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Music Oh my Music: A Network Perspective on Online Music Listening Behaviour

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Short paper

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Abstract

The success of online music platforms depends on the strength of the recommendation systems (RSs) that employ users' interaction data to offer customised music listening experiences. While the RSs incorporate social information, considering network effect (NE) originating from these social actions is at the early stages of the research. Hence, drawing upon research on the RS and NE, we propose the notion of Universal NE (UNE) as a function of the structure of the users' network, data-driven learning, and improvements realised with Artificial Intelligence (AI) that was limited to the size of the network traditionally. Moreover, we argue that listeners differ in the determinants underlying the perceptions of the value of UNE. The findings in this paper will be instrumental in understanding the perceived value of online music platforms and predicting music listening behaviour. The Partial Least Square-Structural Equation Modelling (PLS-SEM) is used to test the empirical data obtained through Last.fm.

Keywords Online music platform, Recommendation system, Network effect, Universal network effect, Music listening behaviour

1 Introduction

With the new developments in technologies and algorithms, the way people access and listen to music has fundamentally altered (Datta et al. 2017). Firstly, people no longer rely on private, mostly limited music collections (Moloney et al. 2008); instead, they have moved to free music streaming platforms containing the most songs. Secondly, online music platforms benefit from the RS—a type of AI utilised in various industries and enriched users' experience and satisfaction (CHA et al. 2019). AI and machine learning techniques learn from collected data; the digital interconnections with items (e.g., listening to the music, like a song) and individuals (e.g., follow, comment). These kinds of changes intellectualise the users' decision in a platform to, ultimately, users get the best options and expected satisfaction (Chen and Horton 2016).

Massive online companies such as Amazon, Facebook, Twitter, Spotify, and Last.fm employ the users' social networking and user interaction with the product and services to offer a social-based recommendation. The algorithm helps recommend the items by analysing two elements: 1) the social actions of each user, and 2) the consumption behaviour. The critical shortcoming in social recommendation research is that they leverage personal preferences, capture usage, and social parameters to provide highly accurate and effective recommendations. But, considering independently identical distributed connections and relationships to translate the impact of metrics on users' behaviour ignores the importance of studying users as a network and the network nature of the social actions (Khan 2018). As part of such a structure, each user's interactions with the system or interconnection with other users cause the exposure to the friends' reciprocal effect (Guidotti and Rossetti 2020), consequently might cause NE. As a good example, actions such as "Like" are apparent to other users and can carry network externalities (Khan et al. 2019).

Therefore, there is a need for appending NE to social network analysis as an open area that was not discussed before in the studies of music recommendation systems. In this way, theoretically, this study utilises the NE theory by accompanying AI and machine learning techniques to propose a new concept of network effect (UNE), which was limited to the network's size traditionally and apply it to enhance recommendation models in the industrial and academic areas. To the best of our knowledge, no previous published study has modelled the new form of NE mathematically in the online platforms with a recommendation system. Utilizing the attributes of the online music platform through the social network theory will enable us to study whether the UNE changes the regular patterns of users' music listening. Hence, this research sought to answer the following three questions.

RQ1. What is the UNE on the online platform (e.g., last.fm)?

RQ2. Whether the changes in the intensity of UNE will change the music behaviour of the listeners (in terms of album, artist, and genre of listening)?

RQ3. What is the variation of the music listening behaviour of users when the intensity of the UNE has changed?

The types of results could be individuals listen to more diverse music and change their listening interests (album, artist, and genre of listening) whenever they perceive different UNE. Therefore, three objectives of this research are 1) extend the current knowledge of findings regarding the method of investigation NE in platforms with recommendation systems; 2) developing a mathematical model of UNE; 3) demonstrate the longitudinal analysis of UNE using empirical data from the Last.fm and its impact on listening behaviour. The rest of this short paper is organized as follows. Section 2 leads to the identification of the prominent literature in NE definitions and music listening behaviour. Section 3 depicts the scale development and the method of the research. Section 4 discusses the empirical work conducted to evaluate the dynamic model of UNE and further design the analysis of music listening behaviour. Section 5 consists of future works and concluding remarks.

