Thanking the Algorithm: Discovering Prosocial Communities Through YouTube Music Recommendation Pathways

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Abstract

What pathways through algorithmic music recommendations help users discover prosocial comment communities? Building on algorithmic awareness and music discovery literature, this exploratory, naturalistic study follows four user personas on YouTube through four music genre seed queries and ten layers of recommendation depth, to analyze the frequency and nature of the prosocial comment communities they encounter. Our results suggest that prosocial communities are accessed more frequently by personas who defy algorithmic classification in their use patterns, and that within prosocial communities users express not just awareness of the recommendation algorithm, but gratitude directed explicitly toward it. This exploratory, context-bound study contributes to understanding how users and algorithms co-construct musical meaning and community, offers methodological insights for studying algorithmic experience and recommendation pathways, and reflects on the ephemerality of prosocial communities within black-boxed discovery platforms.

Keywords: algorithm awareness, music discovery, algorithm experience, network gatekeeping, online communities.

1. Introduction

In our era of digital saturation and social media fatigue, YouTube's music recommendation system occasionally offers users respite not just through songs, but community. Buried in algorithmic pathways, users can discover emotionally resonant music and unexpectedly supportive comment sections. These largely unsearchable spaces, where gratitude, nostalgia, and mutual appreciation thrive, may share attributes of virtual third places such as informality, social leveling and happily anticipated gatherings (Oldenburg, 1999; Putnam, 2000). This exploratory qualitative study investigates how users navigate YouTube algorithmic recommendations to discover these rare and ephemeral "checkpoints" (Mura, 2020), and express appreciation for the content, the community, and the algorithm that brought them there.

Building on network gatekeeping theory (Barzilai-Nahon, 2008), algorithm awareness (Zarouali et al., 2021), music recommendation (Hesmondhalgh et al., 2023), persona-based use patterns (Lee & Price, 2015), and a naturalistic method based on users' algorithm experience (Alvarado & Waern, 2018; Liu et al., 2024), this paper reports on the results of an exploratory content analysis of YouTube music recommendation pathways. Starting with seed queries in four distinct music genres, each of four user personas navigated algorithmic music recommendations based on their characteristic use patterns to ten levels of recommendation depth (Ribeiro et al., 2020). For each recommended video, we then analyzed the ten top-rated comments that users are most likely to encounter to represent the tone of the comment community. We adapted coding frameworks from Madden et al. (2013) and Lamont et al. (2023) to identify the frequency and quality of prosocial comments encountered by the four personas at each step of algorithmic recommendation.

The results suggest that pathways to music discovery and prosocial comment communities are accessed more frequently by "Wanderer" (Lee & Price, 2015) and "Enigma" (YouTube, 2024) personas whose use patterns confound algorithmic gatekeeping, as opposed to purposeful seekers who prioritize consistent indicators such as view count or genre relevance in their recommendation selections.

This exploratory study contributes to understanding algorithm awareness, user agency and network gatekeeping within discovery platforms, specifically the relationship of mutual information asymmetry between users and algorithmic recommendation systems. It extends literature on persona-based use patterns and algorithmic experience, and though context-bound, offers methodological insights for studying recommendation pathways and processes of prosocial community formation.

In these algorithmically surfaced music spaces, users engage in prosocial behaviors that foster expressions of person-person, person-community, and

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person-algorithm connection. The results also suggest that within these comment communities, users express not just awareness of the recommendation algorithm, but gratitude directed explicitly toward it. Through the asynchronous, anonymous conversations that the YouTube comment platform affords, users express wonder, accomplishment and belonging, having earned entrance to these prosocial communities by making a series of good choices from algorithmic recommendations, even if they can only speculate about what those choices were.

Through this exploratory study, we seek to learn more about algorithmic recommendation pathways in music discovery, and the nature and indicators of prosocial communities that users discover, create and perpetuate.

