DISSERTATION PROJECT

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Table of Contents

Chapter 1: Background Research

1.1 Research title

"Enhancing User Experience Through AI (Artificial Intelligence)-Driven Personalised Recommendations in Streaming Services: A Comparative Study of Machine Learning Algorithms"

1.2 Research aim

The rise of streaming platforms like Disney+, Hulu, and Prime Video in the last five years has intensified competition in the industry. Between 2020 and 2023, Netflix, the first major subscription-based streaming platform to gain widespread popularity has lost 13% of its streaming VOD (Video on demand) market share to these competitors, as newer platforms like Disney+ have gained 8% market share and HBO Max also nearing the 10% mark (Demers, 2023). These platforms are attracting users from established services like Netflix, which introduced its streaming service in 2007 and quickly became the leading subscription-based platform. The loss in subscribers can be partly attributed to the rapid increase in subscription fees, platforms such as Disney+ reclaiming their own content and restricting its availability on Netflix, and the growing fragmentation of content across multiple platforms like Apple TV+, Paramount+, Hulu and Disney+ (Jaeger & Grant, 2023). For instance, in February 2025, Netflix increased its UK Standard plan (without adverts) from £10.99 to £12.99 per month, marking an 18% rise. The Premium plan also saw a £1 increase, bringing it to £18.99 per month (Wood, 2025). Additionally, competing platforms are leveraging new technologies to enhance user experience, such as Amazon Prime Video's X-Ray, an AI-powered feature that provides viewers with additional information and recommendations while watching content (Psyduct, 2024).

According to Netflix's Chief Product Officer, Netflix attributes 80% of the subscribers' video choices to its AI driven recommendations, and in 2016 Netflix claimed their recommendations and personalisation saves more than $1 billion per year (McAlone, 2016). This emphasises the importance of AI in shaping user preferences and increasing engagement, not only in Netflix but across a range of streaming platforms such as Spotify and YouTube, where personalised content delivery plays a key role in user retention (Mehrotra et al., 2018).

This study aims to explore and compare the effectiveness of AI-driven recommendation techniques—collaborative filtering, deep learning, and content-based filtering—across streaming platforms like Netflix, Spotify, and YouTube. It also investigates how Natural Language Processing (NLP) enhances personalisation by interpreting metadata to improve user engagement, satisfaction, and retention.

1.3 Research objectives

- Investigate the role of AI in enhancing streaming service recommendations (e.g., Netflix, Spotify).
- Compare various machine learning algorithms for personalised recommendations, focusing on collaborative filtering, deep learning, and content-based filtering.
- Assess the Impact of Personalisation on User Engagement and Satisfaction, examining content consumption patterns.
- Assess the impact of NLP in content categorisation and recommendation.

1.4 Research Hypothesis

- AI-driven personalised recommendations significantly enhance user engagement and satisfaction compared to non-personalised or generic recommendation systems in streaming services.
- The integration of NLP in AI-driven recommendation systems significantly improves the accuracy of recommendations by effectively categorising and interpreting textual metadata.
- AI-driven personalised recommendations lead to higher user engagement, measured by increased watch time and reduced churn rates, compared to non-personalised recommendations.

1.5 Justification of the study

Despite the importance of personalised recommendations in streaming services being well documented, few studies compare the effectiveness and relevance of different AI across different platforms.

This study aims to explore the recommendation techniques used in streaming platforms like Netflix, Spotify, and YouTube, with a particular focus on how AI-driven personalisation enhances user experience, satisfaction, and retention. It will evaluate the effectiveness of AI-

powered approaches such as collaborative filtering, deep learning, and content-based filtering in predicting user preferences (Laiche et al., 2020), while addressing the gap in comparative research on how these techniques perform across different platforms.

Furthermore, the study will examine how personalised recommendations generated by AI influence user engagement and content consumption patterns, offering insights into which methods are most impactful. A specific focus will be placed on the role of Natural Language Processing (NLP) in interpreting metadata—such as descriptions, genres, and user reviews—to improve the precision of recommendations and boost user engagement in an increasingly competitive digital landscape (Malhotra, 2023).

By analysing these approaches comparatively, the study aims to provide valuable insights for optimising AI-driven personalisation strategies within the streaming industry.

1.6 Background on AI in Streaming Services

AI has increased personalisation from user to user in digital streaming platforms by analysing user interactions and enabling customised content recommendations (Matuszewska, 2023).

1.6.1 Early Recommendation systems

Initially, streaming services would employ the use of rule-based systems, which would recommend content based on predefined categories (e.g., comedy, horror, action). These systems would provide generic recommendations which are lacking personalisation, adaptability, and relevance to the user (Restackio, 2025).

1.6.2 Collaborative filtering

Collaborative filtering, one of the earliest ML techniques for recommendation systems, analyses user behaviour to suggest content based on similarities with other users' interests (Li & Hong, 2025).

1.6.3 Content-based filtering

Content based filtering recommends items based on the attributes of the content, this could be genre, descriptions or actors. This approach will help the platform create a profile of the user by analysing previously consumed items, with an aim to recommend similar items (Franco et al., 2023).

1.6.4 Deep learning

Deep learning has revolutionised recommendation systems by allowing for the use of larger datasets and by discovering complex patterns and delivering personalised suggestions (McDonald, 2021). Deep learning utilises artificial neural networks, this allows the technology to mimic the human brain to refine recommendation systems (Abdoullaev, 2023).

1.6.5 Hybrid approaches

Hybrid Systems have been integrated in recent years to deep learning models to enhance recommendations.
 Industry leaders, Netflix, employs a hybrid approach by combining collaborative filtering, content based filtering, and deep learning with an aim to generate precise appropriate content for its users. YouTube leverages deep learning for real time recommendations by analysing website searches, engagement patterns, and watch history (Ming et al., 2021).

1.7 Conclusion

This chapter has outlined the context and rationale behind investigating AI-driven personalised recommendation systems used in streaming services. The growing competition between such platforms has intensified the need for personalisation strategies to keep users. This can be seen by the projected market size of AI-driven recommendation systems, which is expected to reach $3.62 billion by 2029, with a compound annual growth rate of 10.3% (Guridham, 2025). This growth shows the increasing reliance on AI to further user engagement, retention and to be competitive with other streaming services.

Chapter 2: Literature Review

2.1 Introduction

The emergence of AI-driven personalised recommendations has revolutionised how streaming platforms deliver content to their users. These recommendations tailor content suggestions to individual preferences to enhance the user experience (Durani, 2023). AI has since become central in the transformation of streaming; the technology gathers and analyses user data to contextually provide accurate recommendations. It harnesses viewing history, click-through rate (CTR), ratings, time spent on content to curate a more immersive and engaging content discovery experience (Stoyko, 2023). These personalised recommendations have a direct correlation with increased user retention, session duration, and reduced churn rates (Mehta, 2023). This finding is supported by PwC's 2023 Global Consumer Insights Pulse Survey, which observed that consumers who engage with personalised platforms are significantly more loyal and report higher satisfaction levels (PwC, 2023). According to an article by WIRED (2017),. Similarly, YouTube reports that 70% of its watch time stems from algorithm-driven suggestions (Macready and Stanton, 2025), and Spotify's Discover Weekly data showed that over half of users saved at least one song per week to their own playlists, which can attribute success to the algorithms ability to recommend appropriate content (Mudaliyar, 2024). Recent advancements in AI, such as hybrid recommendation systems that combine multiple techniques such as collaborative filtering and deep learning, have further improved recommendation accuracy and engagement (Sabiri et al., 2025). This literature review will discuss AI-driven techniques for recommending such as collaborative filtering, deep learning, and NLP's effectiveness whilst also addressing challenges such as data privacy, scalability, and algorithmic bias.

2.2 Collaborative Filtering

2.2.1 Definition and Methodology

Collaborative filtering (CF) is a widely used recommendation technique based on similarities between users or items (user-based or item-based) (Murel Ph.D. & Kavlakoglu, 2024). Collaborative filtering predicts user preferences by identifying similarities between users or items. It is widely used by streaming platforms like Netflix and Spotify to recommend content based on user behaviour and item similarities (Liu et al., 2020).

For instance, Spotify's Discover Weekly, which partially relies on collaborative filtering, has demonstrated high levels of engagement—over half of its users save at least one recommended song per week (Mudaliyar, 2024).

2.2.2 Strengths and Limitations

CF focuses on user-item interactions, relying on ratings, clicks, and user preferences. It helps identify less popular items preferred by similar users, enhancing personalisation (Koren & Bell, 2021).

CF is scalable and effective, especially for identifying less popular items (Krysik, 2024). However, it struggles with cold-start issues and sparsity, where insufficient data makes recommendations difficult for new users or items (Zhao, 2016).

Cold-start issues occur when there is insufficient user or item data at the beginning of the recommendation process, due to the nature of CF relying on past interactions, this lack of data makes it harder for the technology to provide accurate recommendations, especially for new users or items with limited information (Malshe, 2019).

Sparsity, which is another key issue with the employment of CF, refers to the fact that most users will interact with only a fraction of total items available on a platform. Spotify, for example has a library of over 100 million songs (Spotify, 2024), users only listen to a small portion of this catalogue.

CF algorithms often reinforce popularity bias, this leads to the reinforcement of already popular items, hence limiting exposure to diverse content, this phenomenon is referred to as an echo chamber (Rimaz et al., 2019). Further evidence is provided by Krishnamurthy and Mukherjee (2024), who argue that a lack of diversity in algorithmic recommendations can lead to user disengagement and strengthen echo chambers.

2.3 Deep Learning

2.3.1 Deep Learning in Recommendations in Streaming Services

"Deep learning, a subset of machine learning, is particularly effective in analysing large datasets to predict user behaviour. NLP allows AI to analyse user-generated text, improving content recommendations. Despite its power, NLP faces challenges like language ambiguity and high computational costs (Shah et al., 2024).

2.3.2 Challenges and Limitations

Deep learning models require significant computing power, making them challenging for smaller organisations to implement (Batmaz et al., 2018).

Similar to collaborative filtering, ML can cause overfitting, this is when the technology can struggle to recommend items to new users due to their preferences evolving more than a long-term user, it can also be caused by being too complex (IBM, 2024).

While deep learning can enhance recommendation accuracy, it's lack of transparency of how the model makes its decisions is not easily understood, which can be a problem for users who want to understand or trust the system, research indicates that integrating explainability techniques into deep learning models improves precision and transparency, which enhances user trust (Govea, Gutierrez and Villegas-Ch, 2024). Perri (2023) reinforces this by stating that over two thirds of users are more inclined to trust AI systems when they are provided with clear and explainable recommendations.

2.4 Natural Language Processing (NLP)

2.4.1 Role of NLP in Recommendation Systems

NLP is a type of AI which allows computers to decipher, process and to manipulate human language. This involves deep learning, ML, and other techniques to analyse written and spoken language. These methods allow the technology to interpret meaning, recognise patters and summarise text or speech (Brooks, 2023).

NLP helps analyse user-generated comments such as reviews, comments, and searches. This is done by leveraging sentiment analysis which defined as, tone of words, to detect consumer opinion on content, entity recognition which is the extraction of names, locations, or brands from text (Stryker and Holdsworth, 2024). NLP also utilises intent detection which classifies a user input based on what the technology perceives the consumer wants to achieve (Marshall, 2020).

2.4.2 Techniques and Models

Training large models like BERT (Bidirectional Encoder Representations from Transformers) and GPT-3 requires substantial computational resources, making them expensive to implement (Shah et al., 2024).

GPT (Generative Pre-trained Transformer) models which allow for effective

analysing of data such as song lyrics or user reviews to determine song mood or genre (Zhang et al., 2023).

2.4.3 Benefits and Challenges

NLP can analyse video and audio content, it analyses dialogue, lyrics, and descriptions with an aim to extract themes and topics (Success Team, 2023). This allows for more accurate content categorisation and recommendation.

