

Stewart, M., Tibau, J., Tatar, D., & Harrison, S. (2018). Co-designing for co-listening: Conceptualizing young people's social and music-listening practices. In G. Meiselwitz (Ed.), *Social computing and social media* (pp. 355-374). Springer. https://doi.org/10.1007/978-3-319-91521-0_26

Stock, J. H., & Watson, M. W. (2003). *Introduction to econometrics* (Vol. 104). Addison Wesley Boston.

Street, J. (2004). Celebrity politicians: Popular culture and political representation. *The British Journal of Politics and International Relations*, *6*(4), 435-452. https://doi.org/10.1111/j.1467-856X.2004.00149.x

Suarez, F. (2005). Network effects revisited: The role of strong ties in technology selection. *Academy of Management Journal*, *48*(4), 710-720. https://doi.org/10.5465/AMJ.2005.17843947

Sunitha, M., Adilakshmi, T., Ravi Teja, G., & Noel, A. (2022). Addressing longtail problem using adaptive clustering for music recommendation system. In V. Bhateja, S. S. Chandra, T.-G. C. M., & T. Adilakshmi (Eds.), *Smart intelligent computing and applications, Volume 1. Smart innovation, systems and technologies, vol 282* (pp. 331-338). Springer. https://doi.org/10.1007/978-981-16-9669-5_30

Sutcliffe, A., Dunbar, R. I. M., Binder, J., & Arrow, H. (2012). Relationships and the social brain: Integrating psychological and evolutionary perspectives. *British Journal of Psychology*, *103*(2), 149-168. https://doi.org/10.1111/j.2044-8295.2011.02061.x

Ter Bogt, T. F., Mulder, J., Raaijmakers, Q. A., & Nic Gabhainn, S. (2011). Moved by music: A typology of music listeners. *Psychology of Music*, *39*(2), 147-163. https://doi.org/10.1177/0305735610370223

Ter Bogt, T. F., Vieno, A., Doornwaard, S. M., Pastore, M., & Van den Eijnden, R. J. (2017). "You're not alone": Music as a source of consolation among adolescents and young adults. *Psychology of Music*, *45*(2), 155-171. https://doi.org/10.1177%2F0305735616650029

Thompson, G. F. (2003). *Between hierarchies and markets: the logic and limits of network forms of organization*. Oxford University Press on Demand.

Tiwana, A. (2015). Evolutionary competition in platform ecosystems. *Information Systems Research*, *26*(2), 266-281. https://doi.org/10.1287/isre.2015.0573

Tuck, A. B., & Thompson, R. J. (2021). Social networking site use during the COVID-19 pandemic and its associations with social and emotional well-being in college students: Survey study. *JMIR Formative Research*, *5*(9), e26513. https://doi.org/10.2196/26513

Tucker, C. (2018). Network effects and market power: What have we learned in the last decade? *Antitrust*, 72-79.

Ulleri, P., Prakash, S. H., Zenith, K. B., Nair, G. S., & Kannimoola, J. M. (2021, July 6-8). *Music Recommendation System Based on Emotion* [Paper presentation]. 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India. http://dx.doi.org/10.1109/ICCCNT51525.2021.9579689

Valente, T. W., Coronges, K., Lakon, C., & Costenbader, E. (2008). How correlated are network centrality measures? *Connections*, *28*(1), 16-26.

Van Alstyne, M., & Parker, G. (2017). Platform business: from resources to relationships. *NIM Marketing Intelligence Review*, *9*(1), 24-29. https://doi.org/10.1515/gfkmir-2017-0004

van der Aalst, W., Hinz, O., & Weinhardt, C. (2019). Big digital platforms. *Business & Information Systems Engineering*, *61*(6), 645-648. https://doi.org/10.1007/s12599-019-00618-y

Vargas, S. (2011, August 31). *New approaches to diversity and novelty in recommender systems* [Symposium]. Fourth BCS-IRSG Symposium on Future Directions in Information Access (FDIA 2011), Koblenz, Germany.

Varshney, M., Parel, J. T., Raizada, N., & Sarin, S. K. (2020). Initial psychological impact of COVID-19 and its correlates in Indian Community: An online (FEEL-COVID) survey. *PloS One*, *15*(5), e0233874. https://doi.org/10.1371/journal.pone.0233874

Vieira, K. C., Pinto, G. A., Sugano, J. Y., Carvalho, E. G., & Grutzmann, A. (2021). Does network effect have an influence on the acceptance of Airbnb? *Global Business Review*, 1-15. https://doi.org/10.1177/0972150920988654

Vigliensoni, G., & Fujinaga, I. (2016). Automatic music recommendation systems: Do demographic, profiling, and contextual features improve their performance? Proceedings of the 17th International Society for Music Information Retrieval Conference, 94-100.

