Alliance Manchester Business School BSc (Hons) Information Technology Management for Business with Industrial Experience

Using User Inputs and Individual Preferences to Enhance the Movie Recommendations: A Case of the Netflix Recommendation Algorithm

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Abstract

Movies have long been one of the most common and beloved forms of entertainment. However, in the age of digitization, users often struggle with the “paradox of choice” on streaming platforms. Even with personalized recommendations, many spend considerable amounts of time in the search for a movie that meets their desires. This research employs a design science methodology approach to understand how user inputs can enhance the user experience on streaming platforms and the recommendations provided, with a focus on the Netflix website. The research explores what factors influence movie recommendation accuracy, as well as the most important criteria people have when choosing a movie, using an online questionnaire.

The study develops a website that is a clone of Netflix which has an additional filtering functionality to reflect the identified criteria. This was tested by 10 participants who were also interviewed regarding their experience with it.

The results show that the website was perceived positively, with most people acknowledging that such a solution would reduce the time they spend browsing, by reducing the number of recommendations they receive, and enhancing these by limiting to only what they want to see based on personal preferences or mood.

Acknowledgements

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1. Introduction

From the early scientific experiments of motion photography of Thomas Edison and the Lumière Brothers in the 1890s, it is safe to affirm that movies have since undergone a plethora of changes, both as an art form and as an industry (Mast and Kawin, 2012). When films started being distributed, audiences exhibited an early interest in the various forms of cinema, which continued to technologically improve to attract the public (Dixon and Foster, 2018). Some of these milestones were: the conversion to sound movies, technicolour, large-scale productions, blockbusters, and special effects (Cook and Sklar, 2019). Now, more than a century later, all these advancements created an accessible form of entertainment and an industry that made $101 billion in 2019 (MPA, 2020), with the average adult watching more than 78,000 hours of television in a lifetime (Salo, 2019).

Regardless of the numerous changes films had to undergo, the common denominator in the movie industry has always been the consumer, who is the "ultimate destination of the motion picture value chain" (Wierenga, 2006, p. 674). To a certain extent, the consumer has always been able to experience movies in one form or the other, depending on the change in times, and all these various ways have been enabled by technology. In this sense, digitization has been considered a disruptor that created a "golden age" of movies and television, as it is making them more accessible and easier to distribute, with insignificant marginal costs (Waldfogel, 2017).

Nowadays, the most prevalent trend in watching films is movie streaming platforms, which provide direct digital distribution to consumers internationally. The main examples of such platforms are Amazon Prime, Netflix, Hulu and HBO GO (Aguiar and Waldfogel, 2017). However, the most prominent one is Netflix — launched in 1997 as a DVD rental company and transformed into a streaming media service in 2007 as a response to the shift in consumer habits — Netflix is an industry disruptor as it lies at the intersection of visual arts and technology, allowing users to select from a collection of movies and TV shows on a subscription base (Sim, 2016). Currently, Netflix subscriptions are at 223 million in 190 countries, and the number of total viewers is expected to rise to 781 million in 2026 (Statista, 2022).

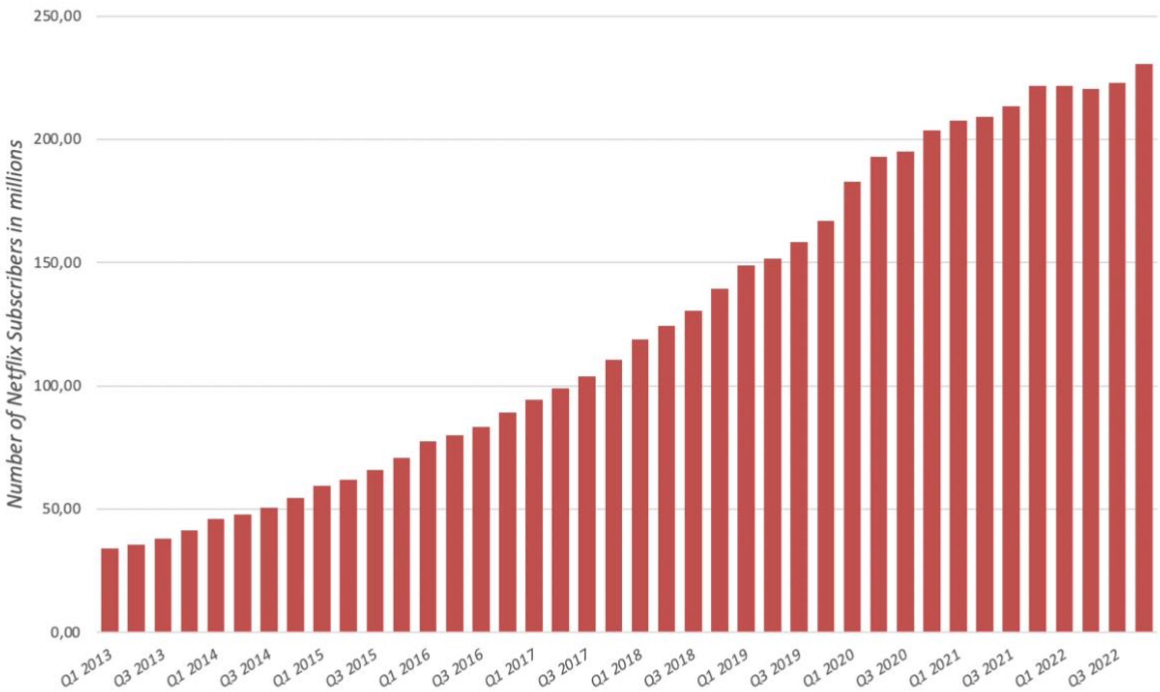

Figure 1 - Netflix subscribers, 2013-2022 (Statista, 2022)

It is crucial for such platforms to grow their customer base, as customers are the main source of revenue, especially for the likes of Netflix which have limited content they produced and own. One way of doing that could be better understanding the customer; in this sense, Netflix and similar platforms use the recommendation algorithm as one of their strengths. In the case of Netflix, their mantra is "Connecting people to movies they love", and even organized a competition offering $1 million to the first individual or team to improve the algorithm by 10% (Hallinan and Striphas, 2014). Given that British consumers spend 187 hours a year browsing for content on streaming platforms, the importance of offering good recommendations increases (Chilton, 2020). However, no two customers are alike, and personal preferences for watching movies cannot be fully quantified or captured in an algorithm. This raises the following question:

How can capturing multiple user preferences be used to reduce search time and improve user satisfaction on movie streaming platforms?

This research was therefore commenced with the aim to explore in what ways capturing multiple user preferences and criteria can be used to improve user experience on streaming platforms.

1.1 Motivation

The motivation behind completing a project about streaming platforms and movie user experiences stems from a personal fascination with the intersection of film and technology, coupled with an interaction with a range of film streaming services.

Also, the author completed a year in industry working for a large movie company, which offered a better understanding of the movie lifecycle and its focus areas, such as the distribution of content on either own streaming platforms or third-party ones.

Lastly, research was conducted to identify how other scholars addressed this issue. It was observed most research was algorithm-centric, focused on technical ways to improve the algorithm, and there was a gap in considering the possibility of user inputs.

1.2 Objectives

The study required several objectives to answer the main question:

- To understand the most relevant factors that people consider when choosing a film.
- To explore why the recommendation algorithm does not always work for Netflix.
- To explore how individual preferences could be integrated with the existing recommendation algorithm by designing a new Netflix interface and testing it.

1.3 Structure of report

Literature review

This will provide a critical review of existing literature in the relevant fields for this project – the movie industry, personal preferences, and movie recommendation algorithms.

Research Methodology

This will break down the research process involved, showing the data collection and analysis techniques, technical development, and user evaluation.

Results

This chapter will further explore the findings, analysing the quantitative and qualitative primary data collected.

Discussion

The findings will be related to the literature and discussed according with the research aims.

Conclusion

The conclusion will include the summarized findings, limitations, and areas for future research and development.

2. Literature Review

This chapter will provide insights into how data is used in the movie industry, recommendation algorithms in the case of Netflix, previous attempts to improve them, as well as individual user preferences when watching movies.

2.1 Uses of Data in the movie industry

Multiple researchers recognize the movie industry as a fruitful research area due to its breadth and depth of data. Moreover, the cost of producing movies is high, and the financing is difficult to obtain without certainty of how movies will perform when distributed to the public. This led to a higher interest in the scientific community to find different ways of predicting movie interest and Box Office numbers, either during the premiere weekend or over a movie's lifetime (Vogel, 2015).

In this sense, Eliashberg (2000) and Marshall (2013) are two of the researchers who conducted multiple studies to try to analyse and predict factors at different stages of the movie lifecycle, such as forecasting awareness, cumulative penetration for the target audience, or forecasting the box office performance (Figure 2).

Stage	Pre-production	Production	Post-production	Marketing	Theatrical	Streaming
Steps	• Greenlight – movie approval • Decisions on cast, director, producers • Financial approvals	• Filming • Production schedule • Hair, make-up • Directors (photography, sound) • Design	• Editing • Sound • Localization • Subtitles • Translations	• Marketing Plan • Target Audience decisions • Marketing strategies (online/offline)	• Distribution of movies in cinemas • Different companies have different time windows to keep the movies in cinema	• Movies are being sold to streaming platforms • Movies are put on the platform owned by the company that made it
Data uses	• Predicting what the customers will enjoy • Predicting the success/failur e of a movie • Predicting the box office numbers	• Forecasting the budget and resources • Allocating resources according to plan	• Data used for automatic translations, language processing • Data used for automatic Quality Control	• Forecasting ways to advertise it and its ROI • Forecast where the target audience will be more engaged	• Forecasting the number of cinema rooms that need to be booked • Forecasting ticket demand • Dynamic pricing of tickets	• Recommender systems to give users options • Forecasting the success of a movie and deciding to stream or not

Figure 2 – Movie lifecycle and uses of data at each stage (Marshall et. al, 2013; Eliashberg et al., 2000)

2.2 The need for recommendation algorithms

Literature has emphasized the need for recommendation and predictive algorithms in response to the "paradox of choice", encountered in many areas of life in a culture of freedom, choice, and self-determination. This draws upon the philosophical perspectives of renowned scholars such as Isaiah Berlin or Amartya Sen, who differentiate between "positive liberty" and "negative liberty" and examine the nature and functional aspect of autonomy in our lives that arise from an information overload (Schwartz, 2004). As a by-product of this paradox, humans tend to struggle when faced with numerous options – in the case of choosing content to watch on Netflix, the average user loses interest after 90 seconds of browsing or after reviewing 10-20 titles (Gomez-Uribe and Hunt, 2015).

Most researchers conceptualize recommender systems as statistical and knowledge discovery tools that offer suitable recommendations to customers in various online interactions, aiming to reduce user browsing time and make recommendations that ultimately increase user retention (Sarwar et al., 2001).

2.3 How do recommendation algorithms work for Netflix?

The primary source of revenue for Netflix is the subscriber base, which raises various business implications and prompts the question of how to retain customers. In this sense, the Netflix Recommender system is a crucial asset for the company. Numerous researchers tried to "deconstruct" the algorithm, which is created by systematically dismembering thousands of movies, tagging them, and getting attributes such as 76,897 movie genres or the moral status of characters which are then combined with user-viewing habits. This data creates personalized suggestions for movies and TV series (Madrigal, 2014). However, researchers often see this algorithm as a "black box", since the patents for it are secret to ensure it maintains its competitive advantage (Hallinan and Striphas, 2014). Netflix employees documented at a high-level the various algorithms that construct this, as illustrated in Table 1:

Algorithm	Purpose
Personalized Video Ranker (PVR)	General ordering of the entire catalogue, blends personalized signals with general popularity.
Top N Video Ranker	Finds the best few personalized recommendations and looks at a subset of the catalogue.
Trending now	Identifies both trends that repeat (e.g.: Christmas movies) and one-off popular choices. Slightly combined with personalization.
Continue watching Ranker	Ranks the subset of content a subscriber started watching based on his intention to resume watching.
Video-Video Similarity	An impersonalized algorithm that computes a list of similar content that computer similar content for each of the items in the catalogue. However, which ones make it to the homepage of a user is personalized.
Page Generation: Row Selection and Ranking	An algorithm that personalizes the homepage based on each user.
Evidence algorithm	Complements the other algorithms by selecting what information should be displayed (e.g.: awards, cast, synopsis).
Search	When the user searches for a particular movie, this algorithm will either suggest the closest option based on the characters inserted or similar choices if it is not in the catalogue.

Table 1 – Different algorithms that make up the Netflix recommender system (Gomez-Uribe and Hunt, 2015)

The Netflix Technology Blog shows a high-level overview of the way these algorithms interplay (Figure 3):

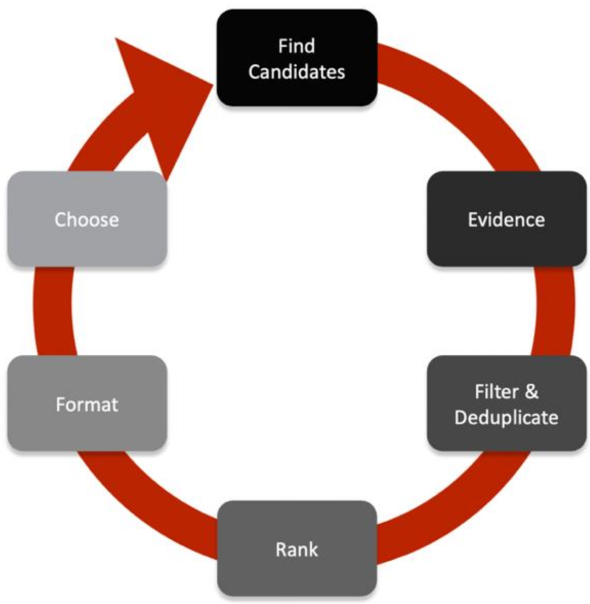

Figure 3 – Process for creating and choosing rows (Netflix Tech Blog, 2017)

The process in Figure 3 will result in the following sorting of content on the main page:

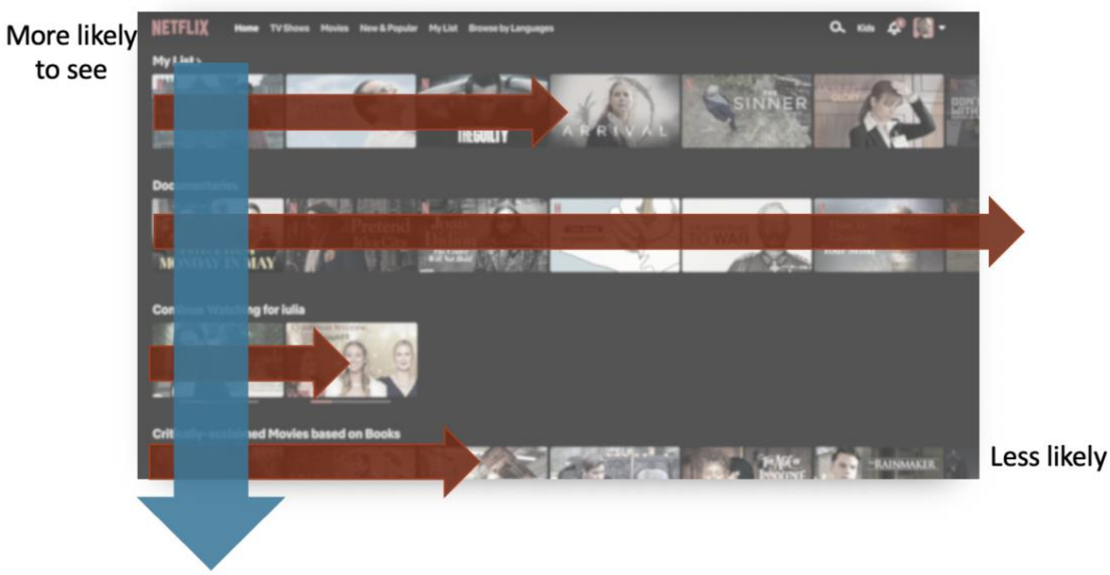

Figure 4 – Navigation Modelling on the main page (Netflix Tech Blog, 2017)

2.4 Disadvantages and limitations of recommendation algorithms

Some of the main disadvantages and limitations of recommendation algorithms that can be applied in the case of Netflix are:

- **Popularity Bias**

As seen above, there is a certain degree of personalization for some of the algorithms, and they generally rely on rules that work for most subscribers. That is because the data coming from the user-item interaction showcases a long-tail distribution of item popularity (a few items receive most of the attention), and it has been shown that models trained on such data further prevail the bias, making popular items dominate the recommendations (Jannach et al., 2015). This results in a “feedback loop” that further promotes limited content (Mansoury et al., 2020). In the case of Netflix, there are instances when this could be improved (e.g.: PVR).