The technology can gauge audience reaction to content, which can help platforms make informed decisions on content production and title purchasing (Munz and Gomez-Perez, 2022).

Despite NLP being able to decipher the intention of phrases and sentences, it can be negatively affected by natural language ambiguity, this refers to words and sentences that have different meanings or interpretations, such as bark which could be a dog noise or tree bark (Moveworks, 2024).

Rimaz et al. (2019) states that a major limitation lies in detection of sarcasm and irony, which can lead to misinterpretations in sentiment analysis, this is because NLP often misclassifies sarcastic content, which affects the accuracy of sentiment-based recommendations. This is corroborated by Getahun (2024) who states that OpenAI is actively developing sarcasm detection tools, this underlines how misinterpretation in sentiment analysis remains a challenge with AI-driven recommendation systems.

NLP struggles with multilingual nuances due to data scarcity and cultural references, leading to misinterpretations (Rimaz et al., 2019).

Another drawback of NLP is the computational resources required. Due to the number of parameters the technologies must compute, these technologies can be expensive. BERT's base model has 110 million parameters, according to GeeksforGeeks (2024) the recommended GPU model for computing data is the Nvidia Tesla V100 which retails for £2,401.20 (Intelligent Servers, 2024). GPT-3, which is a more complex model includes 175 billion different parameters which would cost $4.6 million to train on the most affordable GPU cloud option (Li, 2020).

High costs and data sparsity make these technologies challenging to implement, overlapping with CF's 'cold start' problem (Van Otten, 2024; Zhao, 2016).

2.5 Hybrid Recommendation Systems

2.5.1 Overview and Methodology

Hybrid recommendation systems employ multiple AI techniques to improve the relevance and accuracy of recommendations. These systems combine collaborative filtering, deep learning, and NLP to enhance user experiences. Hybrid approaches allow streaming services to refine recommendations by using both structured and unstructured data, including metadata, reviews, and user engagement analytics. CF, which primarily relies on structured data (IBM, 2025), NLP, which processes unstructured data (Gubitosa, 2024), and deep learning, which utilises both structured and unstructured data (Jurek-Loughrey, 2021), work together to create a more personalised recommendation system. The amalgamation of these techniques allows hybrid models to overcome the limitations of the individual techniques, resulting in more precise and adaptive recommendations. Netflix's hybrid system which integrates collaborative filtering, content-based filtering, and deep learning claims responsibility for over 80% of user content discovery and saves the company over $1 billion annually (Stratoflow, 2024).

2.5.2 Benefits and Challenges

Hybrid recommendation systems address cold-start and sparsity issues by incorporating both content-based filtering and collaborative filtering methods (Boky & Kramin, 2024). They adapt to user behaviour, which in turn leads them to improve long-term recommendation accuracy. This statement is substantiated by Shact et al. (2024), who stated that organisations integrating generative AI and hybrid models report marked performance improvements in customer engagement. Despite this, the hybrid approach requires more computational resources making implementation only viable for larger streaming services (Sabiri et al., 2025). Miranda and Sanchez (2024) echo Sabiri et al.'s position, emphasising that successful implementation of hybrid models requires careful system design to manage architectural complexity and ensure scalability.

2.6 Impacts on User Engagement and Satisfaction

According to a study conducted by McKinsey & Company, companies who utilise AI effectively for customer retention experience a 25% increase in retention, these businesses can also experience a 15% reduction in churn rates, increasing profitability (Psico-smart Editorial Team, 2024).

Netflix's chief production officer attributed 80% of viewers' video choices to their AI-powered recommendation system (McAlone, 2016) which leads to significant cost savings and reduced churn. This indicates users are more likely to watch recommended content, therefore extending their session duration. This is backed up by Widener et al. (2025), whose 2025 survey report found that AI-driven recommendations significantly extended user session durations and improved satisfaction across various age groups.

AI-powered personalisation showed a strong positive effect on customer satisfaction in e-commerce setting (Digital School of Marketing, 2024), this is further backed up by a McKinsley report which states that the implementation of AI-driven recommendation systems led to a 20% increase in customer satisfaction (Sharma, 2024). A study by Zendesk Yli-Ojanperä (2023) states that AI recommendation systems can analyse content based on emotional impact, with an aim to match the viewers' mood further increasing engagement. Bergström (2021) also states that AI powered engines can allow users to find content matching users' emotional state.

In 2023 alone, Spotify invested $1.9 billion into its recommendation technology, reflecting the platforms strategic focus on AI for personalisation and engagement (Mudaliyar, 2024). Additionally, as stated above, Hootsuite (2024) states that YouTube attribute more than 70% of their views to their recommendation system, and according to Dunn (2025), over 90% of surveyed individual report discovering new content through its algorithms.

2.7 Ethical Considerations in AI Recommendations

2.7.1 Algorithmic Bias

AI recommendations can reinforce biases by prioritising the recommending of content similar to users' previous interactions. This is known as the "filter bubble", it occurs when algorithms choose personalised content which further reinforces users' preferences. By analysing users' past actions, AI systems prioritise content which aligns with existing preferences creating a feedback loop which strengthens users' biases (Della Guitara Putri et al., 2024).

The continuous suggesting of similar content can limit exposure to diverse content which creates what Della Guitara Putri et al. (2024) refers to as an "echo chamber".

AI recommendations may reinforce biases by prioritizing content similar to previous user interactions.

Ferrara (2023) suggests that bias-aware algorithms can help mitigate this issue, these AI-powered algorithms are designed to recognise and mitigate biases in recommendation patterns.

2.7.2 Privacy Concerns

AI-driven recommendations collect large amounts of user data, which raises significant privacy concerns. Personal data misuse has become a major issue, which has led to increased regulatory scrutiny and legal actions against tech companies. An example of this would be TikTok who were fined £12.7 million in April 2023 for violating GDPR laws (Heiligenstein, 2023). These platforms often collect more than the necessary amount of data needed for personalised functionality such as location data, device information, personalised preferences and behaviours, which raise questions about user consent and transparency (centraleyes, 2024).

2.8 Conclusion

Despite challenges, AI-driven recommendation techniques—collaborative filtering, deep learning, and NLP—significantly improve user engagement, retention, and satisfaction. While the literature review covers the theoretical effectiveness of these methods, primary research is necessary to capture real user experiences and provide deeper insights into how these techniques impact user engagement and satisfaction.

Chapter 3: Research Methodology

3.1 Research paradigms

A research paradigm is a model that guides the completion of research. It operates on a set of assumptions and beliefs that allow researchers to more easily interpret results and solve problems (Abbadia, 2022). The choice of research paradigm directly influences the methodology, deciding how data is collected analysed and interpreted.

Positivism is a paradigm that relies on reason and measurement; it assumes that information can only be known if it is based on observable and measurable variables (University of Nottingham, 2024).

This research adopts a positivist paradigm, as it involves measurable phenomena, this includes user engagement, watch time, click-through rates, and churn rates. These objective, quantifiable metrics align with the main principles of positivism. The nature of this research allows for relationships to be created between variables using statistics analysis.

Interpretivism, unlike positivism, is subjective rather than objective as it considers different opinions and thoughts rather than fact. While this paradigm is more applicable to qualitative methods, such as open-ended questionnaire or interviews, it is not the primary focus of this research (Nickerson, 2024).

Although interpretivist approaches can offer relevant insight into user perceptions, this study aims to maintain a positivist framework due to the reliance it will have on numerical data and structured analysis. Another considered approach was mixed-method, but was avoided as the final research design focuses solely on quantitative methods which aligns with the goals of analysing measurable user interactions and the evaluating AI-driven recommendation systems. Furthermore, the quantitative method was chosen as positivism aligns with the fundamental design of AI, as machine learning models depend on structured data, to learn, predict and refine algorithms using large datasets (Williams, 2024).

3.2 Choice of research design

Research design is a framework that outlines the methods and procedures for collecting and analysing data in a study (QuestionPro, 2024). In this study, a quantitative descriptive research design will be used to objectively measure user engagement, satisfaction, and recommendation quality in AI-driven systems.

Descriptive research allows for studies to effectively research and analyse for studies which aim to find trends and behaviours in a population without the manipulating of variables, this aligns with the goal of the study which is to assess AI recommendation effectiveness in streaming services (McCombes, 2023). It will allow for an objective analysis of AI-driven recommendations and how they affect user engagement (McCombes, 2022).

Despite being the most appropriate method, descriptive research has limitations. This technique can be limited as the technique cannot determine whether AI-driven recommendations directly cause higher engagement or satisfaction as it focuses on describing phenomena rather than manipulating variables to uncover relationships and trends (Sumeracki, 2018).

However, this approach remains the most suitable option for this research, as the aim is not the manipulation of variables but rather the objective analysis of existing user behaviours and experiences with AI-driven recommendations. It offers valuable insights into real-world patterns and user interactions, which is important in understanding the impact of recommendation systems in practice.

A questionnaire distributed via email will gather insights from students and staff at a local FE (Further Education) College, leveraging diverse age groups to explore user experiences. This approach is appropriate as it collects numerical data and summarises preferences and behaviours. Qualitative methods were not chosen as they focus on subjective experiences and are less aligned with the study's goal of evaluating AI recommendation effectiveness (McLeod, 2023).

Correlational design was opted against as this research focuses on describing user experiences and behaviours, rather than testing the strength of relationships between variables (Cherry, 2023). Furthermore, correlational studies do not allow for in-depth exploration of direct comparisons of methods like collaborative filtering, deep learning or NLP.

In this study a descriptive research method will be employed. This is suitable for gathering user experiences. Descriptive research is a research method describing the characteristics of the population or phenomenon studied (Bhat, 2023). Descriptive research in this study analyses user interactions with AI-driven recommendations, summarising preferences, behaviours, and satisfaction. For this paper experimental design was avoided as this involves manipulating AI-driven recommendations, this paper involves exploring the existing user experiences (Skidmore, Kowalczyk and Lee, 2023).

3.3 Research variables

In this study, both dependent and independent variables are useful to explore how the independent variables impact the dependent variables. An independent variable is the factor which is manipulated to observe its effect on another variable; it is the cause in a cause-and-effect relationship. A dependent variable is the outcome which is measured to understand the effect of the independent variable; it is the effect in the relationship (Caffrey, 2020).

Since streaming platforms such as Netflix, YouTube, and Spotify do not publicise all performance metrics, this study will rely on a combination of publicly available industry data, third-party research, and self-reported questionnaire responses to analyse the variables mentioned.

Independent variables to be used include factors such as the type of recommendation algorithm (e.g. collaborative filtering, deep learning, content-based filtering), which are all elements that influence or cause a change (Bhandari, 2022). Dependent variables that will be analysed include user engagement, watch time, click-through rates, user satisfaction, and churn rates. These dependent variables are what change due to the independent variables (Bhandari, 2022).

Both the dependant and independent variables mentioned will be analysed to measure the effect of AI-driven recommendations.

To ensure clarity, the following definitions are applied to the variables used in this study. User engagement is measured through daily watch time and interaction frequency (Storyly, 2024). User satisfaction relates to perceived recommendation relevance and content enjoyment by the user (Martínez-Navalón *et al.*, 2021). Click-through rate (CTR) is understood as the percentage of AI recommended content which users select or click on (Hayes, 2022). Lastly, churn rate is the percentage of users who stop using a platform, indicating dissatisfaction with recommendations or the service overall (Investopedia, 2024).