2. Literature review

Gatekeeping presupposes that something valuable lies beyond the gate. A range of algorithm experience and music recommender systems research suggests that users of discovery platforms derive value beyond music: community, connection and the algorithmic discovery experience itself. Barzilai-Nahon (2008) develops network gatekeeping theory, and calls for research that "*recognizes the role and power of those subject to gatekeeping, and their possible circumventions of gatekeeping mechanisms"* (p. 1508). DeIuliis (2015) reviews and extends Barzilai-Nahon's work, and sees a dimension of user agency not just through increased transparency of any single platform's algorithmic gatekeeping, but by having more platform choices, and more agency across them.

Bonini and Gandini (2019) discuss the "algo-torial" power of music curation platforms, driven by a human-algorithm relationship: human curators' editorial power enhanced by algorithms and big data. In a review of music recommender systems research (Hesmondhalgh et al., 2023), the authors note the consistent appearance of "popularity bias," defined as how music recommendation algorithms reinforce already popular music, which trades against discoverability. Systems that channel users into predefined categories such as music taste or mood risk overfitting the data, rendering them overly prescriptive and inhospitable to novel use patterns. Researchers including Hagen (2015), Nowak (2016), and Johansson et al. (2017) have studied the satisfaction and value that users perceive when they break through algorithmic limitations of music recommendation platforms, and experience deep discovery.

2.1. Algorithm awareness

Research in critical algorithm studies distinguishes actual and perceived user agency. Gillespie (2014) discusses how algorithms become "entangled with practice" and produce "calculated publics" who define and are defined by the algorithms with which they interact. Karakayali et al. (2017) frame algorithmic recommendation as a similar space of tension, where users guide and receive guidance on their music discovery. Siles et al. (2022) found that TikTok users consciously engage with algorithmic recommendations, and feel that they must actively "train" the app. However, awareness does not imply understanding. Bucher (2018) discusses "algorithmic imaginaries" that reify user practices and shape future recommendations, and Haapoja et al. (2024) studied how Reddit users intentionally engage in "pleasing the algorithm" to gain rewards such as content visibility, and allow community members to debate ethical aspects of algorithm manipulation, and folk theories of how they work.

Zarouali et al. (2021) developed and validated the Algorithmic Media Content Awareness Scale, which was tested across Facebook, YouTube, and Netflix, and also includes a dimension of "human-algorithm interplay." Gran et al. (2020) propose an algorithm awareness user typology: the unaware, the uncertain, the affirmative, the neutral, the sceptic and the critical. While typologies overlap, it is noteworthy that only one type, the affirmative, reflects a positive orientation to algorithms, though all but the unaware are ascribed with elements of intentional agency.

2.2. Personas and music discovery practices

YouTube Recap (YouTube, 2024) offers users a descriptive "personality" based on its analysis of their listening habits. Categories tend to change year to year, and have included personalities such as Vibe Diver, Mellow Mixologist, Deep Wanderer and Alt Explorer. YouTube also identifies an "Enigma" personality for those with listening patterns the algorithm finds unclassifiable. While details of personality indicators are not made public, there is evidence of openness to diverse music genres, and willingness to engage in deep, active exploration of algorithmic recommendations present across several YouTube personalities. In contrast, people who allow algorithms to passively create playlists, and those who prefer known songs and artists, would likely not be characteristic of any of these persona types.

The Spotify platform also uses personas in product development (Torres de Souza et al., 2020) representing individuals' music tastes and their preferred social interactions and contexts where music is played.

Liikkanen and Åman (2016) found that YouTube users preferred serendipitous discovery via algorithmic recommendations and social interactions around content.

The qualities of the music matter as well. Ji et al. (2019) report that “awe-eliciting” music increased listeners’ positive affect and prosociality. Dale et al. (2017) found a similar social dimension in discovery of “self-transcendent” music, as did Zhang and Liu (2025), who studied how older adults assess and navigate media recommendations. Alvarado et al. (2020) studied user perceptions of recommendation algorithms, and propose a framework that distinguishes between the agency of individual users, other users, the algorithm and the organization as four distinct classes of actors, emphasizing the social aspect of their interactions.