- **Demographic Bias**

There has been a growing interest in the field of demographic-aware evaluation of recommendation algorithms. Recent work conducted by Beel et al. (2013) has identified that demographics such as age group and gender influence the quality of the recommendations participants received; one of the experiments conducted showed that, if users provided their age and gender, they received recommendations they accepted. Similar work has been done by Mehrotra et al. (2017), who suggested a framework that allows quantifying the differences in satisfaction between different demographic groups, applied it to search engines and found latent differences in satisfaction between age groups.

- Does not account for **individual preferences.**

Researchers such as Lury (2019) have recognized that we live in an age of “personalization”, where our individual characteristics are involved in multiple areas of our lives that aim to predict or recommend outcomes; relevant examples range from the medical field to education, aiming to remove the “one size fits all” approach. Algorithmic confounding in recommendation systems has been shown to increase homogeneity, undermine the preferences of a minority, and decrease utility (Boratto and Carta, 2010; Chaney et al., 2018). These emphasize the importance of personalized recommendations depending on preferences, rather than generic algorithms, and Netflix admitted they do not store such information for users and disregard it.

- **Does not differentiate** between liked movies and what the user did not like.

The Netflix algorithm recommends movies based on previously seen ones. However, there is the risk of a user watching a movie and not liking it, but because it was a particular genre (e.g.: Science Fiction), that user will be further recommended movies in the same genre. This issue relates to text-based behavioural targeting, where something is assumed to be appropriate just because it is mentioned, without regard to the value to the customer (Ahmed et al., 2011).

- **Cold start problem**

The cold start problem in recommendation algorithms refers to the sparsity of information for both users and items in the algorithm. This makes it difficult to make recommendations for new users or new items. Therefore, when a user first joins a system, there is no data available for their preferences (Lika et al., 2014).

2.5 Previous attempts to improve the Netflix recommendation algorithm.

To date, there have been multiple attempts to improve the Netflix recommendation algorithm (see Table 2 for a summary).

Researcher	**Improvement areas**	**Results**
Abdollahpouri et al. (2017, 2020)	Popularity bias Calibration Fairness	Showed that the feedback loop is stronger for minority groups and leads to the homogenization of users. Correlation between popularity bias and miscalibration of recommendations. Improved coverage of long-tail items without performance losses.
Netflix, Inc.	User engagement User retention	Used intuition and A/B testing to improve engagement by as little as 0.1% for one

(Gomez-Uribe and Hunt, 2015)		metric at a time (chosen "test cells" that are part of the interface or recommendations). Not valid all the time; can pass the statistical tests, but not increase overall metrics.
Netflix Prize: Open-source innovation contest by Netflix (2007)	Goal to achieve a 10% reduction in the error of the recommender system at the time	The main lesson was the need to combine different innovations such as neighbour-based methods that also account for neighbour interactions, similarity functions and regularization (Bell and Koren, 2007).
Bharadhwaj (2019)	Improve the cold-start recommendation issue	Applied meta-learning approaches to improve the initial recommendations for new users of Netflix, which handled it better than the benchmark model.

Table 2 – Attempts to improve Netflix's recommender system

Drawing upon these debates and attempts of improving the algorithm, there are a few reoccurring themes. Firstly, they recognize the algorithm's importance in retaining and converting consumers, therefore spending a plethora of resources on the technology involved (with the examples of the Netflix Prize and their continuous A/B testing). Secondly, there are multiple approaches to implementing new machine learning algorithms and combining them with the existing system to achieve a better quality of recommendations.

However, far less argument exists on the role users can play in this, as they are seen as mere beneficiaries of the recommendations rather than actors in their own sense. There has been little research investigating how users can drive the system by using filters or inputs, resulting in a hybrid system that would not be a hybrid of multiple technologies, but a hybrid of technology and humans (Burke, 2019). Ekstrand et al. (2015) conducted an experimental study allowing the users to switch between different algorithms that would recommend them movies, which offered quite different lists of movies, and found that a high percentage of users switched between the algorithms multiple times before finding an output close to their desires. Moreover, there have also been studies that are in favour of giving users more control regarding movie recommender systems, noting that a user's context (mood, social context) is always changing, although their preferences are relatively static, and users that were given power over their recommendations have also been happier with them (Harper et al., 2015).

2.6 Individual user preferences when watching films.

Multiple scholars have tried to understand the influence of factors such as budget, distribution, awards, release period, and promotional strategy on movie success (Eliashberg, 2000; Hennig-Thurau et al., 2007). Henning-Thurau (2007) identified several movie attributes that exhibited an impact on the customers when choosing a film; these are country of origin, genre, symbolism, star and director power, and marketing.

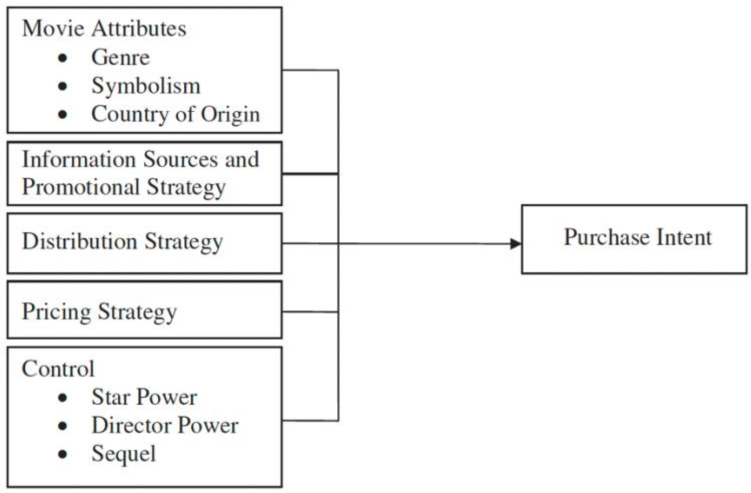

Figure 5 – Conceptual model of intention to watch a movie (Gazley et al., 2011)

Most of the studies on movie consumption and preferences were conducted before streaming platforms became the norm, a time when the average person had to exert more effort when selecting a movie, by either purchasing a physical copy or going into a cinema.

The process of consuming art is often seen as a hedonistic experience, which relates to the emotional aspects of one's interaction with a product (Hirschman and Holbrook, 1982). Hedonism is based on aesthetic consumption, meaning that it has at its base feelings and appreciation of things perceived as beautiful or moving (Charters, 2006). Consumers want experiences that offer an escape from mundane life (Venkatesh and Meamber, 2008). These are linked to the psychological profile and traits. Psychologists have attempted to assess the correlation between these traits and types of movies. For instance, preferences for horror films have been associated with low neuroticism and high sensation seeking (Kaufman and Simonton, 2014). However, it can be recognized that these factors – feelings, emotions, aesthetics – are difficult to quantify and difficult to include in algorithms.

Infortuna et al. (2021) found that affective temperament traits, gender, and age have a significant impact on the preference for movie genres, which are in accordance with various stereotypes in movie preference and gender bias in media consumption. For instance, males prefer horror, action, or thriller, while women favour comedy, romance, or melodramatic movies.

Another aspect that has been recognized as more important lately in terms of predicting movie success is social media. Researchers note that the Facebook “like” exerts a positive impact on how well-received a movie will be, drawing upon aspects of the Social Impact theory, which states that the behaviours of people are impacted by social sources (Ding et al., 2017; Latané, 1981).

Considering all these differences, one of the main arguments against recommendation algorithms is that they lead to heterogeneity, which extends to being seen as a trap for individuality. While several researchers emphasize the importance of individual preferences in content selection, no existing methodology addresses the ability of movie recommender systems to be user-driven.

3. Research Methodology

This chapter will discuss the methods employed for the study and the theory that supports them. The research will address the gaps in the literature using mixed methods and will follow the design research methodology. These will be done to answer the following research questions, posed because of the literature review:

1. What criteria do users of movie streaming platforms have when choosing a movie to watch?
2. How do demographics impact movie selection time and the accuracy of recommendations?
3. How can a movie filtering functionality decrease the time people spend choosing a movie to watch on Netflix and improve user satisfaction?

3.1 Previously used methods

Many researchers have shown an interest in understanding individual user preferences and movie-watching habits (Gazley et al., 2011; Eliashberg et al., 2000; Hennig-Thurau et al., 2007). Moreover, since the introduction of the recommendation algorithms, there have been multiple attempts to improve them using either a user-centric approach or an algorithmic one: Cao et al. (2019) proposed the combination of knowledge graphs with user preference, McNee et al. (2003) suggested different interfaces giving users more freedom, and Netflix themselves introduced “The Netflix Prize” asking people to improve the recommendation algorithm. However, all these studies often have a limited scope, such as a small, non-diverse sample, or focus solely on the technological part (see Appendix A for an overview of the methodologies).

3.2 Mixed methods

In the Journal of Mixed Methods this research paradigm is defined as “an intellectual and practical synthesis based on qualitative and quantitative research” (Johnson et al., 2007, p. 129). Mixed methods research came as a response to address the limitations of using solely one of the qualitative or quantitative approaches and is the method that pragmatism underpins

(Doyle et al., 2009). The pragmatism philosophy is more oriented towards solving problems in the real world, allowing researchers to use more methods and techniques (Yvonne Feilzer, 2010). A deductive approach is used to see if the theory found applies to the instance of Netflix and recommendation algorithms. In practice, both an inductive and deductive approach can be used, regardless of the qualitative or quantitative nature of the data (Hyde, 2000).

This research will first analyse quantitative data from an online survey to complement the findings from the literature. Then, it aims to obtain an in-depth understanding of the user interaction with a proposed web application by using qualitative analysis.

3.3 Design Research

Design Research is a problem-solving paradigm that has its roots in engineering. It has been applied to a variety of fields, mainly in disciplines focused on building artefacts, most notably in Information Systems (Peffers et al., 2007). On a general note, it is a build-and-evaluate loop that is iterated several times before reaching a final product (Markus et al., 2022)

Hevner et al. (2004) also argue that one of the most important guidelines when conducting design research is producing an artefact that addresses a problem, relevant to a business, and its utility must be evaluated rigorously.

However, as highlighted by Easterday et al. (2017), one of the main disadvantages of Design Research is the uncertainty regarding its process, with no consensus on how to do it and a plethora of proposed approaches (Sandoval and Bell, 2004; Bannan-Ritland, 2003). To address this, the Design Science Research Method (DSRM) was suggested by Peffers et al. (2007), and it was followed in this study (Figure 6).

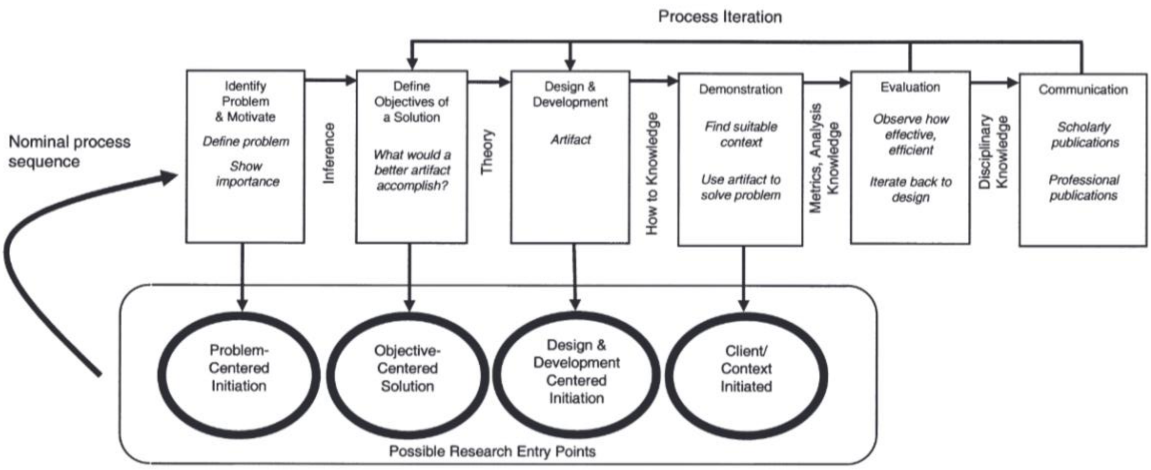

Figure 6 – DSRM Process Model (Peffers et al., 2017)

Figure 7 displays the phases followed, which will only cover one iteration of the process due to the time limitation and will be divided into 4 main steps: 1) Problem Identification, 2) Defining objectives of the solution, 3) Design & Development, 4) Demonstration & Evaluation, and the actions taken for each of them.

	Problem Identification	**Define Solution Objectives**	**Design & Development**	**Demonstration & Evaluation**
Approach	Literature Review	Online Questionnaire	Prototype solution using JS	Usability test and semi-structured interview
Analysis Method	Reviewing previously used methods	Quantitative Analysis	Continuous development, testing, and improvement	Qualitative Analysis
Result	Awareness of the problems and identifying gaps in previous research	Requirements and starting point for solution	Functional interface of Netflix with filtering functionality	Observing user interaction, assessing usefulness of solution

Figure 7 – Adopted Approach for the Design Research

3.4 Questionnaire and Defining Solution Objectives

Defining the solution objectives was done by supplementing the literature review with primary data, for a more recent understanding of the criteria people have when selecting a movie and how accurate the recommendations they receive are, so those results could be implemented in the proposed website.

