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Netflix's machine learning: The correlation between film selection based on tailored thumbnails and genre preference

Bachelor Thesis for Obtaining the Degree
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Submitted to Dr. Lyndon Nixon

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AFFIDAVIT

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ABSTRACT

The rise in popularity of video-on-demand streaming platforms has resulted in a wide range of films being made available to consumers, who can access them from anywhere at any time. With this potentially leading to a paradox of choice and analysis paralysis, Netflix successfully implements recommender systems, incorporating collaborative and content-based filtering algorithms to match content to user preferences facilitating navigation and selection on the platform.

This bachelor thesis focuses on Netflix's personalization and to what extent it influences user behavior. In the scope of the research, central emphasis is given to thumbnails as the representing variable for personalization and film selection for the viewer's final decision-making. To further assess the significance of tailored thumbnails, quantitative research in the form of an online-questionnaire is conducted on the relationship between the movie's title as well as plot description and the movie selection.

The main conclusion drawn from this study was that although no significant difference in the impact of thumbnails, movie titles as well as plot description on users' intent was observed for every genre category, results reveal a significant correlation between the film selection based on thumbnails and age as well as gender.

Keywords: Video-on-Demand, Netflix, Tailored Thumbnails, Genre, Film Selection, User Behavior, Recommender Systems, Machine Learning, Personalization

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LIST OF ABBREVIATIONS

AVA Aesthetic Visual Analysis

VOD Video-on-Demand

1 INTRODUCTION

1.1 Presentation of the Problem

Numerous users have become accustomed to the habit of browsing through video-on-demand services such as Netflix, Disney+, or Amazon Prime Video and often feel indecisive as well as uncertain of which content to select. This has become a common phenomenon in today's digital age, where a vast array of media options are available at our fingertips, leading to a paradox of choice or analysis paralysis (Ye & Kindbom, 2022). The paradox of choice is defined as consumers having too many options to choose from, which in return may cause distress and a negative attitude toward the medium used (Schwartz, 2004). Another occurrence is analysis paralysis which Kurien et al. describe as "over-analyzing (or over-thinking) a situation, or citing sources so that a decision or action is never finally taken, resulting in paralyzing the outcome" (Kurien et al., 2014, p.1). To counteract these events, recommender systems, which are based on machine learning, aid consumers by suggesting products that may be of interest based on extensive data on their behavior (Kumar & Singh, 2019). Machine learning is the most quickly growing technical field. That said, it is of great importance to identify the advantages and disadvantages of technology as it is going to be a vital part of our future (Jordan & Mitchell, 2015). Nonetheless, it has been pointed out that tracking the activity of users raises ethical issues due to the lack of data privacy (Canny, 2002). Moreover, Karumur et al. emphasize that personalization systems analyze user behavior. However, viewers' varying preferences may not be considered (Karumur et al. 2017). Additionally, one should not neglect the fact that personalization raises the problem if the user wants to move between categories or genres. Tailoring content to consumers' preferences may prevent them from expanding their interests and viewing other content. In her study, this phenomenon is referred to as a "*consumption bubble"*, meaning that because Netflix users have limited exposure to what other users are watching, they may become isolated within their own viewing habits, resulting in a substantial quantity of content being missed (Cannella, 2021).

Renowned companies such as LinkedIn, Netflix, and Amazon take advantage of recommender algorithms (Kumar & Singh, 2019). These systems have proven to efficiently match users' preferences to a desired item (Amatrain, 2013). Wang and Zhang mention that, specifically, Netflix successfully implements its machine learning in terms of tailoring its recommendations to genre preference (Wang & Zhang, 2018). Furthermore, Sun et al. introduced an empirical study concluding that there is an association between genre preference and film selection. Nevertheless, other factors have to be taken into account, which may influence the user's final film decision (Sun et al., 2012).

1.2 Aims of the Bachelor Thesis

The thesis' objective is to extend existing research on recommender systems in order to identify the variables that influence film selection. The main research focus is the extent to which thumbnails influence film selection on Netflix, as it is usually assumed that the majority of users dedicate their scrolling through the streaming platform to trailers and plot descriptions (Ye & Kindbom, 2022). Additionally, a survey by Stoll concluded that Netflix was the primary choice of video-on-demand service, with 78 percent of households using the platform, followed by Amazon Prime Video with 72 percent and Hulu with 50 percent (Stoll, 2022). With this in mind, being a relatively new phenomenon, investigation on the matter is significant as there is still a knowledge gap of personalization systems on Netflix – taking explicitly into account the movie's cover images. The aim is to explore further the relationship between thumbnail attractiveness on user choice while taking genre preferences into account (Wang & Zhang, 2018).

1.3 Method of Analysis

Secondary research, mainly peer-reviewed journal articles retrieved from ScienceDirect.com and GoogleScholar.com, will be the source of information. Quantitative data collected from the conducted online-survey will complement existing findings. By implication, closed-end questions in the study include whether the person is more likely to select a movie based on the plot description, thumbnail, or movie title. Moreover, it is of great interest to understand if there is a subconscious impact of thumbnail attractiveness on individuals. However, if there is no significant result, one must assume that users are not significantly influenced by thumbnails in terms of film selection. Therefore, Netflix may need to shift its focus from tailored thumbnails to other areas of personalization systems.

To test the hypotheses of whether thumbnail attractiveness is an effective personalization system to encourage users to select a film taking into account their genre preference, the following research questions have been developed:

Main research questions:

RQ I : What is the relationship between the user's genre preference and the film's thumbnails?

Hypothesis I : The degree of genre preference has an impact on the likelihood of watching a movie based on the most attractive thumbnail.

RQ II : What is the extent to which there is a significant difference between age groups in selecting a film based on a thumbnail?

Hypothesis II : There is a significant association between age and selecting a film based on a thumbnail.

RQ III : What is the extent to which there is a significant difference between genders in selecting a film based on a thumbnail?

Hypothesis III : A statistical significance exists between genders with regard to the selection of films based on thumbnails.

RQ IV : To what extent does the perceived visual appeal of thumbnails significantly influence film choice compared to selections made solely based on plot description or the movie's title?

Hypothesis IV : There is a significant difference between the impact of thumbnails, plot descriptions, and movie titles in film choice.

RQ V : To what degree does genre preference affect the selection of genre-based thumbnails?

Hypothesis V : A significant relationship exists between users' genre preference and the selection of genre-based thumbnails.

Sub-question:

RQ VI : To what extent does a movie's failure to meet the expectations set by its thumbnail image influence viewers' likelihood to continue watching the movie?

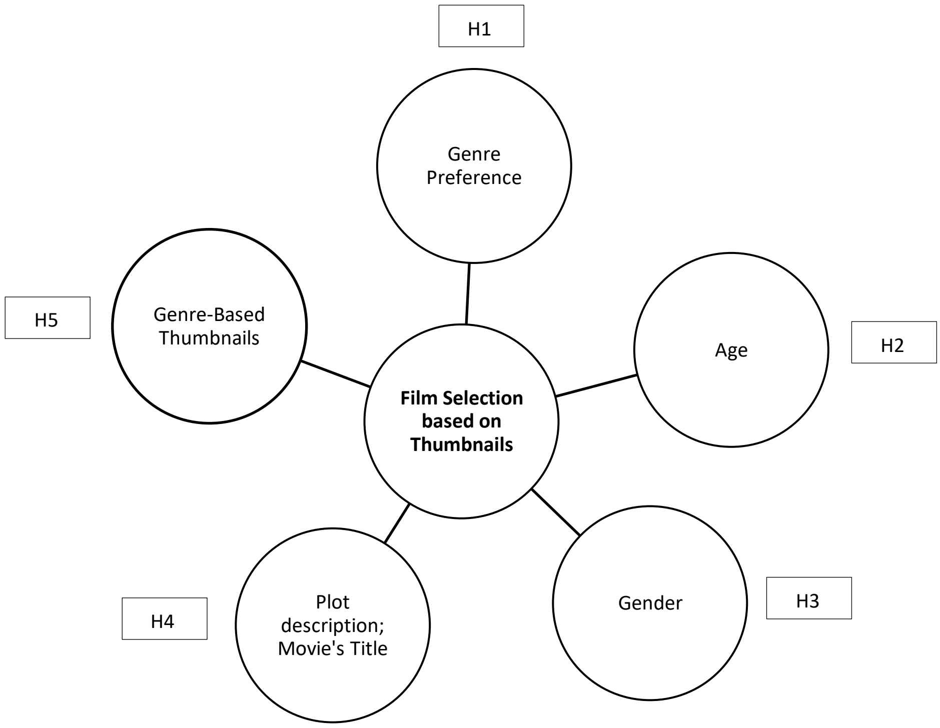

Figure 1: Research Model

2 LITERATURE REVIEW

2.1 A brief insight into machine learning

The following chapter introduces machine learning and algorithms to gain a general understanding of personalization systems. It ultimately allows the reader to acknowledge the importance of the research on (tailored) thumbnails as they may significantly influence consumer behavior on Netflix.

2.1.1 Definition of Machine Learning

Machine learning is a subset of artificial intelligence which can forecast results without human interference. It is an intelligent system that automatically improves on its own based on its previous successes as well as failures. The prerequisite of this phenomenon is a sufficient set of data and computing power (Alpaydin, 2021). “It is one of today’s most rapidly growing technical fields, lying at the intersection of computer science and statistics, and at the core of artificial intelligence and data science” (Jordan & Mitchell, 2015, p. 255). In the following chapters, distinctive forms of machine learning algorithms will be briefly discussed to create a general understanding of the topic. Moreover, the thesis will more closely examine two machine learning techniques, namely collaborative filtering and content-based filtering, as these types of algorithms are used by Netflix (Maddodi & Prasad K, 2019).

2.1.2 Types of machine learning algorithms

Machine learning has various algorithmic strategies to obtain the desired outcome. Ayodele and Mahesh mention six types of machine learning algorithms inter alia supervised learning, unsupervised learning, semi-supervised learning, transduction, and learning to learn (Ayodele, 2013; Mahesh, 2020).

Machine learning algorithms	
Type	Characteristics
Supervised learning	computer exerts classification learning; mapping inputs to anticipate results; It learns from (predetermined) input-output examples
Unsupervised learning	the system learns without a given example; no classification; an established "reward system" specifies success
Semi-supervised learning	computer partly classifies and partly uses unlabeled examples to attain the desired outcome
Reinforcement learning	no pre-determined actions; knowledge gained by trial-error to achieve the highest reward; outputs affect the environment, and the algorithm learns from its feedback
Transduction	comparable to supervised learning, but the system tries to find new paths based on (new) learning inputs/outputs
Learning to learn	knowledge gained by past outcomes; "the algorithm learns its own inductive bias" (Ayodele, 2013, p. 19)

Table 1: Types of machine learning algorithms (Ayodele, 2013; Mahesh, 2020).

Table 1 displays a brief overview of different machine learning algorithms. It sheds light on the various subsets of machine learning to further gain a basic understanding of how Netflix uses machine learning algorithms to introduce its personalized interface to each user. In the following sections, two filtering methods implemented in Netflix's recommender system (Maddodi & Prasad K, 2019) will be introduced, which are based on supervised and unsupervised learning algorithms (Kumar & Singh, 2019).

2.1.3 Collaborative filtering

Collaborative filtering is a machine learning technique whose predictions as well as recommendations are based on other users' ratings or behavior on the product or service (Bobadilla et al., 2011). It is an unsupervised learning algorithm that is commonly used to construct intelligent recommender systems. These systems have been successfully implemented in various sectors, such as movies (Netflix), songs (Spotify), items (Amazon), socials (Facebook), and jobs (LinkedIn) (Thorat et al., 2015). At first, it creates the likelihood of users' preferences and, subsequently, generates suggestions by the ranks of users' selections as well as their forecasted results (Ekstrand et al., 2011). Bobadilla et al. views collaborative filtering as an advantage because the adverse effects of content overload will be diminished (Bobadilla et al., 2011). Consumers are more likely to make use of an item if it is suggested to them (Canny, 2002). A challenge that collaborative filtering faces are data sparsity. Accurate recommendations can only be given if there is sufficient data on the user in terms of their previous actions. A new user is less likely to get matching results based on their preferences (Thorat et al., 2015). However, Canny points out that it unlocks severe privacy issues due to the acquisition of extensive user data in order for the system to recommend precisely (Canny, 2002).

Movies \ Person	X	Y	Z
Breaking Bad	5	1	4
Too Hot to Handle	2	5	1
Money Heist	4	3	5
Stranger Things	3	2	?

Table 2: Recommender system based on collaborative filtering (Thorat et al., 2015).

Table 2 roughly visualizes the incentive behind recommendations based on the collaborative filtering algorithm. The example ratings from 1 to 5 serve solely as an explanation purpose and are not retrieved from existing data. A conclusion can be drawn that person X and person Z show similar genre preferences being action movies ("Breaking Bad" & "Money Heist") as opposed to person Y favoring reality television shows ("Too Hot to Handle"). That said, based on person X viewing history, the algorithm recommends person Z the movie "Stranger Things," which categorizes as an action/science-fiction movie (Thorat et al., 2015).