Among these actors, the user-algorithm relationship has received particular research attention. Savolainen and Ruckenstein (2022) suggest two “horizons” of human-algorithm relations: the instrumental, referencing the unknown technical workings, and the “algorithmic intimacies” that are consciously and systematically pursued when users feel seen and understood by the algorithm. Bucher (2017) identifies “Whoa moments,” when users become aware of the intimate power of algorithms, such as seeing ads on one site for items previously searched on another, or that they already own. Ruckstein and Granroth (2020) argue that successful personalization generates pleasurable feelings of being ‘seen’ and ‘recognized’ by the algorithmic system.

Lee and Price (2015) propose two dimensions of user behavior in music recommendation that combine Investment (individual willingness to engage with the algorithm) and Companionship (willingness to engage in social aspects of music recommendation and listening), and propose seven corresponding personas: Active Curator, Music Epicurean, Guided Listener, Music Recluse, Wanderer, Addict, and Non-believer. While the Active Curator and Music Epicurean personas engage with recommender systems, they tend not to trust them. Only the Wanderer persona “*enjoys the discovery process in general…and is willing to put in some effort to discover new music. The Wanderer will likely accept recommendations from a system as equally as she will accept them from a friend…*” (p. 479).

Building on the persona framework proposed by Lee and Price (2015), Fuller et al. (2016) interviewed 962 users and identified the Wanderer as the most common persona, typified by enjoyment of serendipitous discovery from friends and algorithms alike, and openness to unfamiliar music genres.

Freeman et al. (2022) interviewed 15 active users of music streaming services and describe how through daily interactions with algorithmic features and curation, listeners build complex socio-technical relationships with these algorithmic systems, involving human-like factors such as trust, betrayal and intimacy. Freeman et al. (2023) used naturalistic algorithm experience as a lens to investigate music recommendation and automated curation on several streaming services, and suggest the notion of vibe as an important self-defined dimension of music discovery that is based on impressions, not exhaustive review of posted content. It is essential to foreground the iterative nature of the music discovery experience, as opposed to that of a static search, and that naturalistic algorithm experience is often based on first impressions of both recommended music and surrounding comments, which shapes the design of the present study.

2.3. YouTube comment classification

The challenges of YouTube research with a black-boxed platform algorithm and no information about use patterns or database content have been well-documented (see, for example, Lukoff et al., 2021), and an industry has arisen promising to reveal inside information about algorithmic optimization on YouTube (Bishop, 2020).

Liu et al. (2024) employed automated “sock puppet” agents to create simulated user interactions in an algorithm audit of how YouTube users remove unwanted content from their feeds, and used human coding to label algorithm-recommended channels recommended to their agents.

Madden et al. (2013) analyzed 66,637 YouTube comments and proposed a comment classification scheme consisting of ten broad categories and 58 subcategories. While “Site processes: Site design” and “General conversations: Thanking comments” are both present in the schema, neither directly address user comments directed at the YouTube algorithm. Similarly, “Expression of personal feelings” and its subcategories are described as individual expressions, not those describing the commenters as a group.

Lamont et al. (2023) analyzed 288 comments around two songs posted to YouTube, considering social and navigational dimensions including how the listener discovered the music.

From this brief review, we see warrant for tracing people’s naturalistic pathways through algorithmic music recommendations based on known persona characteristics, and for adapting comment coding frameworks from prior literature for indicators of prosociality in person-person, person-community, and person-algorithm dimensions to address the research question:

RQ: What pathways through algorithmic music recommendations help users discover prosocial comment communities?

3. Method

Our naturalistic approach to algorithmic music discovery attempts to model, select and analyze the data users are likely to encounter through the platform interface when selecting from recommendation options, and assessing the comment communities surrounding each. Critically, we focus on the data presented to users that requires minimal if any scrolling: the first ten comments presented in the default view on a single recommended video (regardless of whether it is a song, album or compilation), and the first ten algorithmic recommendations in the right panel of the default view.

