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How Netflix's Recommendation Algorithms Function in Small Markets – The Case of Serbia[1]

Abstract: This study examines the functionality of Netflix's recommendation algorithms in smaller markets, focusing on Serbia. Through a reverse-engineering experiment involving user profiles with diverse viewing habits, the research highlights the mechanisms of algorithmic personalization and its limitations. The findings reveal that while Netflix algorithms effectively adapt to individual preferences, they rely heavily on global trends and widely consumed content, often struggling with niche or regional preferences. The study further explores how algorithms manipulate user behavior by promoting certain content through tailored visuals and cognitive strategies, and it discusses the challenges of personalization in markets with limited local content.

Keywords: personalization; small markets; algorithmic culture; content adaptation; streaming services; user behavior; regional preferences.

Introduction

The vast data generated through digital media would be meaningless if analyzed manually due to its sheer volume. This process, like data collection, is automated using algorithms that classify, correlate, interpret, and derive actionable insights. These systems are crucial to digital platforms, enabling data collection on users, content, and communication.

One of the most famous examples is certainly Google's rise from a user-focused platform to a global giant, and it highlights the profitability of exploiting behavioral data that users leave.[2] Algorithms analyze this user data to improve services, enhance products, or maximize profits. Streaming services, like Netflix, heavily rely on such algorithm systems for recommendations and analysis. For example, Netflix developed *House of Cards* based on subscriber data analysis.[3]

[1] This paper originated from the doctoral thesis "Communication Strategies for the Promotion and Distribution of Series through the Netflix Streaming Service in Serbia," (Ph.D. diss., Faculty of Philosophy, University of Niš, 2023), https://eteze.ni.ac.rs/application/showtheses?thesesId=8687.

[2] Shoshana Zuboff, *The Age of Surveillance Capitalism* (CLIO, 2020), 10.

[3] Michael D. Smith and Rahul Telang, *Streaming, Sharing, Stealing: Big Data and the Future of Entertainment* (The MIT Press, 2016), 18.

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Netflix operates as a transnational service, adapting to local markets[4] and this requires classifying user data by country and tailoring algorithmic insights accordingly. In smaller markets like Serbia, the limited user base affects the quality of algorithmic conclusions compared to larger markets like the US or Brazil. This study aims to “reverse engineer” Netflix’s recommendation system to assess how well it aligns with Serbian users’ needs and identify its key patterns and tendencies in this context. The broader implications of the research would indicate strategies and approaches to small markets, characteristics, methods, but also the weaknesses and shortcomings of this approach and the ways in which smaller, local SVOD services can fill the potential market’s unused space.

Theoretical framework

An algorithm is described as any well-defined computational procedure that takes some value or set of values as input and produces a value, or set of values, as output.[5] These are software procedures, digital programs, or sequences of programs that are automated[6] and, based on established methodologies, tasks, and information (input components), generate conclusions, identify patterns, and undertake specific actions (output components).

Media algorithms systematically exploit user data, often referred to as *datafication*, and are an integral part of the media experience. Users encounter them routinely when navigating news on social networks, targeted advertising, streaming services, or personalized media.[7] These algorithms are designed to utilize available data optimally by identifying user behavior patterns, habits, preferences, and followed content. Based on this, they perform one of two tasks: define the type of content to be created or direct existing content toward an appropriate target audience. Both tasks are driven by efficiency, but there are certain differences between them. The first adapts content to the audience, while the second aligns the audience with the content.

The task of creating content based on audience activity is described by theorist Philip Napoli as an algorithmic shift in media production, consisting of two related processes:

1. Demand Prediction – algorithms replace analysts by predicting demand trends and potential media content trends based on quantitative data obtained through datafication.
2. Content Creation – algorithms increasingly take on the task of creating content, while human roles shift from direct participation to indirect involvement.[8]

[4] Mareike Jenner, *Netflix and the Re-Invention of Television* (New York: Springer, 2018), 25.

[5] Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, and Clifford Stein, *Introduction to Algorithms*, 2nd ed. (The MIT Press, 2001), 10.

[6] Philip M. Napoli, “Automated Media: An Institutional Theory Perspective on Algorithmic Media Production and Consumption,” *Communication Theory* 24, no. 3 (2014): 341.

[7] Brita Ytre-Arne and Hallvard Moe, “Folk Theories of Algorithms: Understanding Digital Irritation,” *Media, Culture & Society* 43, no. 5 (2021): 807–24.

[8] Napoli, “On Automation in Media Industries,” Integrating Algorithmic Media Production into Media Industries Scholarship,” *Media Industries Journal* 1, no. 1 (2014): 18.

The second task, directing the audience to existing content, seems simpler but involves an additional component: direct communication with the audience, specifically with each individual user. Each piece of media content must reach users who, based on their personality and activity data, are presumed to be interested. Recommendation systems are used for this purpose, proposing content based on specific parameters.

There are two primary recommendation systems:

1. History Data-Based Recommendation (HDBR) – this system analyzes the user's browsing history, classifies it, creates a user profile, and recommends content aligned with their interests;
2. Content-Based Recommendation (CBR) – this system considers user activities and the characteristics of the content they follow to suggest future content. This model is typical for online television and streaming services, as it analyzes both the type of content and the user's behavior.[9]

Both systems have distinct characteristics and varying levels of success depending on the task at hand. Their existence is often justified by the argument that the chaotic nature of the internet makes it nearly impossible for audiences to navigate without algorithmic assistance.[10] However, this does not diminish the fact that algorithm-mediated digital environments have brought significant societal consequences.

As algorithms are omnipresent in politics, economics, information, and education,[11] they have reshaped societal functions. This change is often referred to as algorithmic culture, defined as the practice of using computational processes to sort, classify, and hierarchize people, places, objects, and ideas, as well as the habitual thinking and behavior emerging from these processes.[12] Striphas, one of the originators of the term "algorithmic culture", emphasizes that it implies a dictatorial position of power where algorithms dictate culture, direct audience attention, and fabricate cultural products deemed profitable based on big data and proprietary algorithms.