2.1.4 Content-based filtering

As claimed by Van Meteren & Van Someren, content-based filtering "deals with the delivery of items selected from a large collection that the user is likely to find interesting or useful and can be seen as a classification task. […] A content-based filtering system selects items based on the correlation between the content of the items and the user's preferences as opposed to a collaborative filtering system that chooses items based on the correlation between people with similar preferences" (Van Meteren & Van Someren, 2000, pp. 2–3). The past behavior of the user, its profile, and the information of the item are crucial determinants of this machine learning technique. Thorat et al. mention advantages such as users shaping their own profile with exclusive ratings and, thus, their personal and future recommendations. Moreover, the system may suggest titles that have not been placed by other subscribers yet (Thorat et al., 2015). However, as with collaborative filtering, content-based filtering carries limitations such as accuracy, especially with a new subscriber, data sparsity, scalability, and diversity (Maddodi & Prasad K, 2019). Furthermore, it is complicated for content-based filtering to produce attributes for certain films, and therefore, it is more difficult to generate accurate results. As titles are not ranked by comparing lots of users' behavior as with collaborative filtering, acquiring feedback from consumers is much more challenging in order to assess recommendations' accuracy (Thorat et al., 2015). Lastly, biases need to be taken into account, and as claimed by Maddodi and Prasad K, there should be a higher, diverse range of suggested movies or series instead of accurately trying to match recommendations based on previous behavior only (Maddodi & Prasad K, 2019).

2.2 Measuring the effectiveness of Netflix's recommender system

The following chapter explores the efficiency of the personalization system on Netflix. According to Kumar and Singh, recommender systems are a vital function in managing extensive data of users (Kumar & Singh, 2019). Studies reveal that the average Netflix user discontinues searching for movies after approximately 60 to 90 seconds after looking at 10 to 20 titles. Consequently, the consumer either selects a film or leaves the platform. Netflix saw the benefits of machine learning systems suggesting movies or series to the users and, therefore, shortening the time for finding a desired film. After signing into the platform, the personalized interface, which displays numerous recommendations of titles based on the user's preferences, is the next page that follows (Gomez-Uribe & Hunt, 2015). In 2006, the streaming platform released extensive data, which included over 100 million anonymous user ratings on film. Netflix's incentive was to host a contest, namely the "Netflix Prize" to find the most accurate algorithm that reveals rating predictions to provide recommendations further (Takács et al., 2008). Announced in 2009, the winners, who were to first to create an algorithm that improved the recommendation accuracy by 10 percent, won 1 million dollars (Bell et al., 2010).

The streaming platform currently takes on a hybrid approach by using both collaborative filtering as well as a content-based filtering method. To recommend to their users, Netflix gathers users' data such as IP address, viewing activity, preferences, search history, and time spent watching a medium (Netflix, n.d.). In general, recommender systems collect information on the users' profiles. Creating a new account on Netflix requires the users to enter personal data and select their preferred genres or specific movies and series, which deal as a preliminary parameter for the system (Maddodi & Prasad K, 2019). An advantage of acquiring personality data is the ability to suggest films to user segments who share similar traits (Karumur et al., 2017). As the subscriber begins using the service, the algorithms start to learn the favored content, which will now exceed the users' initial preferences (Maddodi & Prasad K, 2019). According to Geetha et al., "if one compares hybrid recommender systems with collaborative or content-based systems, the recommendation accuracy is usually higher in hybrid systems. The reason is the lack of information about the domain dependencies in collaborative filtering and about the people's preferences in content-based systems" (Geetha et al., 2018, p. 4). That said, linking the two filtering methods allows for more effective suggestions as they improve the system by overcoming the limitations of each respective machine learning technique (Thorat et al., 2015).

Based on the algorithms, Netflix's homepage entails 40 personalized rows, with each proposing 75 movies or series (Kumar & Singh, 2019). Its recommender system comprises the following groups inter alia: "personalized video ranker" (e.g., genre rows; subsets of catalog), "top-N video ranker" (top picks of a user), "trending now," "continue watching" (previously viewed titles), "page generation algorithm" (recommendations based on friends or family sharing the account), and "video-video similarity" (suggestions due to recently watched film). Figure 2 illustrates the concept of Netflix's interface for a profile. The first four rows include "top 10 tv shows in Austria today", "Continue watching," "binge-worthy tv action & adventure," and "trending now":

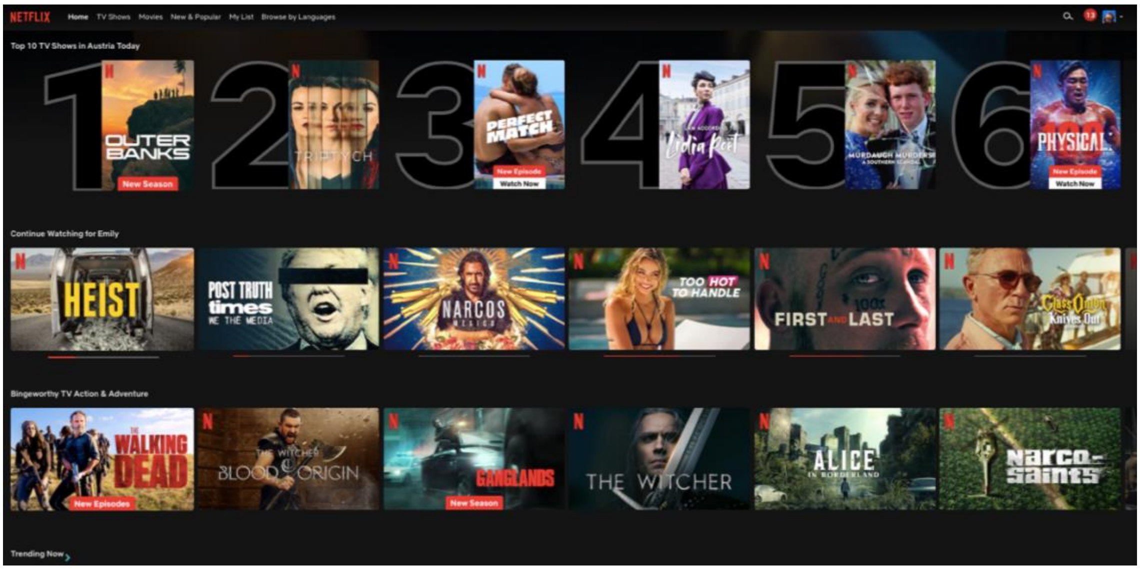

Figure 2: Netflix's Interface – Personalized rows (Netflix.com, n.d.)

As stated by Gomez-Uribe and Hunt, the streaming platform's algorithms affect approximately 80 percent of the members' film selection, while 20 percent can be traced back to search. With this in mind, it can be concluded that Netflix's recommender system based on hybrid filtering is an effective machine learning technique to match potential titles to users' preferences (Gomez-Uribe & Hunt, 2015). However, it has to be pointed out that a recommender system is only accurate if it automatically updates regularly with the content. By implication, in the case of many newcomers making use of the service or Netflix releasing new movies or series, the algorithms need to adapt to the collective ratings of the recent changes or uploads, which consequently expand the pool recommendation (Chandramouli et al., 2011). Lastly, Karumur et al. state that there are increasing difficulties in generating accurate as well as personalized recommendations if there is a high lack of information relating to new subscribers. With this in mind, it is of great significance for video-on-demand sites to assess users' preferences at an early stage to recommend effectively (Karumur et al., 2017). For this reason, Netflix requires the user to choose various preferences from a given selection (Maddodi & Prasad K, 2019).

2.3 Thumbnail Personalization on Netflix

The next chapter sheds light on thumbnails on Netflix, a type of personalization that portrays tailored cover images of each film to individuals on the streaming platform based on their user behavior, such as watch history, to keep them engaged. It usually is their first touchpoint prior to selecting and eventually watching the movie (Netflix.com, n.d.). With this in mind, it is of great importance to understand the impact of thumbnails as it is one of the critical variables that is investigated in the thesis.

On Netflix, every film is represented by a thumbnail. A combination of algorithms (supervised learning) called "Aesthetic Visual Analysis (AVA)" is employed by Netflix, which chooses an adequate thumbnail to present to the user. These algorithms filter, identify, and cluster potential frames out of films (Çakar et al., 2020). After the analysis "frame annotation" of each shot by a program, the images are converted into the presented thumbnail based on the design, characters, and resolution of the image (Cornell University Blog, 2022).

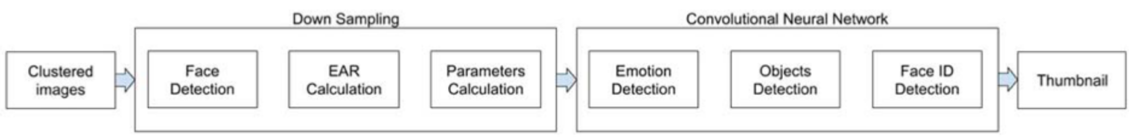

Figure 3: AVA System of Netflix (Çakar et al., 2020, p. 2)

Figure 3 briefly illustrates the process of aesthetic visual analysis (AVA) by Çakar et al. It shows that following the grouping of potential pictures, inappropriate frames are filtered out. This could be due to the quality of the image, such as brightness or dominant colors. The first step, "down sampling," is the analysis of various variables, which includes, for example, the detection of characters having their eye open. Lastly, with the aid of neural networks, items, and faces are detected that demonstrate an emotional expression as well as identity. Since the likelihood of film selection is increased by presenting a renowned actor/actress on the thumbnail, frames are categorized between characters. Frames are then evaluated under human control to omit inadequate images (Çakar et al., 2020).

More recently, the streaming platform used another machine learning algorithm, "Contextual Bandits," which matches a thumbnail to a viewer instantaneously by collecting the user's watch history and interaction with the platform. Due to this algorithm, the artwork for a film can vary daily for every profile (RecoSense, 2021). The cover images can be found in each personalized row (as discussed in Chapter 2.2). The interface can be visualized as an online library or catalog offering a vast assortment of movies (Eklund, 2022). As the streaming platform is considered a video-on-demand streaming site, similar to other successful providers such as Amazon Prime Video or Hulu, all films are promptly available (Krings, 2022). Hence, due to the increasing offerings and accessibility, different visual appeals of movie thumbnails are used to capture the user's attention during film selection (Eklund, 2022). According to Eklund: "Even if two users were given the same title recommendations, appearing left to right in the same order, there is every chance that this recommendation will still visually differ. That is due to the fourth level of personalization, the thumbnail itself, which Netflix describes as customized images designed to target individual users" (Eklund, 2022, p. 6). By implication, to illustrate, a constellation by Amat et al., published in the *Association for Computing Machinery & Netflix TechBlog,* of various thumbnails of the Netflix series "Stranger Things" is displayed below:

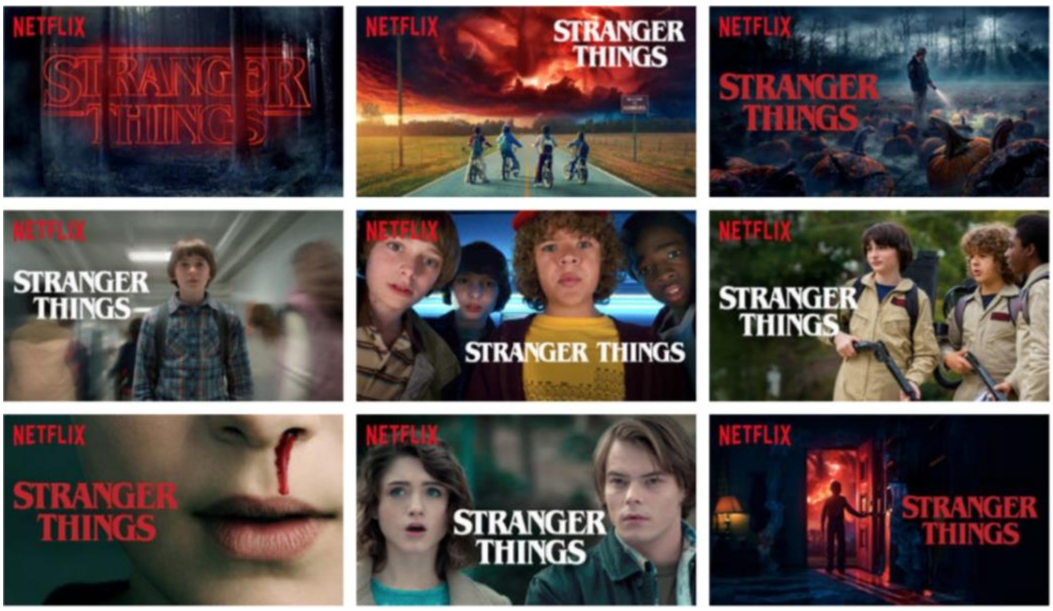

Figure 4: Artwork personalization on Netflix - based on "Stranger Things" *(Amat et al., 2018)*

To simplify the concept, Amat et al. focus in their research on various user preferences such as genre as well as themes. The authors argue that a person who is likely to watch romance tends to select a thumbnail that contains romantic features (Amat et al., 2018). Similarly, the study by Thorat et al. underlines this theory, as depicted in Table 2. As follows the Netflix series "The Witcher" serves as an example to demonstrate the approach. Two thumbnails of the movie are shown. They visually differ and can be categorized into a genre based on the content of the image. To retrieve the thumbnails, a Netflix account with two profiles was used, where each of the thumbnails was shown to one of the users respectively.