3.4.1 Why a questionnaire

After evaluating other data collection methods, a questionnaire was chosen because it enables information collection in a standardized manner while allowing the inference of results to a wider population (Rattray and Jones, 2007). Many researchers acknowledge the various benefits of a survey, such as a straightforward analysis, low cost of time and money, ability to reach a lot of people quickly, anonymity, information regarding a group of people and lack of bias (Gillham, 2008; Denscombe, 2010). A short questionnaire was designed to ascertain participants' attitudes and behaviours towards movie streaming, and their individual preferences.

3.4.2 Questionnaire development

The questionnaire was prepared according to the procedures outlined by Lietz (2010), which cover aspects like question length, specificity and simplicity, question order, and social desirability. Therefore, the questions were designed to be clear, simple, specific, and relevant to the research objectives.

Designing individual questions

Firstly, participants were given a short introduction and description of the study and were presented with the consent form. Therefore, before starting the survey, a filter question regarding consent had to be answered. The first set of questions was designed to identify demographics. Then, the questionnaire asked participants to answer 8 investigative questions with a list of 5 response options each to better understand movie-watching behaviours, considering relevant areas from the literature to ensure content validity. They were asked to select the criteria they consider when choosing a movie and then to rank their choices based on importance. Lastly, the participants were asked to rate the accuracy of the movie recommendations they receive on a scale from 1-10, resulting in 13 questions in total (Appendix B).

Types of questions

The questions in the self-completed survey were close-ended, with options for the respondents to choose from, as these responses can be easier to compare and quicker to answer as they require minimal writing (Kelley et al., 2003).

3.4.3 Process

Tools

The questionnaire was designed using Qualtrics, an online survey tool chosen because of its wide range of functionalities. Moreover, Qualtrics securely saves the responses in its cloud and automatically codes them when exporting.

Visual presentation

Regarding the visual presentation of the survey, which has been recognized to affect response rate (Vicente and Reis, 2010), it followed one colour theme and template offered by the software, had a one-column layout, not too short that it is not relevant, but not too long that participants give up (Rolstad et al., 2011).

Pilot testing

To refine the questionnaire, an expert was first asked to comment on its suitability. Then, pilot testing was conducted informally by 5 people to understand the face validity (if it appears to make sense), how long it takes to complete, and the clarity of questions and instructions (De Vaus, 2013). The questionnaire was then altered accordingly – for instance, additional guidance was given in brackets.

3.4.4 Participants

The sampling method was probabilistic, to ensure each case in the population has the same chance of selection (Berndt, 2020). The participants for the questionnaire were adults who met the eligibility criteria of currently using movie streaming platforms. To maximize the response rate, the questionnaire was delivered via a hyperlink and distributed electronically using social media channels and direct messages, all accompanied by a short description of the study. It also prevented multiple responses from the same IP address. It reached approximately 500 people, out of which 231 (46.2%) filled it in and 213 (42.6%) were eligible, representing various demographics of age, sex, and education level.

3.4.5 Quantitative Analysis

Quantitative analysis was used to analyse the data from the questionnaire, as it only contained numerical or categorical data from the answers. The benefits of this deductive method include being fast and effective, helping to summarize the data and deduct patterns, and producing reliable and factual outcomes (Steckler et al., 1992).

Power BI was used to conduct a graphical initial exploratory analysis, which has the purpose of looking at data from multiple points of view to draw informal conclusions and identify findings that merit closer analysis. However, as it does not have a certain model and its reliability cannot be tested, the findings cannot be carefully verified and further analysis is needed (Morgenthaler, 2009).

To analyse this data and derive findings that can be used for the app development and to draw conclusions relevant to the study, SPSS was used to conduct statistical evaluations such as Kruskal-Wallis tests, frequency distributions, and crosstabs on the data. Qualtrics automatically enters, saves, and prepares the data for analysis in SPSS. Therefore, the data was coded using pre-set codes, stored safely, and exported in the correct data layout.

3.5 Design and Development – Website [1]

This part will focus on the steps taken to develop a functional website which is a clone of the current Netflix webpage, implementing an additional filtering functionality. This was based on the information extracted from the literature review and the issues highlighted in the survey (see Table C2 for a short description of features).

The main limitation of the development of this solution is the inability to access (or replicate) the actual Netflix algorithm, which would be useful for a more thorough understanding of how the solution could be implemented.

3.5.1 TMDB API

Prior to commencing the development, research was done into what datasets or databases contain a comprehensive list of movies, which also include additional information required for each movie, such as production details, release year, and actors. After exploring alternatives like downloading data from IMDB (the Internet Movie Database) and merging it with other sources such as Flixr (containing titles available on Netflix), the author decided to use data provided by TMDB (The Movie Database). This contains movie features ranging from primary info (cast, crew, genre) to translations, provided through a free REST API which supports files in a JSON format (Themoviedb.org, 2022). A form was filled out on the TMDB website to request an API key.

3.5.2 Tools

JavaScript was chosen due to its suitability for web development, the author's previous experience with it, and being the most used scripting language for web applications. Its main characteristics are being an object-based language (allowing for model inheritance), variables can be created easily, values are freely converted from one type to another, and supports APIs (Jensen et al., 2009). More specifically, the asynchronous JavaScript runtime Node.js was used to build this application (Node.js.org, n.d.). This is a framework that develops high-

1 Please refer to Appendix C for more details on development and code examples.

performance applications and supports event call-backs efficiently (Tilkov and Vinoski, 2010).

The development environment used was the Visual Studio Code editor, which is optimized for building and debugging web and cloud applications (Microsoft, 2016). The app was hosted locally using Firebase CLI, as it is a free web hosting platform.

3.5.3 Development Process

Agile Methodology

The development process followed an Agile methodology, which is an approach to software development that focuses on principles such as accommodating change in requirements at any stage of the development process, customer involvement, and creating valuable outcomes (Dingsøyr et al., 2012). The specific Agile methodology followed was SCRUM, which is based on dividing projects into smaller blocks called sprints, assigned to a specific team, and documented in a backlog (Srivastava et al., 2017). However, for this research, considering the solution was developed by one person, the methodology was not followed strictly, but it was used to divide the application into manageable development chunks and decide what features to be developed in each sprint, while also allowing time to make changes (Table C1).

Developing the Netflix clone

The first step in the development process was doing the required technical set-up with the tools described above on a local machine. Then, online resources regarding web development, JavaScript, and creating a simple Netflix clone were used to start the prototyping process. For this, websites like GitHub and YouTube tutorials were used to benefit from previous works done by developers in this sense, who created similar Netflix interfaces, either functional or just front-end. A clone of the Netflix website was first developed, using the TMDB API to extract the movies and display them in rows (Figure 8).

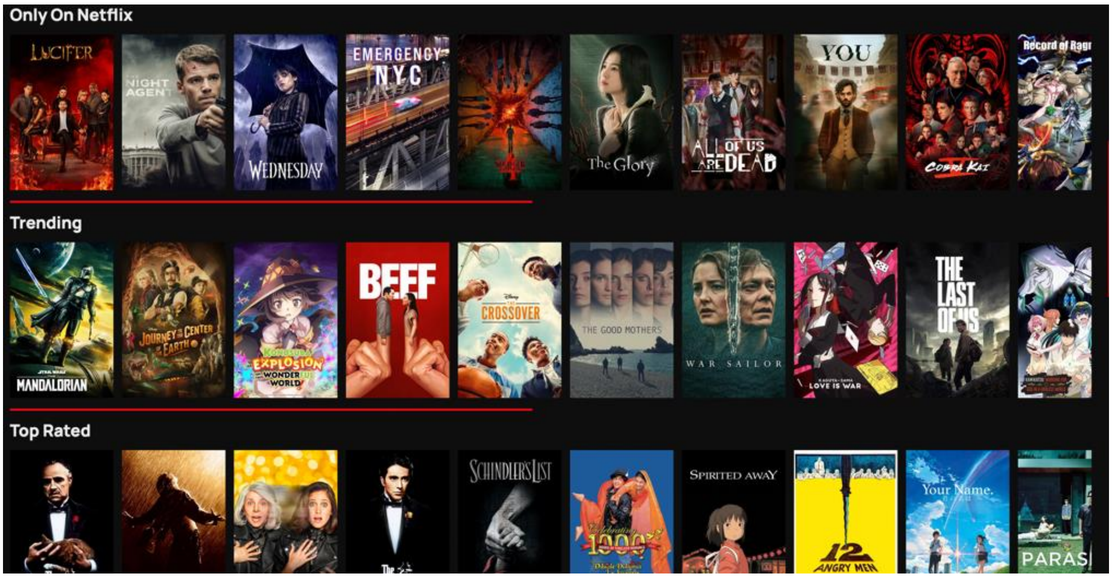

Figure 8 – Screenshot of Netflix clone

Afterwards, the “Search” button and functionality were added, allowing users to search for a specific movie, as seen in Figures 9 and 10:

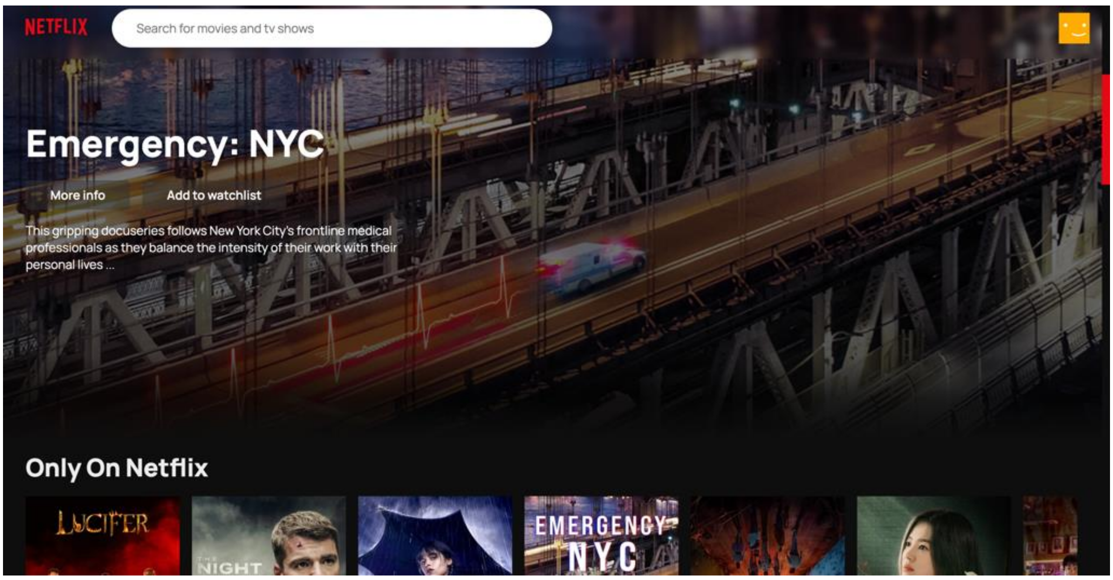

Figure 9 – Home Page with Search functionality

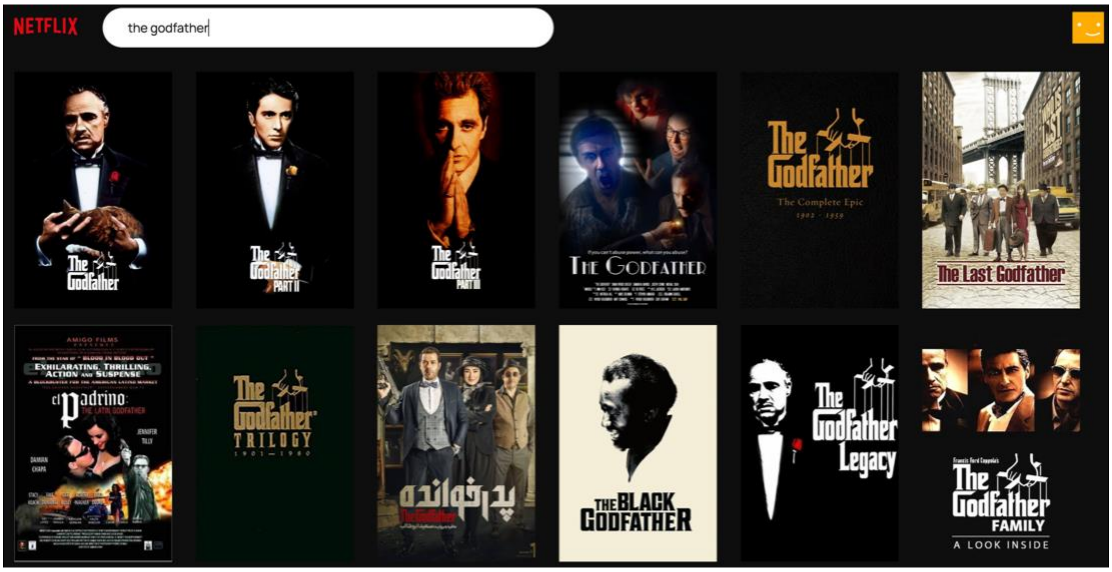

Figure 10 – Page displaying the search results

The individual movie page from Figure 11 was created afterwards: when clicking "more info" after hovering over a movie image, the user can see the individual movie page, which extracts from the API the movie poster, the cast, description, runtime, release date, genres etc.