Even disregarding potential algorithmic misuse, another consequence arises – filter bubbles. This phenomenon results in further fragmentation and disintegration of the audience and public sphere. To fully understand this, the psychological concept of "cognitive dissonance" is essential. It posits that individuals strive for cognitive harmony by resolving any inconsistencies in knowledge, confusion, or contradictions.[13]

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[9] Jiangbo Shu, Xiaoxuan Shen, Hai Liu, Baolin Yi, and Zhaoli Zhang, "A Content-Based Recommendation Algorithm for Learning Resources," *Multimedia Systems* 24, no. 2 (2018): 163.

[10] Sang-Min Choi, Sang-Ki Ko, and Yo-Sub Han, "A Movie Recommendation Algorithm Based on Genre Correlations," *Expert Systems with Applications* 39, no. 9 (2012): 8079.

[11] Napoli, "Automated Media," 340–60; Shu et al., "A Content-Based Recommendation Algorithm for Learning Resources," 163.

[12] Ted Striphas, "Algorithmic Culture," *European Journal of Cultural Studies* 18, no. 4–5 (2015): 396.

[13] Leon Festinger, *A Theory of Cognitive Dissonance* (Stanford: Stanford University Press, 1957).

This leads to selective exposure to information, preferring media that align with their preexisting beliefs.[14]

This tendency creates echo chambers, metaphorically describing an environment where one's opinions, political inclinations, or beliefs are reinforced through repeated interactions with like-minded individuals or sources.[15] Such chambers foster isolation with like-minded peers, leading to biases and polarization. Algorithms are programmed to recognize and amplify such tendencies. While filter bubbles align with the hyper-personalization philosophy of digital media, they differ from echo chambers in several key aspects. Echo chambers exist outside the internet, are self-initiated, and involve awareness of differing opinions. In contrast, filter bubbles are exclusive to digital environments, are imposed without the user's control, and obscure alternative perspectives entirely.[16]

In summary, while user agency, multimedia capabilities, and digital logic have expanded audience autonomy in content selection and creation, datafication and algorithms have transformed media strategies in content creation and distribution, disrupting the traditional dynamic between producers and consumers. The shift from mass communication to personalization and interactivity has altered communication methods and strategies, shaping how audiences engage with media in the digital era.

Methodology

When analyzing service algorithms, a specific experimental approach, "reverse engineering", was applied. This method is developed for the analysis of Netflix's search algorithm by Niko Pajković. His approach involved creating four new profiles, each representing a hypothetical consumer persona with distinct characteristics and viewing habits. These personas watched specific content at various times. Comparative analysis of the recommended content allowed for identifying patterns and principles underlying recommendation systems and algorithmic functionality in response to user behavior.[17]

The method utilized in this research largely mirrors this approach but introduces differences in defining consumer personas. These personas were based on prior analyses that identified prevalent viewer types in Serbia over the last 15 years.[18] Accordingly, the consumer personas were divided into three archetypes of Serbian series enthusiasts:

[14] John Cotton and Rex A. Hieser, "Selective Exposure to Information and Cognitive Dissonance," *Journal of Research in Personality* 14, no. 4 (1980): 518–27.

[15] Matteo Cinelli, Gianmarco De Francisci Morales, Alessandro Galeazzi, Walter Quattrociocchi, and Michele Starnini, "The Echo Chamber Effect on Social Media," Proceedings of the National Academy of Sciences 118, no. 9 (2021): e2023301118, https://doi.org/10.1073/pnas.2023301118.

[16] C. Thi Nguyen, "Echo Chambers and Epistemic Bubbles," *Episteme* 17, no. 2 (2020): 141–61.

[17] Niko Pajković, "Algorithms and Taste-Making: Exposing the Netflix Recommender System's Operational Logics," *Convergence* 28, br. 1 (2022): 214–35.

[18] Milosavljević, "Komunikacione strategije promocije i distribucije serija posredstvom striming servisa Netfliks u Srbiji."

1. Profile 1 – An Older Enthusiast of Domestic TV Shows: a 60-year-old woman, middle-class, living in a rural area, familiar with Russian and skeptical of Western and US culture. Watches shows during lunch. Favorite show: *Moj rođak sa sela* [*My Cousin from the Village*].
2. Profile 2 – The ideal Netflix User: a 26-year-old man, middle-income, married with one two-year-old child, living in a larger city, with a university degree. Enjoys fantasy and drama but keeps up with all new and trending TV shows. Speaks English and German, with politically liberal views. Watches shows at night. Favorite TV show: *Breaking Bad*.
3. Profile 3 – The Typical SerbianViewer: a 43-year-old woman, middle-income, living in a small town, mother of one, with a high school diploma. Works in retail, lacks strong political views, and follows mostly domestic TV shows, with some interest in foreign comedies and mysteries. Favorite series: *Friends*.
4. Profile 4 – An Inactive Profile: tThis profile remained unused and served as a control for comparison.

Time	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**	**Monday**
13:00	P1.		P1.	P1.	P1.	P1.	P1.
14:00		P1.	P1.		P1.	P1.	
20:00	P3.		P3.	P3.	P3.	P3.	P3.
21:00		P3.	P3.		P3.	P3.	
11:00	P2.		P2.	P2.	P2.	P2.	P2.
00:00		P2.	P2.		P2.	P2.	

Table 1 – Viewing Schedule

The user account was registered on a new Windows 10 operating system, accessed exclusively via the Mozilla Firefox browser (version 115.0). This ensured no prior personalization through cookies or browsing history. The account, created on a basic €4.99 monthly plan, was registered on July 3, 2023. Unlike Pajković's study, this research focused primarily on TV shows rather than movies. The research period spanned nine days (July 3–11, 2023). The first day involved account and profile setup, followed by a week-long experiment, with the final day dedicated to analyzing the effects and changes in each profile's home page. For comparative purposes, screenshots of relevant profile sections were captured before and after viewing content daily (507 images).

Research results

The experiment began with the selection of the basic subscription package and the creation of a primary account. The service's initial interaction with the user includes two welcome emails, one of which requests account confirmation via email, followed by phone number verification (likely to confirm the registration and verify the user's country of origin).