3.4 Choice of participants

This study will target students and staff from a local Further Education (FE) college, as they represent an accessible population to contact. This also allows for opinions to be gathered from different age groups. The 18+ range of participants aims to achieve representation across various age groups and occupational roles, e.g. students, teachers. This population will allow for insights into AI-driven recommendations through different demographics, including age and occupation, which may influence user opinions. Additionally, as younger students

may consume content in different ways than mature students or staff of the FE college, this approach allows for insights into generational differences in terms of AI recommendation effectiveness. A limitation of this population is that it only includes individuals in an academic environment, which could skew the dataset towards a more tech-literate audience. However, this limitation will be addressed by targeting respondents from different departments and roles within the college to reflect a wider range of perspectives.

3.5 Sampling considerations

In this paper the aim is to employ a non-random sampling method, more specifically a convenience sampling approach (BYJU'S, 2024). A convenience sampling approach is the process of selecting participants who are easily accessible, which in this case is students and staff from a local FE college (Qualtrics, 2025). This method is appropriate for the current research, as it enables efficient data collection from a known and reachable population within a limited timeframe.

This type of sampling is chosen, as it allows the gathering of at least 60 respondents of different age groups, with presumably different levels of computer literacy which can provide insight into their experiences.

Alternative methods such as random sampling or stratified sampling were considered but ultimately avoided due to being less practical in this scenario.

Random sampling was avoided not only due to the accessibility of participants but also because the technique requires more time to ensure the sample represents the wider population (BYJU'S, 2024). Stratified sampling, which is useful for representing different subgroups (e.g. by age or role) would demand more planning and coordination that was not deemed viable due to the time constraints of this undergraduate research (Murphy, 2024).

As a result, convenience sampling was chosen as it offers a practical balance between accessibility and diversity of participants, allowing for the collection of valuable relevant data. Despite this method coming with its limitations, such as potential bias, these are mitigated by targeting participants from different departments and roles within the FE college.

3.6 Data collection tool & collection procedure

To effectively gather data for this study, a questionnaire tool will collect responses from a targeted group to assess opinions. Given the choice of a quantitative approach, Microsoft

Forms would make sorting data easier due to the mostly multiple-choice nature of the questionnaires (Macheru, M.N., et al. 2024).

These questionnaires will be distributed over email in a local FE college, there is an aim for a sample size of 60 as to gather a large enough range of respondents of students and employees with a minimum participant age of 18. This sample size was chosen based on feasibility and accessibility within the given timeframe.

While a larger sample would improve the statistical power of the questionnaire and answers, a sample anywhere from 60-100 respondents should be sufficient to notice engagement trends. As the study targets students and staff from an FE college, findings may not represent completely generalised responses such as those in different sectors or locations.

To improve generalisability, further research could extend this study to broader user range to strengthen the robustness of the findings. The questionnaire will involve a mixture of multiple choice and Likert scale style questions with a select few open questions to gain more perspectives that might not have been considered for selections in a Likert scale or multiple-choice format question.

A questionnaire was chosen over an interview as this research aims to collect numerical data to analyse user engagement and satisfaction. Additionally, questionnaires allow for a larger sample size, which will reduce variance (Office of the Auditor General of Canada, 2024). After the data has been collected it will be exported to Microsoft Excel and the data will be analysed using metrics such as mean, mode, median, and correlation analysis to identify trends.

3.7 Ethical considerations

Consent will be achieved by including a consent statement at the top of the questionnaire page, explaining that upon completion of the questionnaire, participants agree to the use of their data.

Confidentiality is achieved by password-protecting the questionnaire responses and making them only accessible to the researcher and the dissertation supervisor. Data is stored safely on OneDrive for research purposes and deleted once analysed.

Anonymity is ensured by not collecting personal identifiers such as names or addresses. The only personal information collected is age, which is necessary for the study. Responses will be aggregated which will further ensure that confidentiality is maintained. These precautions are to ensure that the research adheres to ethical standards, ensures transparency in the use of their data (UK Research and Innovation, 2024). This study will comply with GDPR

regulations by insuring consent, data anonymisation, and safe storage of data. This data will be retained for six months before being deleted, in accordance with research guidelines.

3.8 Identifying potential issues

A common issue in questionnaire-based research is receiving an insufficient number of responses, which can affect the strength of the questionnaire, this will be mitigated by extending the timeline of the questionnaire as to allow more time for responses to come in. To further mitigate this issue the questionnaire will be distributed to students in different colleges to ensure greater reach.

Another issue that could occur could be questionnaire fatigue, this is where participants rush through responses because a questionnaire is too long, reducing data quality. To minimize the likelihood of this occuring, the respondents will be informed that the questionnaire will take no longer than 5 minutes to complete, this is to achieve accurate results.

Response bias could occur if participants provide answers dishonestly to suit the questionnaire questions. To minimize this, the questionnaire questions will be neutrally worded, and anonymity of participants identities will be assured.

Due to the technical topics of this paper such as machine learning, deep learning, and NLP, some participants might not understand these concepts, to mitigate this issue, complex questions will be avoided if possible, and there will be simple descriptions of questions if required. ⌷OBJ⌷

Chapter 4: Analysis Outcomes

4.1 Introduction

This chapter presents an analysis of the data gathered through the online questionnaire, designed to explore user perceptions of AI-driven personalised recommendations on streaming platforms such as Netflix and Spotify. With all responses now collected, the chapter outlines the steps taken to prepare and clean the data, the methods used to present the findings, and the statistical techniques applied to identify patterns and relationships within the data. Challenges encountered during the analysis are also discussed in Section 4.6 to ensure transparency and provide context to the results.

Descriptive statistics were used to analyse the cleaned data, and the findings are illustrated through various charts and graphs. The chapter highlights key insights, showcasing trends and patterns that emerged from the responses. Finally, the findings are aligned with the research objectives outlined in Chapter 1.

4.2 Pilot Study

Before distributing the questionnaire to gather feedback from a larger sample size, a pilot study was conducted involving two participants to test the usability, structure, and clarity of the questionnaire. Based on feedback received from the pilot, the following changes were implemented.

- The questionnaire title was changed to be more informative which reflected the research topic

- The description section was revised to ensure ethical compliance which included that by continuing the completion of the questionnaire the participants were giving consent and specified that they have no obligation to complete the questionnaire.

- The questionnaire was changed from 15 multiple choice questions to 13 questions and two open-style questions to encourage more open-style questions and personalised responses to capture more detailed and valuable insights that may not emerge through closed-ended questions alone.

- One question was not initially set to "required", which could have led to missing data. This oversight was corrected to ensure consistency among answers.

These adjustments were made to ensure the final questionnaire was clear, ethically sound, and capable of generating relevant and reliable data to analyse.

4.3 Data Preparation and Cleaning

After collecting responses from the online questionnaire, the responses were exported from Forms to Excel. A data cleaning process was then carried out to ensure the dataset was valid, relevant, and ready for analysis. Data cleaning is a critical preparation step to ensure that the data can be accurately interpreted and to ensure the integrity of the research findings (Harte Hanks, 2025).

The first step of cleaning the data was the removal of unnecessary columns. Several columns are automatically generated by Microsoft Forms which held no analytical value that were removed, these include "Start time", "Completion time", "Email", "Name" etc.

The next stage of cleaning the data involved filtering out responses which were incomplete or lacked relevance, this was only the case for open-ended questions which received responses with no meaningful input, resulting in 21 responses being removed.

For multiple choice questions, in particular "Which streaming services do you use the most?" which allowed for input in "Other" section, entries such as "Youtube" and "YouTube" were standardised.

Lastly, all personally identifiable information such as names and emails were stripped from the dataset to adhere with legacy research guidelines. Despite the questionnaire being anonymous, these fields were still present and were removed to ensure compliance.

Through the process of this cleaning, out of the 86 respondents, 4 responses were excluded due to incomplete or invalid entries, and a further 21 responses were excluded for containing low-quality data. This resulted in 61 valid responses, which are to be used for statistical analysis and visualisation.

4.4 Visualisation of Data and Descriptive Statistics

This section presents the results of the questionnaire using both visual and descriptive statistical analysis. Frequencies, percentages, and key trends are summarised through charts and narrative to highlight patterns in streaming behaviour and user engagement with AI-driven recommendations.

The majority of respondents (49.2%) were aged between 18–24, reflecting the expected demographic bias due to the FE college setting. Older age groups were less represented, with 16.4% aged 45–54, and smaller percentages across 25–34, 35–44, and 55+. The youthful

skew is important when considering engagement patterns with streaming services. As shown in Figure 1, the age distribution highlights a predominantly young audience.
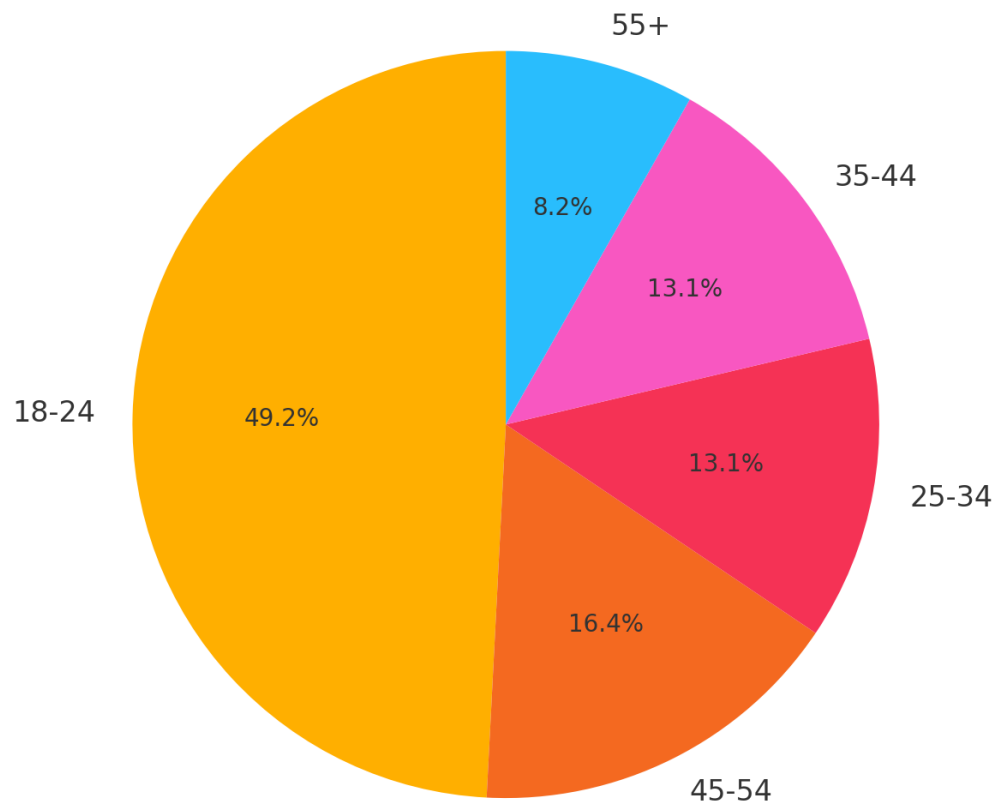
Figure 1 Age distribution