Figure 5: Genre-based thumbnails - fantasy vs. romance - on the basis of "The Witcher"

Based on the idea of Thorat et al. and Amat et al., users' decision-making may vary based on their genre preferences (further determining factors will be discussed in Chapter 2.4). The image on the *left* of Figure 5 portrays two individuals holding a *sword* and preparing themselves for a battle. Next, the picture on the *right* of Figure 5 depicts two characters *kissing*. Viewers, who are fond of *fantasy* movies, will more likely select the thumbnail on the *left* of Figure 5. On the contrary, if the genre *romance* is preferred, the likelihood of the thumbnail on the *right* of Figure 5 being chosen may increase. It has to be pointed out that biases arise, and interpretation of thumbnails may diverge. Furthermore, "The Witcher," as given as an example, is classified under the genre of fantasy (Netflix.com, n.d.). The methodology of the present thesis is based on this theory and carries limitations. These constraints will be further discussed in Chapter 3.

2.3.1 Thumbnails and their importance

Building on the foundation laid in the previous section, this chapter delves deeper into the role and importance of thumbnails on Netflix. An incentive of the company is to retain user engagement. Having said that, it has to be mentioned that the attention span of a viewer may range up to 90 seconds until one skip to the next film. Thumbnails appear to be one of the most effective strategies to raise the user's interest (Cornell University Blog, 2022). Artwork images are the first aspect they see of a film while browsing on the streaming platform (Sahu, 2022). Additionally, Nelson, head of product creative at Netflix, found in his consumer research studies in 2014 that 82% of the user's attention can be derived from thumbnails while scanning through the content on Netflix. Furthermore, the decision to select a film is made on average within 1.8 seconds. With this in mind, the author concludes that the appeal of thumbnails plays a crucial role in raising users' interest (Nelson, 2016).

2.3.2 Thumbnail styles

On the basis of Section 2.3, there may be various constellations of a thumbnail. This chapter serves as a short introduction to potential film artwork designs as the online-survey of this bachelor thesis encompasses questions regarding thumbnails based on *genre, object, plot/scene, and landscape.*

Movie posters, billboards, or DVD cover images are not designed on the same level to raise attention as aimed by Netflix. In other words, the company strives for a higher level of optimization for its personalized thumbnails to capture viewers' interest, which is not necessarily the case for traditional advertising. With this in mind, after extensive research, Netflix developed "stable identifiers for each artwork," as depicted below (Netflix Technology Blog, 2016).

Figure 6: Thumbnail style (Netflix Technology Blog, 2016)

Figure 6 presents the structure of a thumbnail on Netflix, which comprises a background image, the film's title, an optional "new episode" badge, as well as a Netflix logo for the movies originally produced by the company. The movie's title may also be depicted in the respective language of the user (Netflix Technology Blog, 2016).

Furthermore, according to Tsao et al., "a representative frame should hold a strong connection with the gist of the video" (Tsao et al., 2019, p. 54). That being said, a thumbnail displaying two persons kissing may be appropriate for films categorized under the genre of romance. Similarly, movies about wars could be represented by an image showing a battle" (Tsao et al., 2019). Therefore, reverting to Figure 5, it may be concluded that the image on the left may be more adequate for "The Witcher" as it is based on the genre fantasy rather than romance.

2.4 Understanding the film selection process of users on Netflix

Having established a clear understanding of the thumbnails on Netflix, the thesis continues with insights into users' selection on the investigated streaming platform. In general, viewers may start by *browsing* through various categories of movies on Netflix. The types are presented by personalized rows, as discussed in Chapter 2.2, which include trending films, genres, new releases, or top picks. If users long for an explicit movie, they are able to look for a film via the *search bar*. If Netflix does not offer a specific movie, similar films will be suggested. Next, viewers may find multiple films of interest. With this in mind, the *watchlist* serves as a folder to save movies for watching later (Netflix.com, n.d.). After the brief overview of the options a user has in regard to finding a movie to view, users are then able to conduct further assessments of films based on the variables introduced in the next chapter.

2.4.1 Variables that influence viewer's decision making

Next, the chapter explores the factors which influence users' decision-making to comprehend further the independent variable of investigation, "viewer's film selection." In his book "The Paradox of Choice," Schwartz highlights the negative impact the wide range of choices on platforms may have on consumers (Schwartz, 2004). With this in mind, it is of great importance to identify the key variables on Netflix that influence user behavior, as this lays the groundwork to obtain clarity on the research questions.

According to Patch, "Generation Z (approx. 1997 – 2012) account for the vast majority of video-on-demand users". More importantly, it has to be pointed out that media consumption does not necessarily depend on age but on generation. Generational differences in terms of media consumption as well as habits can be observed (Patch, 2018). A survey found that the likelihood of being subscribed to Netflix was the highest, with 78% for this age group in 2021 (Stoll, 2022). For this reason, this section will primarily focus on Generation Z. This demographic segment has experienced a higher level of interconnectedness than any previous generation. Thus, the daily utilization of the internet has led to a market divergence in the behavior patterns of this group. Research shows that the generation is more likely to opt for "*multimedia content (images, videos, etc.) over text, while young adults prefer text that is easy to scan. […] Generation Z is said to have an attention span of about eight seconds, potentially pushing cognitive limits even further*" (Patch, 2018, p. 5). With this in mind, streaming platforms offering an extensive collection of content demonstrate constraints in how the group chooses the films and explores Netflix. The following list by Patch is nine common factors that are likely to impact the decision-making of users of video-on-demand services (Patch, 2018, p.6):

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1. Thumbnail (which can include one or more of the following: title, text, picture)
2. Text description
3. Trailer or introduction video
4. Genre or category
5. List of actors
6. List of directors
7. Trending or popular categorization
8. New releases categorization
9. Related categorization (for example, content similar to previously watched content

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Within the bounds of the bachelor thesis, the research questions will investigate three of these influencers: thumbnail, text description (*here: plot description, movie title)*, and genre. The study by Patch found that older millennials put importance on *categories, text descriptions, and thumbnails*. In contrast, younger millennials focused on *categories, trailers, and text descriptions* (Patch, 2018). The journal article by Djamasbi et al. states that millennials generally favor images considering their attention span, as thumbnails provide a quicker comprehension compared to text (Djamasbi et al., 2010). Lastly, Generation Z puts great emphasis on *categories, text descriptions, and trailers.* Thumbnails ranked in the middle regarding their level of significance among Generation Z, although they generally claim to prefer images over text.

All segments of the investigation placed *actors* and *directors* as the least significant factors. Having said that, the generations put more importance on *thumbnails, text descriptions, categories or genres, and trailers* when selecting a film rather than the other variables listed (Patch, 2018).

With thumbnails having the most significant influence on the participants in Patch's study, qualitative findings reveal the following reasoning behind this phenomenon by an individual:

"*I think it is very important because as soon as you see a picture you have a feeling what kind of show it is, because that is the first things you look at I think it is more appealing than the description.*" (Patch, 2018, p. 8).

Genre and category were ranked the second most impactful factor by the majority of participants after thumbnails. Few individuals claim that they perceive genre and category as even more significant than cover images. This can be derived from the fact that it simplifies the selection process while browsing through the *genre* category instead of having to focus on each image. Individuals in the qualitative study stated that they start by scanning through *genre* rows for the following explanation:

"I'm at home alone, so I don't want to watch something scary, I want to watch something funny, something that makes me feel like I'm not alone." (Patch, 2018, p. 11).

In terms of text description, it was argued that:

"*I feel it is quite important...they do not give too much information away, just enough to get you hooked*." (Patch, 2018, p. 8).

With this in mind, those variables were selected for analysis in the present study. In the scope of the online-survey, the influence of *trailers* will not be further explored.

2.4.2 The influence of personal preferences and traits on user behavior

Next, the thesis briefly sheds light on the extent to which personal preferences impact user behavior to gain a further better understanding of the final decision-making of a film. Empirical evidence indicates that personality traits significantly correlate with behaviors as well as preferences. Variables that are influenced include "newcomer retention, the intensity of engagement, activity types, item categories, consumption versus contribution, and rating patterns" (Karumur et al., 2017, p. 1). Preferences and user activity in the context of these factors are developed by underlying psychological constructs comprising "personality, self-efficacy, emotions, and attitudes" (Karumur et al., 2017, p. 2). In the scope and relevance of the thesis, the preference for the *genre* will be considered as the variable representing users' preferences. Research reveals that various personality types prefer different genres. Nevertheless, the study by Karumur et al. draws the conclusion that there is no significant difference in the overall genres of films that viewers select, although users show somewhat a preference for watching more content in particular categories compared to others (Karumur et al., 2017). Furthermore, research reveals that while comedy and drama, as well as horror and thriller, tend to compete more with one another than with other genres, science fiction, and animated genres fall into a separate category. Action, on the other hand, is in direct competition with various genres because it is placed equally apart from science fiction, thriller, horror, and animated movies. Additionally, findings indicate that viewers who prefer horror films are less inclined to select comedy and dramas and more likely to enjoy thrillers (Gazley et al., 2011).

2.5 The impact of visual representation on user engagement and decision making

After gaining a general understanding of the thumbnails on Netflix as well as user's film selection, the following section integrates the previous chapters in order to obtain comprehensive knowledge on the matter, specifically with regard to the methodology of the present thesis.

Previous studies prove that there is a "positive correlation between the size of the largest image on a web page and visual appeal" (Djamasbi, 2010, p. 310). However, Patch's research found that the size of an image could have a negative influence on perception. The participants consider a larger image as disrupting as it is viewed as an advertisement (Patch, 2018). Next, the journal article by Djamasbi et al. concludes that the likelihood of perceiving a website as visually appealing increases with images, specifically displaying celebrities and a short description (Djamasbi, 2010). Having said that, the following subchapter delves further into the extent to which thumbnails may play a role in the decision-making of users.

2.5.1 The relationship between thumbnails' appeal and viewer's film selection

Qualitative data shows that the film's cover images present a high impact on content selection. Moreover, thumbnails typically were the initial factor for taking the movie into account. In rare instances, the content was selected exclusively based on the cover image. According to Tsao et al., actors/actresses depicted in thumbnails are a vital component since they are the critical element in the movie (Tsao et al., 2019). Participants of Patch's study underline this by stating that they favor thumbnails that display people. Moreover, one participant claims that they prefer thumbnails where the main emphasis is directed towards one actor/actress of the movie. Data shows that 50 percent of the participants selected thumbnails that represented one protagonist. In contrast, 25 percent of the chosen cover images depicted two to three persons, while the other 25 percent portrayed more individuals (Patch, 2018). Moreover, thumbnails that show a renowned individual may increase the likelihood of selecting a movie as it creates an emotional bond with the viewer (Djamasbi, 2010). Furthermore, Netflix discovered that thumbnails presenting villainous characters generate more clicks as opposed to other frames. In his blog, Phan displayed numerous thumbnails of the series "Dragons – Race to the Edge" and highlighted that the images depicting a villain outdid the others in terms of selection (Phan, 2022). The illustration below visualizes three frames from the movie. The images are retrieved from different sources and put together to exemplify the theory. Based on the concept, the thumbnail on the right (bordered in blue) would be the cover art that is more successful.

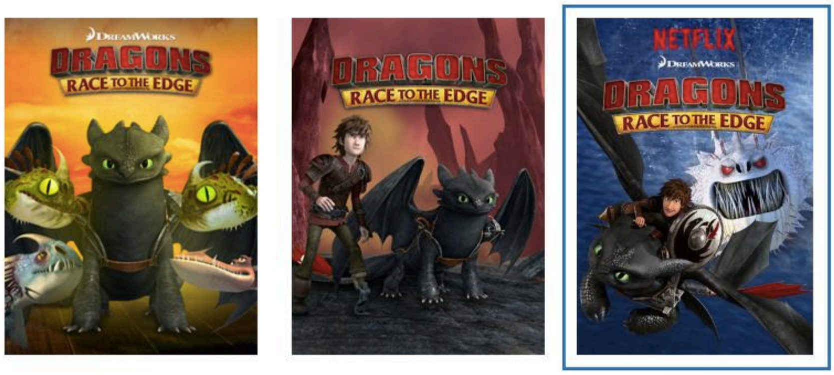

Figure 7: Thumbnail's attractiveness based on characters (Phan, 2022)

The thumbnail's appeal may also increase if the frame displays happy moments or a user's favorite animal (Çakar et al., 2020). Moreover, research shows that thumbnails perform better when the characters express distinct emotions, as opposed to serious or somber expressions, which fail to engage the user. Thus, it may be stated that the greater the range of emotions depicted in a cover image, the more effective it will be (López, 2020). As follows, this theory is visualized with the pictures of the series "Unbreakable Kimmy Schmidt." The thumbnail at the bottom (bordered in blue) shows two characters clearly conveying emotions as opposed to the ones at the top.