All initial screens and recommendations across profiles were identical, displaying "Trending" content and the top ten most-watched TV shows and films in Serbia that day. This suggests the algorithm relies on geographic location for recommendations. On the first viewing day, the domestic TV show enthusiast watched domestic movie *Bad Blood* [*Nečista krv*] due to the absence of domestic shows. The typical viewer chose the detective comedy *Brooklyn Nine-Nine*, while the ideal user selected the drama *Ozark*. After viewing, no significant changes were noted in the suggested content, indicating that the algorithm requires time to adapt to user activity. By day two, each profile showed some personalization. The typical viewer was recommended *Suits* along with new categories such as "30-Minute Laughs" and "Romantic Movies", primarily suggesting short comedies. Similarly, *Suits* was also recommended to the ideal user, despite differing preferences, with new categories such as "Emmy-Winning US TV Shows". The curated selection under "Top Picks for Ideal Netflix User" highlighted popular shows, likely influenced by *Ozark's* critical acclaim (26 awards, including six Emmys), allowing the algorithm to refine its understanding of this user type quickly. In contrast, the domestic TV show enthusiast struggled due to limited regional content on the platform. Her profile continued to show popular titles in Serbia, illustrating a significant difference in adaptation between her and the ideal user. This underscores the algorithm's reliance on widely viewed content for predicting preferences, as less popular or niche content leaves it uncertain about user interests. These findings indicate that recommendations are shaped not only by individual behavior but also by broader viewing trends from Netflix's global user base. On the second day, unable to find regional content, the domestic TV show enthusiast opted to watch the 2021 Polish drama-comedy *The Land*.

This selection did not result in significant changes to the algorithm's recommendations the following day. She searched "Russia" and chose the comedy Russian Doll, watching two episodes. By the third day, the typical viewer was greeted with The Office as a primary recommendation, alongside categories like "Critically Acclaimed TV Shows" and "Award-Winning TV Shows." Since this profile had only watched shows, the list of the top 10 most-watched shows remained prominent. The ideal user exhibited similar trends, with categories from the previous day still present.

The inactive profile displayed no significant changes in its recommendations. Initially identical to the other profiles, it continued to present a mix of unrelated titles and genres. A new category "Casual Viewing" emerged, featuring random comedies, documentaries, and dramas. This category appeared to represent an algorithmic attempt to ease the "tyranny of choice" by offering a curated selection of lighthearted content.

On the fourth day, noticeable differences emerge among the profiles, with the domestic TV show enthusiast profile standing out significantly. The only new category that appears here is "Polish-Language Movies & TV", and this occurs after watching just one Polish film. This did not happen after watching content from the domestic film industry, which is likely due to the lack of other domestic offerings. Since 2016, Netflix has invested over $110 million in producing original shows in Poland,[19] due to the significant subscriber base in the country[20] and to comply with differing regulatory frameworks. This necessarily points to reduced algorithmic maneuverability in countries producing fewer shows and films.

Nearly all suggestions after viewing Russian Doll – featuring a predominantly female cast – are shows and films with female protagonists. Even when this is not the case, the thumbnails of suggested shows almost exclusively feature women. When men and women are shown together in the thumbnails, women are often depicted in erotic poses, with shows' titles implying such themes (Image 1). Since gender is not specified during profile creation, it might seem surprising that the algorithm could infer the user's gender after just three days. However, this is more likely due to the first two viewed pieces of content not providing the same volume of relevant data on user preferences. The third selection, being significantly more popular, allowed the algorithm to make more reliable predictions about potential interests. Netflix has repeatedly stated that its algorithms do not collect data on gender or ethnicity, asserting that such occurrences result solely from analyzing viewed content and A/B testing.[21] The domestic show enthusiast continued watching the same shows as the previous day.

The other two profiles also continued with their previously watched content. For the typical viewer, numerous comedies were still suggested, now categorized under a particularly specific title, "All Laughs, No Laugh Track" (Image 2).

The initial screen for the ideal user profile appeared vastly different from that of the domestic TV show enthusiast. New categories included Exciting US Supernatural TV Shows, Exciting Movies, Geeked: Sci-Fi, Fantasy, Superhero & More, and TV Dramas Based on Books. Nearly all these niche suggestions directly resulted from the nature of The Witcher series, even after watching just two episodes. Viewing Ozark in the first two days also contributed to a new, highly specialized category: Binge-worthy Dysfunctional-Family TV Dramas. The prominence of the term exciting was notable, as both shows watched by this user are highly suspenseful. This term appeared not only in category titles and types of content but also in the imagery selected for series thumbnails, often depicting men in threatening stances (Image 3).

The fifth day of the experiment revealed another mode of communication employed by Netflix: notifications. The domestic TV show enthusiast received a notification via the bell icon, inviting her to explore upcoming shows and films. These

[19] Stjepan Hundic, "Why Netflix Is Betting Big on Poland (and You Should Too)," *The Hollywood Reporter*, May 20, 2022, https://www.hollywoodreporter.com/business/business-news/netflix-betting-big-on-poland-cannes-2022-1235143865/.

[20] Catalina Iordache, Tim Raats, and Adelaida Afilipoaie, "Transnationalisation Revisited through the Netflix Original: An Analysis of Investment Strategies in Europe," *Convergence: The International Journal of Research into New Media Technologies* (2021): 13, https://doi.org/10.1177/13548565211047344

[21] Fatima M. Gaw, "Algorithmic Logics of Taste: Cultural Taste and the Netflix Recommender System" (Ph.D., diss., Faculty of Arts and Social Sciences, 2019).

notifications did not appear for the other three profiles. It is plausible that the recommendation system, noting her limited engagement with only one show, used this feature to extract additional information about her tastes and preferences. The profile for this user became even more tailored, favoring comedies and especially erotic content. New categories included Sex Comedies and International TV Shows. Interestingly, for the first time across all three profiles, the category Watch in One Weekend appeared, likely because it was a Saturday. This confirmed that the algorithm considers not only location but also the day of the week when suggesting content. Regardless of the type of series and films watched, the most popular and widely viewed content consistently ranked highest in the suggestions across all three profiles. Thus, despite the minimal thematic connection between the watched shows and films, the first category, simply titled TV Shows, recommended The Witcher, Breaking Bad, and Better Call Saul. Given the profile's initial concept, most suggestions did not align with the user's presumed preferences and habits, prompting her to select the Croatian film Faraway.