2 Background

2.1 Network Effect (NE) Notion

Numerous businesses have recognized NE as an accelerator that enables the diffusion and success of the company; famous examples are Amazon, Netflix, Microsoft, Facebook, Uber, and Airbnb. These very profitable firms consequently pose a platform business model that leads to NE (Gregory et al. 2020). Therefore, NE as a way of building business growth is well-established in marketing research;

for example, Stremersch et al. (2010) illustrate several cases for which the growth process of the business depends on NE and investigate the success of the company. As another example, Rong et al. (2019) introduce users as the primary resources of the online video platform and find that the innovative services enhance the NE to attract more users and stick them to the system to guarantee the business's success.

The first neoclassical economic studies explore the phenomenon of NE primarily based on the network's size to determine it (Afuah 2013). But in recent years, there are pieces of evidence that emphasize the importance of thinking beyond size. Primarily, social network sites that showed incredible growth between users disappeared straight away (Tucker 2018). Similarly, the development of the NE that led to the prosperity of Facebook over the last few years has begun to decelerate. These unfortunate results are incompatible with the logical outgrowth of success and market dominance because of traditional NE theories and just considering the number of users in a platform. Furthermore, the machine learning techniques and availability of data in recommendation systems theorise a new category of NE —data network effect that can be used to improve users' perceived value (Gregory et al. 2020). In the face of these drastic changes to NE and its distribution, the new IS technology (recommendation systems) has altered the traditional NE concept.

In the conventional model, the network effect is just limited to the network's size without considering any contribution gains from the same number of users over time. Therefore, this research contributes to the literatures on NE that consider metrics beyond the size (e.g., Afuah 2013; Cennamo and Santalo 2013; Khan et al. 2019; Parker 2017; Suarez 2005). We theorise, model, and measure the network values originating from UNE that utilise novel metrics complied with the definition of (Godes et al. 2005, pp. 416-417) "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". UNE reflects the network value trend based on the three categories of the user's social network structure, engagement with the system, and digital interaction.

2.2 Music Listening Behaviour

Researches that investigate how people use music in their everyday life or connect music listening behaviour with the personal characteristics of the individuals introduce the music taxonomies like artist, album, and genre as the indicators of the music listening behaviour. However, studies have either used all these indicators (e.g., Datta et al. 2017; Schedl and Hauger 2015) or focused on some of them (e.g., Ferwerda et al. 2017; Herrera et al. 2010). The dynamic model of user-item interactions examines online listening behaviour overtime to find consumption and changes (diversity) (Rafailidis and Nanopoulos 2015). The dynamic model of user preferences in the recommendation system shows many possibilities that allow users to test various items adjust their tastes accordingly (Rafailidis and Nanopoulos 2015). Similarly, listening to music attenuates over time, the listeners adopt more diverse music and online streaming impacts on quantity, variety in consumption, and new music discovery (Datta et al. 2017).

Still, no one investigates the cause of the changes in behaviour under the NE concept. The originality of this study lies in the fact that it is one of the few scholarly investigations focusing on the ever-evolving approach to the NE. In a longitudinal analysis, we will examine how UNE changes' consequence causes variability and changes in listening behaviour. There is a social dynamic between people joining a network, which can influence their attitudes, behaviours, and preferences (Carmagnola et al. 2009). Therefore, it is assumed that there is a mutual relationship between NE, user behaviour, and interactions with the platform as the observable behaviour of the user. The goal of this paper is to enhance the recommendation process by applying UNE measurement as different input data and study user behaviour. Using more sources into one recommendation system can provide more relevant information to the user (Pfeiffer and Benbasat 2012).

3 Methodology

3.1 Scale Development

This study requires extracting the secondary data, including users' friendship, music listening history, and digital profile of users. Music recommendation studies encounter the lack of standardized music datasets, which have detailed listeners' characteristics (Schedl and Ferwerda 2017). Last.fm has the potential to operate as a service for data collection and exploratory data analysis, which has been used regularly in previous research. It has created a recommendation system based on an algorithm that predicts how consumers would like specific music based on previous ratings, searches, listening history, and social connections. This platform enables users to connect and use music as social objects, share interests with other users. Consequently, individuals have more chances to discover music based on similar people and shared interests (Hagen and Lüders 2016). This service conveys the music-based social networking that allows us to conduct empirical research on the combination of NE and RS.

This quantitative research employs snowball sampling of the users in Last.fm who were very active in their profile and thus were inclined to participate more in the tasks of engagement and to establish friendships. We are using Last.Fm API "chart.getTopArtists", to retrieve the last top artists and listeners through the artists' web page. We use the data of the 1000 single users (the top mainstream listeners of the year) to create the network of individuals during the first step and then broaden the sampling by networks of friends (following and followers). To collect the taxonomies in defining music listening behaviour, for each user, the top 500 tracks and 50 most popular tags are downloaded.