Figure 8: Thumbnail's attractiveness based on emotions (López, 2020)

In terms of age, a participant in Patch's study also put emphasis on the variable during their decision-making: *"I clicked this one because it looks like a younger group of people."* (Patch, 2018, p. 11). Another aspect that is considered is the font of the movie title, as it provides a subtle indication of the movie at hand. Lastly, it has to be pointed out that due to cultural distinctions, different versions of thumbnails may be preferred over other images in a country (López, 2020).

In their research paper "How Does Interface Design and Recommendation System In Video Streaming Services Affect User Experience?" Ye and Kindbom explored how Netflix's user interface design, as well as its recommender system, impact user behavior among younger generations (Ye & Kindbom, 2022). The authors gathered qualitative and quantitative data to understand the viewers' perspectives on the matter. By implication, a question involved respondents to state if they are concerned with their privacy as the streaming platforms collect data in order to generate tailored content. From a sample of 20 participants, 10% revealed that they do not favor the tracking of their watch history by Netflix. Moving on, participants were asked whether they are fond of the idea that the video-on-demand service shapes the thumbnails based on users' behavior (Ye & Kindbom, 2022):

"*Based on what you have previously watched and where you are located, Netflix changes its thumbnails, such as showing certain actors on them that you might be interested in. Do you like the idea of Netflix changing the thumbnails to make its movies and series more appealing to you?* (Ye & Kindbom, 2022, p. 23)"

The researchers found that the majority perceive thumbnails as a vital component in their film choice. Nevertheless, in regards to cover images being personalized and constantly changed for each user, 20% of the respondents argued that they do not prefer this algorithm. The reasoning behind this statement is that the varying thumbnails may cause confusion as they displeasure irregularity. In contrast, 65% of the survey participants disclosed that films might raise the attention as well as the attractiveness of the movie if the thumbnail is tailored. To complement these findings, the master's thesis by Cannella revealed that a participant in her interview stated that "personalized thumbnails influenced how she would choose her content on Netflix" (Cannella, 2021, p. 35). In addition, according to another interviewee, the appeal of thumbnails stems from their ability to alter as one progresses watching a series. Netflix knows how far a person has progressed in a film and uses this information to generate tension and urge them to watch more by incorporating it into thumbnails, encouraging them to click and continue viewing the content (Cannella, 2021).

In the interview of Ye and Kindbom, the individuals were asked to state the factors that made them select the films given as the examples within the research. The highest impact was recommendations made by family or friends (count: 6) as well as suggestions made by Netflix or advertisements (count: 6), followed by thumbnails (count: 5). Moreover, participants were prompted to view the trailer and read the plot description. Afterward, they revealed that they would not continue watching the movie as it failed to meet the genre expectations set by the thumbnail (Ye & Kindbom, 2022). Last but not least, the study by Ye and Kindbom asked about the extent to which thumbnails are essential in film choice.

"*Do you believe thumbnails play a part in the decisions you make when you're watching Netflix?* (Ye & Kindbom, 2022, p. 26)"

The majority answered with *Yes* (count: 8), followed by the argument that covers images may raise primary interest (count: 5) or reveal information about the "*age of the movie*" or actors (count: 3) (Ye & Kindbom, 2022).

2.5.2 The impact of genre representation in thumbnails on user behavior

The next section extends the previous chapter to delve deeper into the relationship between genre in thumbnails and film selection. Having discussed the various factors that impact thumbnails' attractiveness, including the influence of characters as well as emotions, research indicates that viewers are capable of easily associating a thumbnail with a genre. For instance, protagonists showing happy emotions can be connected to comedy movies, sadness with drama, fear with horror, and love with romantic films. This phenomenon of being able to relate emotions to a genre may occur in milliseconds. However, it is vital to bear in mind that the thumbnails may be interpreted differently (López, 2020). In her article, López asks the readers to which genre the following cover images refer.

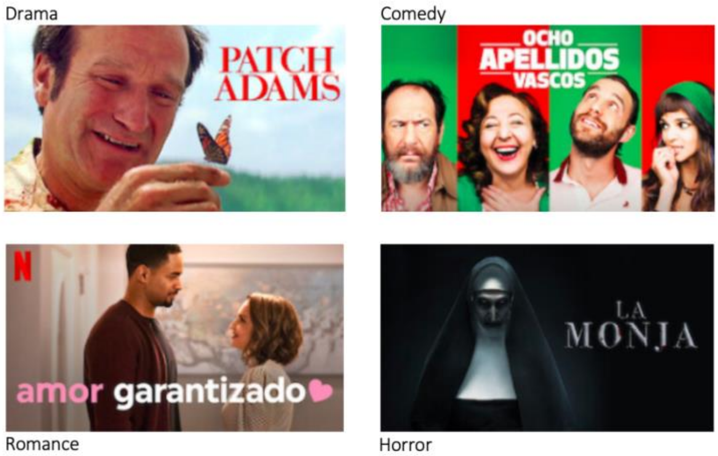

Figure 9: Genre representation in thumbnails (López, 2020)

Figure 9 depicts four movies where the characters show distinctive emotions. With this in mind, each of the images can be assigned to a genre that reflects those feelings. Nevertheless, it has to be mentioned that the connections are highly subjective, and the illustration solely serves as an example to explain the concept. The Figure is not based on significant data (López, 2020).

In terms of cover images reflecting the movie's genre, as discussed in Section 2.3.2, research indicates that "the attractiveness outweighs the representativeness in the rationale behind ranking" (Tsao et al., 2019, p. 58). Having said this, a thumbnail embodying the genre of the movie may not be the determining factor of users selecting the film as opposed to the perception of thumbnail appeal.

The online-questionnaire conducted in the thesis, which will be discussed in the next chapter, will further complement these findings.

3 METHODOLOGY

The following chapter provides an overview of the selected research design as well as the approach. Moreover, it discusses the survey development, analysis of the results, and the limitations.

3.1 Research design

A quantitative-descriptive research design appears to be the most appropriate method as the main objective is to identify an association between the variables “thumbnail attractiveness” and “likelihood of selecting the movie” with respect to genre (Hypothesis 1). Moreover, it allows the researcher to draw conclusions based on the sample data that may be applied to a larger population (Mertler, 2019). With the thesis having a postpositivist worldview, the aim is to explore a link between categorical variables through statistical analysis (Creswell, 2014). In order to assess whether tailored thumbnails are an effective machine learning technique to stimulate users in selecting a film, we simplify the examination and take “thumbnails’ attractiveness” and “film selection” as the representing variables to test the hypothesis. Having said that, the main focus lies on correlation and consequently testing whether the visual appeal of a thumbnail, the independent variable, influences the users’ film selection, the dependent variable. According to Netflix.com, the company’s recommendations system does not take demographic variables such as age or gender into consideration (Netflix.com, n.d.). For this reason, those user characteristics act as control variables. An online-questionnaire on *Google Forms* will be the instrument for primary data collection as results from the sample may be generalized to a larger population (Creswell, 2014). Launched in March 2023, a convenience sample of 104 participants was gathered through social media postings on Instagram, Snapchat, WhatsApp, and word-of-mouth. The survey was established to address the following aims of the thesis:

- To examine the relationship between thumbnails’ attractiveness and viewer’s likelihood of selecting the movie with respect to genre.
- To determine the influence of tailored thumbnails in the form of genre preference based on controlled aspects in the image.
- To assess whether there is a significant difference between age or gender regarding the impact of thumbnails.

- To evaluate the extent to which thumbnails have a more significant influence on film choice than the movie's plot description or title.
- To what extent does a movie's failure to meet the expectations set by its thumbnail image influence viewers' likelihood to continue watching the movie?

These objectives reflect the research questions of the thesis and provide a greater understanding of the influence that recommendation systems have on users' decision-making. The results will be discussed in Chapter 4.

3.2 Survey Development

The research tool used to collect the data is an online-questionnaire created on *Google Forms* and published between the 3rd of March and the 14th of March, 2023. The purpose of this approach is to gain insight into users and the importance of thumbnails on Netflix among consumers varying in age and gender based on their genre preference.

The survey begins by collecting information on users' backgrounds, such as age and gender. To determine the participants' familiarity with Netflix, it was asked how often they watch movies on the streaming platform. Next, participants had to select the variable that they perceived as the most influential during their film selection. To further assess users' characteristics, the survey poses the question about their genre preferences.

Survey Part 1 : Basic Information

1) Gender
2) Age
3) Netflix viewing frequency
4) Influential factors in movie selection
5) Movie genre preferences

The second part of the questionnaire serves to address the research questions with a practical approach by placing five movies for investigation. As the genre is being controlled for, "Irreplaceable You", "The Polka King", "The Perfection", "Extinction", and "The Longest Night" is the five Netflix movies presented which embody different genres respectively (romance, comedy, horror, science-fiction, and thriller). This method was adapted from the study by Mattar et al. (2019). Questions included participants rating the movie titles (from extremely unlikely to extremely likely) based on the likelihood of choosing the film solely based on the name. Similarly, the plot description for each movie was presented, and the survey asked to select the degree (from extremely unlikely to extremely likely) to which they would watch a film based on the content given only.

Survey Part 2 : Influential factors in movie selection

6) Indicate your level of likelihood to watch the following movies, as indicated by the film's title provided.
7) Indicate your level of likelihood to watch the following movies, as indicated by the plot description provided.

To evaluate the participants' opinions on thumbnails, the third section of the questionnaire discusses the critical variable of the thesis. By implication, a semantic-differential scale ranging from 1 (unhelpful) to 5 (helpful) is introduced to examine whether the participants view thumbnails as useful in making their final film selection (Voss et al., 2003; Huffman et al., 2014). Moreover, the study required participants to select the thumbnail which they perceived as the most visually attractive. Five thumbnails for each of the five movies are presented, and every thumbnail embodies a category. Respectively, from left to right, the thumbnail subjectively represents a character-based-, genre-based-, object-based-, plot/scene-based-, and ultimately landscape-based cover image. As the aim of this research is inter alia to find a relationship between the selection of genre-based thumbnails and users' genre preference, a genre-based image that represents the film's category was chosen. In addition, reverting back to chapter 2.4 as well as 2.5, thumbnails that represent actors/actresses are utilized as findings reveal that protagonists in the cover images may have an influence on behavioral intent. Moreover, thumbnails need to properly communicate information and capture users'' attention by introducing visually attractive images. While renowned characters, color vibrancy, brightness, and quality are relevant to the aesthetics of thumbnails, factors like element complexity and object complexity are seen as fundamental elements for informativeness (Koh & Cui, 2022). For this reason, scene-based, object-based, and lastly, landscape-based thumbnails were selected for the online-questionnaire. As follows, an example of this question type in the survey is presented, which displays the movie "The Longest Night".

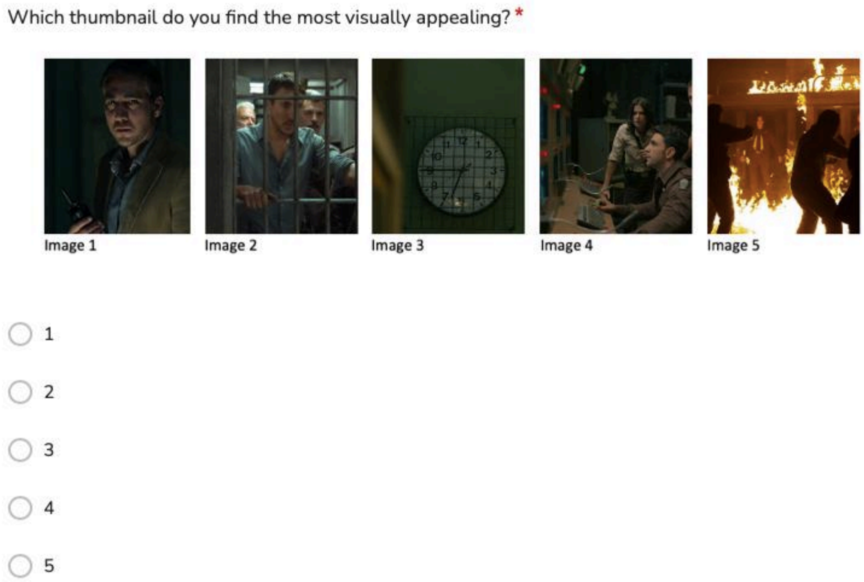

Figure 10: Survey question example : Selection of the most appealing thumbnail

It is then asked how likely the participant is to watch the film solely based on the thumbnails' attractiveness on a 5-point Likert scale adapted from Balderjahn et al. (2018), as seen in Figure 11. Point 1 indicates that the person is very unlikely, whereas point 5 denotes a strong likelihood of selecting a film based on the thumbnail only (Balderjahn et al., 2018). According to Tsao et al., "The attractiveness criterion involves a measurement of the appeal of a frame" (Tsao et al., 2019, p. 54). With this in mind, the variable "attractiveness" and "appeal" will be used interchangeably.