Following two days of viewing Lupin, Netflix's recommendation system substantially adjusted its approach to the typical viewer. Categories shifted from predominantly comedies to European TV Shows, Police Detective TV Thrillers, and Binge-worthy Crime TV Thrillers. On this weekend day, this user opted for a mystery comedy, blending her two favorite genres, selecting Dirk Gently's Holistic Detective Agency.

For the ideal user profile, the suggested content prominently featured Netflix's most popular titles. Alongside the term exciting, action-themed categories like Action & Adventure Movies and Get in on the Action appeared. Thumbnails often depicted men in threatening or dynamic action poses.

The interface for the domestic TV show enthusiast saw no significant changes, while the typical viewer encountered new categories such as European TV Shows, French-Language Movies & TV, and Eastern European Movies & TV. The latter category was absent from the domestic TV show enthusiast's profile, despite her viewing three films and one series from the region. This discrepancy suggests that the algorithm categorized her preferences differently, emphasizing female protagonists, romance, and sex. In contrast, the typical viewer did not watch any Eastern European content, with location likely playing a more significant role. This highlights that similar viewing volumes and durations do not guarantee equivalent levels of personalization within the same timeframe. The ideal user profile, significantly more personalized, included almost all the most prominent Netflix titles alongside new categories, such as Acclaimed Writers, Suspenseful European TV Dramas, and Suspenseful Conspiracy TV Sci-Fi & Fantasy. This profile's consistent association with terms like exciting, action, and suspenseful, and its focus on sub-genre classification distinguishes it further.

The last two days, all three users followed two shows recommended by the algorithm, based on the highest assumed popularity. For the domestic TV show enthusiast, the first day featured the sitcom *The Kominsky Method* while the typical viewer watched German sci-fi drama *Dark*. The following day, guided by the algorithm's best recommendations, the domestic TV show enthusiast selected two episodes of the Polish crime comedy *The Green Glove Gang*, the typical viewer watched the sitcom *Seinfeld*, and the ideal user followed the sci-fi drama *Snowpiercer*.

On the eighth day, home screen of the domestic TV show enthusiast, influenced by the content deemed most suitable by the recommendation system, featured several new categories within the comedy genre – *TV Comedies about Friendship*, *Buddy TV Shows*, and *Girls Night In*. Images predominantly showcasing women were still prevalent, but there was a noticeable trend of depicting two individuals in friendly postures or shared activities (Image 4). Positive imagery extended even to suggestions significantly different from the user's viewing history. For example, in *Lupin*, the lead actor holds a puppy. Notably, none of the suggestions insinuated violent, aggressive, or unpleasant content, even when such themes are central to the series. Despite the apparent personalization, the profile was not tailored as expected based on this hypothetical user's characteristics and preferences. Most content was from English-speaking regions, with a minimum of TV shows and films relevant to someone preferring domestic and regional productions. This discrepancy likely arises from the limited availability of such content on the platform. Nonetheless, it gives the impression that the algorithmic system prioritizes and favors certain types of content.

The typical viewer in Serbia followed primarily comedies and mysteries, but these contained elements of other genres. Consequently, the algorithm offered the broadest range of suggestions for this profile. Each category was distinct, spanning *Retro TV*, *International Police Detective TV Shows*, *Children & Family TV*, and *Critically-Acclaimed Exciting TV Dramas*. Series images depicted characters in active poses – pointing to something, preparing for action, or reacting to situations (Image 5). Despite the algorithmic suggestions being followed for the last two days of the experiment, more time would be required to crystallize a unique and less diverse set of recommendations for this profile.

The ideal user profile, by contrast, was significantly more uniform and focused on two directions: trending and new content and productions featuring sci-fi elements. This was evident in categories such as *Trending Now*, *Top Searches*, and *New Releases*, as well as specific subcategories and alternative genre labels emphasizing sci-fi. Series images frequently depicted futuristic scenes, space, or imaginary aliens (Image 6). Results for this profile indicate that if a user focuses on a specific type of content for an extended period of time, the system quickly hyper-personalizes their profile based on that activity, creating a 'filter bubble' that significantly limits exposure to other genres unless actively searched for by the user.

Finally, the inactive profile was intended to be a control group to establish differences in algorithmic behavior when active versus inactive due to user activity. It was assumed that a new profile would not undergo changes. However, this did not occur. The algorithm significantly altered the categories it suggested, most of which were general, based on traditional genre classifications. By the last day, there were also highly specific categories like *Strong Black Lead*, *Scandinavian Movies & TV*, and

Women Behind the Camera. Since there was no user input to guide the algorithm, it is likely that it experimented with specific categories to spark interest and prompt activity in the inactive profile. Another noteworthy trend for this profile was the significant proportion of content aimed at children (Image 7). Since there was no user activity to base recommendations on, it suggested that the recommendation system had to rely on other mechanisms for these assumptions. A plausible hypothesis, requiring further investigation, is that the algorithm inferred that a household with three active profiles following serious shows and films likely includes at least one child.

If this hypothesis were further explored, it could reveal inter-profile communication, suggesting that part of the algorithmic system considers the entire account's activity during personalization, not just that of individual users.

Conclusions of the experiment

After someone becomes a Netflix user, the service communicates with them in three main ways – via email through which the user registered, and through which he receives notifications and promotional materials; via reminders and notifications on the user's profile and recommendations; and by personalizing the homepage in accordance with the viewer's tastes. All these aspects, as well as the results that will appear in a search based on keywords that the user can carry out, are part of the same complex system of algorithmic personalization[22]. An experiment determined that personalization on the service is carried out by combining three methods:

1. By suggesting specific TV shows and films from the best to less recommended;
2. By highlighting specific subgenres and taste communities from the most relevant to less relevant;
3. By adjusting the image of a show or film so that it is appealing to the user.