3.2 Conceptual Model

Figure 1 shows the dynamic model of the UNE and its constructs to analyse user behaviour. The model is built on two concepts. The concept of novel NE argues that not only the number of friends or connections might impact the value or contribution to the system, but also the network structure and construction of the contacts, engagement with the system that shows the commitment of the user, and the digital profile exert the influences on the network of the user. The concept of data NE argues that whenever users have more connection with the system, the platform gains more data to provide personalized services. Any tie that binds the user to the system and lets the algorithm knows more about the user exacerbates the network effect's dynamic form and could impact user behaviour.

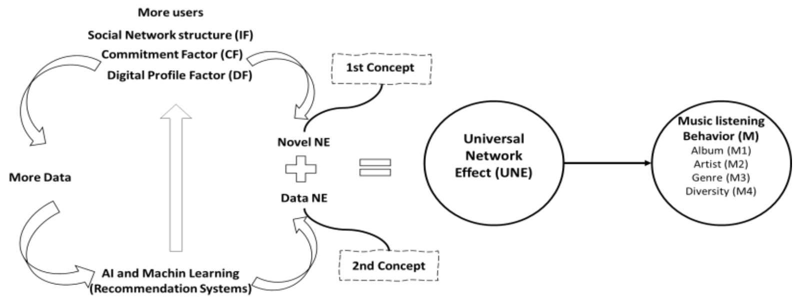

Figure 1. A dynamic model of the UNE and music listening behaviour

3.3 Variables

To answer the first research question, we will measure the independent variable UNE as the function of 1) The user's social network structure, which shows the Impact Factor (IF) of each user, 2) Engagement as the Commitment Factor (CF) for each user, and 3) Digital interactions with the platform as the Digital profile Factor (DF) (Table 1).

	Metric	**Meaning**
Network Structure	• Degree Centrality • Betweenness Centrality • Closeness Centrality • Structural Hole • Network Ties • Trust	Access and control over network flows, invest in building the right ties within the network (Afuah 2013; Bischoff 2012; Kane et al. 2014; Khan et al. 2019)
Commitment Measurement	• Time to first play • Sessions with play • Play-Count Function (Total and average daily number of plays)	Links to the distribution of engagement and usage (Oestreicher-Singer and Zalmanson 2013; Schedl et al. 2015)
Digital Profile	• Like • Shout (comment) • Tag • Playlist • Events • Obsessions	The observable digital content contributes to NE and improvement of the RS's algorithm (Agrawal et al. 2018; Bischoff 2012; Khan et al. 2019; Oestreicher-Singer and Zalmanson 2013; Tucker 2018)

Table 1. List of UNE Metrics Beyond the Size (Metrics, meaning, and references)

To answer the second and third research questions, 1) Changes in music consumption in Album (M1), Artist (M2), Genre (M3), and 2) Diversity in taste (M4) measure the dependent variable Music Listening Behaviour (M). The changes in music consumption and the diversity of a music taste are collected based on the technique introduced by Schedl and Hauger (2015) and Datta et al. (2017) (Table 2).

Indicator	Meaning
Changes in music consumption	The number of unique new artists, albums, and genres listened to by a user for the first time, divided by the total number of distinct artists, albums, and genres listed. (in each interval)
Diversity	How often the user listened to each track in the music collection on average.
Concentrating on a personal favourite	A distinct number of unique artists, albums, and genre tags in a users' listening profile.
Repeat consumption	The number of unique new artists, albums, and genres played more than once, divided by the total number of unique new artists, albums, and genres.

Table 2. Music Listening Behaviour Definition

4 Finding and Discussion

4.1 UNE Mathematical Modelling

A leading theoretical equation estimates the UNE (Equation 1) by replacing Equations 2, 5, and 6 for the IF, CF, and DF (Table 3). In Equation 1, t is the time of the observation for user i. UNE (N,t) at time t, within the integral of all n individuals in the network, is the UNE of the whole network (Equation 7). To measure the network ties and trust between users, the average values of Facebook (Equation 3) and Twitter (Equation 4) is used using the model introduced by Khan et al. (2019). A discussion of the properties of the ego network circles falls outside this paper's scope, and we refer the reader to (Sutcliffe et al. 2012). Feature rescaling by Equation 8 normalises UNE values between 0 to 1.