Figure 11: Survey Question Example: Likelihood of selecting the movie

Survey Part 3 : Impact of Thumbnails

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8) How useful are thumbnails in helping you make decisions about the films you watch?

9) How often do you select a movie to watch online based on the attractiveness of its thumbnail image?
10) How likely are you to continue watching a movie that does not live up to the expectations set by its thumbnail image?
11) *Irreplaceable You* – Which thumbnail do you find the most visually appealing?
12) *Irreplaceable You* – Based on the image you selected above as the most visually appealing, how likely are you to watch the film?
13) *The Polka King* – Which thumbnail do you find the most visually appealing?
14) *The Polka King* – Based on the image you selected above as the most visually appealing, how likely are you to watch the film?
15) *Extinction* – Which thumbnail do you find the most visually appealing?
16) *Extinction* – Based on the image you selected above as the most visually appealing, how likely are you to watch the film?
17) *The Perfection* – Which thumbnail do you find the most visually appealing?
18) *The Perfection* – Based on the image you selected above as the most visually appealing, how likely are you to watch the film?
19) *The Longest Night* – Which thumbnail do you find the most visually appealing?
20) *The Longest Night* – Based on the image you selected above as the most visually appealing, how likely are you to watch the film?

Questions 11-20 are displayed, as seen in Figures 10 and 11. The selected thumbnails for the respective movies may be viewed in the appendix of the thesis.

The last part of the online-questionnaire poses a multiple-choice question to indicate the movie they favor the most of each of the films presented. In addition, the participants had to state why they selected that particular film. Finally, as a control question, it is questioned if an individual has already watched one of the movies in the questionnaire. However, in their study, Tsao et al. divided the participants into two groups. One segment had already seen one of the movies, and the other indicated that they did not. Results show that "prior viewing experience does not affect the performance assessment" (Tsao et al., 2019, p. 58). For this reason, the last question solely serves for information purposes and will not be considered in the analysis.

Survey Part 4 : Final Film Selection

21) Which of the following movies would you most likely watch?
22) What made you select this movie?
23) Have you already watched any of the specified films?

The main emphasis is given to the individuals being *likely* to *extremely likely* to select a movie based on the thumbnail, only which matches their genre preference, and ultimately choosing that particular film in their final selection. In addition, it will be observed whether the individual selected a genre-based thumbnail as the most visually appealing.

3.3 Measurement Item Table

Construct	Measurement	Source
Film Selection	I watch movies on Netflix.	Rubenking & Bracken (2021)
Film Selection	Based on the image, how likely are you to watch the film?	Kim et al. (2021)
Film Selection	Which of the following movies would you most likely watch?	Kim et al. (2021)
Film Selection	What made you select the movie?	Kindbom & Ye (2021)
Genre likelihood to choose a film	Please indicate the likelihood of watching the following genre	Kim et al. (2021)
Movie Title Likelihood to choose a film	Please indicate the likelihood of watching the next movie, as indicated by the film's title provided.	Kim et al. (2021)
Plot Description Likelihood to choose a film	Please indicate the likelihood of watching the following movie, as indicated by the plot description provided.	Kim et al. (2021)
Thumbnail Attractiveness	In your opinion, which of the following factors has the greatest influence on your decision to select a movie to watch online?	Liu et al. (2017)
Thumbnail Attractiveness (Genre-based image)	How useful are thumbnails in helping you make decisions about the films you watch?	Patch (2018)
Thumbnail Attractiveness (Genre-based image)	How often do you select a movie to watch online based on the attractiveness of the thumbnail image?	Patch (2018)

Table 3: Measurement Item Table

The measurement item table depicted above showcases the constructs of interest and how they are stated in the questionnaire for further analysis. It should be noted that the questions from the table are not identically replicated from the respective source, but they established a foundation for testing the variables of the subject matter. Thus, considering the reliability of variables and question type, any conclusions based on this information ought to be carefully considered and validated through further research.

3.4 Data Analysis and Results

Hypothesis I : The degree of genre preference has an impact on the likelihood of watching a movie based on the most attractive thumbnail.

To test whether users' characteristics in terms of genre preference significantly affect the likelihood of selecting a film based on the thumbnail in the respective genre category, the Spearman test will be conducted. The Spearman rank test is a type of correlation coefficient that measures the relationship between two ordinal variables by classifying their values as opposed to their actual values. It is denoted by *rho* and is suitable for ordinal data in the case of "genre preference" and "likelihood to watch a movie based on the most attractive thumbnail". By ranking the data, the Spearman rank correlation can identify strictly monotonic relationships between variables, which can then be represented as a linear relationship. Additionally, this method is fairly resistant to outliers. Moreover, the Spearman coefficient, similar to the Pearson coefficient, ranges from -1 to +1 and can represent either a perfect monotonic association (= -1 or +1) or no relationship (= 0). A detailed interpretation of this correlation can be seen in Table 4. Furthermore, the analysis of confidence intervals and p values for the Spearman coefficient follows the same rules as those for the Pearson correlation (Schober et al., 2018). In case of a result equal to or lower than the 0.05 alpha level, the p-value is significant, and one can verify the hypotheses. On the contrary, if larger than the designated level, one must reject it and conclude that there is no significant relationship between the user's film selection based on thumbnails and genre preference (Creswell, 2014). It is commonly applied to similarity measures that observe an association between two users' behavior, mainly linked to content-based as well as collaborative filtering strategies (Symeonidis et al., 2008). Notably, a non-parametric test is used when the sample size is small and random (Bower, 2003).

Spearman Rho	**Strength**
0.00 – 0.20	Negligible
0.21 – 0.40	Weak
0.41 – 0.60	Moderate
0.61 – 0.80	Strong
0.81 – 1.00	Very Strong

Table 4: Interpretation guidelines for the Spearman rho's (ranked) correlation (Prion & Haerling, 2014)

To achieve more meaningful results, data of the variables are binned, meaning that the scales "extremely unlikely" and "unlikely" as well as "extremely likely" and "likely" are merged together to conclude that participants are respectively either likely or unlikely. The Spearman test will be performed for each genre category, and a general analysis will be provided, taking all the categories into consideration.

Hypothesis II : There is a significant association between age and selecting a film based on a thumbnail.

To explore a significant association between age, the Pearson chi-square test will be used as it is able to find a correlation among categorical data. To determine the strength of this relationship, Cramer's V value is taken into account for the analysis in the case of significance (Creswell, 2014).

Cramer's V	Strength
> 0.00	Negligible
> 0.05	Weak
> 0.10	Moderate
> 0.15	Strong
> 0.25	Very Strong

Table 5: Interpretation guidelines for the Cramer's V (Akoglu, 2018)

The Cramer's V is a statistic with a 0–1 range and no negative values, as seen in Table 5. If the value is near 0, there is no strong correlation between the variables. The value, however, suggests a very strong association between the variables if it is more than 0.25. In other words, the greater the relationship, the larger the value of Cramer's V (Akoglu, 2018).

Lastly, it should be noted that data has been binned to achieve more conclusive results. As the central focus lies on *thumbnails,* confounding variables such as *plot description, movie title, genre preference*, *and actors/actresses* have been merged into "other". Furthermore, due to unequal age distribution, with the majority of respondents being 18-24 years of age, older participants are binned into the category "25+".

Hypothesis III : A statistical significance exists between genders with regard to the selection of films based on thumbnails.

Similarly to hypothesis II, to find a relationship between gender and film choice, the Pearson chi-square test will be used as it is able to find a correlation among the nominal variables. In addition, the determining factors of movie selection will be binned, as discussed in the previous hypothesis. Moreover, it has to be pointed out that for this hypothesis, one case where a participant has not revealed their gender "prefer not to say" has not been taken into account. This is to achieve more conclusive results in terms of gender.

Hypothesis IV: There is a significant difference between thumbnail attractiveness, plot, and movie title in film choice.

Moving on, a statistical test, namely the Wilcoxon rank test, is used to compare two related samples, matched samples, or repeated measurements on a single sample. When the population is not assumed to have a normal distribution, it can be used in place of the t-test for dependent samples to see if their population mean ranks differ. With this in mind, this non-parametric test is conducted to compare the difference in the impact of the movie's plot description, thumbnail, and title on users' film selection. Results show whether the population means ranks for these three variables differ (Refugio, 2018). In addition, as it is controlled for the genre, the test will be conducted for each film.

Hypothesis V : A significant relationship exists between users' genre preference and the selection of genre-based thumbnails.

To investigate the extent to which tailored thumbnails affect film selection, the thesis analyses the impact of genre-based thumbnail, which serves as the representative variable of "tailored" images, with respect to users' genre preference. Having said that, the Pearson chi-square test will be performed as the hypothesis concerns categorical variables, and results will be observed per movie category (Creswell, 2014). Furthermore, to produce more relevant results, the data of the variables are binned. This means that the scales "extremely unlikely", "unlikely," and "neutral," as well as "extremely likely" and "likely," are converged in order to interpret that individuals are respectively either likely or unlikely to watch a genre. Similarly, since the central focus is on "genre-based thumbnails", the alternative thumbnail categories from the selection are merged into "other thumbnails".

Moreover, to provide a better understanding of the results, graphs, and tables are presented in the thesis. Tables provide an overview of the age groups as well as gender and whether thumbnails influenced their film selection. The latter – a bar chart – displays the relative result of how many participants were influenced by thumbnails in their film choice concluded based on their selected genre preference.

3.5 Limitations

Results have to be interpreted with caution as the test carries limitations. Due to the small sample size, it is impossible to universally apply the outcome to the whole population, especially in terms of location, age or gender. In addition, the results of the hypothesis need to be evaluated critically as the samples of females and males are not equally distributed. Furthermore, the thumbnails used in the online-questionnaire are retrieved from existing Netflix movies or series, and therefore, response bias may occur (Creswell, 2014). Additionally, it has to be pointed out that the images presented in the survey as "thumbnails" do not accurately reflect the thumbnails displayed on Netflix. The cover images serve as proxy variables to test whether artwork influences film selection. The thumbnails have been retrieved from sources online, and screenshots were taken out of the respective movie trailers published by Netflix. Furthermore, testing if specifically "*tailored* thumbnails" affect users' decision-making comes with restrictions. As a representative variable, five images based on different categories are presented in the questionnaire to ask participants which they perceive as the most attractive and whether they would select the movie solely based on the thumbnail. Similar to previous research, the evaluation of thumbnails for each category is highly subjective. Thus, the online-survey is regarded as a highly subjective online-survey (Tsao et al., 2019). Further constraints include that a movie may be associated with multiple genres. For this reason, five movies were aimed to be selected which do not coincide with each other's category. The types of genres of the respective films are assigned by Netflix. Last but not least, there may be confounding variables that impact the users' movie choice as it is not limited to genre, thumbnails, plot description, and movie title, as introduced in the questionnaire. Nevertheless, these variables are chosen as they are the prevalent determining factors (Patch, 2018).

4 SUMMARY AND INTERPRETATION OF SURVEY

This chapter analyzes the online-questionnaire and draws conclusions based on statistical tests. The survey was carried out between the 3rd of March and the 14th of March 2023, and 104 valid cases have been obtained.

4.1 Sample Description

Figure 12 displays the participants' characteristics of the online-questionnaire. The majority of survey respondents were female (68.3%) and individuals between the ages of 18 and 24 years old (64.4%).

Gender	Counts	% of Total
Female	71	68.3 %
Male	32	30.8 %
Prefer not to say	1	1.0 %

Age	Counts	% of Total
18 - 24	67	64.4 %
25 - 34	21	20.2 %
35 - 44	3	2.9 %
45 +	13	12.5 %

Q3_Netflix_Frequency	Counts	% of Total
Never	3	2.9 %
Occasionally	42	40.4 %
Rarely	12	11.5 %
Regularly	31	29.8 %
Very often	16	15.4 %

Figure 12: Sample Characteristics

In general, it is found that the sample is familiar with the streaming platform since most subjects indicated that they occasionally watch *to very often* films on Netflix. Hence, this outcome implies how relevant research on recommendation systems on video-on-demand services is for people of all ages, not exclusively restricted to younger demographics. However, it has to be pointed out that results have to be viewed with caution taking into consideration the scale reliability. The study's sample size is relatively small, which may restrict the generalizability of the findings to a larger population. Furthermore, the unequal gender distribution in the sample may have an influence on the results, thus, requiring careful interpretation as well. Lastly, to avoid bias, the survey asked participants whether they had already viewed any of the specified films.

Results show that 12 cases exist where individuals had watched one of the movies. Nevertheless, as discussed in the chapter Limitations, response bias cannot be avoided in the questionnaire as in a natural environment, it is impossible to eliminate participants' preexisting familiarity or interest in the Netflix films. Even if an individual has not seen any of the introduced films, they may have been exposed to conversations or reviews about it and, thus, may hold certain beliefs or prejudices towards it. For this reason, the thesis takes the 12 cases into account, recognizing that every Netflix user may approach the thumbnail with some degree of preconception.