For personalization in each of these three ways, it was concluded that several types of information are used:

1. Territory – no profile is completely unpersonalized when the user logs in for the first time, as there are always two categories present: "Top 10 Movies in Serbia Today" and "Top 10 TV Shows in Serbia Today". A new profile, in two different countries, will never look completely the same, both for this reason and due to the different offerings in each country. Location is relevant from the perspective of the country, region, and language in which the show or film that the user has watched was made, especially if the service can offer more content from that area (which is not the case for Serbia).
2. Time – the algorithm requires a certain period to register new activity and adjust to changes (less than one day), but also it takes into account the day of the week and weekends, when the viewing period is longer due to free time, offering content that can be fully watched over these two days. Due to the

[22] Harald Steck, Linas Baltrunas, Ehtsham Elahi, Dawen Liang, Yves Raimond, and Justin Basilico, "Deep Learning for Recommender Systems: A Netflix Case Study," *AI Magazine* 42, no. 3 (2022): 9.

nature of the experiment, it was not possible to determine whether the length of viewing (which was relatively the same for all) or the time of day during which content is viewed impacts personalization and the method of internal communication.

3. General trend obtained from the datafication – if a show or a film is lesser-known, especially if it is in another language, personalization will be significantly lower and slower. On the other hand, if a work is popular, changes in the appearance of the homepage will be drastic and quicker, meaning that the recommendation system does not rely only on the habits and practices of each individual user, but also on trends in a larger sample.
4. Presence or absence of activity – this is almost a tautology, but it should be noted that if the activity on a profile is high, all three methods will be applied, while if there is no activity, the algorithms will be forced to experiment and encourage the user in different ways.
5. Type of activity, i.e., the type and genre characteristics of selected content – the most significant part of what defines the algorithm's approach is the selection of content itself and the information about the genre characteristics they possess. At the most basic level, it was determined that if a user mainly watches TV shows, they will be recommended much more frequently than films, and vice versa. This also means that this service has a highly dominant CBR algorithm, based on content characteristics[23]. When it comes to selection based only on specific sub- or alt-genres, the algorithm used in Netflix is called the PVR (Personalized Video Ranker), while for selecting the best content from the entire database, regardless of genre, the Top N algorithm is used.[24]

However, this is only one part of what the recommendation algorithm system does. It has been observed that in almost every segment, in addition to trying to adapt content to the user's tastes, it also tries to adjust the user's taste to certain content. This was most evident in the fact that the most well received and new seasons of popular TV shows were almost always suggested, even when the user did not follow any show of that genre. Examples of this can be seen in the recommendations for shows such as *The Lincoln Lawyer* (Image 3, Image 4), *Black Mirror* (Image 1, Image 3), or *Pure Chemistry* (Image 2, Image 4). However, there are two much more specific examples of this "manipulation" of the algorithm. The first one, particularly interesting, is the change of a show image in relation to the viewer's taste. In addition to the aforementioned examples, all three profiles, in the last days of the experiment, were exposed to suggestions for two shows – *Lupin* and *Sex Education*. However, the image illustrating these two shows was significantly different on all three profiles (Image 8). To the typical viewer, who likes mysteries and comedies, *Lupin* is illustrated with a photo of the main character holding a book toward the camera, hinting at a mystery, while *Sex*

[23] Shu et al., "A Content-Based Recommendation Algorithm for Learning Resources," 163.

[24] Carlos. A. Gomez-Uribe and Neil Hunt, "The Netflix Recommender System: Algorithms, Business Value, and Innovation," *ACM Transactions on Management Information Systems* (TMIS) 6, no. 4 (2015): 3.

Education is illustrated with a comedic photo of two men on bicycles looking at each other. To the ideal user, *Lupin* is represented by an image of the character standing on a height, at night, wearing a coat with Paris glowing below, while *Sex Education* is illustrated with a photo of two girls positioned next to each other, looking worried in the direction behind the camera. This is entirely in line with the epithets "exciting" and "tense", which the algorithm associates with this profile. On the other hand, a fan of domestic TV shows could perceive the *Lupin* series completely differently since she was shown the main actor holding a dog, and since the algorithm assumes that erotic shows are particularly close to this user, *Sex Education* is rather explicitly illustrated with a photo of cookies in the shape of female genitalia.

It should be noted that these images changed during the experiment, especially in the case of the domestic TV show fan, with whom the algorithm system "struggled" for the first few days. However, this does not change the conclusion that after significant personalization, the same show is presented differently to different users depending on their tastes and preferences. These differing expectations represent a form of manipulation and direction, as the content itself is always the same. Not only are the most popular shows always suggested, but after seven days of initially watching very different content on each profile, the system claims that some of the same shows in all three (or four) cases are extremely compatible with the tastes of all hypothetical users. *Peaky Blinders*, regardless of the profile type, always has almost a hundred percent match (Image 9), and this is particularly interesting in the case of an inactive profile, where, although very violent, it is literally placed next to the children's cartoon *Grizzy and the Lemmings* (Image 10).

In the case of the inactive profile, it is clear that there is no feedback that would narrow the scope and accuracy of suggested shows and films, so such inconsistencies were expected. On the other hand, the fact that a very popular show is close to all hypothetical tastes can somewhat be justified by its popularity, which the algorithm uses as an argument for its omnipresence, but this cannot explain the high correlation with the tastes of each user. Therefore, it is justified to conclude that there are certain contents, particularly those produced by Netflix, that are favored and, by different methods such as manipulation of the title photo, are always shown as appropriate for users. This is, in fact, one of the functions of all communication strategies, cognitive (through percentage of compatibility) and affective (through photos) manipulation.[25]

It is important to emphasize that algorithmic strategies will not be equally successful with every user. If the tastes of a user in Serbia are similar to those of the hypothetical ideal user, personalization will be highly effective, as a very narrow selection of the most popular, most awarded, and newest action, tense, and exciting works will be recommended. If the tastes are closer to those of the typical viewer, more time will be needed to align and determine the typical content this user likes, but they will always be able to find several works that match their tastes. The reasons for this lie in the fact that there are many shows and films that differ significantly in sub-genre