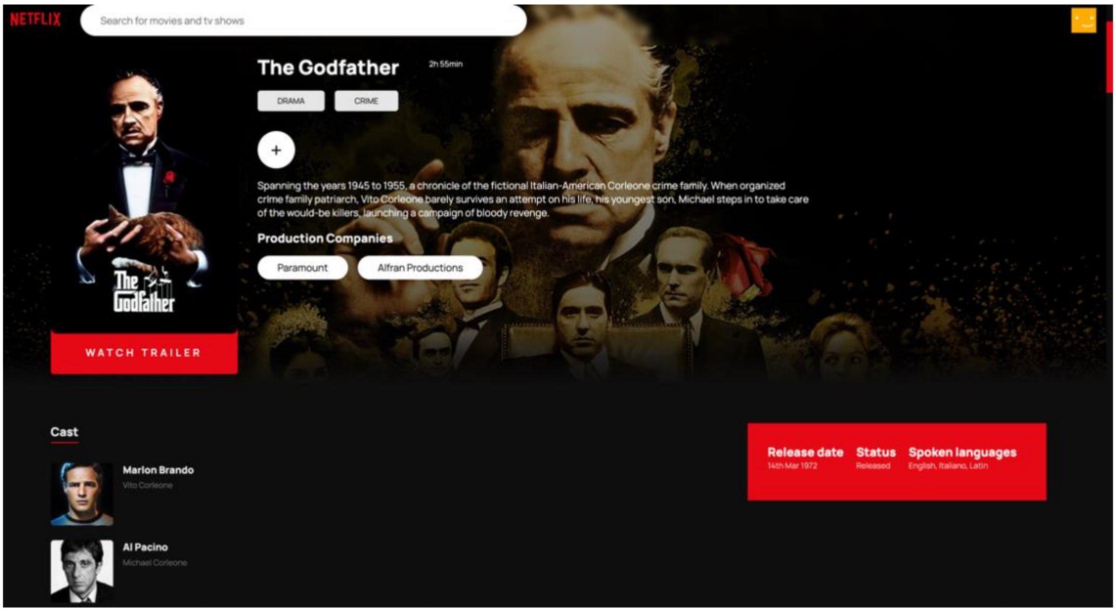

Figure 11 – Individual movie page

After replicating the already existing functionalities of Netflix, the creation of the filter functionality started. Firstly, a dropdown filter button was added to the home page. This displays the main criteria selected by users in the questionnaire, allowing multiple selections, deletion of criteria, and choosing multiple values for one criterion (i.e.: a movie that has "thriller" and "action" as genre and has a vote of 7), and returning the movies that meet those criteria, as shown in Figure 12.

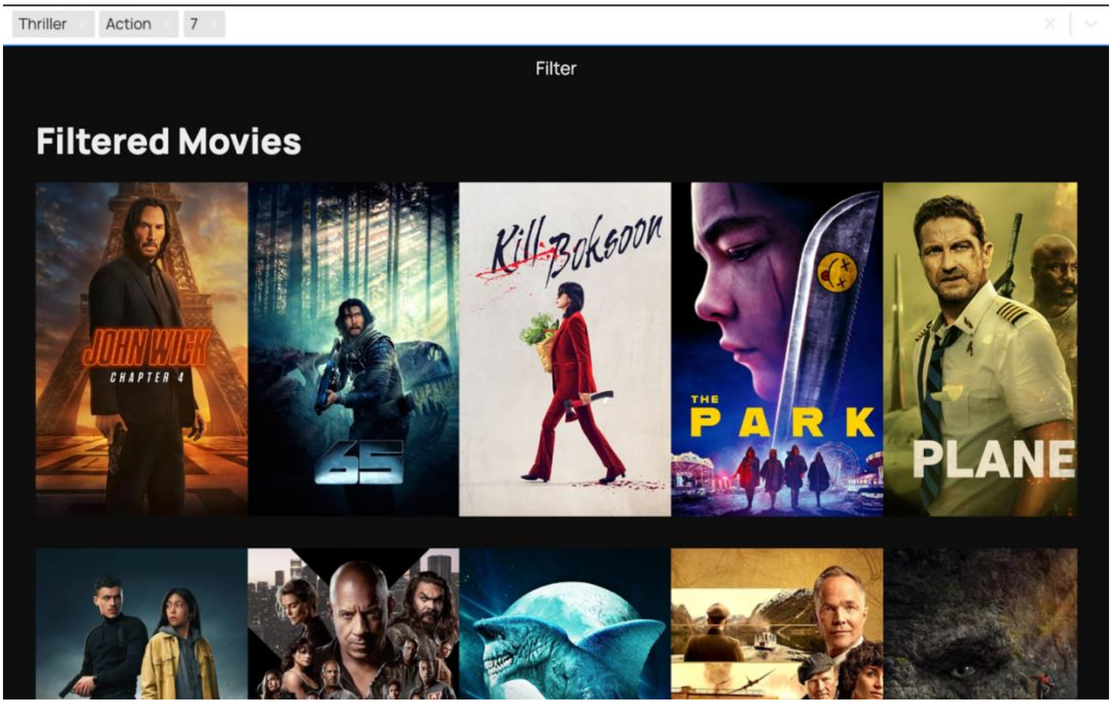

Figure 12 – Page with filtered movies

3.6 Evaluation – Usability test and interview

Hevner and Chatterjee (2010) emphasize the importance of complementing the research design process with behavioural understanding, as technology and behaviour are considered inseparable in IS research. On a philosophical note, these align with the pragmatism philosophy which highlights that truth (theory), and utility (effective artefacts) are also inseparable. To rigorously test it, a usability test was conducted, followed by a semi-structured interview.

3.6.1 Usability test

As defined by the ISO, usability is “the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use” (ISO 9421-11:1998, definition 3.1). The specific usability evaluation method employed in this study was user-based evaluation, where users directly participated by doing typical tasks with the website. Their behaviours were observed, and it was assessed whether the website was performing as expected, or if there were any flaws (Bastien, 2010).

The process was a synchronous remote one, as the researcher and the participant were not in the same room but communicated via Zoom, as it allows for time efficiency and cost saving (West and Lehman, 2006).

The specific steps followed were those outlined by Bastien (2010), as seen in Table 3:

Step	Procedure
Definition of test objectives	Related to the aim of the study and previous quantitative analysis and app development, the objective of the test is to assess if the functionalities of the proposed website work as expected, as easy to interact with.
Recruitment of participants	Asked personally online, from a various demographics to see if that has an impact, non-probabilistic
Tasks participants will have to realize	The tasks were for the users to: use the search bar, use the filter functionality, interact freely with the system to find a movie they liked, using multiple pages
Choice of how data will be collected	Data was collected by extensive note taking, user observation, as well as the interaction being recorded and transcribed afterwards.
Preparation of the test environment	A Zoom.com account was already set up, and participants were given control over the screen (as the app was locally hosted), which was tested before the start of the test.
Selection of data analysis procedures	The qualitative data collected was analysed through thematic analysis in NVivo.
Presentation and communication of results	The results can be found in the Results section of this research, as well as the thematic analysis.

Table 3 – Usability test steps overview

3.6.2 Semi-structured Interview

Primary data was collected through semi-structured interviews, where the users were asked to describe whether a filtering functionality would help them and why, how easy it was to use, and how filtering could help for the recommendations they usually receive on Netflix or similar streaming platforms (Appendix D). Additional questions were asked depending on the situation, or the users were asked to elaborate on certain answers and give overall feedback. The entire process lasted 10-15 minutes for each participant.

3.6.3 Participants

10 people were asked and agreed to take part in the usability test and interview. Subjects ranged in age from 18 to 62, 6 women and 4 men, to represent various demographics and observe whether this has an impact. The sampling approach was purposive, as the researcher reached out to people assumed to be free to participate and were already Netflix users and have an interest in movies (Christof Wolf et al., 2016). This was done for them to accurately describe the recommendations they receive there and compare the website interfaces. However, 6 of the participants were in the 18-25 age group, which opens the possibility of bias regarding preferences or interaction with the system which may be influenced by their younger age. They all consented to be recorded for the duration of the experiment. The process was conducted over a two-week period and scheduled according to the participants' availability.

3.6.4 Tools

The process was conducted via Zoom, as it allows for more freedom in scheduling the tests and interviews, and the audio was transcribed using Otter.ai.

As the website was locally hosted, the participants were given control over the author's screen to use the website from their own computer. NVIVO was then used to analyse the qualitative data collected.

3.6.5 Qualitative Analysis

Thematic analysis is generally defined in literature as a method for systematically identifying themes across a qualitative data set and is recognized as a widely used qualitative analysis method (Braun and Clarke, 2012). This type of analysis was chosen for this study to draw conclusions regarding attitudes using the data collected in the interviews.

Willig and Rogers (2017) outline multiple phases of the thematic analysis process, which were also followed in this research. The first step is familiarising with the data, which was done during data collection, and by reading the interview transcripts before starting the analysis. Then, codes were generated by attaching meaningful, short labels to segments of the data that were relevant to the research. For this, an open-code scheme was followed, with regular iterations of calibrating and merging the codes. In this way, 30 codes were created. The third phase, theme development, was done after all interviews were coded. This was selecting what is useful for answering the research questions while identifying broader patterns by combining codes. Lastly, the 6 resulting themes were reviewed and defined, which is more of a narrative analytic that is coherent and unified.

3.7 Ethical Considerations

Prior to distributing the survey and conducting the experiment, ethical clearance was obtained from The University of Manchester and the project supervisor, by completing and signing a form attesting that all ethical criteria were met. All the participants were presented with an information consent sheet, outlining the anonymity of the data collected, confirming they were over 18, providing an overview of the study, and their options to withdraw at any point or delete the data they provided (Appendix E). The participants in the interviews also verbally consented to have their answers to be transcribed.

4. Results

This section of the research will present the results obtained after conducting data analysis on the primary data collected through the survey and the semi-structured interviews. Specifically, quantitative analysis was done on the questionnaire data, while the transcribed interviews were analysed through thematic analysis. The results aim to respond to the research questions.

4.1 Survey Results

The purpose of the survey was to respond to the first two research questions, regarding criteria when choosing a movie and the impact of demographics on selection time and recommendation accuracy. Moreover, the results were meant to set the requirements for the website development.

The first set of questions gathered information about the participants' demographics, to use in further analysis and explore if the subsequent answers differ between groups.

Regarding the age group, most respondents were aged 18-24 (52.3%), and the least common group was 55 and over (7%). As this was a considerable difference, these were normalized for subsequent analysis.

What is your age group?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24	112	52.3	52.3	52.3
	25-34	31	14.5	14.5	66.8
	35-44	23	10.7	10.7	77.6
	45-54	33	15.4	15.4	93.0
	55 and over	15	7.0	7.0	100.0
	Total	214	100.0	100.0	

Table 4 – Frequency distribution table of age groups

Most respondents hold at least a high school diploma (34.1%) or a bachelor's degree

(30.4%).

What is your highest/current education level?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school	73	34.1	34.1	34.1
	Certificate/ Diploma	10	4.7	4.7	38.8
	Bachelor's degree or equivalent	65	30.4	30.4	69.2
	Master's degree or equivalent	53	24.8	24.8	93.9
	Doctoral degree or equivalent	13	6.1	6.1	100.0
	Total	214	100.0	100.0	

Table 5 – Frequency distribution table of education level

The split between male and female participants was almost equal, with slightly more males (53.1%).

What is your gender?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	113	52.8	53.1	53.1
	Female	100	46.7	46.9	100.0
	Total	213	99.5	100.0	
Missing	System	1	.5		
Total		214	100.0		

Table 6 – Frequency distribution of genre

Afterwards, the variable measuring the recommendation accuracy (as perceived by the users) and time spent choosing a movie were explored.

The skewness of the recommendation accuracy was found to be -.963, indicating that the distribution was left-skewed. The kurtosis of the recommendation accuracy was 1.673, indicating that the distribution was heavier compared to normal distribution.

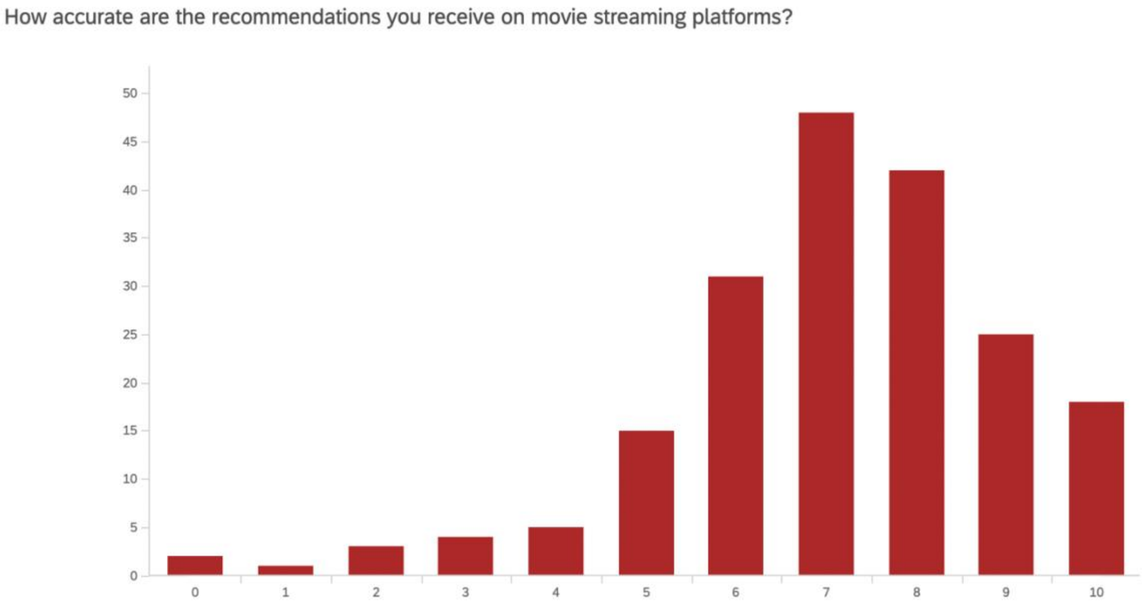

Figure 13 – Histogram of recommendation accuracy

More than 41% of respondents claim they spend more than 10 minutes selecting a movie, while only 10.70% spend less than two minutes (assuming they simply select from the recommendations they receive).

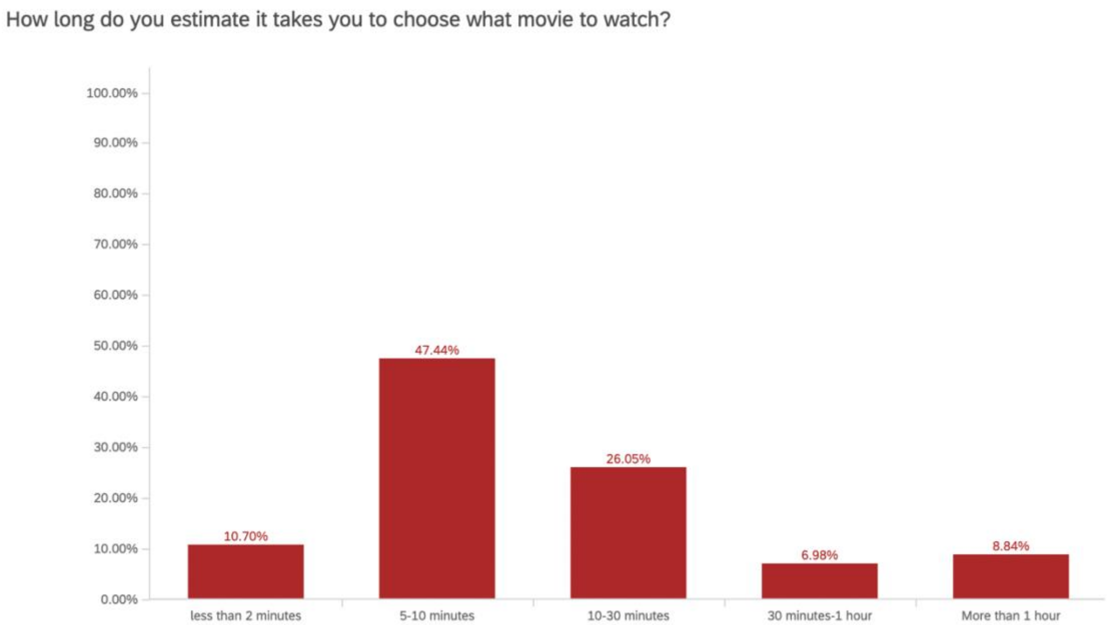

Figure 14 – Time spent choosing a movie

4.1.1 Demographics and time to choose a movie.

Crosstabs were performed for each of the demographic variables and the time spent to choose a movie, as both were ordinal.