4.2 Discussion of Results

This section investigates the findings of the online-questionnaire using Jamovi, a computer program for data analysis, to conduct the statistical tests based on the hypotheses and research questions that have been developed (Jamovi, 2022).

4.2.1 Hypothesis 1 & Sub-question V

Hypothesis I : The degree of genre preference has an impact on the likelihood of watching a movie based on the most attractive thumbnail.

To explore the first research question, the Spearman rank test will be taken to analyze the two categorical variables (Creswell, 2014). Additionally, the survey asked participants to reveal how often they select a film based on the attractiveness of the thumbnail (Q4). Results are depicted in Figure 13:

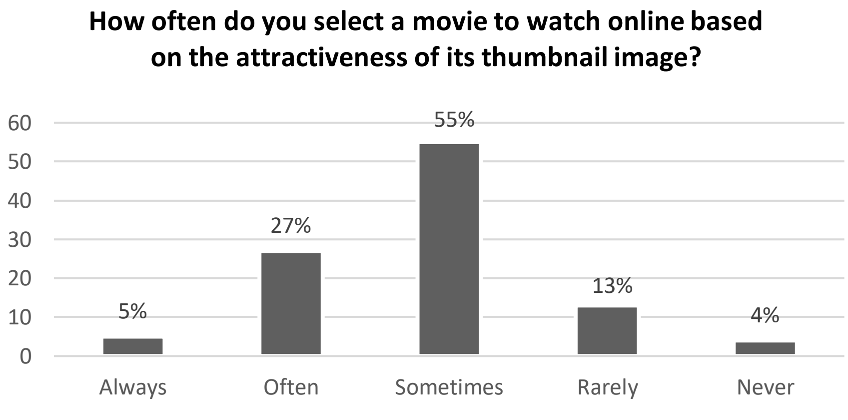

Figure 13: Question 4 – Results: Film Selection based on Thumbnail Attractiveness

It is found that the majority believes that their movie choice is *sometimes* determined by the appeal of thumbnails. On the contrary, 4% of survey respondents argued that they *never* select a film based on the cover image's attractiveness. To further gain an understanding of the influence of thumbnails, the online-questionnaire enquired participants to indicate how helpful they perceive them on a scale from 1 (not helpful at all) to 5 (extremely helpful). Findings reveal the following:

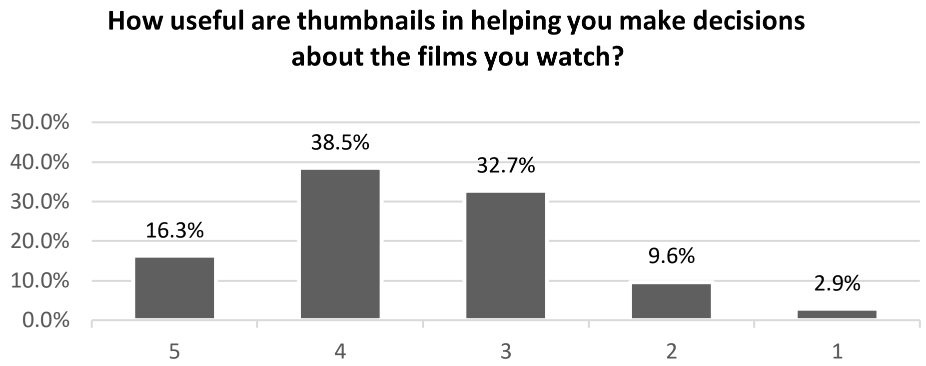

Figure 14: Question 8 – Results: Thumbnail Helpfulness

The data in Figure 14 reveals that the sample generally considers thumbnails helpful during their film selection. Being moderately left skewed, most respondents (38.5%) indicate that they perceive thumbnails as useful on level 4 and extremely helpful on level 5 (16.3%). In contrast, 12.5% of the participants find that cover images are not helpful while choosing a movie. The remaining survey respondents (32.7%) indicate on point 3 that thumbnails are a relatively neutral factor for helping their decision-making. With these findings in mind, it may be concluded that thumbnails have an overall impact on Netflix users during their movie choice.

To assess the statistical significance, the Spearman rank test will be conducted to find a relationship between the two categorical variables (Cresswell, 2014). The p-value will be examined between the likelihood of watching the movie based on the most attractive thumbnail (Q12, Q14, Q16, Q18, Q20) in regards to the respective genre (Q5).

Irreplaceable You – Romance

Correlation Matrix

		Q12	Q5
Q12_Thumbnail_Likelihood_To_Watch_IrreplaceableYou	Spearman's rho	—	
	p-value	—	
Q5_Genre_Likelihood_Romance	Spearman's rho	0.544 ***	—
	p-value	< .001	—

Note. * p < .05, ** p < .01, *** p < .001

Table 6: Hypothesis 1 Result – Spearman Rank (Romance)

Conducting the Spearman rank test, one may draw the conclusion that there is a significant correlation between film selection based on the thumbnails presented of the movie *Irreplaceable You* and users' genre preference as the p-value is below 0.001, which is smaller than the designated level as indicated in Table 6. Observing Spearman's rho, the value 0.544 denotes a moderate association between the constructs.

The Polka King – Comedy

Correlation Matrix

		Q5	Q14
Q5_Genre_Likelihood_Comedy	Spearman's rho	—	
	p-value	—	
Q14_Thumbnail_Likelihood_To_Watch_ThePolkaKing	Spearman's rho	0.090	—
	p-value	0.365	—

Note. * p < .05, ** p < .01, *** p < .001

Table 7: Hypothesis 1 Result – Spearman Rank (Comedy)

Next, in regards to the genre category *Comedy*, results of the non-parametric test show that the images displayed for the movie *The Polka King* have no significant effect on the users' final movie choice considering their genre preference as the p-value equals 0.365, which is greater than the alpha level. For this reason, Spearman's rho value of 0.090 needs not to be interpreted.

Extinction – Science Fiction

Correlation Matrix

		Q16	Q5
Q16_Thumbnail_Likelihood_To_Watch_Extinction	Spearman's rho	—	
	p-value	—	
Q5_Genre_Likelihood_ScienceFiction	Spearman's rho	0.370 ***	—
	p-value	< .001	—

Note. * p < .05, ** p < .01, *** p < .001

Table 8: Hypothesis 1 Result – Spearman Rank (Science Fiction)

Given that the p-value for the Spearman rank test is smaller than 0.001, as shown in Table 8, which is lower than the specified level, one may conclude that there is a significant correlation between the film choice based on thumbnails of the movie *Extinction* and users' genre preference. Furthermore, evaluating Spearman's rho for the strength of this relationship, it can be concluded that there is a weak association between the variables as the value amounts to 0.370.

The Perfection – Horror

Correlation Matrix

		Q5	Q18
Q5_Genre_Likelihood_Horror	Spearman's rho	—	
	p-value	—	
Q18_Thumbnail_Likelihood_To_Watch_ThePerfection	Spearman's rho	0.127	—
	p-value	0.200	—

Note. * p < .05, ** p < .01, *** p < .001

Table 9: Hypothesis 1 Result – Spearman Rank (Horror)

By using the non-parametric test, it can be concluded that there is no significant observation between the users' movie selection based on the most attractive thumbnail of *The Perfection* and their genre liking because the p-value, which is 0.200, is higher than the designated level, as shown in Table 9. Thus, Spearman's rho can be neglected for this interpretation.

The Longest Night – Thriller

Correlation Matrix

		Q20	Q5
Q20_Thumbnail_Likelihood_To_Watch_TheLongestNight	Spearman's rho	—	
	p-value	—	
Q5_Genre_Likelihood_Thriller	Spearman's rho	0.392 ***	—
	p-value	< .001	—

Note. * p < .05, ** p < .01, *** p < .001

Table 10: Hypothesis 1 Result – Spearman Rank (Thriller)

Last but not least, the genre thriller represented by the movie *The Longest* Night will be examined. As the p-value for the Spearman rank test is below 0.001, as shown in Table 10, which is lesser than the designated alpha level, it may be assumed that there is a significant correlation between the film choice based on the thumbnail's attractiveness and genre preference. Since Spearman's rho is 0.392, a weak relationship between the observed variables can be assumed.

In summary, for the sample in the thesis, hypothesis 1 is accepted for the genre categories *romance, science fiction, and thriller,* as there is a significant correlation between film choice based on the most attractive thumbnail and users' genre liking. Furthermore, the strength of this relationship can be assessed as weak to moderate. The null hypothesis fails to be rejected for *horror and comedy* due to insignificant findings. After having examined the relationship between film selection based on thumbnail attractiveness and genre liking, the next section will delve deeper into the differences in age groups.

4.2.2 Hypothesis 2

Hypothesis II : There is a significant association between age and selecting a film based on a thumbnail.

Table 11 depicts the result of the statistical test. Based on the Pearson chi-square, the value amounts to 0.028. As this is lower than the designated alpha level, the null hypothesis is rejected. Therefore, one may conclude that a significant correlation exists between age and users' final film selection.

Contingency Tables

	Q22_Final Film Selection Influence		
Q2_Age	Thumbnail	Other	Total
25+	10	27	37
18-24	33	34	67
Total	43	61	104

χ^2 Tests

	Value	df	p
χ^2	4.86	1	0.028
N	104		

Table 11: Influence of Thumbnails on different Age Groups

Moreover, Cramer's V indicates a strong association between the two categorical variables with a value of 0.22, as depicted in Table 12.

Nominal

	Value
Phi-coefficient	0.22
Cramer's V	0.22

Table 12: Hypothesis 2 – Cramer's V Results

Moving on, the chart below displays the percentage of the extent that cover images affected the respondents' final film choice for each age group respectively.

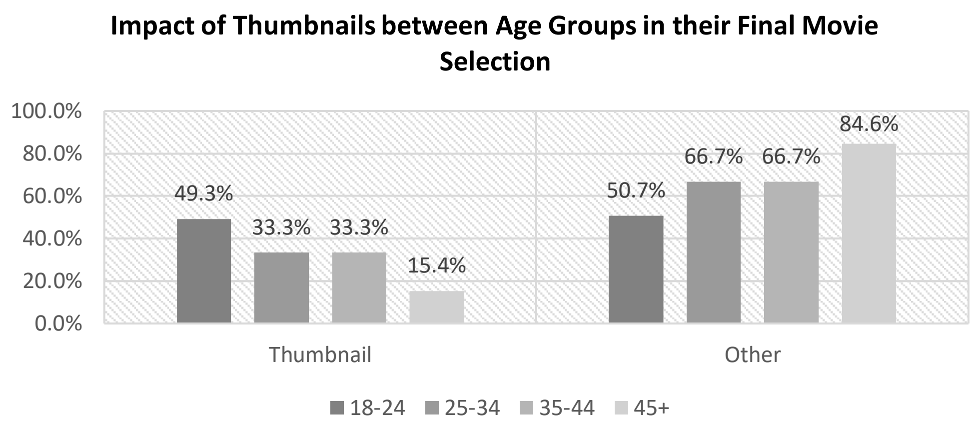

Figure 15: Influence of Thumbnails on different Age Groups (Chart)

In general, it may be concluded that other variables, as opposed to thumbnails, have a greater impact on users regardless of age. Nevertheless, if we compare the factors individually, thumbnails are the main influence for the age group *18-24* (count: 33) and in their movie choice, followed by genre (count: 13) and plot description (count: *18-24*: 12). Due to the small sample size, interpretation regarding the other age groups has to be drawn with caution because no distinctive result can be obtained. However, as per the responses, it may be argued that older generations *25+* are less incentivized to watch a movie based on images and prefer to orientate themselves per genre as well as a movie title. Overall, Figure 20 shows that thumbnails impacted 15.4% of the group *45+*, while other categories determined 84.6% of their choice. Furthermore, it has to be pointed out that the participants who stated that they are influenced by multiple factors all revealed that thumbnails were one of their determining variables.

4.2.3 Hypothesis 3

Hypothesis III : A statistical significance exists between genders with regard to the selection of films based on thumbnails.

The thesis continues to explore a significant association between gender and the selection of movies on Netflix based on thumbnails. On the basis of the Pearson chi-square test, which was conducted for this hypothesis, there is a significant result as the p-value amounts to 0.013. This is lower than the designated alpha level, and thus, the null hypothesis may be rejected.

Contingency Tables

	Q1_Gender		
Q22_Final Film Selection Influence	**Female**	**Male**	**Total**
Thumbnail	36	7	43
Genre	12	11	23
Movie title	9	1	10
Plot Description	8	10	18
Combination	4	2	6
Other	2	1	3
Total	71	32	103

χ^2 Tests

	Value	df	p
χ^2	14.5	5	0.013
N	103		

Table 13: Influence of Thumbnails on different Genders

To evaluate the strength of the relationship, Cramer's V can be analyzed. As depicted in Table 14, the value is 0.376, which is said to be a very strong association (Akoglu, 2018).