3.1. Personas

Using content and thematic analysis, we examined recommendation pathways taken and comment threads encountered by four personas, reflecting use patterns identified in previous literature and in YouTube's data-driven "personalities" (YouTube, 2024). For this study, personas are named for the primary variable driving their decision about which recommendation to accept from the options presented, with a parenthetical alignment with personas proposed by Lee and Price (2015):

- **Algorithm:** Always clicks the highest algorithm-recommended video. (Addict; embraces recommendations uncritically)
- **Popularity:** Always clicks the recommendation with highest view count among the top 10 presented. (Guided Listener; values social aspects of recommendation and interaction)
- **Genre:** Always clicks the most genre-relevant recommendation from among the top 10 presented, given the genre seed query. Evidence generally included title or image. In cases where multiple options could be chosen, we selected the one presented highest in the recommendation list. (Music Epicurean, Active Curator; actively shape results, less trust in algorithmic recommendations)
- **Random:** Clicks a random video from among the top 10 recommended, determined by a random number generator. (Wanderer; open to but not bound by recommendations)

Following Sui et al. (2022), a new YouTube account was created for each persona, with no prior watch history or logins.

3.2. Genre seed queries

Discovery implies novelty, and previous research emphasizes the emotional, evocative nature of unfamiliar music serving as both motivation and reward for those who follow algorithmic recommendation pathways. Therefore, our seed queries are drawn from lesser known genres with primarily instrumental music, to minimize the influence of text-based dimensions of recommendation, and debates around well-known artists or song lyrics in the comments. While music genres and common instruments resist hard definition, we operationalized our genre seed queries focusing on these typical aspects and instruments:

- **Bossa nova**, Brazilian nylon string acoustic guitar
- **Dark academia**, solo classical piano
- **Ambient lo-fi**, electronica and sound samples
- **Space rock**, electric guitar and synthesizer

Searches were run on Firefox versions 138 and 139, macOS 15, from the United States, which is a limitation of this study. Also, browser history and cookies were cleared before and after each persona's genre-based seed query and recommendation navigation process, which trades against naturalistic validity. For each persona, we ran an initial seed query on each of the genres above, selected the highest-returned video according to the priority of the persona, reviewed and analyzed the top ten comments surrounding the video, then made a persona-based selection from the top ten recommendations in the right panel. We repeated this process to ten layers of algorithmic recommendation depth for each genre seed query, then again for each of the four personas.

Selection criteria included videos with instrumental music, a static image, with comments enabled. Exclusion criteria were videos with vocals, lyrics, graphics, slideshows, animations or live performance footage, pinned comments, sponsored content, and videos with comments disabled. Mouse-over previews and brief plays were permitted to assess eligibility. Recommended videos were opened in a new tab, so if they did not meet selection criteria, the original list of recommendations remained accessible. When selection criteria were not met, the next item in the recommendation list was considered. Videos already selected that reappeared in recommendations within the same persona-genre pathway were excluded.

Following this process, each of the four personas encountered ten sequentially recommended videos from each of the four genre seed queries. Overall, we analyzed 196 videos, 36 of which were eliminated for not meeting inclusion criteria, resulting in 160 total videos, or 40 per persona. Additionally, 19 videos appeared in multiple persona-genre pathways.

3.3. Prosocial comments

For prosocial comment identification and analysis, we follow the naturalistic algorithm experience framework suggested by Freeman et al. (2023). We adapted the top-level comment categories proposed by Madden et al. (2013), and those of Lamont et al. (2023) focused on music discovery, to estimate how many of the top ten comments connected to a video could be coded as prosocial, including dimensions of person-person, person-community and person-algorithm.