*What is your gender? * How long do you estimate it takes you to choose what movie to watch? Crosstabulation*

Count

		How long do you estimate it takes you to choose what movie to watch?					
		less than 2 minutes	5-10 minutes	10-30 minutes	30 minutes-1 hour	More than 1 hour	Total
What is your gender?	Male	16	53	26	6	11	112
	Female	7	49	29	9	6	100
Total		23	102	55	15	17	212

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.157	.263
	Cramer's V	.157	.263
N of Valid Cases		212	

Tables 7 and 8 – Crosstabs for gender and time spent choosing a movie.

To see the nominal association, the symmetric measure of Cramer's V was calculated, which a chi-squared based method (V = .157), having a significance value of p = .263. To interpret its significance, it was compared to a critical value. This value was calculated according to the sample size of 213 and the degrees of freedom for a 2x5 table (df = 4), the resulting value being 0.361 at a significance level of 0.05. However, this indicates a weak relationship.

The same procedure was applied for crosstabs for age group (V = .157, p = .181) and education level respectively (V = .159, p = .157). These also show no significance.

Therefore, no statistically significant correlation was found between the demographical measures and the time users spend choosing a movie.

4.1.2 Demographics and recommendation accuracy

A Kruskal-Wallis H test showed that there is no statistical significance in recommendation accuracy between the different age groups, $\chi^2(2) = 3.408$, p=.492, with the highest mean rank for recommendation accuracy of 109.15 for the 55 and over age group, and the lowest rank of 81.97 for the 25-34 age group.

Test Statistics

	How accurate are the recommendations you receive on movie platforms? (0-bad, 10- good) - Accuracy
Kruskal-Wallis H	3.408
df	4
Asymp. Sig.	.492

a. Kruskal Wallis Test
b. Grouping Variable: What is your age group?

Table 9 – Kruskal-Wallis H test

However, the mean recommendation accuracy score was different between age groups, especially between the 55 and over age group (M = 7.6154, SD = 1.325) and the 25-34 age group (M= 6.8065, SD = 1.30178).

		How accurate are the recommendations you receive on movie platforms? (0-bad, 10- good) - Accuracy
		Mean
What is your age group?	18-24	7.01
	25-34	6.81
	35-44	7.33
	45-54	7.29
	55 and over	7.62

Table 10 – Average recommendation accuracy score depending on age group

The same test conducted for the gender and recommendation accuracy also showed no statistical significance between the two, with $\chi^2(2) = .124$, p = .724, and similar mean ranks for males and females.

Another finding is that, compared to the 18-24 age group, those older than 24 are more likely to do their own research of a movie instead of listening to social media, or even to recommendations from friends (Figure 15).

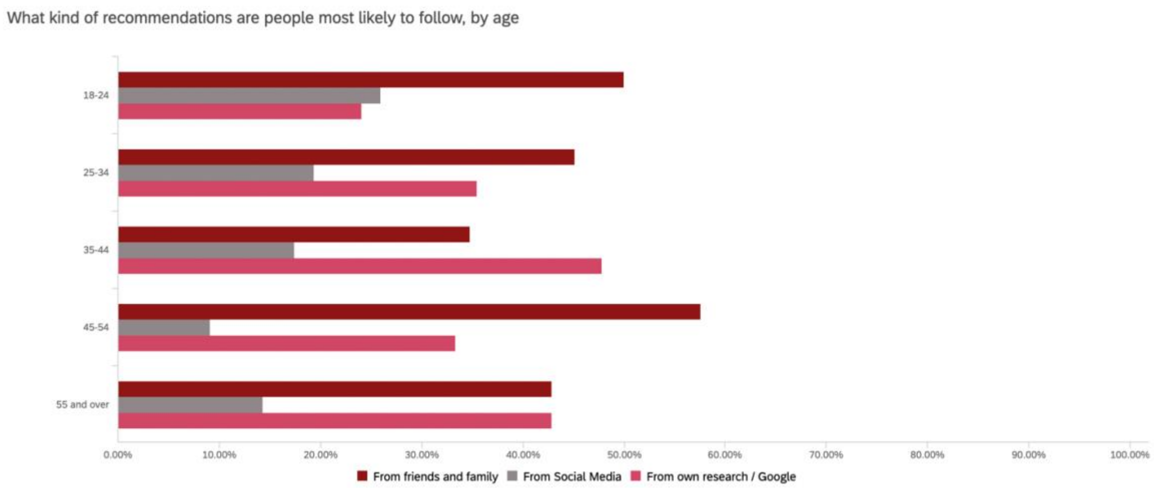

Figure 15 – Age and the type of recommendations people are more likely to follow.

4.1.3 Time spent choosing a movie and recommendation accuracy.

The highest significance found between a categorical variable and the recommendation accuracy was for time spent choosing a movie. 41.32% of respondents generally spend more than 10 minutes choosing a movie. Those who spend more than 1 hour deciding what movie to watch rate their recommendations the lowest (M = 6.80), value which was almost the same (M = 6.66) for those who spend between 10 and 30 minutes.

Therefore, the recommendation accuracy scores are generally lower for people who spend more time deciding.

4.1.4 Movie user preferences and criteria

To answer the research question about the criteria that people consider important when choosing a movie to watch, they were asked to select what is important and rank their options.

The criteria having the highest percentages of being chosen were Actors in the movie (26%), Genre (25%), Online ratings (20%). For the less selected criteria, the percentages were much lower: 8% of people chose Awards, 8% chose Movie director, 7% Country of origin and 6% Year of production. These were consistent with the way people ranked them – the 3 most popular were also the most prevalent in top 3 preferences. The results were consistent across age groups and genders. This resulted in the following requirement figure:

Figure 16 – Requirements for criteria to include in the filter functionality.

4.2 Semi-structured Interviews results

Thematic analysis was used to answer the final research question, exploring how user preferences can be integrated with the current Netflix interface, and further understand what opinions people have on that.

An initial word cloud was done using the responses, and the most frequent words appeared to be positive, such as “good”, “narrow”, and “help”.

Figure 17 – NVivo Word Cloud

From the entire data set containing the interviews, 30 final codes were created, which were divided into 6 main themes, as shown in Table 11:

Theme: Movie preference criteria **Codes:** - Movie vote - Movie release date - Movie length - Movie genre - Movie summary - Movie actors - Movie language	**Theme: Filter functionality** **Codes:** - Filtering is useful - Good filtered results - Filter is not useful - Get used to filter - Filter again - Filter is easy to use	**Theme: Netflix recommendations** **Codes:** - Good recommendations that need further filtering - Good Netflix recommendations - Netflix recommendations are mixed - Netflix is lacking criteria
Theme: Website interaction **Codes:** - Using the filter - Use more pages before filtering - Changing the filter - All information in one place	**Theme: Movie decision factors** **Codes:** - Not knowing what to watch - Movie depends on mood - Already know what to watch	**Theme: Website suggestions and Feedback** **Codes:** - Filter UX suggestions - Filter still returning many results - Best-match filtering - Filter still returning many results

Table 11 – Themes identified and codes for each, ordered by number of appearances

Several areas for investigation were identified, which will be now further discussed (full descriptions can be found in Appendix F).

- *Movie preference criteria*: the factors that participants mentioned when asked to filter according to personal preference.

This was consistent with the questionnaire results and literature to a certain extent. While movie vote was not a popular criterion in the survey, 8 participants out of 10 also chose the movie vote as a filtering criterion. A similar case was for the release year, which 6 participants considered important. It was also clear that genre was valued the most, with all the participants selecting at least one genre, and that actors or language were not that relevant to them. Participants were generally observed to browse through the actors on the individual movie page, but did not have specific ones they searched for.

- *Filter functionality*: this refers to the instances where the participants used or expressed their feelings towards the filter function within the app.

Overall, a substantial majority of the interviewees admitted the filtering functionality would be helpful when asked about it (Figure 18). Several recognized that it would be useful to filter the recommendations they receive and narrow them down, while some admitted to having specific things they look for from the beginning when choosing a movie. Many expressed a positive attitude towards filtering, admitting that it would be a good first step: *“would help me browse between less movies. So instead of taking 20 movies that I'm seeing, I'll just switch between five movies to read the summary and see everything I like.”* The main situations identified where it would not add value are when users already know what to watch, or when they generally use Netflix to simply browse for movies until finding an acceptable one to watch, in which case participants would not need to use a filter at all, situation highlighted by 4 participants. Some were reluctant to say whether it would be useful in all instances when they use Netflix but admitted it could be a good option to have just in case.

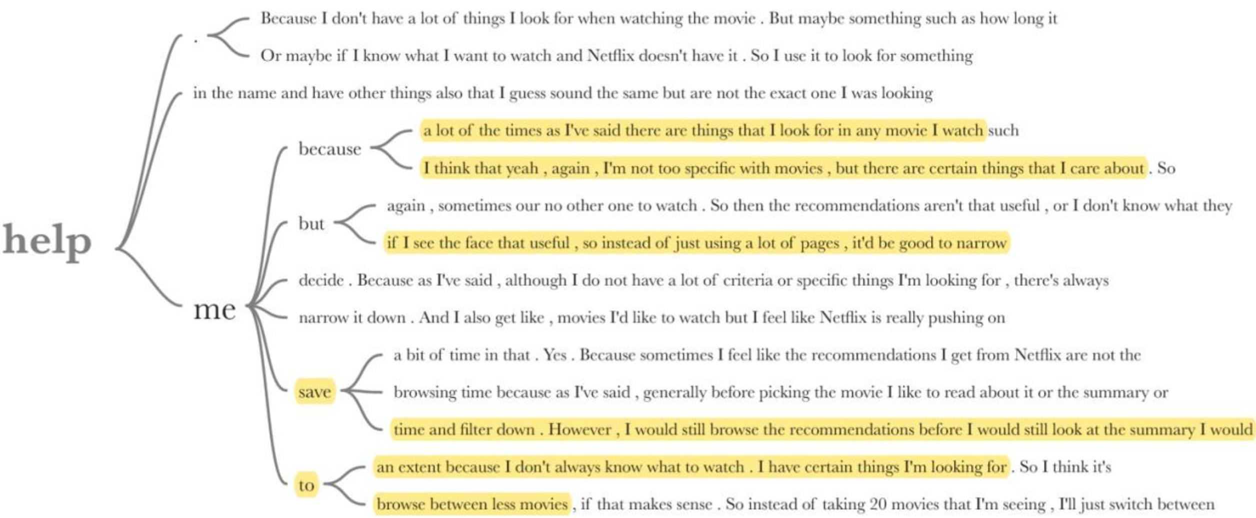

Figure 18 – NVivo word tree for how helpful the filter is

- *Netflix recommendations*: the participants’ opinions regarding the recommendations they are currently receiving on Netflix.

Participants had mixed views on the recommendations they receive on Netflix. They acknowledged that these are generally good, while several noted that sometimes these are either mixed, bad, or they felt like Netflix was trying to force its original content and promote some movies that are not related to their preferences – *“I guess they’re mainstream or viral, but they’re not for me”.* More than half the participants admitted it could be combined with the recommendations to decrease their browsing time. However, 2 participants said the recommendations they receive are good and they usually choose from those, so no need for filtering would be necessary.

- *Website interaction*: observations related to how the users interact with the website and the things they voice when using it, including the results from the usability test.

The tasks users were asked to perform were generally executed easily, as their interaction was observed. All the participants used the filter functionality throughout the test, while 8 participants used the filter without being prompted to do so at all. Some described the experience as *"straightforward"* while noting similarities between this filter and the ones they encounter on other websites. Most participants browsed easily between pages, modified the parameters of the filter, and a few of them voiced they appreciated having all this different information on one single website, rather than having to open new tabs to check details about a movie. The oldest participant struggled with finding the filter, clicking the "filter" button after selecting everything, asked questions about the steps she should take, and overall, the process lasted longer.

- *Movie decision factors*: the feelings the participants had in relation to the way they watch movies, which relate to more subjective, heuristic aspects.

It emerged that participants do not have a standard when it comes to the way they choose a movie, as it depends on factors such as mood (*"maybe I want something more relaxed, maybe I want something more dramatic").* For these participants, the summary of a movie was something they mentioned more, as they want a more detailed understanding before committing to something to watch. Moreover, when initially asked to search for any movie, 80% did not know what to search for and took a considerable amount of time to decide.

- *Website suggestions and feedback*: future directions for improvement as suggested by the users, or issues they identified during use.

The last question of the interview was related to any feedback the participants had. The most common aspect they suggested was improvements for the UI and UX of the filter, as some noted aspects like a bigger font, or a slider button for some of the values to allow users to select a range, while one user mentioned not being able to see the filter button on one of the pages. Some highlighted that the filter still returns a lot of results and suggested a "best-match" approach to order what is shown – returning the movies that meet all the criteria first, and then the ones that meet at least of the criterion.

After analysing the themes, the following thematic map emerged to show an interaction of the 6 themes with the website and the movie selection process:

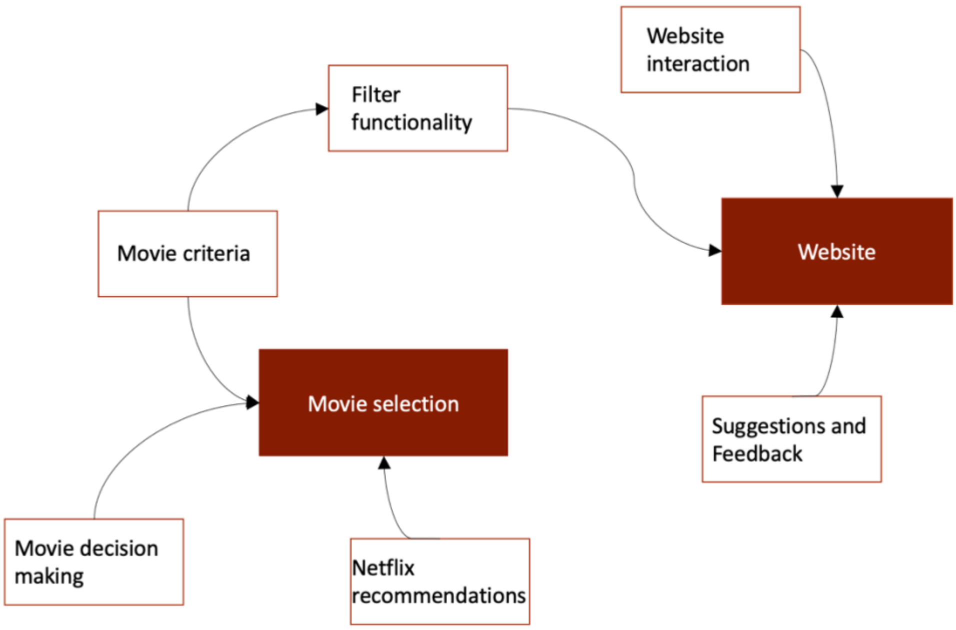

Figure 19 – Thematic Map

This shows that the website is impacted by the website interaction theme (how people use it), suggestions and feedback theme (what improvements people would like to see for the website), and by the filter functionality, which impacts the website by the changes to its aspect and what it can display. The movie selection process is impacted by the movie criteria, which are the factors people consider, the Netflix recommendations they receive, and the movie decision-making, which relates to the subjective and heuristic aspects of choosing a film. The movie criteria theme also impacts the filter functionality, since it determines what filtering factors people choose.