UNE(t,i) *= Impact Factor(IF) × [Commitment Factor(CF) + Digital Profile Factor (DF)]*	*Equation 1*
Impact Factor (IF) *= (Degree Centrality + Betweenness Centrality + Closeness Centrality + Structural Hole + Network Tie & Trust)/5*	*Equation 2*
$\textbf{Network Ties and Trust } (\boldsymbol{NTT}) = \left(\frac{2}{100}\alpha_1 + \frac{8}{100}\alpha_2 + \frac{23}{100}\alpha_3 + \frac{67}{100}\alpha_4\right) \times n_i$ *(Facebook model)*	*Equation 3*
$\textbf{Network Ties and Trust } (\boldsymbol{NTT}) = \left(\frac{1}{100}\alpha_1 + \frac{3}{100}\alpha_2 + \frac{9}{100}\alpha_3 + \frac{22}{100}\alpha_4 + \frac{65}{100}\alpha_5\right) \times n_i$ *(Twitter model)*	*Equation 4*
$\textbf{Commitment Factor } (\boldsymbol{CF}) = \left[\left(\textbf{Time Distance}: \frac{Time\ to\ first\ play(TFP) + Sessions\ with\ play(SWP)}{2}\right) \times (\textbf{Activity}: Play - Count\ Function(PCF))\right]$	*Equation 5*
Digital Profile Factor (DF) *= [Like + Shout (Comment) + Tag + The number of playlists + Events + Obsessions]*	*Equation 6*
UNE (N,t) = $\sum_{i=1,..,n}$ *UNE (t,i)*	*Equation 7*
$\boldsymbol{x_{new}} = \frac{x - x_{min}}{x_{max} - x_{min}}$	*Equation 8*

Table 3. Leading Equations to Estimate the UNE Function

The key numbers of the investigation are *provided* in Table 4. The striking results emerge from analysing the UNE level based on different metrics. On average, 87% of the value of the UNE is from 12% of the study population. Interestingly, 67% of the users engaged in the commitment category have not used the digital profile features to create the network value. The evidence we found points to the fact that in the music industry, digital activities are viewed as complementary rather than integral to content. Figure 2 presents the social structure, commitment, and digital behaviour patterns of users as a function of the registration time. Developing a dynamic model to measure the UNE in this research explains how with the static number of users, they still create value for the platform. Therefore, engaging in DF activities and conducting a social structure contribute to more value. Such a result is not justifiable with the traditional form of NE limited to the network size.

Result Type	**Value**	**Result Type**	**Value**
Time of Investigation	07-Aug-20	The average number of Tags (NOT)	1
The average number of friendships	162	The average number of Playlists (NOP)	1
Total play count	183	The average number of Events (NOE)	1
Average daily play count	185	The average number of Obsessions (NOO)	9
The average number of Like (NOL)	360	Max UNE	0.676
The average number of Shouts (ONS)	34	Min UNE	≈0

Table 4. Summary of the Investigating UNE (Average value of the network)

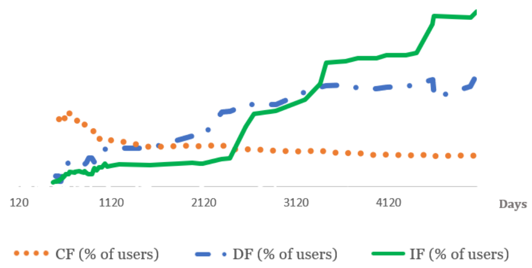

Figure 2. IF, CF, and DF Patterns over Time

4.2 Longitudinal Analysis of Music Listening Behaviour

This dynamic model will analyse the changes in the UNE level over time in a longitudinal analysis to find the within-subject changes of the same individuals and repeatedly capture the assessment of individuals' behaviour. A systematic data analysis in this study is based on the intensity of UNE at three points of data collection: 1) the beginning of this study, 2) after three months, and 3) after six months of analysis of the UNE level. By utilising the PLS-SEM, two types of associations will be considered; the first one is between the indicators and the latent variable, in which the impact of each indicator on the latent variable is measured; the second relationship is among latent variables, in which a path shows the effect of UNE on music listening behaviour.

To ascertain the intervention's impact only and ensure that specific findings are coming from the UNE level and not just from general trends (e.g., current music hits), we take into account the music charts that are relevant for that moment in time. The guideline "tutorial on the use of PLS path modelling in longitudinal studies" (Roemer 2016) for PLS modelling will be applied to analyse the model. It should be noted that when writing this short paper, the first stage of the longitudinal analysis has been done, and the authors do not have access to the changes in behaviour.