Voigt, S., & Hinz, O. (2015). Network effects in two-sided markets: Why a 50/50 user split is not necessarily revenue optimal. *Business Research*, *8*(1), 139-170. https://doi.org/10.1007/s40685-015-0018-z

Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS Quarterly*, *28*(1), 107-142. https://doi.org/10.2307/25148626

Walls, J. G., Widmeyer, G. R., & El Sawy, O. A. (1992). Building an information system design theory for vigilant EIS. *Information Systems Research*, *3*(1), 36-59. https://doi.org/10.1287/isre.3.1.36

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C. S., & Ho, R. C. (2020). Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. *International Journal of Environmental Research and Public Health*, *17*(5), 1729. https://doi.org/10.3390/ijerph17051729

Wang, S., Xu, C., Ding, A. S., & Tang, Z. (2021). A novel emotion-aware hybrid music recommendation method using deep neural network. *Electronics*, *10*(15), 1769. https://doi.org/10.3390/electronics10151769

Weber, M. (1968). *Economy and society: An outline of interpretive sociology*. University of California Press. https://doi.org/10.1002/9780470755679.ch3

Weitzel, T., Wendt, O., & Westarp, F. V. (2000). Reconsidering network effect theory. Proceedings of the 8th European Conference on Information Systems (ECIS), 91.

Wel, F. V., Maarsingh, W., Bogt, T. T., & Raaijmakers, Q. (2008). Youth cultural styles: From snob to pop? *Young*, *16*(3), 325-340. https://doi.org/10.1177/110330880801600305

Williams, K., & Durrance, J. C. (2008). Social networks and social capital: Rethinking theory in community informatics. *The Journal of Community Informatics*, *4*(3). https://doi.org/10.15353/joci.v4i3.2946

Wooldridge, J. M. (2005). Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models. *Review of Economics & Statistics*, *87*(2), 385-390. https://doi.org/10.1162/0034653053970320

Wooldridge, J. M. (2021). Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. http://dx.doi.org/10.2139/ssrn.3906345

Xu, W., Li, T., Liang, W., Yu, J. X., Yang, N., & Gao, S. (2019). Identifying structural hole spanners to maximally block information propagation. *Information Sciences*, *505*, 100-126. https://doi.org/10.1016/j.ins.2019.07.072

Yang, J., Chae, W., Kim, S., & Choi, H. (2016). Emotion-aware music recommendation. In A. Marcus (Ed.), *Design, user experience, and usability: Novel user experiences . DUXU 2016. Lecture Notes in Computer Science* (pp. 110-121). Springer. https://doi.org/10.1007/978-3-319-40355-7_11

Yeung, T. Y.-C. (2020). *Did the COVID-19 pandemic trigger nostalgia? Evidence of music consumption on spotify*. https://dx.doi.org/10.2139/ssrn.3678606

Young, H. P., & Levenglick, A. (1978). A consistent extension of Condorcet's election principle. *SIAM journal on Applied Mathematics*, *35*(2), 285-300. https://doi.org/10.1137/0135023

Yousefian Jazi, S., Kaedi, M., & Fatemi, A. (2021). An emotion-aware music recommender system: Bridging the user’s interaction and music recommendation. *Multimedia Tools and Applications*, *80*(9), 13559-13574. https://doi.org/10.1007/s11042-020-10386-7

Zhang, J., & Luo, Y. (2017). Degree centrality, betweenness centrality, and closeness centrality in social network. Proceedings of the 2017 2nd International Conference on Modelling, Simulation and Applied Mathematics (MSAM2017), 300-303. https://doi.org/10.2991/msam-17.2017.68

Zhang, L. (2013). The definition of novelty in recommendation system. *Journal of Engineering Science and Technology Review*, *6*(3). https://doi.org/10.3390/electronics10151769

Zhang, W. R., Wang, K., Yin, L., Zhao, W. F., Xue, Q., Peng, M., Min, B. Q., Tian, Q., Leng, H. X., & Du, J. L. (2020). Mental health and psychosocial problems of medical health workers during the COVID-19 epidemic in China. *Psychotherapy and Psychosomatics*, *89*(4), 242-250. https://doi.org/10.1159/000507639

Zhou, T., Lu, Y., & Wang, B. (2009). The relative importance of website design quality and service quality in determining consumers' online repurchase behavior. *Information Systems Management*, *26*(4), 327-337. https://doi.org/10.1080/10580530903245663

Zhu, C., Wang, X., & Zhu, L. (2017). A novel method of evaluating key nodes in complex networks. *Chaos, Solitons & Fractals*, *96*, 43-50. https://doi.org/10.1016/j.chaos.2017.01.007

Ziv, N., & Hollander-Shabtai, R. (2021). Music and COVID-19: Changes in uses and emotional reaction to music under stay-at-home restrictions. *Psychology of Music*, *50*(2), 475-491. https://doi.org/10.1177%2F03057356211003326

Appendix A. Ethical Approval

WAIKATO MANAGEMENT SCHOOL
TE RAUPAPA

THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

Waikato Management School
The University of Waikato
Private Bag 3105
Hamilton 3240
New Zealand

Amanda Sircombe
Research and Postgraduate Manager
Phone +64 7 838 4376
Email amandas@waikato.ac.nz
www.management.ac.nz/research

Mona Ghaffari

25 June 2020

Dear Mona

Ethical Application WMS 20/58
An Empirical Investigation into Music Listening Behaviour in the Presence of the Network Effect

The above research project, as outlined in your submitted application, has been granted Ethics Approval for Research by the Waikato Management School Human Research Ethics Committee.