YouTube emerged as the dominant platform among respondents (80.3%), followed by Netflix (68.9%) and Spotify (59%). Other platforms like Amazon Prime Video (34.4%) and Disney+ (31.1%) were less commonly used. This suggests a strong reliance on platforms with diverse content and advanced AI recommendation systems. Figure 2 visualises the overall platform

usage trends among the sample.
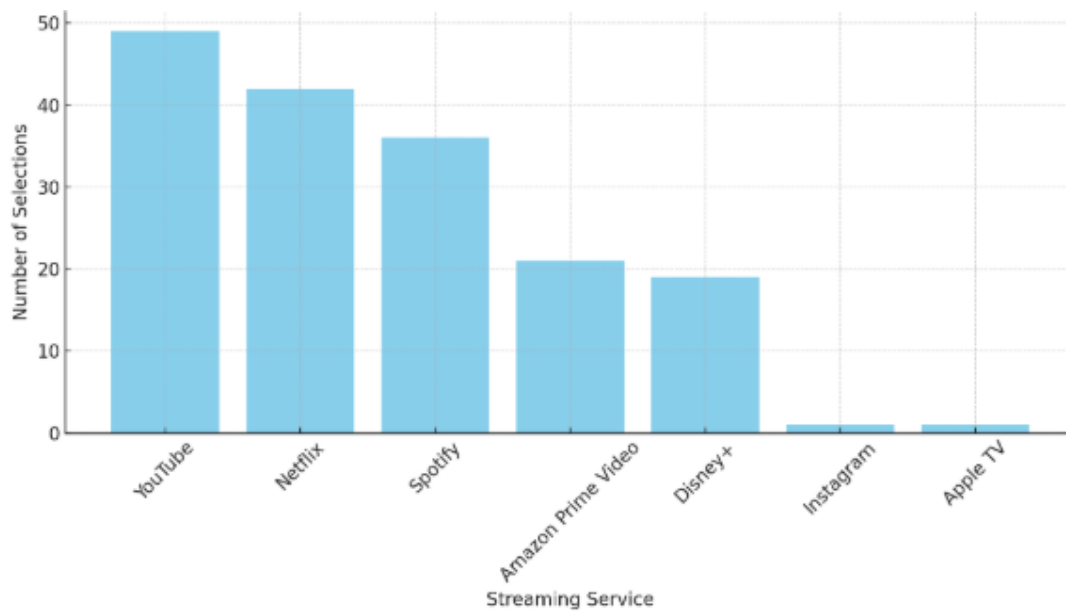
Figure 2 Streaming platform usage

Daily engagement with streaming services was reported by 83.6% of respondents, suggesting that streaming has become a habitual part of everyday entertainment. Only 15% of users accessed services a few times a week or less frequently. High daily usage underlines the critical role of recommendation systems in maintaining engagement. This pattern is
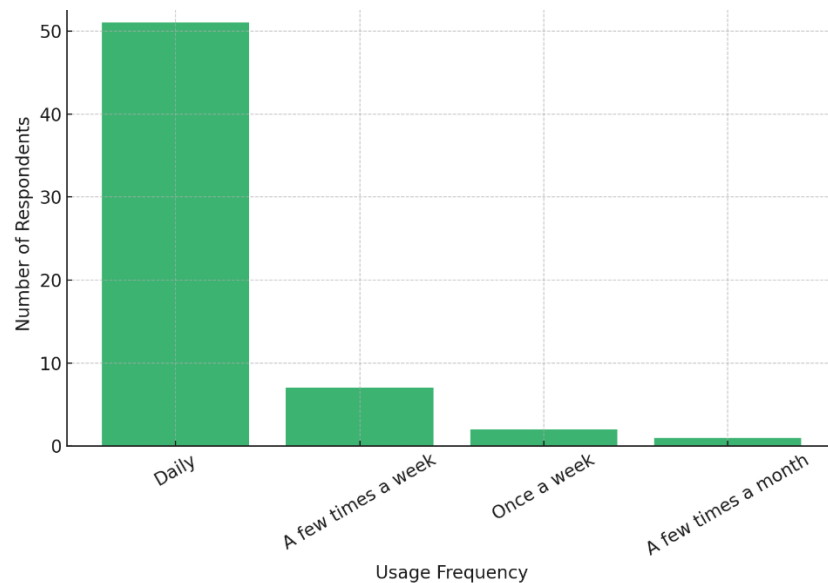
illustrated in Figure 3.

Figure 3 Frequency of streaming service usage

A significant proportion of participants (44.3%) indicated they often rely on AI-generated content suggestions, while 41% used them occasionally. Only a small minority (11.5%) rarely or never used recommendations, indicating widespread interaction with algorithmic suggestions. These habits reflect the importance of recommendation quality. The distribution

is displayed in Figure 4.
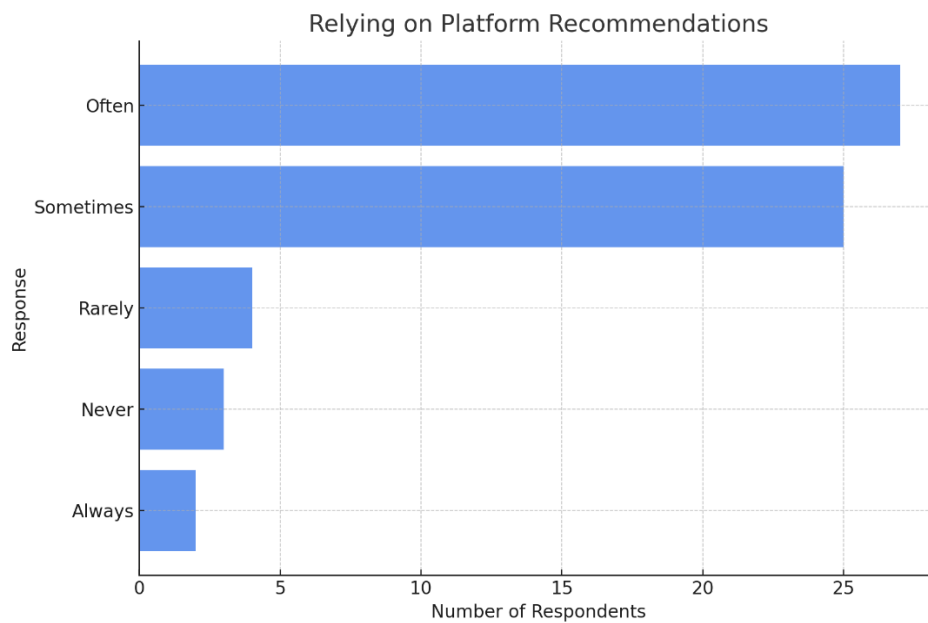
Figure 4 Relying on Platform Recommendations

As seen in Figure 5, the majority of users found AI-driven recommendations enhanced their experience on streaming platforms. 59% felt that recommendations somewhat improved their overall platform experience, whilst 19.7% stated a significant improvement. On the other hand, a further 19.7% felt that recommendations made no difference, and 1.6% respondent even reported that they did find them helpful at all.

These findings show that while not all users rely heavily on recommendations, most perceive them as beneficial to some degree.
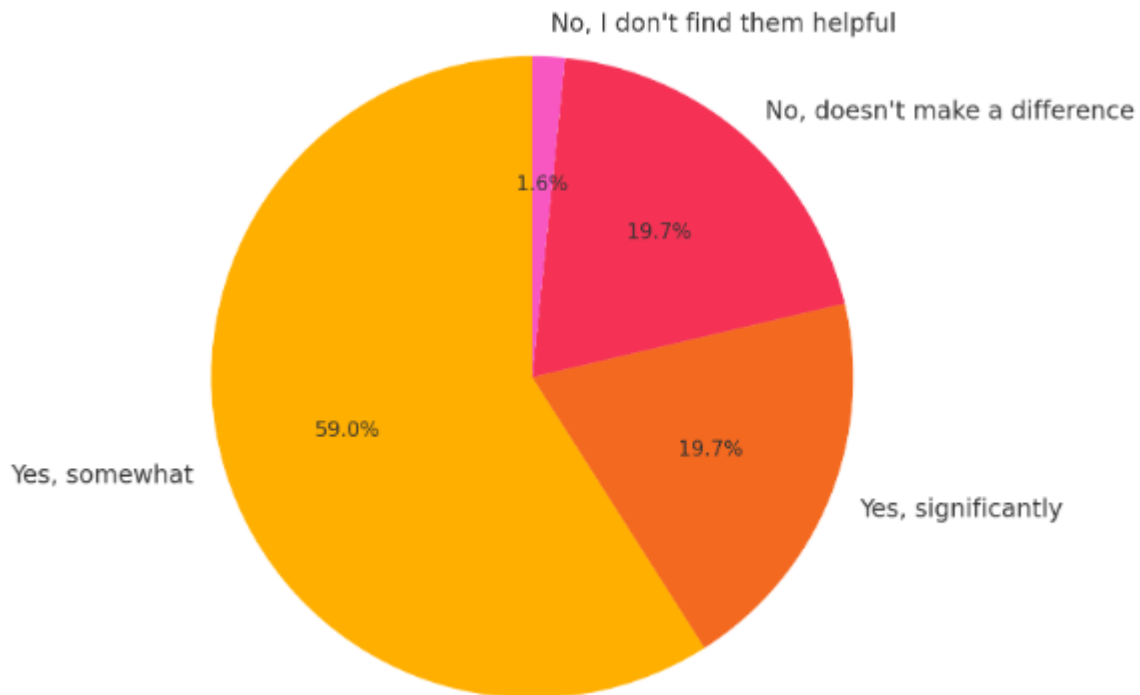
Figure 5 Perceived Usefulness of Platform Recommendations

The majority of users found that AI-driven recommendations enhanced their experience on streaming platforms. 59% felt that recommendations somewhat improved their overall experience, and 19.7% stated a significant improvement. Only a small portion found no benefit. This perception is illustrated in Figure 5.
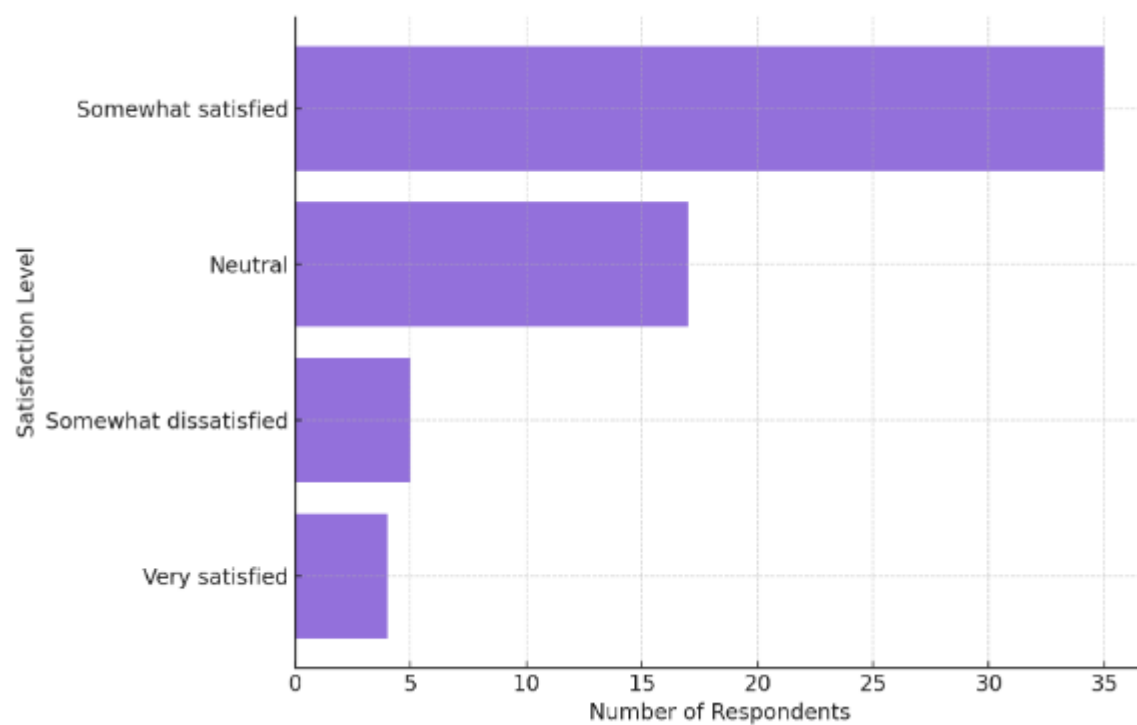
Figure 6 User Satisfaction with Recommendations