4.3 Theoretical and Practical Contributions

The theoretical and practical contributions are anticipated as follows. Firstly, this research is established a controversial approach regarding NE measurement, aims to call into research question 1 UNE in a platform business model, or how to model the NE mathematically beyond network size? The dynamic model will explain how NE characteristics are affected by recommendation systems based on the platform business model to measure the level of the UNE. Therefore, it also contributes to the network theory applied to many businesses, not limited to social network sites, because when there is a network, then there is a network effect. Recognizing the drivers of the UNE and the way to measure it widely will soon be considered as the most important strategic resource of the economic returns, irrespective of the past decade's great deal on the resource-based view (RBV) of the firm.

Secondly, conceptualising UNE as an additional indicator that users bring to the music streaming platform and specify the leading indicators to measure it possibly helps measure music listening behaviour (Research question 2 and 3). Therefore, this study uses the longitudinal analysis, that has rarely been used to analyse the NE and offers the potential to study listening behaviour. With growing attention to the importance of NE-related strategies between platforms' managers, exploring it with AI technology might benefit and serve the market. Overall, by applying this study, companies with a network market might benefit from social links analysis by detecting the UNE as a determining instrument for the company to increase the stickiness and engagement of the users and measure the changes in their behaviour.

5 Further Work and Conclusion

The dynamic model in this short paper explains how NE characteristics are changing recently and measures the value of the UNE. Our technique clearly shows the importance of users as the co-creator of the value of the platform. If many businesses assess their NE level using the UNE developed in this research, then it will provide valuable benchmarks so platform businesses can compare their level with other companies. The novelty of the proposed study enables us to analyse, characterize, and carry these properties forward to understand how and why user behaviour might change in a network with a recommendation system. The network could be music streaming platforms like Last.fm and Spotify or ride-sharing apps like Uber and Zoomy. In the context of recommendation systems, we believe that this study brings an important message for the effective use of NE in the social recommendation systems. Findings suggest the following opportunities for future research:

- Measure the social media Returns of Investment (ROI) using the UNE model
- Validate the Dunbar theory in this platform in comparison with Facebook and Twitter. (Research into solving this problem is already underway in progress.)
- Investigating whether results generalize to platforms other than Last.fm
- Test improvement in recommendation system algorithms using the UNE model

6 References

Afuah, A. 2013. "Are Network Effects Really All About Size? The Role of Structure and Conduct," Strategic Management Journal (34), pp. 257-273.

Agrawal, A., Gans, J., and Goldfarb, A. 2018. Prediction Machines: The Simple Economics of Artificial Intelligence. Harvard Business Press.

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, pp. 47-56.

Carmagnola, F., Vernero, F., and Grillo, P. 2009. "Sonars: A Social Networks-Based Algorithm for Social Recommender Systems," User Modeling, Adaptation, and Personalization. UMAP 2009. (5535), pp. 223-234.

Cennamo, C., and Santalo, J. 2013. "Platform Competition: Strategic Trade-Offs in Platform Markets," Strategic Management Journal (34:11), pp. 1331-1350.

CHA, N., CHO, H., LEE, S., and HWANG, J. 2019. "Effect of Ai Recommendation System on the Consumer Preference Structure in E-Commerce: Based on Two Types of Preference," 21st International Conference on Advanced Communication Technology (ICACT), pp. 77-80.

Chen, D. L., and Horton, J. 2016. "Research Note—Are Online Labor Markets Spot Markets for Tasks? A Field Experiment on the Behavioural Response to Wage Cuts," Information Systems Research (27:2), pp. 403-423.

Datta, H., Knox, G., and Bronnenberg, B. J. 2017. "Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery," Marketing Science (37:1), pp. 5-21.

Ferwerda, B., Tkalcic, M., and Schedl, M. 2017. "Personality Traits and Music Genre Preferences: How Music Taste Varies over Age Groups," 1st Workshop on Temporal Reasoning in Recommender Systems (RecTemp) at the 11th ACM Conference on Recommender Systems, Como, August 31, 2017.: CEUR-WS, pp. 16-20.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., and Verlegh, P. 2005. "The Firm's Management of Social Interactions," Marketing letters (16:3/4), pp. 415-428.