[25] Mirko Miletić, „Komuikacione strategije – pokušaj teoretske konceptualizacije," *Komunikacije, mediji, kultura – Godišnjak Fakulteta za kulturu i medije* 3, no. 3 (2011): 13–32.

characteristics but can be grouped into the categories of comedy or mystery, which are the most popular in Serbia. While the lack of hyperpersonalization was observed as a possible consequence in this profile, a positive aspect is that this profile, at the very least and at the latest, avoided the algorithmic 'filter bubble' problem[26], meaning it has much greater choice and maneuverability in selection. This is not the case with the other two profiles, although for completely different reasons. With the ideal user, it is about conscious and intentional selection of what aligns with their tastes, while with the domestic show enthusiast, personalization was a matter of necessity, as in the absence of what she primarily watches, she had to 'submit' to the service's offering, and in this process, she was defined by some other hypothetical tastes, which were not planned and set at the beginning of the experiment (female comedies, buddy comedies, sexual and erotic shows).

Concluding remarks

Reactions and adaptations through notifications, email communication, and most notably the algorithmic recommendation system reflect the activities, needs, desires, and preferences of users, especially when these align with what Netflix can offer. However, when a user from Serbia wishes to follow the domestic content, this adaptation becomes significantly more challenging, and their needs will not be adequately met. Instead, based on other information regarding the content they follow, their taste will be steered in different directions. This does not imply that internal communication strategies do not exist in this case; rather, they serve a different purpose. While in the first case, the primary focus is on reacting to and supporting the user's existing preferences, for those following domestic content, algorithmic manipulation and redirection toward similar or new tastes and desires will be at play. It can be assumed that this inability to adequately satisfy the existing tastes and desires of a segment of the public, particularly those oriented toward domestic production and language, which constitutes a significant portion of the population, is one of the reasons why Netflix has not created specific communication approaches and strategies for this country. The disadvantages of this approach and the inability to fully meet the expectations, tastes and habits of specific types of audiences in Serbia open up space for smaller, local services and truly personalized approaches to domestic users in a more concrete and complete fulfillment of their needs, as opposed to directing and tailoring tastes in accordance with global trends.

It is important to note that the experiment was conducted over the span of just one week, and it is certain that more detailed and high-quality personalization requires additional time. The results indicate that the personalization was not equally effective for every typified representative of the population in Serbia during this period.

[26] Eli Pariser, *The Filter Bubble: What the Internet Is Hiding from You* (Penguin Press, 2011).

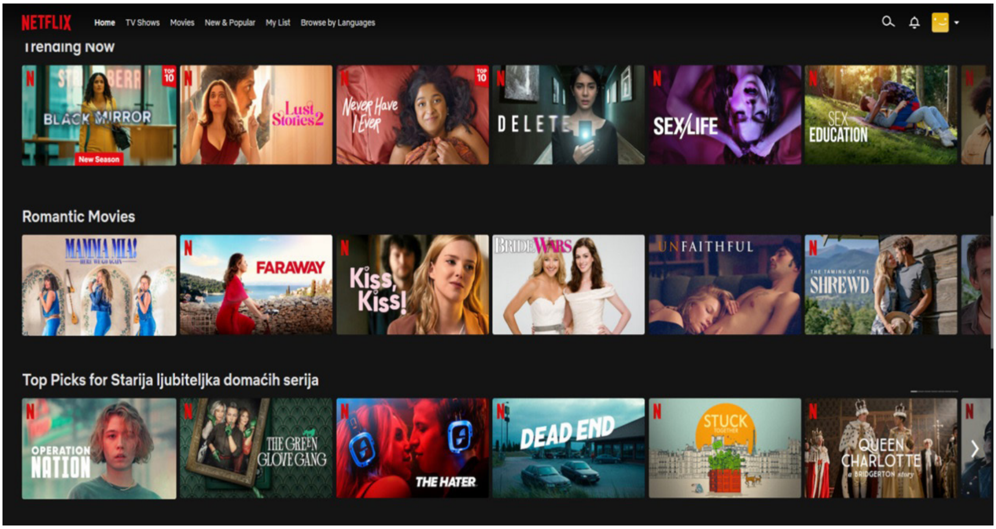

Image 1: Interface with suggested shows for the domestic series enthusiast on day 4 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

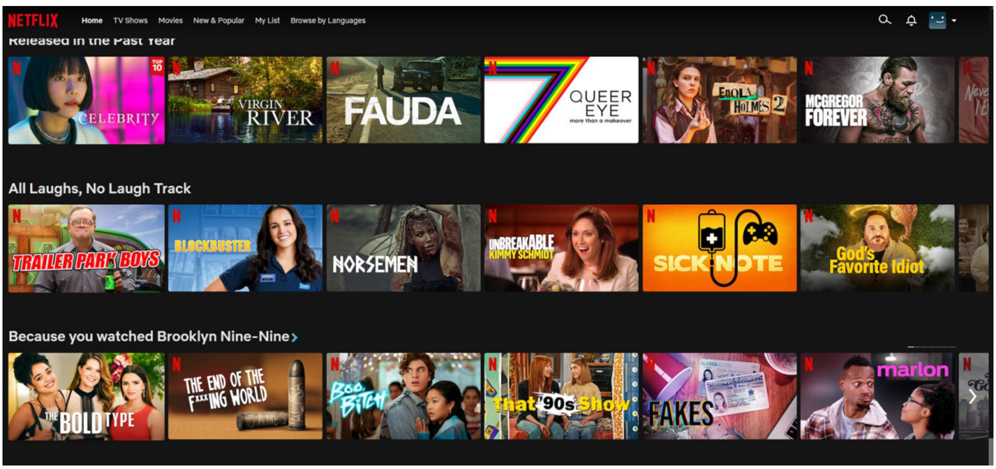

Image 2: Interface with suggested shows for the typical viewer on day 4 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