We coded the first ten comments presented in the default view of each of the 160 music videos, to estimate the frequency of prosocial comments at each level of recommendation depth that each persona encountered. The 1600 total comments were initially coded as found, though a mismatch emerged between exclusive and hierarchical codes. Following the literature, we anticipated some comments coding for algorithm awareness, but within this group we observed a distinct subset of comments expressing explicit gratitude toward the algorithm. We believe this is a sufficiently novel finding to highlight as a separate code, though it comes at the expense of hierarchical/exclusive coding consistency. A secondary coder then reviewed a spreadsheet with a random subset of comments and the four preliminary codes, and agreement was 95%. As multiple codes were permitted for all comments, in the few cases of disagreement, both codes were applied. Also, selected replies to first-presented comments were subsequently analyzed as discussed in section 4.

Examples of comments coded prosocial include:

- Algorithm awareness (person-algorithm): e.g., "*The algorithm brought me here*."
- Gratitude directed toward the algorithm (person-algorithm, emerged as a distinct subset of algorithm awareness): e.g., "*Thanks my algo!*"
- Supportive comments directed toward users (person-person): e.g., "*Been there brother*."
- Community sentiment (person-community) e.g., *"We were chosen," "Here my soul back from the abyss found some light." "We have discovered the time machine my friends."*

Conversely, comments about the music content, artist/creator, poster/uploader or sound quality, as well as spam or nonsense posts were not coded as prosocial.

While we report the frequency of each observed code to begin to map the terrain of prosocial communities in algorithmic music recommendation, this is a qualitative exploratory study, and our intent is for the results to be viewed as illustrative cases.

4. Results and discussion

In Figure 1, we present an overview of the prosocial comments encountered by each persona across all four genre seed queries to ten levels of recommendation depth, and a detailed breakdown by persona and genre seed query in Table 1. With 1600 comments coded, the relative rarity of prosocial top comments (80) was notable, but subsequent review revealed additional prosocial comments in the replies to top comments, even those not initially coded as prosocial. Our naturalistic method did not account for comment replies that users were unlikely to encounter without additional clicks, indicating a higher incidence of prosocial comments.

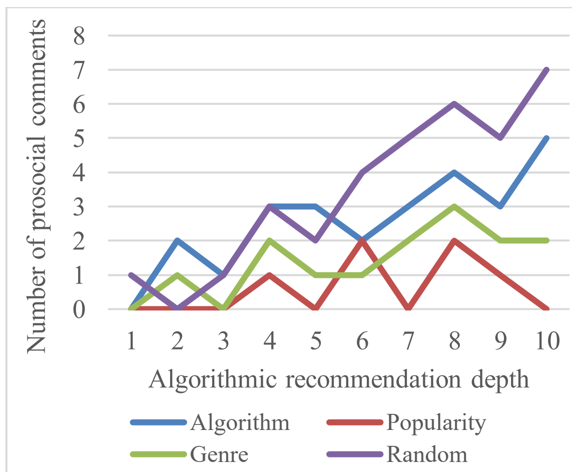

Figure 1. Prosocial comments encountered (y-axis) at each level of recommendation depth (x-axis) by each Persona, across all four genre seed queries.

Our results suggest that the frequency of prosocial comments tends to rise with increasing levels of recommendation depth, and are more often encountered by the Algorithm persona, who always chooses the highest algorithm-recommended video, and the Random persona, who by definition has no pattern in their recommendation selections.

The Genre persona yielded perhaps the most surprising findings, as we anticipated that people seeking, discovering and sharing music within a specific genre would build prosocial communities around that common interest, but this was not evidenced in the videos and comments we observed. The Popularity persona encountered the fewest prosocial communities, which may reflect a more passive, disengaged approach to music discovery.

Table 1. Prosocial comments by Persona, Genre seed query and level of recommendation depth, from top 10 comments on 160 videos (n=1600).