5. Discussion

This chapter will discuss the findings presented above in relation to the literature review section. While the findings of this research were mainly consistent with previous literature, there were unexpected areas and aspects observed in the results.

5.1 Movie recommendation accuracy and time spent choosing movies.

The recommendation accuracy variable was considerably left-skewed, indicating that although recommendations are generally good (on average, rated approximately 7 on a 1-10 scale), certain users still need improvements on it. Moreover, there was a high percentage (41.32%) of respondents who spend more than 10 minutes (some of whom spend more than 1 hour) choosing a movie. The highest significance was found between the time spent choosing a movie and the recommendation accuracy, which were negatively impacting each other. It can be assumed that people who receive inaccurate recommendations are more likely to spend a considerable amount of time finding something that suits their preference, which is intuitive. The results from the interview suggest that users do that by browsing between multiple pages on Netflix, or even external websites, which generally takes time. In such a case, this browsing process could be aided by having the filter display all the criteria from the beginning and eliminating some of the steps of browsing.

This study supports evidence from previous observations (e.g., Chilton, 2020) that, even in an age of perfecting recommendations, certain users still spend time choosing what to watch, as recommendation algorithms do not always fulfil their needs.

5.2 Demographics, time spent choosing a movie and movie accuracy.

On the question of how demographics impact the recommendation accuracy and time spent choosing a movie, this study found no significant correlation between the two.

Demographics do not significantly impact the time users spend choosing a movie, nor the accuracy of the recommendations. However, the recommendation accuracy still has different mean values depending on the age group, with it being more accurate for the older group (55 and over), and the least accurate for the 25-34 age group. This study has been unable to demonstrate the demographic bias in movie recommendation algorithms. This inconsistency may be due to the fact that the demographics bias as a concept is explained on a general note for all recommendation algorithms, and it might not be the case for the movie recommendation algorithms specifically.

One interesting finding is that people older than 25 are more likely to do their own research when it comes to deciding what to watch, rather than listening to recommendations from social media or even from friends and family. As reinforced by the thematic analysis, they admit to switching between multiple Netflix pages or even different websites before deciding what to watch. This can add to the findings of Ding et al. (2007), who recognized the implications of Social Impact theory and the significance of social media when choosing a movie. Ding's study can therefore be complemented by adding the age factor to it, considering that different age groups attribute different levels of importance to social media.

5.3 Criteria and preferences when choosing a movie.

The second research question aimed to better understand the most important criteria people consider when choosing a movie. This became even more important after the analysis of the demographics and movie recommendation accuracy scores: the movie accuracy rating was skewed, with a considerable amount of people receiving below-average recommendations. However, this was not explained by the demographic variables as there were no significant correlations found between these and the accuracy. Therefore, one logical explanation could be that these are different because of individual preferences and criteria, which are not always captured accurately by the recommendation algorithm.

This study found that movie genre, online ratings, and actors are the criteria chosen by most participants in the survey, which were also ranked high in terms of importance in the questionnaire. These results slightly differ from those identified by Gazley et al. (2011) or Henning-Thurau et al. (2007), who recognize additional factors like country of origin, awards, release year or director as more relevant.

However, from the interviews and usability tests on the website, the movie rating, release date, length, and genre were often chosen by users as criteria when asked to browse for a movie. It is difficult to explain this result, but it might be related to the fact that people would not put in the extra effort to gather all that additional information but are more likely to select it when they are presented with it. An alternative explanation might be the participants felt constrained to use as many criteria from the filter as possible to achieve a narrow list in the context of the usability test.

As discussed in the literature, most studies looking into movie preferences were conducted longer ago (e.g.: Eliashberg in 2000). At the time, the main ways of watching a movie were renting one, buying the DVD, or seeing it in a cinema, which came at a considerably higher cost per movie, resulting in people paying more attention to the film they choose. However, nowadays, the more common practice is paying for a monthly subscription including thousands of movies to choose from, with virtually no cost of switching between them if the initial choice does not satisfy. Therefore, this study addresses this gap by providing a more recent understanding of the factors people consider when being faced with the option of choosing between multiple films depending on the information available, as the importance of factors might have changed now that it is so easy to also choose a different movie if the initial one is not matching their desires.

5.4 Integrating filtering with Netflix to improve streaming platform experience.

These findings were used to create a website similar to Netflix, while accounting for the preferences users mentioned in the survey, to have a more in-depth understanding of the criteria, as well as how the users would perceive such a solution.

The qualitative analysis also found that users often refer to aspects such as “mood”, “vibe”, or “feel” when asked about choosing a movie. This finding broadly supports the work of other studies in this area linking aesthetics and mood to movie-watching behaviour. Moreover, it is defined as a hedonistic experience that accounts for psychological traits and is based on feelings (Hirschman and Holbrook, 1982; Charters, 2006). These findings may be taken to indicate there is a benefit in giving users the power to narrow down the recommendations they are shown based on what they are feeling at a certain point in time, which is impossible for a recommendation algorithm to quantify and include when making suggestions.

Another aspect of the qualitative analysis that is consistent with the literature is the popularity bias in recommendation algorithms as described by Jannach et al. (2015) or Mansoury (2020). This bias leads to recommending the items that are most popular at a certain point in time. In the interview, participants mentioned seeing “mainstream” or “viral” films on the home page of Netflix that are not well-tailored to them. These are not always of interest to the users, and plenty of times they are not related to what the user would normally choose. This can be explained by the limited original movies Netflix produce, which they can promote quite aggressively to their users to ensure they have a high return on investment from these: the cost of producing a movie is high, whereas advertising it on their own platform is considerably cheaper.

Regarding the interaction with the website and usability results, as described in the “Website interaction” theme, most users completed the usability test tasks easily, considering them straightforward, or used the filter functionality when asked to narrow down the results without being explicitly asked to do so. This suggests the website is designed intuitively, and such a functionality can in theory be combined with the existing interface without a disruption in the user experience. However, concerns regarding its design were expressed, how it would be different depending on age group, as well as questions on how it would look like on other devices such as on TV.

Overall, during the usability test and semi-structured interview, there was a positive sentiment regarding the website and the use of a filtering functionality. The users admitted they would benefit from being able to narrow down the recommendation they receive or use the filter to overcome the popularity bias or feeling overwhelmed. This is a particularly reassuring finding, as it can therefore be assumed that the browsing time would decrease, and the recommendation accuracy increase. However, a few mentioned they would not use it in all cases (such as using Netflix only for the purpose of browsing, or already knowing what to watch), but it would be a “nice to have” feature. It supports the idea that users should have more power regarding recommendation algorithms and that their happiness with their recommendations increases when they have more power over it, as observed by Ekstrand et al. (2015) or Harper et al. (2015). One possible implication of this is that filtering can also help with the issue of the “paradox of choice”, by offering fewer options to choose from that are tailored for the user.

Another problem of the recommendation algorithms that has been highlighted in literature is the "cold start problem" when new users do not receive appropriate recommendations for a while until the system learns their preferences and behaviours. By having a filter, they could select from the beginning what they want to see and create their own initial list of movies when signing up for a platform. This can come with the advantage of Netflix (or the specific streaming website) being able to gather the data the user selects in the filter and use it to train the recommendation algorithm, therefore providing it with information on the user much sooner after sign-up and providing an accurate recommendation list quicker.

6. Conclusion

This section will summarize the key findings of the research, reflect on the limitations encountered and discuss avenues for further research.

The analysis done through mixed methods answered the 3 research questions mentioned in the methodology chapter. Firstly, this research could not prove that demographic factors exert a considerable impact on the recommendation accuracy perceived by the users, as suggested by the survey results. Secondly, it found the main factors that influence a person's choice of movies, with the most common ones being genre, actors, and online ratings. These slightly differ from those suggested by previous studies, and offered a starting point for developing a website that could integrate these with the current state of the Netflix website. The final question regarding the benefits of integrating a filter functionality with Netflix was answered by participants who conducted a usability test and were involved in an interview. The response to such a solution was positive. Moreover, the qualitative data collected provided further insights into users' opinions regarding the movie recommendations they receive on Netflix (which are mixed) or the time they spend choosing a movie (which depends on factors such as "mood", which are difficult to capture by a machine). The criteria they chose for the filtering functionality on the website were different to the ones in the questionnaire, with a few possible explanations including that if they have the information on a single page, they may be more likely to select it.

In conclusion, based on the presented evidence, the researcher suggests there is a significant use that could be derived from integrating user inputs with the results from the recommendation algorithm to enhance the user experience on Netflix. This finding could also be extrapolated to other movie streaming platforms, considering they are structured similarly. Overall, this research provides a practical example of how algorithms can be "humanized" by giving users the freedom to personalize what they wish to see through user inputs.

6.1 Limitations

Several limitations exist in this research, which should be addressed in future studies if they are to be completed similarly.

The main limitation of the research was the time frame for completion, which was 8 months, during the academic year. This impacted the website quality, as its functionality, user interaction and user experience were the aspects that were prioritized. Only one Agile development cycle could be completed, with small changes being made throughout the usability testing, mostly to fix errors. If time had not been a limitation, more development cycles would have been completed, as suggested by the principles of design research.

Another limitation of the study was the small sample size for the usability test and interviews, which was also an indirect result of the time limitation to complete the testing, as well as the amount of time that eligible participants were available. Therefore, with a small sample size, caution must be applied, as this might prevent the findings from being extrapolated.

Regarding the validity and reliability of the survey results, only the validity could be assessed through content and face validity, as mentioned in the methodology. However, because of the way the questions were structured and the types of responses (not measuring constructs), these could not be tested for reliability through statistical measures. Because of the time limitation, the test-retest method also could not be applied. However, this does not impact the results of the study, as there were no biases in selecting the questionnaire sample, and it ensured all the other best practices such as pilot testing or expert validation.

One limitation that could not be mitigated was the lack of access to the Netflix recommendation algorithm, and the website not being fully integrated with it. It would have been beneficial to see how participants react to having their own personalized recommendations they can filter and choose from. However, this is perceived as a “black box” that not a lot of people have access to. Another limitation regarding the movies shown was that thousands of movies came up, as the database used stores all movies regardless of their availability on streaming platforms. This resulted in an information overload, as mentioned by some participants.

6.2 Future considerations

There is abundant room for further progress in determining how the recommendation algorithm from Netflix can be combined with individual user preferences to offer better recommendations and decrease browsing time.

Firstly, to develop a full picture of user preferences and how accurate their recommendations are, further research can be conducted in these areas, by possibly using the results from the qualitative analysis (such as the criteria people choose for filtering or how they interact with the system) to conduct further analysis for a larger sample.

Moreover, there are certain variables mentioned by researchers, which were not considered for the purpose of this research. These include promotional strategy (marketing), distribution strategy (what platforms the movie is available on and when), and pricing (both the sum invested in buying the movie and how much subscriptions cost). This information is difficult to obtain, as it is usually dependent on the production company and strategic business decisions they take. Therefore, further studies, which take these variables into account, need to be conducted. This could help offer a more in-depth understanding of how consumers choose a movie, while also relating it to promotional factors.

Lastly, one recommendation for future improvement of this research can be the continuous development of the interface that people can test. The feedback and suggestions, as described in the results, can provide a starting point for perfecting the website and re-testing to observe how users interact with it once it has a seamless user experience. Also, choosing a database that only contains movies available on Netflix (or simply fewer films displayed) might be useful not to overwhelm participants. Moreover, creating different interfaces depending on the device the streaming platform is accessed from (such as a Smart TV, or smartphone) and testing them might provide useful insights into how people would use them, and if filtering would be equally easy to use.