Nominal	
	Value
Phi-coefficient	NaN
Cramer's V	0.376

Table 14: Hypothesis 3 – Cramer's V Results

Next, Figure 21 illustrates how thumbnails impacted the participants' final movie selection for each male and female, respectively, compared to other variables such as movie title, plot description, or genre. As the sample in terms of gender is not distributed equally, results have to be interpreted carefully. Moreover, as there was only one case where a respondent did not want to reveal their gender "*Prefer not to say*", this result will also not be considered in the visualization.

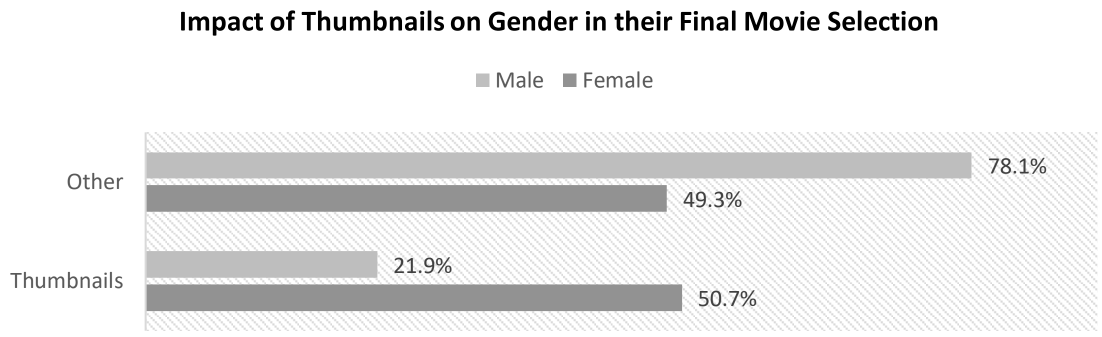

Figure 16: Influence of Thumbnails on different Genders (Chart)

The chart above reveals that females (50.7%) were more likely to be affected by thumbnails than males (49.3%). Genre and the movie title are the subsequent variables that influence female film decisions. With respect to males, the highest determinant was the genre, followed by plot description and, eventually, thumbnails.

4.2.4 Hypothesis 4

Hypothesis IV : There is a significant difference between the impact of thumbnails, plot descriptions, and movie titles in film choice.

The following Tables depict the results of the Wilcoxon rank test for each genre and corresponding film.

Irreplaceable You – Romance

In terms of the category romance, no significant difference in the influence between the observed variables is retrieved as the p-values are above the designated alpha level of 0.05.

Paired Samples T-Test

			Statistic	p
Q12_Thumbnail_Likelihood_To_Watch_IrreplaceableYou	Q6_Title_Likelihood_IrreplaceableYou	Wilcoxon W	945 [a]	0.321
	Q7_Plot_Description_IrreplaceableYou	Wilcoxon W	608 [b]	0.169
Q7_Plot_Description_IrreplaceableYou	Q6_Title_Likelihood_IrreplaceableYou	Wilcoxon W	764 [d]	0.771

Note. H_a $\mu_{\text{Measure 1 - Measure 2}} \neq 0$

[a] 47 pair(s) of values were tied

[b] 60 pair(s) of values were tied

[d] 48 pair(s) of values were tied

Table 15: Hypothesis 4 – Wilcoxon Rank Test Results (Romance)

The Polka King – Comedy

Looking at the genre comedy, results are significant between thumbnail and title as well as plot description and title. With this in mind, it may be assumed that there is a difference in the impact of the compared factors.

Paired Samples T-Test

			Statistic	p
Q13_Thumbnail_Likelihood_To_Watch_ThePolkaKing	Q6_Title_Likelihood_ThePolkaKing	Wilcoxon W	1590 [a]	< .001
	Q7_Plot_Description_ThePolkaKing	Wilcoxon W	1142 [b]	0.084
Q7_Plot_Description_ThePolkaKing	Q6_Title_Likelihood_ThePolkaKing	Wilcoxon W	2126 [d]	< .001

Note. H_a $\mu_{\text{Measure 1 - Measure 2}} \neq 0$

[a] 42 pair(s) of values were tied

[b] 28 pair(s) of values were tied

[d] 35 pair(s) of values were tied

Table 16: Hypothesis 4 – Wilcoxon Rank Test Results (Comedy)

Extinction – Science Fiction

For science fiction, the outcome shows a significant difference in the impact of thumbnail and plot as well as plot and title, as the p-value is below 0.05.

Paired Samples T-Test

			Statistic	p
Q15_Thumbnail_Likelihood_To_Watch_Extinction	Q6_Title_Likelihood_Extinction	Wilcoxon W	791 [a]	0.062
	Q7_Plot_Description_Extinction	Wilcoxon W	1421 [b]	< .001
Q7_Plot_Description_Extinction	Q6_Title_Likelihood_Extinction	Wilcoxon W	428 [b]	< .001

Note. H_a $\mu_{\text{Measure 1 - Measure 2}} \neq 0$
[a] 55 pair(s) of values were tied
[b] 47 pair(s) of values were tied

Table 17: Hypothesis 4 – Wilcoxon Rank Test Results (Science Fiction)

The Perfection – Horror

Results for the correlation with thumbnails indicate a p-value above 0.05. For this reason, the null hypothesis fails to be rejected for *horror*. However, a significant result can be observed between the plot description and title, as the value 0.047 is lower than the alpha level. Thus, the null hypothesis may be rejected in this case.

Paired Samples T-Test

			Statistic	p
Q17_Thumbnail_Likelihood_To_Watch_ThePerfection	Q6_Title_Likelihood_ThePerfection	Wilcoxon W	725 [a]	0.401
	Q7_Plot_Description_ThePerfection	Wilcoxon W	930 [a]	0.388
Q7_Plot_Description_ThePerfection	Q6_Title_Likelihood_ThePerfection	Wilcoxon W	442 [b]	0.047

Note. H_a $\mu_{\text{Measure 1 - Measure 2}} \neq 0$
[a] 47 pair(s) of values were tied
[b] 54 pair(s) of values were tied

Table 18: Hypothesis 4 – Wilcoxon Rank Test Results (Horror)

The Longest Night – Thriller

Lastly, in regards to the genre thriller, a significant result can be observed between plot description and thumbnails, as seen in Table 19.

Paired Samples T-Test

			Statistic	p
Q20_Thumbnail_Likelihood_To_Watch_TheLongestNight	Q6_Title_Likelihood_TheLongestNight	Wilcoxon W	1402 [a]	0.084
	Q7_Plot_Description_TheLongestNight	Wilcoxon W	1078 [b]	< .001
Q7_Plot_Description_TheLongestNight	Q6_Title_Likelihood_TheLongestNight	Wilcoxon W	981 [d]	0.223

Note. H_a $\mu_{\text{Measure 1 - Measure 2}} \neq 0$

[a] 37 pair(s) of values were tied

[b] 51 pair(s) of values were tied

[d] 36 pair(s) of values were tied

Table 19: Hypothesis 4 – Wilcoxon Rank Test Results (Thriller)

All in all, results show that there is a significant difference between the impact of thumbnails and plot descriptions or movie titles for the genres *science fiction, comedy, and thriller*. In addition, there was only one obtained case where the thumbnail and title significantly differed. This may be due to the fact that the movie's title is usually combined with the thumbnail in the natural environment. In contrast, there have been three significant results for the movie title and plot description.

Last but not least, Figure 22 displays the relative impact of the contributing factors concerning the respondents' final film choice. It underlines the findings from Chapter 2.4.1, where the authors found that thumbnails are the primary influence of movie selection among Generation Z. Since the majority of the sample in this study are participants between the ages 18-24, this assumption may be proved because with 41.3% thumbnails were selected as the critical variable that made them choose the respective film. The factors that followed are genre (22.1%) and plot description (18.3%). In terms of "Other", there are five cases in which survey participants stated that they selected a film based on a *combination of factors*, where thumbnails were always included in their response, such as thumbnails and movie titles or thumbnails and plot descriptions. In addition, as discussed in Section 2.3.2, cover images usually incorporate the title with the thumbnail (a combination. However, due to the scope of the thesis, testing of the subject matter was simplified (Netflix Technology Blog, 2016). That being said, it can be assumed that thumbnails ultimately have an influence on users' choices, but in a natural setting, individuals may still take into account other aspects.

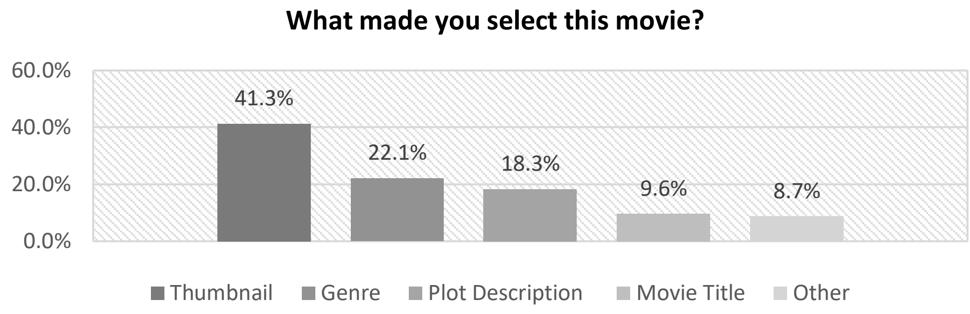

Figure 17: Final Movie Selection Determinants (Total Sample)

4.2.5 Hypothesis 5

Hypothesis V : A significant relationship exists between users' genre preference and the selection of genre-based thumbnails.

The following hypothesis deals with the extent to which *tailored* thumbnails influence users' choices. As discussed, the influence of representing variable "thumbnails' attractiveness" based on the consumers' genre is investigated.

Irreplaceable You – Romances

Contingency Tables

	Q11_Thumbnail_Selection_IrreplaceableYou		
Q5_Genre_Likelihood_Romance	**Genre–Based Thumbnail**	**Other Thumbnail Category**	**Total**
Unlikely	7	37	44
Likely	14	46	60
Total	21	83	104

χ^2 Tests

	Value	df	p
χ^2	0.87	1	0.351
N	104		

Table 20: Hypothesis 5 – Pearson chi-square Results (Romance)

As seen in Table 20, no significant result was observed. Participants were more likely to select another thumbnail category other than the image, which aimed to represent *romance* the most.

The Polka King – Comedy

Contingency Tables

	Q13_Thumbnail_Selection_ThePolkaKing		
Q5_Genre_Likelihood_Comedy	Genre–Based Thumbnail	Other Thumbnail Category	Total
Unlikely	4	21	25
Likely	16	63	79
Total	20	84	104

χ^2 Tests

	Value	df	p
χ^2	0.22	1	0.638
N	104		

Table 21: Hypothesis 5 – Pearson chi-square Results (Comedy)

Observing the group comedy, there is also no significant result obtained.

Extinction – Science Fiction

Contingency Tables

	Q15_Thumbnail_Selection_Extinction		
Q5_Genre_Likelihood_ScienceFiction	Genre–Based Thumbnail	Other Thumbnail Category	Total
Unlikely	6	46	52
Likely	14	38	52
Total	20	84	104

χ^2 Tests

	Value	df	p
χ^2	3.96	1	0.047
N	104		

Table 22: Hypothesis 5 – Pearson chi-square Results (Science Fiction)

With an outcome of 0.047, the p-value indicates a significant relationship between the selection of the thumbnails and the likelihood of watching the respective genre. The value of Cramer's V is 0.20, indicating a strong association. Most survey respondents were likely to select a thumbnail other than the image aiming to represent the genre the most.

The Perfection – Horror

Contingency Tables

	Q17_Thumbnail_Selection_ThePerfection		
Q5_Genre_Likelihood_Horror	Genre–Based Thumbnail	Other Thumbnail Category	Total
Unlikely	10	76	86
Likely	6	12	18
Total	16	88	104

χ^2 Tests

	Value	df	p
χ^2	5.39	1	0.020
N	104		

Table 23: Hypothesis 5 – Pearson chi-square Results (Horror)

The p-value for horror reveals a significant result as it is lower than the designated alpha level. Having said that, a significant correlation can be observed between participants' genre liking and their selection of thumbnails. Table 23 indicates that the majority who are unlikely to watch horror were more likely to select an image that does not represent the film's genre. Moreover, Cramer's V amounts to 0.23, which denotes a strong relationship between the variables under investigation.

The Longest Night – Thriller

Contingency Tables

	Q19_Thumbnail_Selection_TheLongestNight		
Q5_Genre_Likelihood_Thriller	Genre–Based Thumbnail	Other Thumbnail Category	Total
Unlikely	15	36	51
Likely	20	33	53
Total	35	69	104

χ^2 Tests

	Value	df	p
χ^2	0.81	1	0.369
N	104		

Table 24: Hypothesis 5 – Pearson chi-square Results (Thriller)

Finally, no significant association was observed between the thumbnail selection of The Longest Night and the genre preference of thriller.