28

A majority of respondents (57.4%) reported being somewhat satisfied with AI-driven recommendations, with 6.6% very satisfied. 27.9% were neutral, and only 8.2% were somewhat dissatisfied. These satisfaction levels are summarised in Figure 6.
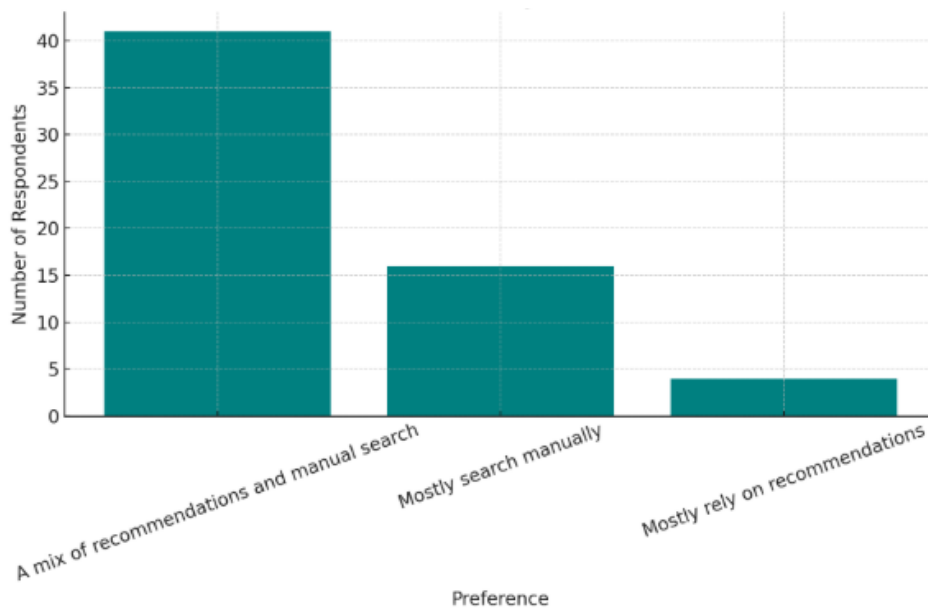
Figure 7 Content Discovery Preferences

When asked about their preferred method for discovering content, 67.2% of users reported using a combination of AI-driven recommendations and manual search. 26.2% preferred manual searching, while only 6.6% relied entirely on recommendations. This is represented
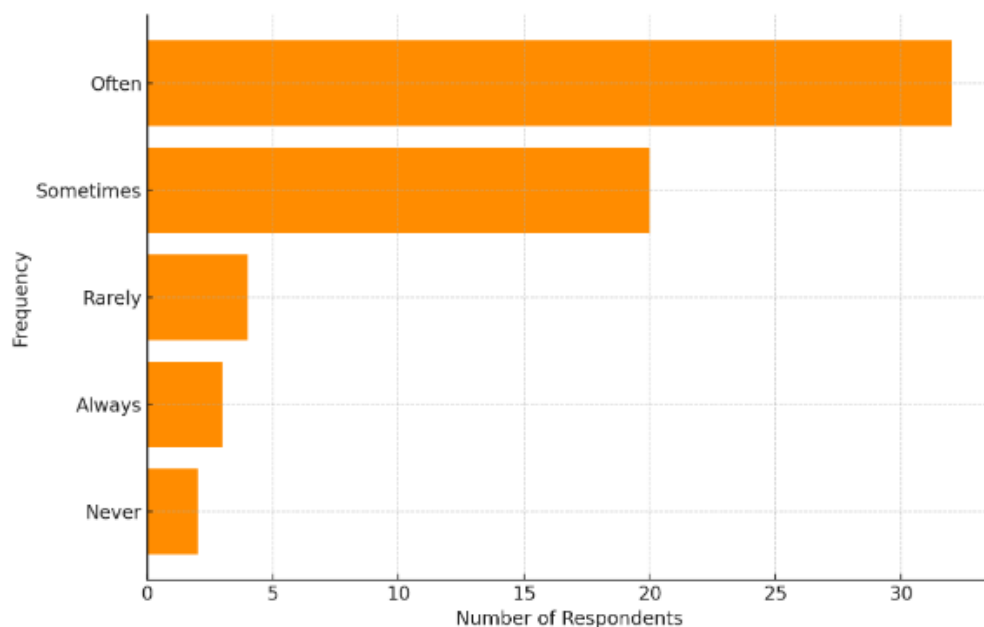
in Figure 7.

Figure 8 Frequency of Engaging with Recommended Content

For the question asking whether AI-driven recommendations increase time spent on streaming platforms, the majority (39 out of 61, or 63.9%) of respondents reported their viewing or listening habits were unaffected by recommendations. However, a substantial

proportion of respondents (22, or 36.1%) indicated that they spend more time on streaming platforms as a result of recommendations.

This finding is important, as it suggests AI recommendations despite not universally increasing the session times of the participants, contributes to extended use of streaming platforms for over a third of users. This implies that the continued improvement of AI-driven recommendations can directly boost watch time and user retention. This is represented in Figure 9.
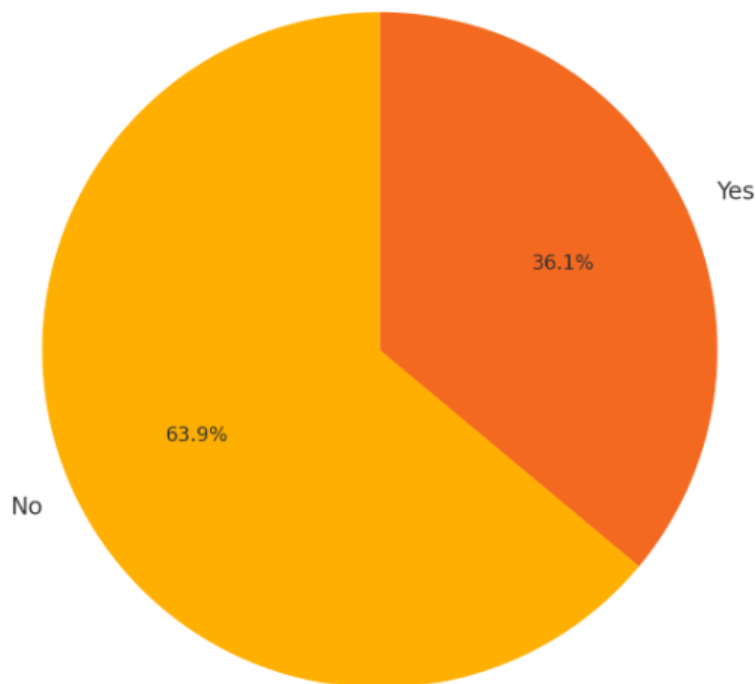
Figure 9 Session duration as a result of recommendations

When asked if AI-driven recommendations increased their time spent on streaming platforms, 63.9% reported no change, while 36.1% said they spend more time due to recommendations. These findings are illustrated in Figure 9. This is represented in Figure 10.

Categorised Sentiment Toward AI Recommendations (Open-Ended Responses)
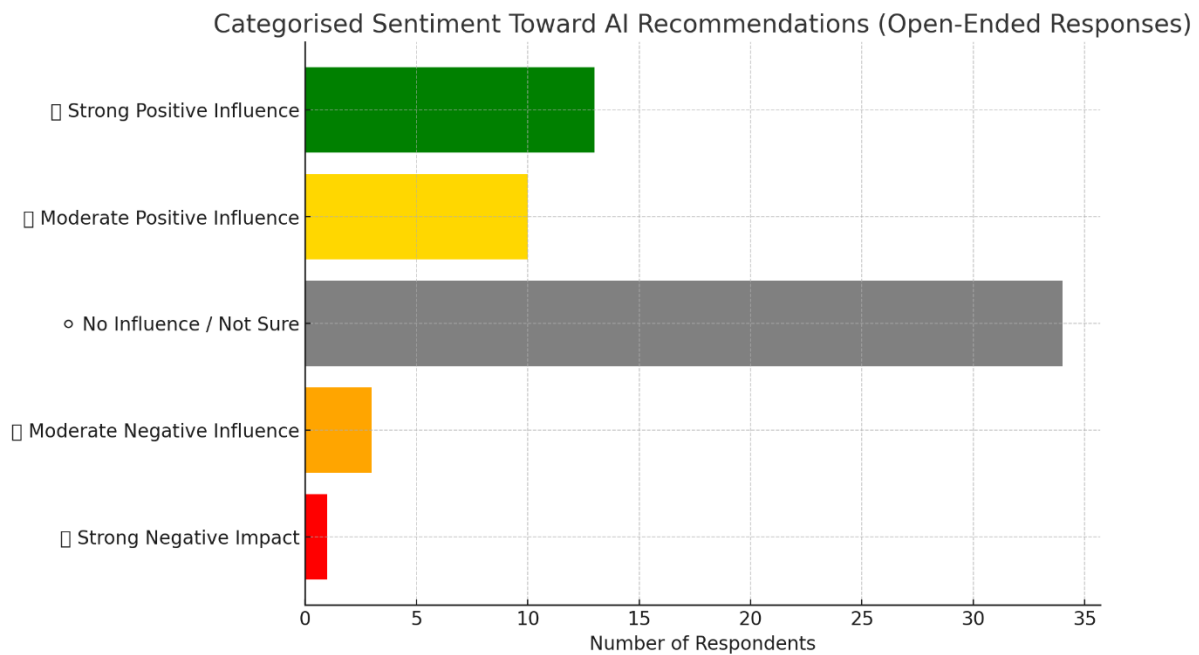
Figure 10 AI-driven recommendations influence to subscribe or remain subscribed to a streaming service?

In response to how AI-driven recommendations influenced decisions to subscribe or stay subscribed, 21.3% reported a strong positive influence, while 16.4% described a moderate influence. 55.7% indicated no influence or uncertainty, and a small percentage (6.5%) reported a negative impact. This is shown in Figure 10.
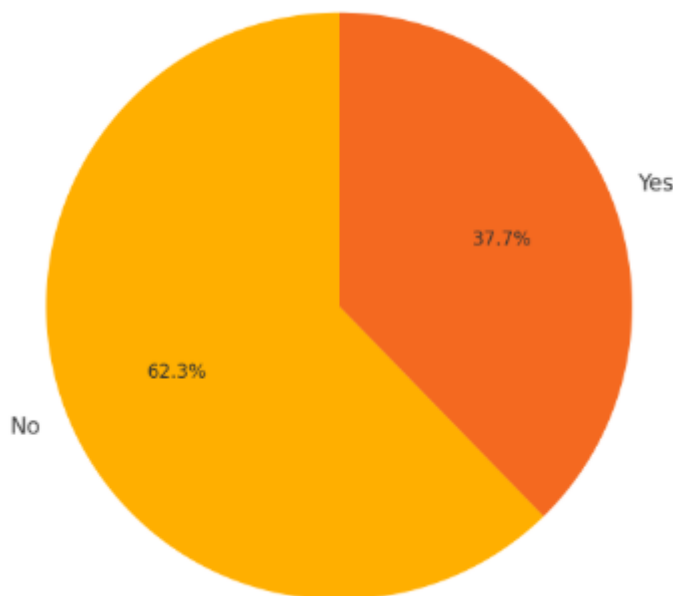
Figure 11 Have you switched platforms due to poor recommendations

Participants were asked of the likelihood of cancelling streaming service subscriptions if the platform recommendations no longer match their interests. Just over a quarter of respondents (16 out of 61 or, 26.2%) indicated that they would be very likely to cancel, with another 14

participants (23%) selecting somewhat likely. Just under a quarter of the respondents (15, or 24.6%) remained neutral, while 11 individuals (18%) said they would be somewhat unlikely, and 5 (8.2%) stated they would be highly unlikely to cancel if they felt the platform recommendations were not aligned with their interests.