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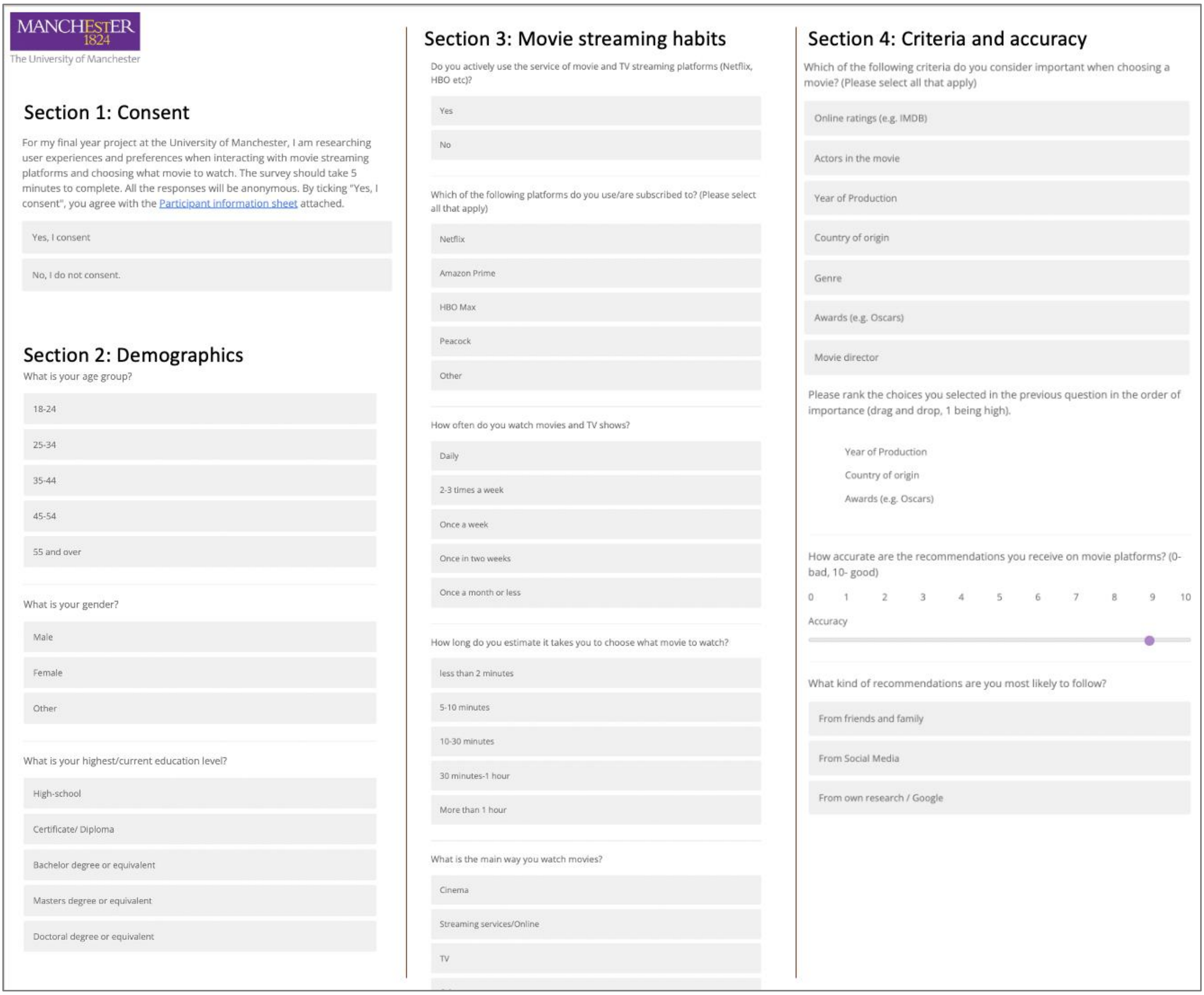
Appendix A – Methodology Review

Study	**Methodology**	**Findings/Study aim**	**Limitations**
Gazley, A., Clark, G. and Sinha, A. (2011). Understanding preferences for motion pictures.	4 Surveys distributed across 4 weeks, creating a model to quantify movie-going decision	Found that a movie's country of origin is important, as well as the genre and friend recommendations	Respondents were largely female (63%) and aged 18-29
Eliashberg, J., Jonker, J.-J., Sawhney, M.S. and Wierenga, B. (2000). MOVIEMOD: An Implementable Decision-Support System for Pre-release Market Evaluation of Motion Pictures.	Creating a technical model that was evaluated by the exhibitors and distributors of movies	Creating a model that is a behavioural representation of the consumer adoption process for a movie to produce forecasts for awareness and adoption intention	Dutch-focused, mainly created for marketing purposes
Hennig-Thurau, T., Houston, M.B. and Walsh, G. (2007). Determinants of motion picture box office and profitability: an interrelationship approach.	Path-analysis model that tests hypotheses derived from literature, focusing on the interrelationships between the important factors that determine movie performance	Distinguish direct and indirect factors that can determine the movie success, as well as their importance when choosing a movie to watch in cinema	Focused on audiences who go into cinema to watch a movie; only sampled 361 movies; lack of a fully developed measurement model
Cao, Y., Wang, X., He, X., Hu, Z. and Chua, T.-S. (2019). Unifying Knowledge Graph Learning and Recommendation: Towards a Better Understanding of User Preferences.	Translation-based User Preference model that integrates with Knowledge Graphs, followed by quantitative experiments	Supplementing the incomplete nature of knowledge graphs with user-item interactions (account for user preferences more)	Does not deal with the cold-start problem; does not account for more complex preferences
McNee, S.M., Lam, S.K., Konstan, J.A. and Riedl, J. (2003). Interfaces for Eliciting New User Preferences in Recommender Systems	User experiment, participants divided in 3 groups receiving different interfaces, followed by a brief survey to assess their opinions	Contrasts system-controlled recommendation approaches with ways that the users can rate items, to solve the problem of "cold-start". Users felt the system better understood them when having the possibility to interact and rate items, which also had a higher retention	Trade-off between increasing user control and increasing the user workload; not all users finished all the tasks on the proposed systems

Hallinan, B. and Striphas, T. (2014). Recommended for you: The Netflix Prize and the production of algorithmic culture.	Comparative review of the different models proposed as part of the Netflix Prize contest	Explores the work required to render algorithmic systems and the "algorithmic culture"	Highlights that engineers developing the algorithms become dictators of cultural items, leading to possible biases
Beel, J., Langer, S., Nürnberger, A. and Genzmehr, M. (2013). The Impact of Demographics (Age and Gender) and Other User-Characteristics on Evaluating Recommender Systems.	Uses empirical data collected through Docear, evaluating 37,000 recommendations received by 1,028 users using Click Through Rate (CTR)	Using demographics and user characteristics to see if they have a difference in how often people click on recommendations	Its focus was on research paper recommender systems
Mehrotra, R., Anderson, A., Diaz, F., Sharma, A., Wallach, H. and Yilmaz, E. (2017). Auditing Search Engines for Differential Satisfaction Across Demographics.	Used the log data from a random subset of Bing users and performed context matching, quantitative and statistical analysis, multilevel modelling to observe differences. Enhanced this data with comScore data. Measured by click count and graded utility	Explores how machine learning algorithms can underserve certain groups of people. Found differences regarding age	Focused only on search engine machine learning
Holbrook, M.B. (1993). Nostalgia and Consumption Preferences: Some Emerging Patterns of Consumer Tastes.	Age-homogenous sample to assess the relationship between nostalgia proneness and movie preferences. Another heterogenous sample to see if the preferences are correlated	Explores the impact of the extent to which people are prone to nostalgia as a personality trait to the type of movies they choose to watch	Focused on only one aspect of personality (nostalgia proneness) and its relation to movie choosing; samples of 20 people
Infortuna, C., Battaglia, F., Freedberg, D., Mento, C., Zoccali, R.A., Muscatello, M.R.A. and Bruno, A. (2021). The inner muses: How affective temperament traits, gender and age predict film genre preference.	A cross-sectional study with a survey administered to 689 adults	Explores how affective factors, temperamental traits and demographics impact the preference for movie genres	Only studies the relationships for movie genre, and the affective traits are difficult to quantify, and are part of the social cognition field

Table A1 – Methodology Review

Appendix B – Full Survey Questions



MANCHESTER 1824
The University of Manchester

Section 1: Consent

For my final year project at the University of Manchester, I am researching user experiences and preferences when interacting with movie streaming platforms and choosing what movie to watch. The survey should take 5 minutes to complete. All the responses will be anonymous. By ticking "Yes, I consent", you agree with the Participant information sheet attached.

- Yes, I consent
- No, I do not consent.

Section 2: Demographics

What is your age group?

- 18-24
- 25-34
- 35-44
- 45-54
- 55 and over

What is your gender?

- Male
- Female
- Other

What is your highest/current education level?

- High-school
- Certificate/ Diploma
- Bachelor degree or equivalent
- Masters degree or equivalent
- Doctoral degree or equivalent

Section 3: Movie streaming habits

Do you actively use the service of movie and TV streaming platforms (Netflix, HBO etc)?

- Yes
- No

Which of the following platforms do you use/are subscribed to? (Please select all that apply)

- Netflix
- Amazon Prime
- HBO Max
- Peacock
- Other

How often do you watch movies and TV shows?

- Daily
- 2-3 times a week
- Once a week
- Once in two weeks
- Once a month or less

How long do you estimate it takes you to choose what movie to watch?

- less than 2 minutes
- 5-10 minutes
- 10-30 minutes
- 30 minutes-1 hour
- More than 1 hour

What is the main way you watch movies?

- Cinema
- Streaming services/Online
- TV

Section 4: Criteria and accuracy

Which of the following criteria do you consider important when choosing a movie? (Please select all that apply)

- Online ratings (e.g. IMDB)
- Actors in the movie
- Year of Production
- Country of origin
- Genre
- Awards (e.g. Oscars)
- Movie director

Please rank the choices you selected in the previous question in the order of importance (drag and drop, 1 being high).

- Year of Production
- Country of origin
- Awards (e.g. Oscars)

How accurate are the recommendations you receive on movie platforms? (0-bad, 10- good)

0 1 2 3 4 5 6 7 8 9 10

Accuracy

What kind of recommendations are you most likely to follow?

- From friends and family
- From Social Media
- From own research / Google

Figure B1 – Full survey questions

Appendix C – Website Development

Sprint	**Name**	**Description**	**Dates**
1	Technical set up	Technical set up on local machine, set up VS code, Firebase, TMBD API key request fill in form and wait for approval.	6-8 March
2	Home Page Dev	Arrange the front end, pull the movies from TMBD API, and arrange them in rows similarly to Netflix. Create functionality when hovering over each movie tile, the buttons to "add to list" and "view info" appear, and when selecting to view more info, it redirects to an individual movie page.	8-12 March
3	Search Bar Dev	Add the "search button" on the home page, create the functionality behind it using string matching, and this should navigate to a new page that displays the movies that are a match for that searched string.	12-15 March
4	Individual movie page	Pull from the TMDB API the relevant information according to lit review and questionnaire (cast/actors, year of production, summary, production companies, languages etc).	15-20 March
5	Filtering functionality	Create button on the home page that is a dropdown filter. This has the main criteria identified in the questionnaire. It will then "match" the criteria selected to the list of movies and return an array of the movies that meet all the criteria selected.	20-26 March
6	Filtered movies page	This will take the results returned by the filtering functionality and arrange them in a similar manner as the main page and search page. Each movie tile will be displayed individually. The filter button is still visible on that page, and the user can change the filters even more (either add or delete filters).	27-31 March

Table C1 – Agile Sprints

Feature	Description
Home Page	Main Page, like Netflix, that pulls all movies from TMDB API in a similar way as Netflix, diving them in areas such as "Only on Netflix" or "Popular Now". The user can scroll down, or sideways for the rows that display movies in a carousel manner. On top of the page there is a randomly selected, popular movie and a short display of its main information, with its poster shown largely.
Individual Movie Page	Page that displays information about a specific movie. Information includes Cast (with pictures for each actor), movie length, genre(s), summary, production company, release date, status, spoken languages.
Search Page	When using the "Search" button on top of the home page, the user can search for a specific movie. This will return that movie, or movies with a similar name or containing the same words. The results returned will be everything that is a match from TMDB. This is a new page that pops up when the user starts typing in the search bar.
Filtered Page	The user uses the filter button to narrow down the results shown based on personal preference. This returns a page that displays the movies similarly to the Search page, containing all the movies that meet that specific criterion selected.

Table C2 – Website pages and their descriptions

Online websites like GitHub, YouTube tutorials, or Stack Overflow were used for the free resources provided by developers who previously conducted similar work, as replicating the Netflix front-end was done numerous times both by front-end and back-end developers. Some of these were adapted and combined to reach the final website the users tested in this experiment, for example:

https://github.com/AhmedTohamy01/React-Netflix-Clone ;
https://github.com/imrhlrvndrn/netflix-clone ;
https://www.youtube.com/watch?v=HAb3KWkynOc ;
https://www.youtube.com/watch?v=XtMThy8QKqU&t=11456s .

The individual TMDB API key, which had to be requested and approved:

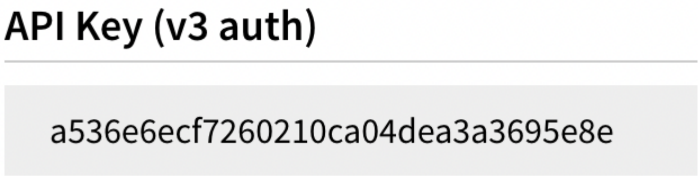
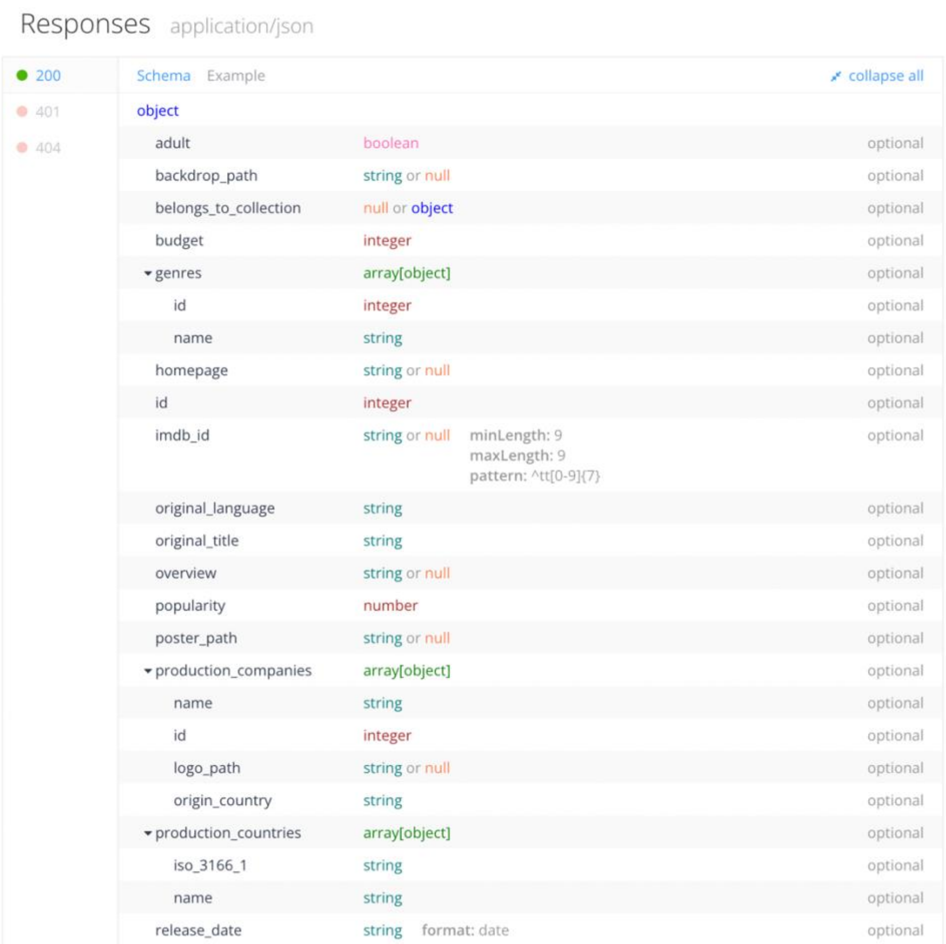


Figure C1 – personal TMBD API key

All the information regarding the TMDB API can be found on their dedicated API website (https://developers.themoviedb.org/3/getting-started/introduction), including aspects like availability or request limits. Figure X is an example of the responses for the movie object (i.e., the information that can be requested for a movie).