Please note: should you make changes to the project outlined in the approved ethics application, you may need to reapply for ethics approval.

Best wishes for your research.

Kind regards,

Amanda Sircombe

Amanda Sircombe
WMS Research and Postgraduate Manager

Appendix B. Co-Authorship Forms

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Wahanga Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 3 of the thesis.

Music Oh my Music: A Network Perspective on Online Music Listening Behaviour

Paper accepted and presented in the Australasian Conference on Information Systems (ACIS 2020).

Nature of contribution by PhD candidate	Collaboration on developing research ideas, data collection, data analysis, findings interpretation, and manuscripts writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Gohar F. Khan	Collaboration on developing research ideas, data analysis, and findings interpretation
Bruce Ferwerda	Collaboration on findings interpretation and manuscripts editing
Shivendu Pratap Singh	Collaboration on findings interpretation

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Gohar F. Khan	G.K	**May 25, 2023**
Bruce Ferwerda		**May 26, 2023**
Shivendu Pratap Singh	Shivendu Pratap Singh	May 31, 2023

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Wahanga Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 4 of the thesis.

Covid-19 and Socially Connected Music Listeners: Social Dynamics of Music Streaming Platforms

Paper accepted and presented in the Institute for Operations Research and the Management Sciences (INFORMs 2022).

Nature of contribution by PhD candidate	Collaboration on developing research ideas, data collection, data analysis, findings interpretation, and manuscripts writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Gohar F. Khan	Collaboration on developing research ideas, findings interpretation, and manuscript editing
Shivendu Pratap Singh	Collaboration on data analysis and findings interpretation
Bruce Ferwerda	Collaboration on data collection

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Gohar F. Khan	G.K.	**May 25, 2023**
Shivendu Pratap Singh	Shivendu Pratap Singh	May 31, 2023
Bruce Ferwerda		**May 26, 2023**

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Postgraduate Studies Office
Student and Academic Services Division
Wahanga Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 2 of the thesis.

The Network Effects Construct for Online Platforms: Toward an Integrated Theory, Metrics, and Mathematical Framework
Paper under review after revision submitted for the 2nd Round to the Communications of the Association for Information Systems (CAIS) Journal

Nature of contribution by PhD candidate	Collaboration on developing research ideas, data collection, data analysis, findings interpretation, and manuscripts writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Gohar F. Khan	Collaboration on developing research ideas, data analysis, findings interpretation, and manuscript editing
Bruce Ferwerda	Collaboration on findings interpretation and manuscript editing
Shivendu Pratap Singh	Collaboration on findings interpretation

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Gohar F. Khan	G.F.K	**May 25, 2023**
Bruce Ferwerda		**May 26, 2023**
Shivendu Pratap Singh	Shivendu Pratap Singh	May 31, 2023

Postgraduate Studies Office
Student and Academic Services Division
Wahanga Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 4 of the thesis.

The impact of COVID-19 on online music listening behaviors in light of listeners' social interactions
Paper under review after revision submitted for the 2nd Round to the Multimedia Tools and Applications Journal

Nature of contribution by PhD candidate	Collaboration on developing research ideas, data collection, data analysis, findings interpretation, and manuscripts writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Gohar F. Khan	Collaboration on developing research ideas, findings interpretation, and manuscript editing
Shivendu Pratap Singh	Collaboration on data analysis, findings interpretation, and manuscript editing
Bruce Ferwerda	Collaboration on data collection and findings interpretation

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Gohar F. Khan	G. K	**May 25, 2023**
Shivendu Pratap Singh	Shivendu Pratap Singh	May 31, 2023
Bruce Ferwerda		**May 26, 2023**

Postgraduate Studies Office
Student and Academic Services Division
Wahanga Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter 3 of the thesis.

The Impact of Network Effects on Online Music Listening Behaviors: A Longitudinal Study

This paper will be submitted to the Journal of the Association for Information Science and Technology.

Nature of contribution by PhD candidate	Collaboration on developing research ideas, data collection, data analysis, findings interpretation, and manuscripts writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Gohar F. Khan	Collaboration on developing research ideas, findings interpretation, and manuscript editing
Bruce Ferwerda	Collaboration on data collection, findings interpretation, and manuscript editing
Shivendu Pratap Singh	Collaboration on findings interpretation and manuscript editing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
Gohar F. Khan	G.F.K	**May 25, 2023**
Bruce Ferwerda		**May 26, 2023**
Shivendu Pratap Singh	Shivendu Pratap Singh	May 31, 2023