These results show that a significant portion of the respondents would consider cancelling if personalisation fails to align with their interests. This is seen in Figure 12.
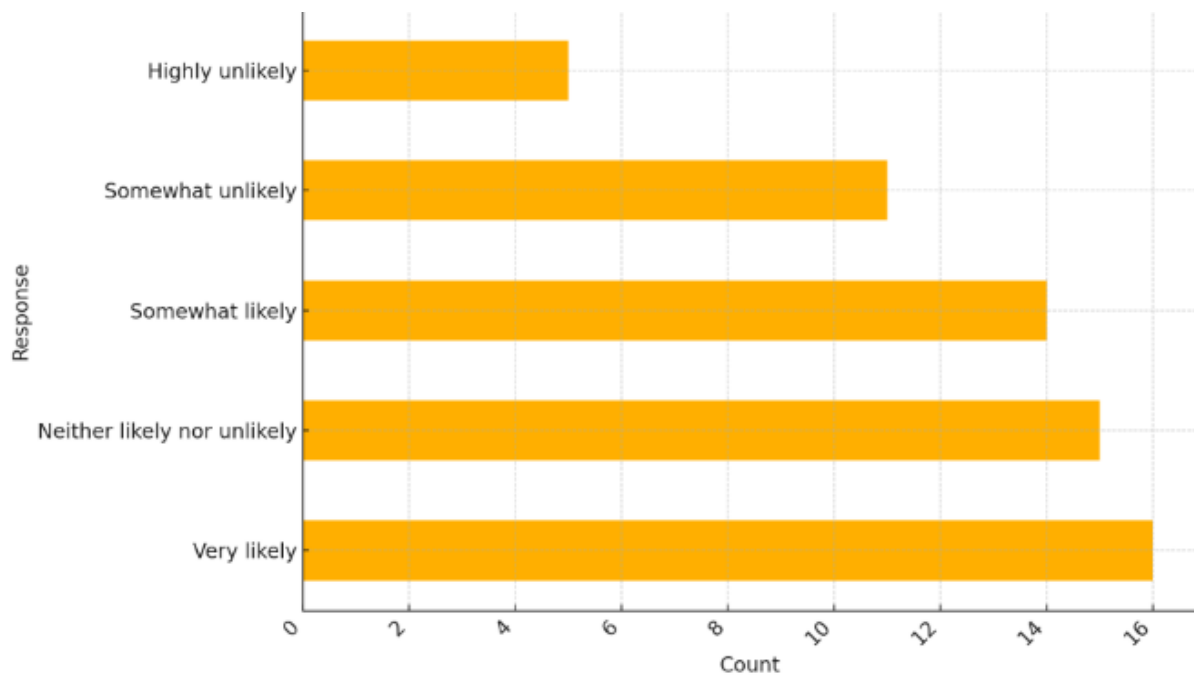
Figure 12 Likelihood to cancel subscriptions due to relevance of recommendation systems

72.1% stated that recommendations sometimes aligned with their interests, while 26.2% said they mostly aligned. Only 1.6% felt recommendations were often unrelated. This alignment of AI-generated recommendations with user interests is shown in Figure 13.
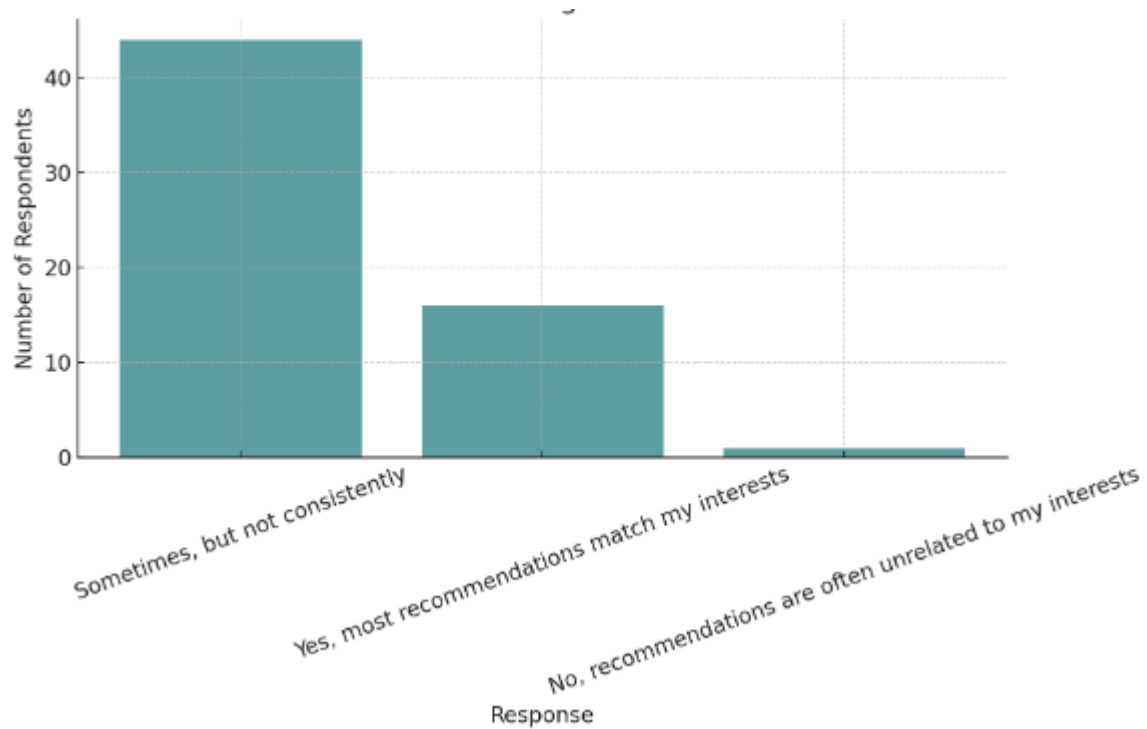
Figure 13 Perceived alignment of AI-generated content recommendations with users' interests

In the penultimate question, the respondents were asked whether they had noticed any improvements in AI-driven recommendations as they continue to engage with the platform. Most respondents (50.8%) believed that recommendations have become more accurate over time. A further 31.1% felt their recommendations had somewhat improved, but not significantly. These findings suggest that while over 98% of the users believe that at least some degree of learning by the AI, there is still a portion of the user base who may not experience the full benefits of AI personalisation.
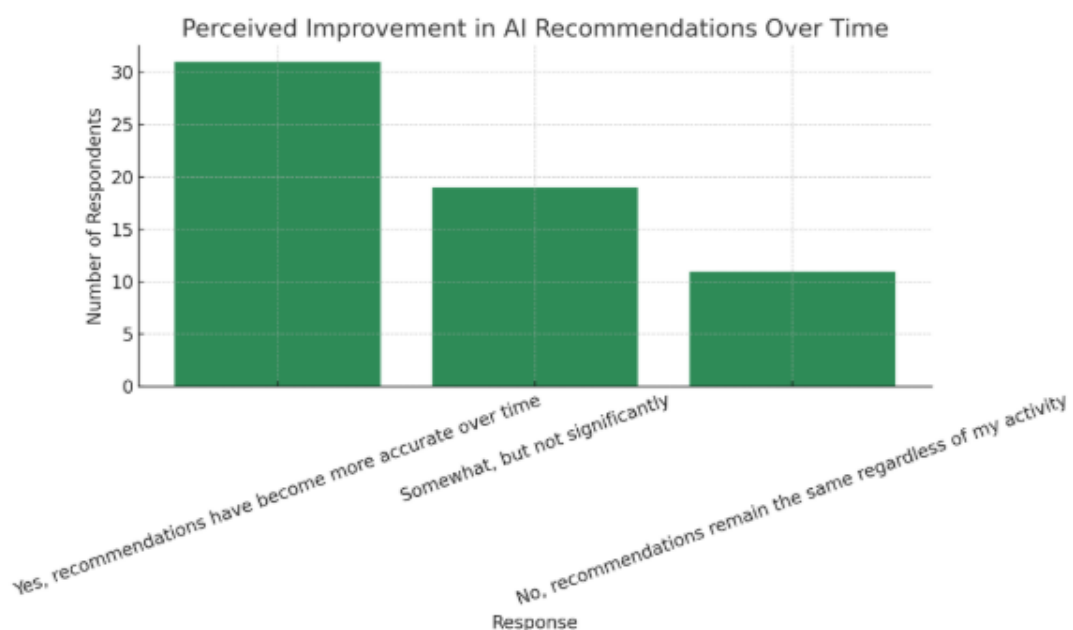
In response to how AI recommendations impacted their streaming experience, 39.3% reported a very positive impact, 16.4% moderately positive, 23% neutral. A moderately negative perception was indicated by 11.5%, and 9.8% claimed a strong negative impact with users describing issues associated with data sparsity. This distribution of perceptions is shown in Figure 15.
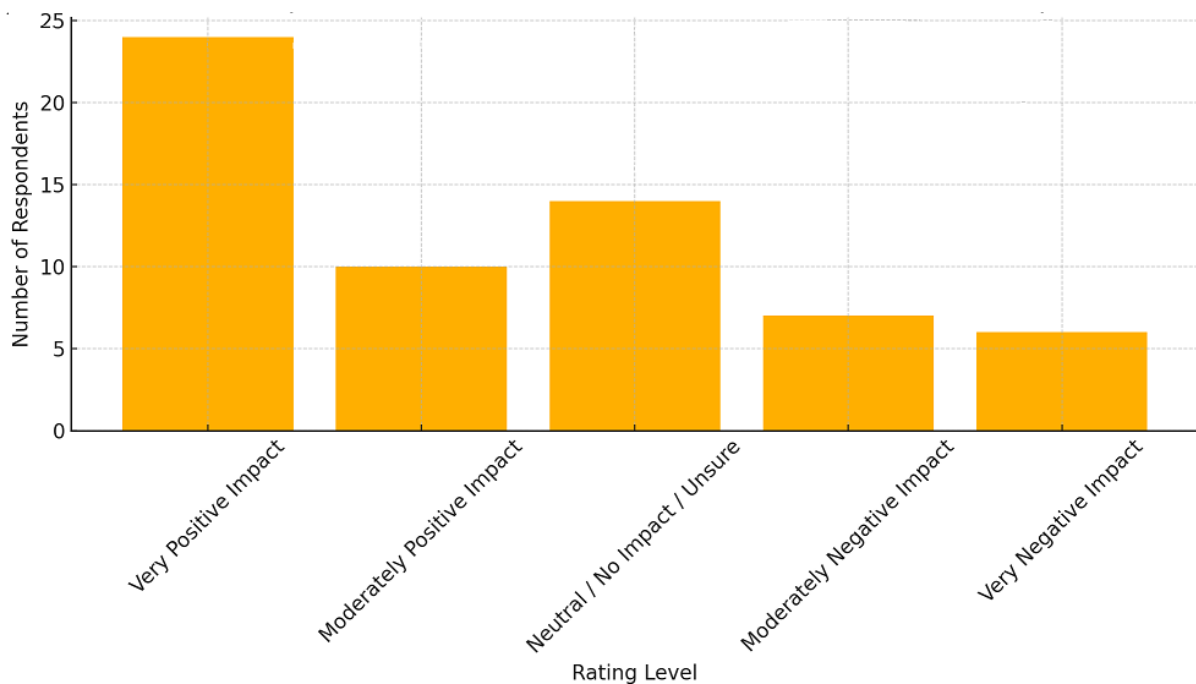
Figure 15 Distribution of participant perceptions regarding the impact of AI-driven recommendations on their streaming experience

4.5 Inferential Statistics

This section presents the inferential statistical analysis conducted to determine where there is a statistically significant relationship between the user reliance on AI-driven recommendations and their satisfaction with those recommendations. While descriptive analysis gives an outline of general trends, inferential statistics determines whether patterns in the data are due to chance or if these two variables have a meaningful relationship.