Persona Genre seed query	**Recommendation depth**										**Total**
	1	2	3	4	5	6	7	8	9	10	
Algorithm	**0**	**2**	**1**	**3**	**3**	**2**	**3**	**4**	**3**	**5**	**26**
Bossa nova	0	1	0	1	1	1	2	2	2	2	12
Dark academia	0	1	1	0	1	1	1	1	1	2	9
Ambient lo-fi	0	0	0	1	0	0	0	0	0	0	1
Space rock	0	0	0	1	1	0	0	1	0	1	4
Popularity	**0**	**0**	**0**	**1**	**0**	**2**	**0**	**2**	**1**	**0**	**6**
Bossa nova	0	0	0	0	0	0	0	0	0	0	0
Dark academia	0	0	0	1	0	1	0	1	1	0	4
Ambient lo-fi	0	0	0	0	0	1	0	1	0	0	2
Space rock	0	0	0	0	0	0	0	0	0	0	0
Genre	**0**	**1**	**0**	**2**	**1**	**1**	**2**	**3**	**2**	**2**	**14**
Bossa nova	0	0	0	1	0	1	1	3	1	1	8
Dark academia	0	0	0	0	0	0	0	0	0	0	0
Ambient lo-fi	0	0	0	1	1	0	0	0	0	1	3
Space rock	0	1	0	0	0	0	1	0	1	0	3
Random	**1**	**0**	**1**	**3**	**2**	**4**	**5**	**6**	**5**	**7**	**34**
Bossa nova	0	0	0	0	1	0	1	1	0	0	3
Dark academia	0	0	0	0	0	2	1	2	1	2	8
Ambient lo-fi	1	0	1	2	1	1	2	3	4	4	19
Space rock	0	0	0	1	0	1	1	0	0	1	4
Total	**1**	**3**	**2**	**9**	**6**	**9**	**10**	**15**	**11**	**14**	**80**

4.1. Personas

The Popularity persona encountered the fewest prosocial comments (6). Consistently selecting the recommendation with the highest view count may signal to the algorithm to suggest more of the same. High-view videos tend to draw more comments, and the most highly rated tend to be informational, such as details about the artist or recording session, rather than social. Per Lee and Price (2015), people who prefer more crowd-driven (Active Curator, Music Epicurean) or passive (Addict, Guided Listener) music discovery may be reflected in the experience of the Popularity persona.

The Genre persona encountered the next fewest prosocial comments (14), as their choices signaled to the algorithm their primary interest in genre-relevant music. The recommendation options presented rarely strayed from the seed genre, and most had very high views (in excess of one million) within the genre, yielding fewer top comments coded prosocial. When the Genre persona encountered prosocial comments, they tended to be attached to videos with far fewer views, some posted recently enough to bear the "New" label, as if the algorithm intentionally mixes in new content for those demonstrating a narrow interest track.

The Algorithm persona encountered 26 prosocial comments, most of which tended to appear after following seven consecutive recommendations. By consistently selecting the highest recommended video, the Algorithm persona tended to be presented with a more diverse range of genres relative to their seed queries. For example, though most prosocial comments were observed in the bossa nova and dark academia seed queries, the music selected at greater recommendation depth tended to drift outside those initial genres.

The Random persona encountered 34 prosocial comments, the most of any persona in the study, and tended to encounter them earlier, after following six consecutive recommendations. While the inclusion of this persona might be perceived as a control condition against which to compare more tangible personas, the Random persona best reflects the commonly observed "Wanderer" and "Enigma" personas from previous literature, who exhibit the least predictable recommendation preferences and use patterns.

4.2. Prosocial expressions

In the second phase of data analysis, we attempted to identify and code prosocial expressions encountered in the first phase, using comment classification adapted from previous research. Given the sparse data (80 prosocial comments of 1600 total), the observed but uncoded prosocial replies to top comments mentioned earlier, and the frequency of comments with elements of two or even three codes (39 of 80, yielding 126 total codes applied to the 80 prosocial comments observed), we therefore present this phase of our findings as a descriptive analysis.