Responses application/json

200 | 401 | 404

Schema Example collapse all

object

adult	boolean		optional
backdrop_path	string or null		optional
belongs_to_collection	null or object		optional
budget	integer		optional
genres	array[object]		optional
id	integer		optional
name	string		optional
homepage	string or null		optional
id	integer		optional
imdb_id	string or null	minLength: 9 maxLength: 9 pattern: ^tt[0-9]{7}	optional
original_language	string		optional
original_title	string		optional
overview	string or null		optional
popularity	number		optional
poster_path	string or null		optional
production_companies	array[object]		optional
name	string		optional
id	integer		optional
logo_path	string or null		optional
origin_country	string		optional
production_countries	array[object]		optional
iso_3166_1	string		optional
name	string		optional
release_date	string	format: date	optional

Figure C2 – TMDB API Example responses for a movie (developers.themoviedb.org, n.d.)

```javascript
const handleFilterSubmit = () => {
  const selectedGenres = selectedOptions.filter((option) => option.value !== 'genres').map((option) => option.value).join(',');
  const selectedVoteAverage = selectedOptions.filter((option) => option.value === 'vote_average').map((option) => option.options[0].value).join(',');
  const selectedLanguage = selectedOptions.filter((option) => option.value === 'with_original_language').map((option) => option.options[0].value).join(',');
  const selectedReleaseDate = selectedOptions.filter((option) => option.value === 'primary_release_date').map((option) => option.options[0].value).join(',');

  const apiUrl = `https://api.themoviedb.org/3/discover/movie?api_key=a536e6ecf7260210ca04dea3a3695e8e&language=en-US&sort_by=popularity.desc&include_adult=false&
  setFetchUrl(apiUrl);

};
```

Figure C3 – Code example with API pull requests depending on what is selected in the filter

```javascript
const filterMovies = (movies) => {
  const { genre, voteAverage, originCountry, releaseDate } = filters;

  let filteredMovies = movies;

  if (genre) {
    filteredMovies = filteredMovies.filter((movie) => {
      return movie.genre_ids.includes(genre);
    });
  }

  if (voteAverage) {
    filteredMovies = filteredMovies.filter(
      (movie) => movie.vote_average >= voteAverage
    );
  }

  if (originCountry) {
    filteredMovies = filteredMovies.filter((movie) => {
      return (
        movie.production_countries.findIndex(
          (c) => c.iso_3166_1 === originCountry
        ) >= 0
      );
    });
  }

  if (releaseDate) {
    filteredMovies = filteredMovies.filter((movie) => {
      return movie.release_date.slice(0, 4) === releaseDate;
    });
  }

  return filteredMovies;
};
```

Figure C4 – Function for filtered movies, returning movies depending on user selection.

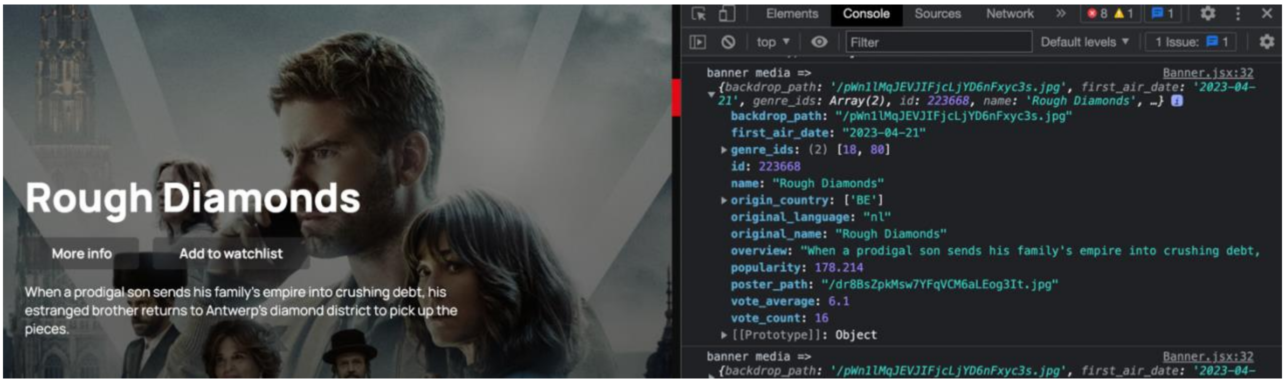


Figure C5 – Side by side view in browser with what is displayed and the developer view of fetched information.

Appendix D – Usability Test/Semi-structured interview Questions

Main Questions:

1. Can you use the search bar to look up a specific movie?
2. Can you find a movie based on your personal preference, using criteria like year of production, rating, language?
3. Can you use the filter functionality to narrow down the results shown to you?
4. Can you choose from that list of movies something that you would like to watch?
5. Do you think such a functionality would help you spend less time deciding what movie to watch compared to the normal Netflix page and why?
6. If you already have the movie recommendation list from Netflix, do you think this functionality would help you filter down those recommendation list and save time?
7. Is there any other feedback or comments you would like to add to the way this page is functioning?

Additional or Follow up Questions:

1. Do you generally look up more information when deciding on a movie?
2. Why did you go back to select more filters and delete that one?
3. Why did you first select some filters, and added more after?
4. (When browsing a lot on a particular page) Are you looking for anything specific?

Appendix E – Ethical Considerations

The University of Manchester
Faculty of Humanities
Alliance Manchester Business School

Undergraduate Research Ethics Form

This form is to be completed where any element of your coursework involves you gathering or holding data from human participants in **any** form (e.g. interviews, surveys, observation or testing).

All participants should be presented with a completed Participation Information Sheet and **must** sign the designated section of this sheet before any element of your research is undertaken. This same procedure applies for participants completing an online survey or telephone interview etc.

Student name(s) and number(s)	Iulia Teodora Midus 10530099
Programme of study	Information Technology Management for Business with Industrial Placement
Course Code	BMAN31260
Course Title	ITMB Final Year Project 2022-2023
Name of dissertation or project supervisor / course coordinator	Dr. Tahir Abbas Syed
Title of dissertation / project / coursework / assessment	How can user inputs improve the browsing time on movie streaming platforms?

Summary of dissertation / project / coursework / assessment, outlining methods to be used

The aim of the project is to find a way in which user inputs can be integrated with the existing recommendation system on Netflix to reduce the browsing time.
The methods used for this project will be mixed. Firstly, a survey will be conducted to better understand movie watching habits and preferences. Then, a solution will be developed, and a prototype will be tested by a smaller sample to find ways of improvement, improve it, and determine whether it has any improvements compared to the current process.

Figure E1 – Research Ethics Form

Ethical Considerations

Question 1. Will any of these participants be from the following groups? Yes or No please tick (✓) one box:	YES	NO
		✓

- Children under 18
- The elderly
- Adults with learning difficulties
- Adults in emergency situations e.g. those in refuge camps or seeking asylum
- Adults with mental illness (particularly if detained under mental health legislation)
- Adults with dementia
- Adults from non-English speaking backgrounds
- Patients or clients of professionals
- Prisoners or parolees
- Young offenders
- Participants involved in illegal activities
- Adults in Scotland who are unable to consent for themselves
- Any other groups who could be considered vulnerable/unable to give informed consent

Question 2. Will any of these issues apply? Yes or No please tick (✓) one box	YES	NO
		✓

- Payment or incentives will be given to research participants (e.g. gifts/money/free service)
- Participants will discuss any topics or issues that might be sensitive, embarrassing or upsetting
- Criminal or other disclosures requiring action could take place during the research
- Observe or involve participants without their knowledge or consent
- Does your research raise any issues of personal safety for you or other researchers involved in the project?

If you answered ***No*** to Questions 1 and 2 above then you are free to undertake your research providing you abide by the following conditions.

- You must always use the School's participant information sheet to gain consent from any individuals involved.
- If your research alters at any time before submission to include any of the participants listed in Question 1 or the issues listed in Question 2, then this approval is revoked and you must speak immediately to your supervisor or course coordinator

If you answered ***Yes*** to either Questions 1 or 2 above then ethical approval cannot automatically be granted by Manchester Business School. Please discuss this further with your dissertation supervisor or course coordinator before continuing further. Additional advice is also available from the School's Academic Ethics Officer, Dr Nadia Papamichail – n.papamichail@manchester.ac.uk

Please tick (✓) to show you understand the ethical approval process:

✓	I have read through questions 1 and 2 above and I can confirm that my research does not need additional ethical approval.

Signature (Student)	**Iulia Teodora Midus**	**Date**	**7/12/2022**

I agree that the research undertaken by this student does not require additional ethical approval.

Signature (Supervisor)…………………………………………… Date …………………

Once signed by your Supervisor/Course Coordinator, please submit a copy of this form to the Undergraduate Office, AMBS 2.091. This will be recorded on your student file.

Figure E2 – Research Ethics Form (continued)

MANCHESTER 1824
The University of Manchester

How can user inputs and preferences reduce the browsing time on movie streaming platforms?

Participation Information Sheet

You are being invited to take part in a research study as part of a project at the University of Manchester entitled "How can user inputs and preferences reduce the browsing time on streaming platforms?". It is a project involving at this stage an anonymous online survey. Before you decide to participate, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. Please ask if there is anything that is not clear or if you would like more information. Take time to decide whether you want to participate. Thank you for reading this.

Who will conduct the research?

The person conducting the research is Iulia Teodora Midus, final-year undergraduate student, under the supervision of Dr. Rotimi Ogunsakin.

Title of the research

"How can user inputs and preferences reduce the browsing time on movie streaming platforms?"

The study looks at how different individual preferences influence how people choose to watch movies on streaming platforms. This further aims to explore how these customer preferences can be integrated with the current recommendation algorithm at Netflix, by being users more decision and filtering power.

What is the aim of the research?

Reduce the browsing time on Netflix and streaming platforms by incorporating consumer preferences.

Why have I been chosen?

You have been asked because you are likely to be watching movies or using streaming platforms.

Figure E3 – Participation Information Sheet (1)

What would I be asked to do if I took part?

You will be asked to complete a short survey that should take no longer than 5 minutes. This is entirely anonymous, and the questions are about movie-watching habits and personal preferences when choosing a film.

What happens to the data collected?

The data will be entirely anonymous, and the only demographic information collected will be about gender and age. The data will be analyzed to observe correlations between multiple factors presented, understand general movie-watching habits, and integrate the findings in the research project. The data will only be accessible to the person conducting the research and the supervisor and procedures will be followed to ensure no one else has access.

How is confidentiality maintained?

There is no personal data collected in the survey.

What happens if I do not want to take part or change my mind?

It is up to you to decide whether to take part. If you decide to take part, you will automatically be directed to the survey. If not, and you select accordingly in the first question, the survey will end for you.

Will I be paid for participating in the research.

Unfortunately, we cannot offer payment for taking part in this survey.

What is the duration of the research?

The survey should take around 5 minutes to complete.

Where will the research be conducted?

It is entirely online, from your own device.

Will the outcomes of the research be published?

The outcomes will be solely used for the Final Year Project of the student.

Contact for further information: iulia.midus@student.manchester.ac.uk

Figure E4 – Participation Information Sheet (2)

Consent Form

If you are happy to participate, please review the following and select "Yes" in the questionnaire:

1. I confirm that I read the attached information sheet on the above project and have had the opportunity to consider the information and ask questions and had these answered satisfactorily.
2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving a reason and without giving a reason and without detriment to any treatment/service.
3. I understand that the responses will be recorded (anonymously).

Figure E5 – Participation Information Sheet (3)

Appendix F – Thematic analysis full theme descriptions

Click here if you wish to see the transcripts for all 10 interviews, found in a Word document and separated by Interview number.

Theme 1: *Movie preference criteria.* This maps out participants' movie preferences and the criteria they keep in mind when trying to decide what movie to watch. These are what the participants mentioned in the conversation, or the ones they ended up selecting on the filtering button dropdown. These are similar to the criteria that is highlighted by literature, as well as the findings from the questionnaire. Although they are not the same for all participants, some of the most common ones are "movie vote" or "movie release date", and less popular ones are "movie actors" or "movie language". However, some participants select more than 3-4 criteria, while others stick with a one, which then might translate into the fact that although some are more commonly selected, their relative importance depends on the user. This theme does not consider the indifferent comments regarding one of these criteria (e.g.: "I'm fine with all languages", "I don't care that much about ratings"), so only counts the ones where the participant is using that criteria to decide or add it in the filter. These also include participants that did not consider one criterion from the beginning but use it when asked to further narrow down the results shown ("Let's choose the language as well").

Theme 2: *Filter functionality*. This refers to all the units of data that came because of the participants using the filtering functionalities, and the codes are about the attitudes and opinions people have on mainly two things: whether the filter functionality is useful, and how are they interacting with it. Regarding its use on the platform, participants found it generally easy to use and interacted with it without being prompted, and admitted it was easy to use and they are familiar with such functionalities from other websites (one of the younger participants noted similarity with fashion websites). Regarding finding it useful or not, the opinions were mixed, but a majority admitted it would be useful, or it would be at least "a nice to have", allowing them to decide whether to use it or not depending on the situations. The users felt that movie watching "depends on the mood", which backs up the literature that admits movie watching is a hedonistic, aesthetic experience.

Theme 3: *Netflix recommendations*. This theme gathers the feedback and opinions users had regarding the recommendations they receive on their own Netflix page. These are generally positive, with most users admitting the recommendations are good and they usually browse through them before deciding on a movie from the recommended ones. However, a lot admit that, although the recommendations are good, they need further filtering. A smaller proportion state that the recommendations they receive feel like either Netflix is "pushing their own content which is not relevant", or they are simply "not the best for me" (this leading to a code called "mixed recommendations").

Theme 4: *Website interaction*. This refers to the way the users interact with the website, and notes in codes the different interactions. This focuses on their habits about the filter since most of the interaction with the overall system was as expected. One example is the fact that users use more pages before filtering, admitting to switching between them to decide on a movie. However, they admit that having all the information in one place is useful, and they can use that information to change the parameters on the filter, which many users have done ("I'll just check this to see more info").

Theme 5: *Movie decision factors*. This maps out what the users point out regarding how they want to see a movie. This refers to how often they mention movie watching depends on the mood, and that would subsequently relate to the other themes, since the website interaction or using the filter would depend on that ("I think it would be nice, especially if I know exactly beforehand, like I want to watch in a mood, I mean, what vibe I have for a movie."). Other such factors mentioned were not knowing what to watch when wanting to see a movie, or already being decided on what movie to watch, so just going on the platform to select that one.

Theme 6: *Website suggestions and feedback*. This includes the feedback the users had about the way the website is structured, how different functionalities work, or comments on the UX of the Filter button and page. One user suggested returning a "best-match" after filtering, so starting from movies that meet all criteria most closely (so if he selects 3 genres, movies that have all 3 genres, rather than either one of those genres). From some users, the filter being more obvious or having a higher font was also another suggestion that could be easily implemented in subsequent development, or how the criteria should be presented (like a slider for the years). Another user noted the "filter" button was missing when moving to one of the pages (the individual movie page), which was a development error. In this category, questions and suggestions about the device they use to watch the movies on also fit (e.g.: TV).