To test the hypothesis that a user's satisfaction is related to how often they rely on AI-driven recommendations such as "Recommended for You" or "Top Picks", a Chi-square test was conducted. These variables can be tested against each other as they are both independent variables and can be tested for association. A contingency table was created using four levels of satisfaction (Very Satisfied, Somewhat Satisfied, Neutral, Somewhat Dissatisfied) against four levels of reliance (Always, Often, Sometimes, Rarely). The observed frequencies and

expected values were compared to determine whether the differences between the groups were large enough that they were unlikely to have occurred by chance.

The result was p = 0.0138, since the p value was less than 0.05, the result indicates that the relationship between the two variables is statistically significant at the 95% confidence level, while 95% is the standard threshold for statistical significance, the 98.62% confidence level found using the Chi-square test strengthens the reliability of this finding which is especially relevant due to the constraints of the sample size of the study (JMP, 2025). This result suggests that the observed relationship between the two variables is unlikely to have occurred by chance, therefore indicating that increased reliance on AI-driven recommendations is meaningfully associated with greater user satisfaction. The full Chi-square calculations are provided in Appendix B.

4.6 Challenges and Limitations

There we're many challenges and limitations in the questionnaire; one issues would be data sparsity in open-ended responses. Some of the responses lacked sufficient detail which despite best efforts makes interpretation subjective. Another issue is the sampling demographic, the sample was skewed towards younger users (18-24), which potentially biased trends in engagement or familiarity with AI.

Furthermore, these responses could've benefited from deeper manual cleaning to address issues such as grouped responses, vague open-ended responses, fast completion speed which could have led to low-effort or redundant responses which could introduce contradiction or inconsistencies.

Additionally, some participants may not have fully understood what "AI-driven recommendations" referred to, especially due to streaming platforms not traditionally making these systems explicit.

However, this these did not significantly affect the validity or reliability of the research findings.

4.7 Conclusion

The analysis of 61 questionnaire responses revealed that AI-driven recommendations indeed play a significant role in content consumption, user satisfaction and discovery across streaming platforms. Despite respondents generally expressing positive views on the technology, many described inconsistencies and weaknesses in their recommendations. This suggests that despite AI-driven recommendation systems being effective at increasing

engagement for users, data sparsity challenges and limited transparency in the algorithms continue to affect the usefulness of the technology. These findings help contribute to a better understanding of AI-driven personalisation is perceived by users and how the technology performs in real-world user environments and to inform how to refine the technology.

Chapter 5: Discussion

5.1 Introduction

This chapter explains the key findings of the research to conclude outcomes of the hypothesis and research objectives outlined. The aim was to understand how AI-driven personalised recommendation systems can influence user engagement and satisfaction in streaming services. This study explored the roles of natural language processing, machine learning, collaborative filtering, and hybrid recommendation systems' ability to enhance recommendation accuracy. The following section will discuss the results of the research, evaluate the hypothesis of the study, and reflect on the research objectives and whether they have been achieved.

5.2 Summary of Key Findings

The analysis of the questionnaire responses revealed important findings about the perception of AI-driven recommendations and the effectiveness of the technology in streaming services. Over 85% of respondents reported using streaming services daily, and a majority (85.2%) interacted with recommendation features at least "sometimes", this indicates a strong reliance on these AI-driven suggestions.

Over three-quarters of respondents (78.7%) felt that AI-driven recommendations improved their experience on streaming services, with 64% reporting some level of satisfaction with their suggestions.

Despite the majority of respondents saying AI-driven recommendations did not affect their usage time, over one-third (36.1%) reported that recommendations directly increased their time spent on platforms.

Results indicated that 37.7% had unsubscribed from services due to poor recommendations, which further highlights the importance of effective recommendations in reducing churn.

Two-thirds of users preferred a mix of using AI recommendations and manual search, this suggests AI works best whilst being complemented with manual search.

81.9% of respondents believed that AI recommendations improved with continuous use, this suggests the ability for the technology to adapt from user to user.

A Chi-square tests confirmed a significant association (97.62% likelihood) between the reliance on AI-driven recommendations.

5.3 Discussion of Hypothesis

5.3.1 Hypothesis 1

AI-driven personalised recommendations significantly enhance user engagement and satisfaction compared to non-personalised or generic recommendation systems in streaming services.

The findings from both the literature review and primary research provide strong support for this hypothesis. In chapter 4, 59% of respondents believed that recommendations somewhat improved their streaming experience, and a further 19.7% felt they significantly improved it. Furthermore, over 64% of participants were at least somewhat satisfied with the recommendations they received.

These results suggest that AI-driven systems positively effect the overall user experience by improving the relevance of content provided. Additionally, the Chi-square test revealed a significant statistical relationship between user reliance on AI recommendations and the satisfaction levels, this supports the idea that those who depend more on their recommendations are more likely to be satisfied with their streaming service.

These findings closely align with existing literature, as McAlone (2016) stated, Netflix credits 80% of its streamed content to its recommendation systems. Furthermore Mudaliyar (2024) stated that Spotify's Discover Weekly playlist which is powered by collaborative filtering, led to over half of its users to save at least one recommended track a week.

However, some researchers state that heavy reliance on AI-driven content suggestions could impact autonomy. Faas et al. (2024) found that algorithmic decision-support systems, while mostly effective, may reduce users' sense of control over time. In the context of streaming, this could mean that even accurately curated recommendations may lead to reduced satisfaction if users feel the system limits their natural content exploration experience.

This hypothesis appears well-supported on platforms where AI-driven content discovery is central to the services' experience (e.g. Netflix, Spotify) in contrast to platforms like YouTube, where users still commonly manually search for content. These differences emphasise the importance integrating recommendations in an appropriate manner as to allow users to feel in control of their content consumption choices.

5.3.2 Hypothesis 2

The integration of NLP in AI-driven recommendation systems significantly improves the accuracy of recommendations by effectively categorising and interpreting textual metadata.

Evidence gathered from the primary research, complemented by insights from the literature review, highlights the effectiveness of Natural Language Processing in enhancing the precision of AI-driven recommendations. The technology has become a core part of recommendation systems, allowing platforms to understand user-generated content such as reviews, comments, and search queries. The literature review explained models such as BERT and GPT, these technologies analyse language within given context and extracts meaning from user data, which enhances the recommendation relevance (Shah et al., 2024; Zhang et al., 2023).

The descriptive data extracted from chapter 4's questionnaire further supports this hypothesis. In 72.1% of cases respondents reported that the majority of recommendations received at least "sometimes" aligned with their interests, and a significant number of responses (26.2%) indicated consistent alignment with interests. This suggests that systems employing advanced interpretation of metadata, which includes sentiment analysis or topic modelling, are effectively narrowing down content to direct to the appropriate audiences.

Moreover, 50.8% of participants indicated that their recommendations improved with continued engagement, which implies that NLP-enabled systems are capable of adapting based on user behaviour and evolving interests. This supports the broader narrative that NLP refines recommendations by interpreting subtle linguistic cues such as tone, emotion, and intent.

Despite these strengths with the technology, some limitations were noted in the literature. NLP can struggle with sarcasm, ambiguity of content, and multilingual nuance (Rimaz et al., 2019. Getahun (2024) reports that leading AI developers such as OpenAI are actively developing sarcasm detection tools to address these challenges, which highlights the importance of correct interpretation of context and tone. This indicates that even advanced NLP models can misinterpret certain human language or context. Despite this, these worries can be mitigated by overwhelmingly positive sentiment from respondents, as only 1.6% indicated that recommendations were often unrelated to their interests. This suggests that despite the limitations, the current stature of NLP techniques can be considered effective at interpreting user preferences and generating relevant content user-to-user.

Overall, the hypothesis is strongly supported. The ability of NLP to interpret textual metadata plays a critical role in generating personalised and relevant recommendations. Ongoing improvements in NLP, including the development of sarcasm detection tools by industry leaders as reported by Getahun (2024) and sentiment disambiguation, should further enhance the precision of recommendations in the future.

5.3.3 Hypothesis 3

AI-driven personalised recommendations lead to higher user engagement, measured by increased watch time and reduced churn rates, compared to non-personalised recommendations.

The analysis of primary data alongside findings in the literature review, provide support for this hypothesis. User engagement was assessed through multiple indicators including frequency of streaming services, session duration, and platform loyalty due to poor recommendations.

In Chapter 4, despite 63.9% of respondents stating that recommendations did not significantly increase their time spent on platforms, a notable 36.1% reported that recommendations directly led to an increase to their watching or listening time. While this may not represent a universal effect, it suggests a significant subgroup whose experience is improved due to personalised content. This supports the observation by Widener et al. (2025) who noted that AI systems can improve personalisation over time by learning from users' interaction with the platform.

In terms of the aim of minimising churn rates, 37.7% of respondents reported unsubscribing from a streaming service due to poor recommendations. This high figure underlines the importance of accurate AI recommendations in retaining users. Furthermore, when asked how likely respondents would be to cancel a service if recommendations became misaligned with their interests, nearly 50% of respondents indicated that they would be "somewhat likely" to "very likely". This directly supports the notion that the quality of recommendation systems influences platform loyalty, which supports the hypothesis that AI-driven recommendations can reduce churn rates.

Further hypotheses result can be concluded from the Chi-square test result from Chapter 4, which found a statistically significant relationship between users' reliance on AI-driven recommendations and satisfaction, suggesting that greater reliance on AI-driven recommendations is closely linked to higher levels of satisfaction, and may contribute to enhanced user engagement. This is reinforced by Sharma (2024), who found that improved

recommendation systems directly correlate with reduced churn and increased retention, with some platforms reporting a 20-25% rise in customer retention after implementing more advanced AI-driven recommendation tools.

While the link between recommendations and churn rate is strong, these recommendations do not consistently impact watch time for all users. This could be due to the consumption behaviour of 67.2% of respondents who indicated they consume a balance of manual searched content and AI-driven recommendations. Therefore engagement may be influenced not only by recommendation quality but by overall platform usability and content availability, this is further evidenced by findings from Staples, J. (2024) who stated that 52% of users reported user interface playing a significant role in their decision to subscribe, additionally 51% felt overwhelmed by the quantity of recommended content, which indicates that despite accurate algorithms, volume of recommended content can hinder user engagement. Additionally, limitations exist in collecting accurate engagement due to the questionnaire being a self-reporting style of data collection by nature. Users may underestimate or miscalculate the influence of recommendations on their session length, as may platforms (e.g. YouTube, Spotify) seamlessly integrate recommendations into the user interface, which makes their impact less obvious to users.

To summarise, the hypothesis is supported particularly in the AI-driven recommendations ability to reduce churn. While increased session duration is indicated in over one third of users, the full extent of this impact may be underreported. Improvements in precision of the technology through hybrid recommendation strategies are likely to strengthen these relationships in the future.

5.4 Discussion of Research Objectives

Investigate the role of AI in enhancing streaming service recommendations (e.g., Netflix, Spotify).

The findings demonstrate the integral role AI plays in delivering more relevant and personalised experience on streaming platforms. As discussed in 5.3.1, the majority (83.7%) of respondents reported AI-driven recommendations at least somewhat improving their streaming experience. McAlone (2016) and Mudaliyar (2024) reinforces this, citing Netflix's reliance on recommendation systems accounting for 80% of content streamed, and Spotify's success with collaborative filtering through their Discover Weekly. These findings emphasise the importance of AI in improving platform engagement and assisting in user's viewing experiences.

Compare various machine learning algorithms for personalised recommendations, focusing on collaborative filtering, deep learning, and content-based filtering.

Despite the survey data not explicitly asking for users to compare different machine learning models, the literature review provided a strong comparison. Collaborative filtering, which finds success in user-to-user similarity matching (seen in Spotify), deep learning's ability to model complex user habits over time, and content-based filtering which allowed for matching user preferences to curated content. While CF is the most used of these algorithms, deep learning approaches are becoming increasingly favoured due to their scalability particularly in broader catalogues of content (Zhang et al., 2023). These models are heavily dependent on the platform goals such as content diversity or precision.