Algorithm awareness (49 observed) was the most commonly coded comment type, prosocial in the sense that it reflects a person-algorithm relationship. Examples of algorithm awareness expressions included:

- *When some of the most soulful music is introduced to me by a soulless algorithm. Future.*
- *youtube always comes in clutch with random ass recommendations like this and they're all straight up BANGERS*
- *When the Algorithm inherently knows my love for 80's Epcot.*
- *Sometimes my algorithm really gets it right and blesses me though; this is one of those times.*

Thanking the algorithm (33 observed), a subset of algorithm awareness focused on expressions of explicit gratitude toward the algorithm, was the next most commonly coded prosocial comment type, though it sometimes proved difficult to distinguish from algorithm awareness. Being aware of algorithmic intervention and expressing happiness at the music discovered as a result may or may not imply algorithm-directed gratitude. Higher confidence examples of this code include:

- *Like some missive from an alien lifeform chronicling the distant cosmos of our collective consciousness. Thank algorithm for this transmission*
- *Bookmarked, playlisted, shared. Ty YT!*
- *youtube recommendation sometimes shines light on the right places. thank you!*

Supportive comments directed toward other users (22 observed) indicate prosocial concern for others surrounding music discovery as part of shared identity, (Karakayali et al., 2017), but without an explicit community component. Examples include:

- *This is a true gem. like a very nice wine that you do not share at a party, but rather with someone who understands it*
- *I love meeting you here at YouTube Check points just to see how everyone's doing. Stay strong.*
- *This is why I love YouTube. I've been a deep diver of music for 40 yrs and there's always more to be discovered. The only thing missing is being in the record store with the newly discovered album in hand. Then to have some other random patron notice it in my hand and approach me to tell me how awesome it is and then to show me more albums like it. That's what's missing from all this access. The shared experience.*

Community sentiment comments (22 observed) indicate that people perceive a community surrounding a music recommendation, and see themselves as part of it (Gazan, 2009). Expressions tend to include "we" and "us" statements, and range from a sense of wonder that the community exists, folk theories of how they earned passage and membership, and metaphors of music discovery as a physical journey shared by all present, fueled by algorithmic recommendations. Examples include:

- *I love the comment sections in uploads like this one. No arguing, no hostility, just people vibing together and sharing stories.*
- *my time has come friends, I have been chosen, happy to be here.*
- *guys, if the algorithm chose us, it means we all here very special human being. so cheer for us*
- *Sometimes you find a video like this one. One that really resonates with you in a special way that fills your spirit. Then you read the comments and begin to think, Hey! These people get it. I wish I could find more people like this to hang with.*

As discussed previously, 39 of the 80 prosocial comments could be described with multiple codes, and some were encountered as replies to top comments:

- *The Youtube algorithm - We can make a religion out of this.*
- *Hail to the AlgoGod*
- *The algorithms never lie my brother*
- *When your nervous system needs soothings from the world's noise and YT algorithm's got your back*
- *mythical algorithm pull*
- *Dear YouTube algorithm, Please keep recommending me videos like this one. - Everyone grooving to this shit rn*

- *Okay, algorithm. I caved. You were right. This is great.*
- *The AI Changed its mind. It's going to give some of humanity a chance. Hah*

The results suggest that prosocial communities express awareness of, and appreciation for, the music, people and algorithms that co-create these virtual spaces where they feel understood and seen (Ruckstein & Granroth, 2020). We also find support for Savolainen and Ruckenstein's (2022) sense of algorithmic intimacy providing not just connection, but breathing space and escape. For users who find and contribute to prosocial music discovery communities, uncritical relaxation, sharing and enjoyment are most commonly observed expressions, as opposed to attempts to explain or reverse engineer their experience.

Barzilai-Nahon (2008) foregrounds the dynamic relationships between individuals, communities and algorithms: "*interactions are created or transformed between groups and individuals due to network gatekeeping"* (p. 1508). Our results suggest that for some users, network gatekeeping in music discovery may be taking place in an environment of mutual information asymmetry. Users can only speculate about why they receive particular recommendations, and algorithms cannot analyze random use patterns as effectively. Prosocial communities may be more likely to arise and thrive at these boundary conditions.