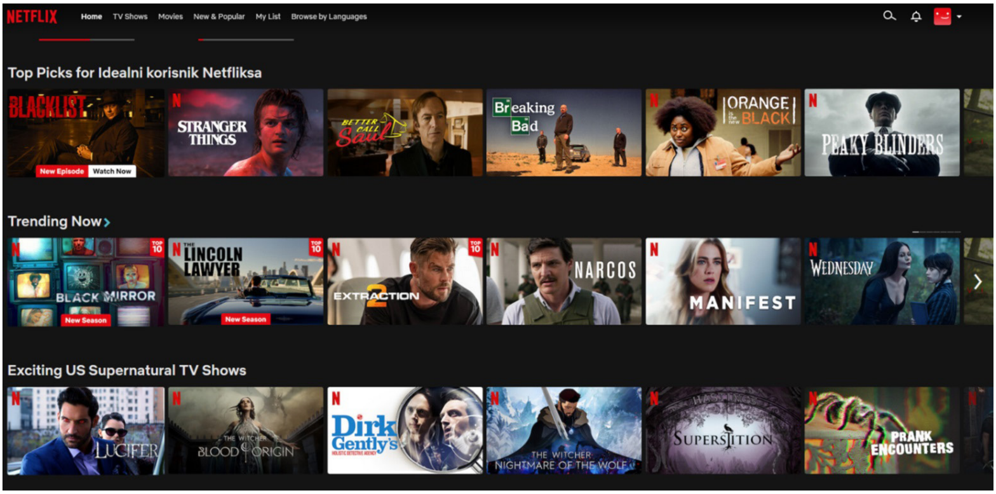

Image 3: Interface with suggested shows for ideal user profile on day 4 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

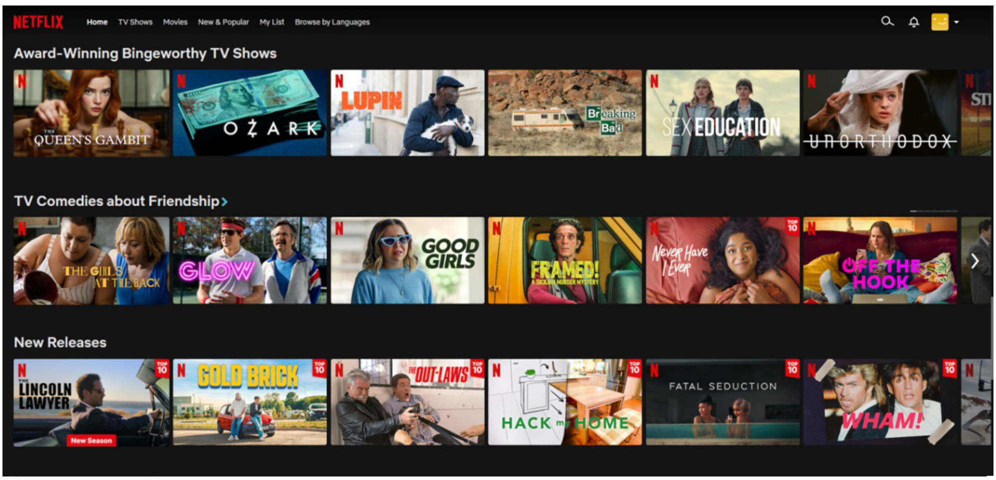

Image 4: Interface with suggested shows for the domestic show enthusiast profile on day 8 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

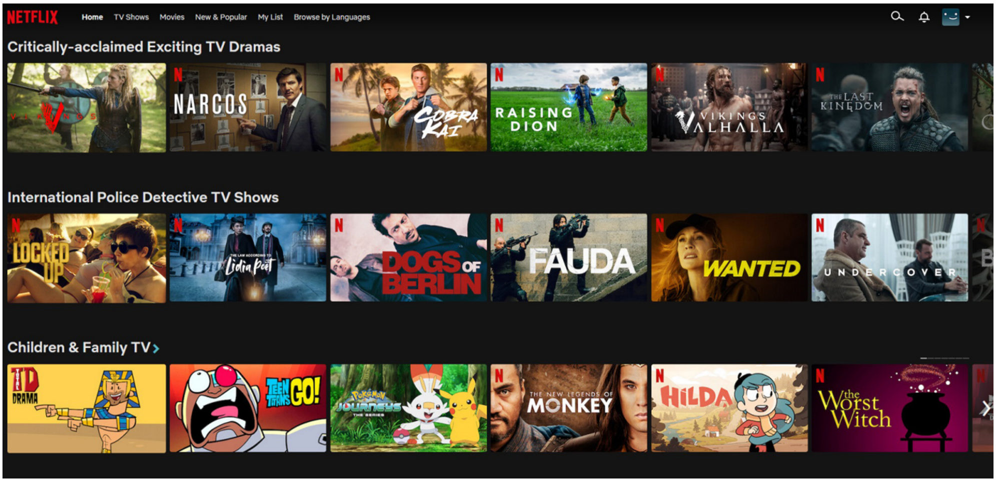

Image 5: Interface with suggested shows for the typical viewer profile in Serbia on day 8 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

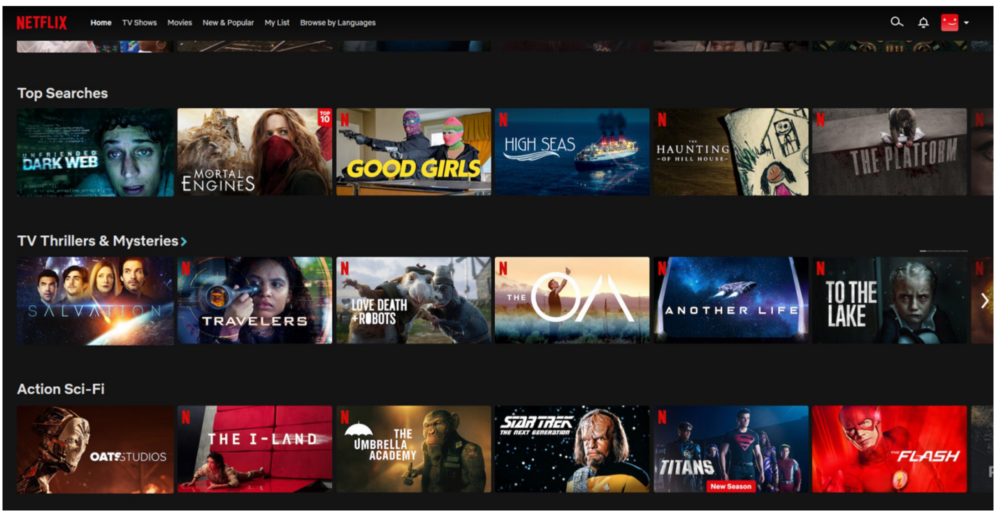

Image 6: Interface with suggested shows for the ideal user profile on day 8 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