Concluding that one may draw the conclusion that there is a significant relationship between the selection of genre-based thumbnails and the likelihood of watching the movie for *horror* and *science fiction*. The null hypothesis fails to be rejected for the remaining genre categories.

4.2.6 Sub-question VI

RQ VI : To what extent does a movie's failure to meet the expectations set by its thumbnail image influence viewers' likelihood to continue watching the movie?

The last research question of the thesis highlights the importance of thumbnails once more. Respondents to the online-questionnaire were asked to select the likelihood of them proceeding to view a film even though the previously presented thumbnail did not match the content's expectations, such as genre or plot. Results reveal that the majority of participants (50.9%) would be *unlikely* to *extremely unlikely* continue with the film if anticipated differently as per the thumbnail.

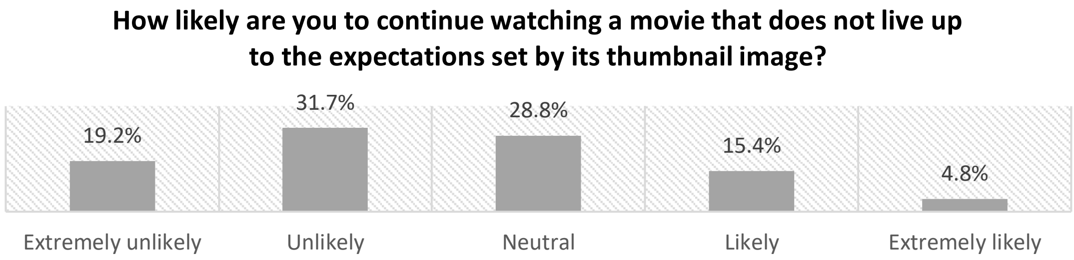

Figure 18: Thumbnail Perception and the Likelihood to Continue Watching

4.3 Hypotheses' Results Table Summary

Hypothesis	**Genre** (if applicable)	**P-Value**	**Hypothesis**
H1: The degree of genre preference has an impact on the likelihood of watching a movie based on the most attractive thumbnail.	Romance	< 0.001	Accepted
	Comedy	0.365	Rejected
	Science Fiction	< 0.001	Accepted
	Horror	0.200	Rejected
	Thriller	< 0.001	Accepted
H2: There is a significant association between age and selecting a film based on a thumbnail.		0.028	Accepted
H3: A statistical significance exists between genders with regard to the selection of films based on thumbnails..		0.013	Accepted
H4: There is a significant difference between the impact of thumbnails, plot descriptions, and movie titles in film choice. [1]Thumbnail + Title [2]Thumbnail + Plot [3]Plot Description + Title	Romance	[1] 0.321	Rejected
		[2] 0.169	Rejected
		[3] 0.771	Rejected
	Comedy	[1] < 0.001	Accepted
		[2] 0.084	Rejected
		[3] < 0.001	Accepted
	Science Fiction	[1] 0.062	Rejected
		[2] < 0.001	Accepted
		[3] < 0.001	Accepted
	Horror	[1] 0.401	Rejected
		[2] 0.388	Rejected
		[3] 0.047	Accepted
	Thriller	[1] 0.084	Rejected
		[2] < 0.001	Accepted
		[3] 0.223	Rejected
H5: A significant relationship exists between users' genre preference and the selection of genre-based thumbnails.	Romance	0.351	Rejected
	Comedy	0.638	Rejected
	Science Fiction	0.047	Accepted
	Horror	0.020	Accepted
	Thriller	0.369	Rejected

Table 25: Hypotheses' Results Table Summary

5 CONCLUSION

Several peer-reviewed journal articles indicate that renowned companies use machine learning systems to tailor their content to users efficiently. In particular, Netflix is recognized for implementing its personalization systems successfully and encouraging its users to remain on its streaming platform. With this in mind, the thesis' purpose is to complement existing research and explicitly find evidence on how tailored thumbnails, measured by thumbnail attractiveness, influence users' film selection on Netflix with respect to their genre preference.

Recommendation systems aid in solving the problem of the *paradox of choice* as well as *analysis paralysis* by suggesting personalized content that may raise user interest based on their preferences. Furthermore, appealing thumbnails may rapidly capture their attention and create curiosity in the film, prompting them to make a fast decision. Nevertheless, one should be aware of the *consumption bubble* as users may show interest in watching content outside of their usual preferences. With personalization systems, these films usually may not be listed.

To address the established research questions, an online-questionnaire collected relevant data from a convenience sample of 104. Overall, statistical tests reveal that a significant relationship between movie choice based on thumbnails and users' genre preference exists for *romance, science fiction, and thriller*. Answering research question II, the extent to which there is a significant difference in age and the determining factors of movie selection is strong. Generation Z is more likely to be impacted by thumbnails than individuals over the age of 25. Furthermore, regarding gender, there is a very strong association between the variable and the contributing factors of film choice. The majority of female participants were more likely to be impacted by thumbnails than males, whose most significant influence was the genre in regard to their film choice. Moreover, thumbnails significantly influenced survey participants for the genre categories *comedy, science fiction,* and *thriller* compared to their plot description or movie title. Lastly, the selection of the type of thumbnails is significantly correlated to the users' genre preference for the group *horror* and *science fiction*. All in all, a pattern may be found for *science fiction* as significant results are discovered for all observations, except the test between thumbnail and movie title.

Future studies which include a more representative sample may be relevant to investigate the impact of thumbnails on different target groups such as age and gender. To take this research further, it would be interesting to analyze how tailored plot descriptions and various prompts may influence different users. Moreover, due to the scope of the present thesis, confounding variables have not been explored in greater detail and may be vital for investigating the causal factors of film choice. In addition, further research may be necessary for the visual elements comprising a thumbnail and how they influence film choice. In the present thesis, analysis was simplified and, thus, limited to thumbnails based on genre, characters, scenes, objects, and landscape. Lastly, future research may focus on the potential of tailored images across various domains. By implication, placing personalized content in sectors such as fashion, fitness, and products on Amazon or music album covers on Spotify may be an effective approach to enhance user engagement.

The key takeaway from this research is that recommender systems play a crucial role in users' behavioral intent, whose effects may extend beyond video-on-demand services such as Netflix. Understanding consumer preferences is essential in building efficient visual aids to attract and maintain viewers across various channels. The success of Netflix's machine learning, which curates tailored thumbnails for its users, showcases the effectiveness of this approach. Thus, given the benefits, it would be worthwhile for not only video-streaming companies but also other industries to explore as well as expand upon this strategy.

"If the Starbucks secret is a smile when you get your latte... ours is that the Web site adapts to the individual's taste."

Reed Hastings, Co-Founder of Netflix

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7 APPENDIX: SURVEY QUESTIONS

Introduction

Bachelor Thesis Questionnaire Research : Netflix's Recommender Systems

Dear Participants,

I am Emily Brunner, a bachelor's student in international management at Modul University Vienna. As part of my thesis, I am exploring the influence of Netflix's recommender systems. I kindly invite you to take part in my survey, which will take approximately 10 minutes and consists of 23 multiple-choice-questions.

Participating in this survey is completely voluntary and confidential. Your contribution will have a significant impact on my thesis and I am grateful for your time and support.

If you have any inquiries regarding the questionnaire, please do not hesitate to contact me via the following email address: 61904136@modul.ac.at.

Best regards,
Emily Brunner

Question 1

What gender do you identify as? *

- Male
- Female
- Prefer not to say
- Other...

Question 2

What is your age? *

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 +

Question 3

I watch movies on Netflix. *

- Never
- Rarely
- Occasionally
- Regularly
- Very often

Question 4

In your opinion, which of the following factors has the greatest influence on your decision to select a movie to watch online? *

- Genre
- Thumbnail
- Movie title
- Plot description
- Other...

Question 5

Please indicate how likely you are to watch the following movie genres. *

	Extremely unli...	Unlikely	Neutral	Likely	Extremely likely
Romance	○	○	○	○	○
Comedy	○	○	○	○	○
Science-Fiction	○	○	○	○	○
Horror	○	○	○	○	○
Thriller	○	○	○	○	○

Question 6

Please indicate your level of likelihood to watch the following movies, as indicated by the film's title provided. *

	Extremely unli...	Unlikely	Neutral	Likely	Extremely likely
Irreplaceable Y...	○	○	○	○	○
The Polka King	○	○	○	○	○
Extinction	○	○	○	○	○
The Perfection	○	○	○	○	○
The Longest N...	○	○	○	○	○

Question 7

Please indicate your level of likelihood to watch the following movies, as indicated by the plot description provided. *

	Extremely unli...	Unlikely	Neutral	Likely	Extremely Like...
A stunning ca...	○	○	○	○	○
Determined to...	○	○	○	○	○
Plagued by dr...	○	○	○	○	○
Armed forces ...	○	○	○	○	○
A once-promis...	○	○	○	○	○

Question 8

How useful are thumbnails in helping you make decisions about the films you watch? *

	1	2	3	4	5	
Not helpful at all	○	○	○	○	○	Extremely helpful

Question 9

How often do you select a movie to watch online based on the attractiveness of its thumbnail image? *

- ○ Always
- ○ Often
- ○ Sometimes
- ○ Rarely
- ○ Never

Question 10

How likely are you to continue watching a movie that does not live up to the expectations set * by its thumbnail image?

	1	2	3	4	5	
very unlikely	○	○	○	○	○	very likely

Question 11

Which thumbnail do you find the most visually appealing? *

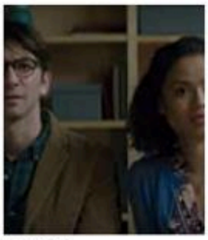
Image 1


Image 2

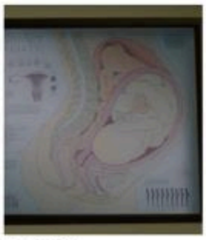
Image 3

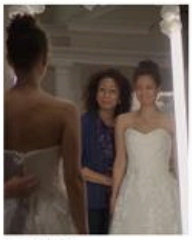
Image 4

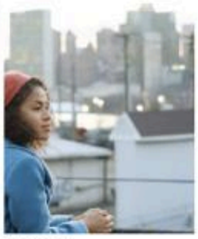
Image 5

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Question 12

Based on the image you selected above as the most visually appealing, how likely are you to * watch the film?

	1	2	3	4	5	
very unlikely	○	○	○	○	○	very likely

Question 13

Which thumbnail do you find the most visually appealing? *

Image 1 Image 2 Image 3 Image 4 Image 5

○ 1

○ 2

○ 3

○ 4

○ 5

Question 14

Based on the image you selected above as the most visually appealing, how likely are you to watch the film? *

	1	2	3	4	5	
very unlikely	○	○	○	○	○	very likely

Question 15

Which thumbnail do you find the most visually appealing? *

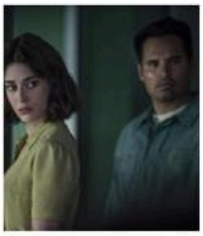
Image 1


Image 2


Image 3


Image 4

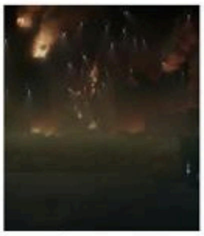
Image 5

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Question 16

Based on the image you selected above as the most visually appealing, how likely are you to watch the film? *

	1	2	3	4	5	
very unlikely	○	○	○	○	○	very likely

Question 17

Which thumbnail do you find the most visually appealing? *


Image 1


Image 2


Image 3


Image 4


Image 5

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Question 18

Based on the image you selected above as the most visually appealing, how likely are you to watch the film? *

	1	2	3	4	5	
very unlikely	○	○	○	○	○	very likely

Question 19

Which thumbnail do you find the most visually appealing? *


Image 1

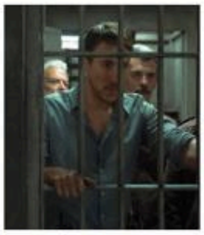
Image 2


Image 3

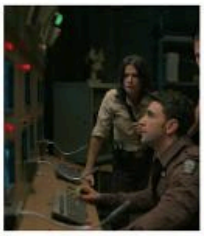
Image 4


Image 5

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

Question 20

Based on the image you selected above as the most visually appealing, how likely are you to watch the film? *

	1	2	3	4	5	
very unlikely	○	○	○	○	○	very likely

Question 21

Which of the following movies would you watch most likely? Please select. *

◯ The Polka King

◯ Extinction

◯ The Perfection

◯ The Longest Night

◯ Irreplaceable You

Question 22

What made you select this movie? *

- ◯ Genre
- ◯ Thumbnail
- ◯ Movie title
- ◯ Plot Description
- ◯ Other...

Question 23

Have you already watched any of the specified films? Kindly indicate your response by selecting the appropriate option if applicable.

- ☐ Irreplaceable You
- ☐ The Longest Night
- ☐ The Perfection
- ☐ Extinction
- ☐ The Polka King

The End

Thank you for taking the time to complete this survey !

Your input is greatly appreciated and will play a crucial role in the success of my bachelor thesis. Your answers will be kept confidential and used solely for the purpose of the research.