Returning to the research question, the pathways through algorithmic music recommendation that helped users discover prosocial comments and communities tended to be traversed by the Random and Algorithm personas, who did not take consistent paths through the recommendations. We also find evidence that the Random and Algorithm personas are presented with recommendations that support a social dimension of music discovery, identified in previous literature as a characteristic of analogous Wanderer/Enigma personas.

In contrast, Popularity and Genre personas, who consistently selected recommendations along a single dimension, encountered fewer prosocial comments. For all personas, prosocial comments tended to be encountered at greater levels of recommendation depth.

4.3. Limitations and future work

In addition to the inherent limitations of studying YouTube or any black-boxed platform, our observation of prosocial comments occurring outside the naturalistic selection criteria, for example by tracing comments to replies not visible in the default view, is a limitation of this study, and suggests the need for multi-method approaches that integrate more robust automated harvesting of comments and replies with persona-based naturalistic algorithm experience analysis, to reveal greater nuance and agency within comment communities. For example, some expressions of gratitude toward the algorithm might be conflated with expressions of celebration for beating algorithmic gatekeeping, and discovering music and community on the platform few others find.

Our study design incorporated four genre-based seed queries, resulting in 160 videos selected for inclusion, 1600 comments, analyzed through the lens of user personas that share common characteristics, but are not rigidly defined. Because of these choices and other limitations identified throughout the paper, the results cannot be viewed as generalizable. However, successive recommendation layers revealed other recurring genres that could serve as promising seed queries in future work, and yield new insights into music discovery. These include lounge, math rock, psychobilly, library music, chillout, incidental music, mall music, old money, vaporwave and officewave.

Future research might also investigate the rapid rise of AI-generated music appearing in YouTube recommendations. Some carry intentionally misleading signals of authenticity, such as AI-created images that appear to be old vinyl album covers, and parenthetical years in title (e.g. 1972) that may have been used to prompt the AI, but have no relationship with when the music was created. Comment sections focused on appreciating music provide a qualitatively different experience than those debating its authenticity. The extent to which AI-generated music is embraced or shunned within algorithmic recommendation pathways and comment communities is of immediate concern to music discovery platforms and users, and may echo how people's attitudes have evolved toward algorithms themselves.

5. Conclusion

With a few rare and treasured exceptions, places change. Discovering a place, a community, a vibe, even one as transient as comments surrounding a discovered song, can feel like a reward and respite from the treadmill of searching and scrolling.

Drawing on research in algorithm awareness, music discovery and network gatekeeping theory, this study employed a naturalistic, qualitative, exploratory design to investigate how persona-based users navigate algorithmically recommended music on YouTube, and how flexibility in genre and recommendation selections impacts their discovery not just of music, but prosocial expressions around it. The results suggest that even when platform-mediated conversations are limited to lurking, liking or briefly commenting, users express appreciation that they have been "chosen" by the algorithm, and foster a sense of belonging in a shared virtual space where they are both conscious and unaware of how they arrived there.

Algorithms aren't free. Users of music discovery platforms are well aware that their usage data is tracked, captured and monetized, and that the same algorithm that yields an occasionally sublime recommendation could at any moment decide to share that same recommendation with other recognizable YouTube personas—value extractors and attention seekers—and its prosocial nature is lost.

Though outside the present study, as if to underscore the ephemeral nature of prosocial communities around algorithm-recommended music, subsequent informal visits to a few of the videos and comment communities in this study revealed that they had changed to the point where they would no longer meet selection criteria. Comment threads were pockmarked with bot-uprated spam, shitposting trolls and self-proclaimed producers boasting about having sampled the track in their own creations. Prosocial comments were flooded out to the point where they were more likely to be accessed by automated scrapers than browsing humans. Videos with dreamy, evocative music now contained jarring intrusions of unskippable ads. Some previously coded comment threads seemed no longer to exist at all, until it was discovered that copycat uploads with the same album cover image and title had been posted, to siphon views from the original.

Still, most of the prosocial communities observed in this study remain active. Reading through their expressions of appreciation, support and wonder is its own kind of music.

6. References

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