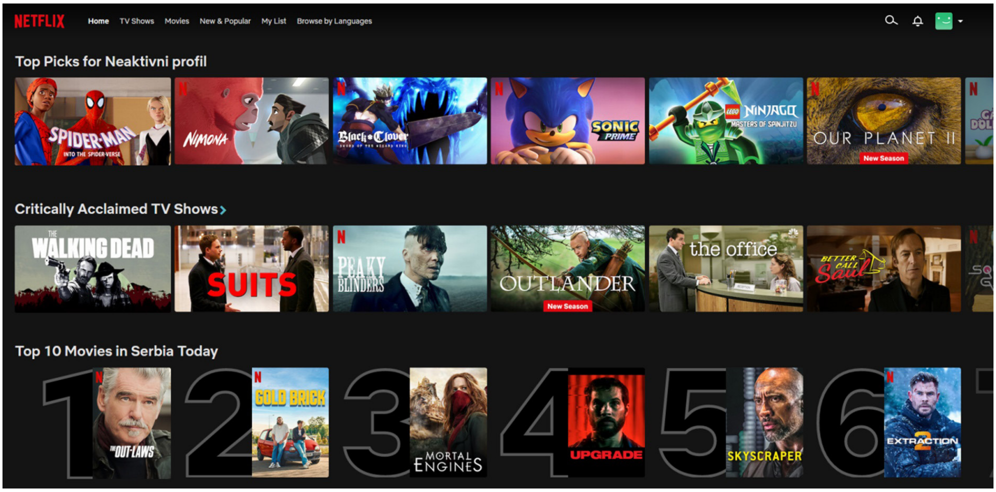

Image 7: Interface with suggested shows for the inactive profile on day 8 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

Image 8: Differences in the suggestion images of Lupin (top row) and Sex Education (bottom row) for the typical viewer (left), the ideal user (middle), and a domestic show enthusiast (right). Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

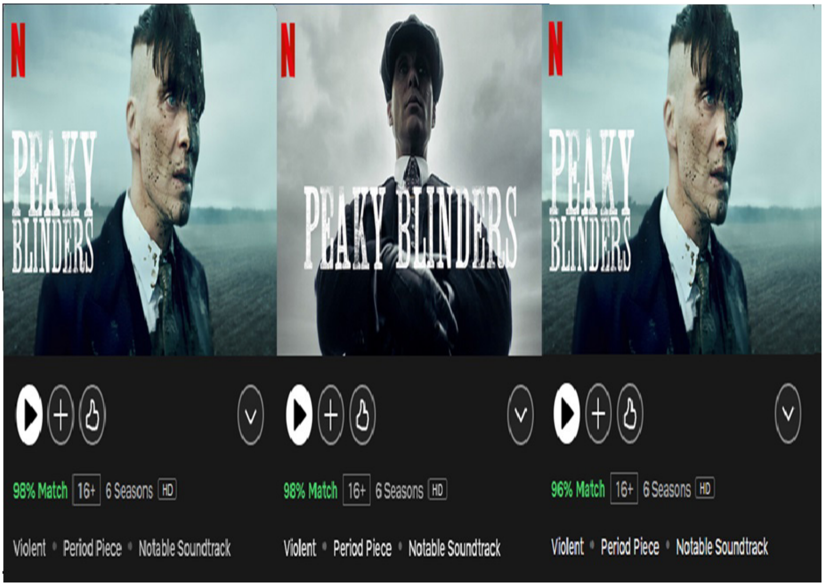

Image 9: The level of compatibility of the show Peaky Blinders with the tastes of the typical viewer (left), the ideal user (middle), and the domestic show enthusiast (right) on day 8 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

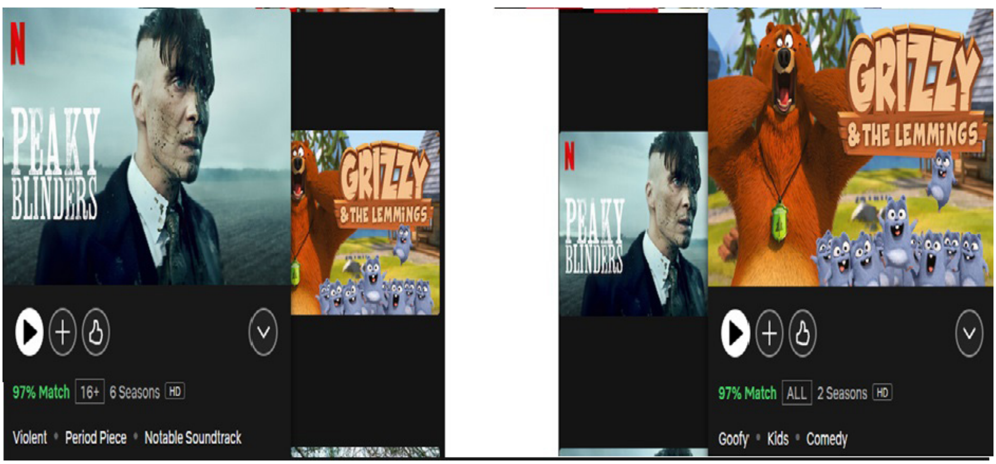

Image 10: The level of compatibility of the show Peaky Blinders (left) and Grizzy and the Lemmings (right) with the tastes of an inactive profile on day 8 of the experiment. Screenshot of Netflix user interface. Captured from the Netflix desktop application, July 2023. © Netflix. Used for illustrative purposes in academic work.

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