Gregory, R., Henfridsson, O., Kaganer, E., and Kyriakou, H. 2020. "The Role of Artificial Intelligence and Data Network Effect for Creating User Value," Academy of Management Review.

Guidotti R., Rossetti G. (2020). “Know Thyself” How Personal Music Tastes Shape the Last.Fm Online Social Network. In: Sekerinski E. et al. (eds) Formal Methods. FM 2019 International Workshops. Lecture Notes in Computer Science (12232). Springer, Cham.

Hagen, A. N., and Lüders, M. 2016. "Social Streaming? Navigating Music as Personal and Social," The International Journal of Research into New Media Technologies (23:6), pp. 643-659.

Herrera, P., Resa, Z., and Sordo, M. 2010. "Rocking around the Clock Eight Days a Week: An Exploration of Temporal Patterns of Music Listening.," 1st Workshop On Music Recommendation And Discovery (WOMRAD) (ACM, Barcelona).

Kane, G. C., Alavi, M., Labianca, G., and Borgatti, S. 2014. "What’s Different About Social Media Networks? A Framework and Research Agenda," MIS quarterly (38:1), pp. 275-304.

Khan, G. F. 2018. Creating Value with Social Media Analytics : Managing, Aligning, and Mining Social Media Text, Networks, Actions, Location, Apps, Hyperlinks, Multimedia, & Search Engines Data. Seattle, Washington: CreateSpace.

Khan, G. F., Mohaisen, M., and Trier, M. 2019. "The Network Roi: Concept, Metrics, and Measurement of Social Media Returns (a Facebook Experiment)," Internet Research, (30:2), pp. 631-652.

Moloney, B., Cybulski, J., and Nguyen, L. 2008. "Value Perception in Music Information Systems," ACIS 2008 Proceedings, pp. 679-689.

Oestreicher-Singer, G., and Zalmanson, L. 2013. "Content or Community? A Digital Business Strategy for Content Providers in the Social Age," MIS Quarterly (37:2), pp. 591-616.

Parker, G. 2017. Platform Revolution : How Networked Markets Are Transforming the Economy - and How to Make Them Work for You. New York, NY: W.W. Norton.

Pfeiffer, J., and Benbasat, I. 2012. "Social Influence in Recommendation Agents: Creating Synergies between Multiple Recommendation Sources for Online Purchases," ECIS 2012 Proceedings.

Rafailidis, D., and Nanopoulos, A. 2015. "Modeling Users Preference Dynamics and Side Information in Recommender Systems," IEEE Transactions on Systems, Man, and Cybernetics: Systems (46:6), pp. 782-792.

Roemer, E. 2016. "A Tutorial on the Use of Pls Path Modeling in Longitudinal Studies," Industrial Management & Data Systems (116:9), pp. 1901-1921.

Rong, K., Xiao, F., Zhang, X., and Wang, J. 2019. "Platform Strategies and User Stickiness in the Online Video Industry," Technological Forecasting and Social Change (143), pp. 249-259.

Schedl, M., and Ferwerda, B. 2017. "Large-Scale Analysis of Group-Specific Music Genre Taste from Collaborative Tags.," The 19th IEEE International Symposium on Multimedia (ISM2017), pp. 479-482.

Schedl, M., and Hauger, D. 2015. "Tailoring Music Recommendations to Users by Considering Diversity, Mainstreaminess, and Novelty," The 38th international ACM sigir conference on research and development in information retrieval, pp. 947-950.

Schedl, M., Knees, P., McFee, B., Bogdanov, D., and Kaminskas, M. 2015. "Music Recommender Systems," in Recommender Systems Handbook. Springer, pp. 453–492.

Stremersch, S., Lehmann, D. R., and Dekimpe, M. G. 2010. "Preface to “the Chilling Effects of Network Externalities”," International Journal of Research in Marketing (27:1), pp. 1-3.

Suarez, F. 2005. "Network Effects Revisited: The Role of Strong Ties in Technology Selection," Academy of Management Journal (48:4), pp. 710-720.

Sutcliffe, A., Dunbar, R., Binder, J., and Arrow, H. 2012. "Relationships and the Social Brain: Integrating Psychological and Evolutionary Perspectives," British journal of psychology (103:2), pp. 149-168.

Tucker, C. 2018. "Network Effects and Market Power: What Have We Learned in the Last Decade?" Antitrust Retrieved, from http://sites.bu.edu/tpri/files/2018/07/tucker-network-effectsantitrust2018.pdf.

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