Assess the Impact of Personalisation on User Engagement and Satisfaction, examining content consumption patterns.

Personalisation can be seen to influence user engagement and satisfaction, but the technology's impact varies user-to-user. As discussed under Hypothesis 1 and 3, one third of respondents reported an increase in session duration due to recommendations, while nearly 50% noted dissatisfaction when recommendations were not accurate, which is a key indicator of potential churn. The Chi-square test further indicates a link between satisfaction levels and reliance on recommendations. This suggests that personalisation increases engagement when accurate but can have the opposite effect if poorly executed.

Assess the impact of NLP in content categorisation and recommendation.

While questionnaire responses suggest that recommendations often align with user interests, there is no confirmation whether respondents interacted with NLP-powered systems. Therefore, NLP's impact can only be concluded on existing literature.

Studies highlight that platforms such as Netflix use NLP to analyse reviews, user behaviour, and metadata to improve the quality of recommendations (Malhotra, 2023). BERT and similar models can analyse nuanced language, such as context and sentiment (Zhang et al., 2023). Despite this, as reported by (Rimaz et al., 2019) challenges remain such as sarcasm and content ambiguity, which can affect performance despite best attempts by OpenAI and other industry leaders (Getahun 2024). In summary, literature strongly confirms that NLP enhances content categorisation and precision of recommendations in streaming services.

5.5 Implications of Findings

The findings show that AI-driven personalised recommendations significantly improve user satisfaction, which supports the need for continuous investment to fine tune the AI-driven

algorithms. The positive link between satisfaction and reliance on AI suggests how important these systems are in reducing churn. As highlighted by the literature and supported with the primary data, user satisfaction is closely tied to perceived relevance of recommended content. Secondly, the comparison of ML algorithms highlights an important strategic consideration for developers. While collaborative filtering remains effective for establishing similarities between users, deep learning offers superior personalisation, especially in diverse content libraries. This suggests that future systems may benefit from hybrid models which implement CF with deep learning and content-based methods to optimise recommendations from user-to-user.

Thirdly, the study reinforces the role of NLP in improving recommendation accuracy by allowing platforms to interpret user-generated content and metadata. Despite this, limitations in current NLP models, particularly in interpreting content that is sarcastic or ambiguous, shows that recommendations are still not always precise. This highlights the need for technological improvements in context understanding and sentiment analysis, areas where organisations are already investing in.

These findings also show that despite the increase of engagement through personalisation, it is not universally effective. From the questionnaire, approximately two-thirds of users stated that AI-driven recommendations did not increase their session duration, with other reports suggesting platform usability, content availability, and user autonomy also play a significant role in user engagement.

Finally, the broader implication is that despite AI technologies being significant factors in shaping the user experience. Despite this developers and platform managers should be mindful of concerns around autonomy, content filtering, and algorithmic influence on consumption habits remain relevant. Systems must aim to guide users toward content they are likely to enjoy whilst simultaneously allowing them to explore independently.

In summary, this study highlights that personalised recommendation systems are pivotal to user retention and engagement in streaming services, but the technology must be refined to meet user expectations, ethical responsibilities, and technological challenges.

5.6 Recommendations for Future Research

Based on the findings and limitations of this study, several recommendations can be made for future research in AI-driven personalised recommendations in streaming services.

Firstly, future studies should seek to gather more direct evidence in specific AI technologies, such as Natural Language Processing (NLP), collaborative filtering, and deep learning and

how they affect the user experience. While this research studied their impact from literature, a more focused approach such as platform specific or interviews, would allow researchers to evaluate the impact of different technologies.

In addition, future research should attempt to expand the participant demographic to achieve more generalised findings. Future research should aim to include a wider age group, participants with different levels of technological familiarity to gather information on a diverse range of user preferences and behaviours.

Furthermore, future work should explore different challenges of AI-driven recommendations in more depth, particularly issues such as algorithmic bias, autonomy, and transparency of the technology. As these technologies become more advanced, there is a growing need to detail how their recommendations are shaped, and to allow users to keep control over their content discovery.

Lastly, research could investigate long-term effects of personalised streaming experienced. While this study's scope was on immediate user satisfaction and engagement, studies could alternatively explore the result of long-long term exposure to personalised streaming, in terms of user loyalty, diversity of content subjects are exposed to, and platform dependency over time.

In summary, by addressing these areas, future research could be able to better understand the evolving role of AI in streaming services and contribute to the successful development of recommendation technologies.

5.7 Conclusion

This study investigated the role of AI-driven personalised recommendations in influencing user engagement and satisfaction on streaming platforms. The findings of the study showed that AI-driven recommendations improve user satisfaction, assist in reducing churn, and benefits from different technologies such as collaborative filtering, deep learning, and NLP. Despite most hypotheses being supported, results from both the primary and secondary research concluded that recommendations do not impact all users equally. In hypotheses 3, results showed that AI-driven recommendations did not consistently lead to increased watch time, which suggests other factors such as content availability, platform familiarity, and usability are important in shaping user engagement. Limitations such as relying on self-reported data from respondents, and uncertainty over the use of specific technologies were noted.

Overall, AI-driven personalisation remains critical for enhancing streaming services, ongoing improvements in these technologies in terms of ethical design, precision, contextual awareness are necessary to continue being successful.

Chapter 6

6.1 Introduction

This chapter will conclude the study by summarising the findings on how AI-driven personalised recommendations enhance user engagement and satisfaction in streaming services. It will review the main findings and discuss the effectiveness of different AI-driven algorithms; collaborative filtering (CF), deep learning (DL), Natural Language Processing (NLP) technologies, and highlight how these approaches affect the user experience. This chapter also aims to decide whether hypothesis and research objectives were supported, offering final observations on the impact AI has in shaping the user experience.

6.2 Key findings

Upon conclusion of the primary and secondary research, it was determined that AI-driven personalised recommendations are an important factor in user engagement and satisfaction. The primary research of 61 respondents concluded the following key findings.

Over 78% of user's experiences were enhanced by AI recommendations, with a further 64% reporting satisfaction with their suggested items.

The conclusion of a Chi-square test indicated that with a 98.62% confidence level, that greater reliance on AI-driven recommendations is meaningfully associated with greater user satisfaction.

37.7% of respondents reported unsubscribing from a streaming service due to poor recommendations, which further highlights the role of personalisation in reducing churn rate within a platform.

6.3 Discussion of Machine Learning Approaches

The comparative study of machine learning algorithms, namely CF, DL, NLP, and content-based filtering, which are reinforced with literature review findings, showed different techniques used to recommend items.

CF was widely effective at creating a user-to-user similarity between similar users, although it must be noted that this technique faced issues with cold start issues and popularity bias. DL exhibited better personalisation ability, which is especially appropriate for large content libraries, as it models complex patterns of user behaviour over time.

Content-based filtering, not dissimilar to CF, curated recommendations by matching user profiles with content characteristics but was less effective when the user preferences evolved too quickly for the algorithm to populate appropriate recommendations often enough.

NLP, which offers a superior recommendation accuracy due to its ability to interpret user-generated text, but challenges with the technique remain due to its inconsistencies with sarcasm detection and multilingual interpretation.

The study suggests that combining CF, DL, and NLP as a hybrid model is the most effective solution to curate accurate recommendations, whilst minimising the weaknesses of each technology.

6.4 Implications of Findings

This research carries implications for technology development, future academic studies and service providers.

For streaming service providers, these findings underline the importance of investing in AI recommendation systems. Improved recommendation accuracy not only improves user satisfaction but is in direct correlation with lowering churn rates, which is important in creating a strong competitive advantage against other streaming services, especially those with strong AI-driven recommendation systems.

For the development of AI recommendation systems, the integration of CF, DL, and NLP techniques in a hybrid recommendation system, offers the best path forward for achieving better personalisation results. Despite this, ongoing improvements are necessary to further develop NLP algorithms in relation to integration of sarcasm and multilingual nuances detection.

From an academic perspective, the study supports a large collection of evidence regarding the sophistication of user engagement behaviours and suggests that personalisation improvements must not compromise users' content exploration freedom and user autonomy.

6.5 Limitations of the study

Despite producing meaningful results, the limitations of the study which must be acknowledged.

The first limitation is that participants' responses may not reflect their behaviours on streaming services or understand the technologies influencing their streaming experiences. Secondly, due to the survey involving students and staff at a local FE college, the responses limit the generalisability of findings and lack more diverse populations. Lastly, the broad

scope of the study served as a limitation, covering multiple AI technologies across different streaming platforms limited the ability to explore a single technology or platform in great depth.

6.6 Recommendations for Future Research

Due to these limitations, there are recommendations for future research:

Future research could aim for a more qualitative approach, such as interviews to understand behavioural or emotional insights. A further suggestion would be regarding demographic, inclusion of a broader range of ages, occupations, and cultural backgrounds would better help generalise the findings. Future studies could focus on one specific model or platform to allow for more in-depth analysis of technical and behavioural outcomes. Lastly, future studies could explore user concerns around transparency of algorithms, fairness of recommendations, and diversity of content, areas which are all important in AI-driven systems.

6.7 Final reflection

To summarise on this research, it is evident that AI-driven recommendations significantly enhance user satisfaction and loyalty in streaming services. This study has further uncovered that user engagement is not determined only by recommendations accuracy, but on other factors such as platform familiarity and usability, and user autonomy.

This study contributes valuable insights on how machine learning algorithms influence user experience but ensuring to highlight challenges that these technologies face. As streaming services improve their AI-driven recommendation systems by investing in the technology, the platforms' success will be determined also by allowing user freedom, maintaining user trust, and satisfaction.

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Appendix A: Meeting 1

South West College Undergraduate Degree Dissertation Supervision Record

SCHOOL OF Mathematics and Computing. Degree Title OU BSc Honours Computer Science Top Up

Name of student: Hugh Kelly

Date of supervisory meeting: 27/01/25

Personnel present: Michael Gillen and Hugh Kelly

Title of project: Enhancing User Experience Through AI (Artificial Intelligence)-Driven Personalised Recommendations in Streaming Services: A Comparative Study of Machine Learning Algorithms

Principal supervisor: Michael Gillen

Additional supervisors: N/A

Key aims set at last meeting:

1) N/A

2) N/A

3) N/A

Progress made on each item: N/A

Progress made in today's meeting: N/A

Proposed plan and action points for next meeting:

Action Point 1 – Reword Hypotheses to make them more understandable when it comes to proving or disproving them.

Action Point 2 – Begin the designing of survey with a mixture of open and closed questions

Action Point 3 – Make sure that all questions asked in survey have some form of link to one of the hypotheses to make sure the results are relatable.

Supervisor Comments:

You've made a strong start on your dissertation chapters, with only minor refinements needed. It's always beneficial to design and create the survey early so it can be distributed to college staff and students before a flood of other surveys leads to it getting lost in emails. When designing the survey, it's crucial to consider the hypotheses and ensure that the questions generate results that align with them, making the research study robust and meaningful.

Signed: (Supervisor) Date: 27/01/25

Student comments:

Signed: (Student) Date:

Appendix B: Meeting 2

South West College Undergraduate Degree Dissertation Supervision Record

SCHOOL OF Mathematics and Computing. Degree Title OU BSc Honours Computer Science Top Up

Name of student: Hugh Kelly

Date of supervisory meeting: 24/03/25

Personnel present: Michael Gillen and Hugh Kelly

Title of project: Enhancing User Experience Through AI (Artificial Intelligence)-Driven Personalised Recommendations in Streaming Services: A Comparative Study of Machine Learning Algorithms

Principal supervisor: Michael Gillen

Additional supervisors: N/A

Key aims set at last meeting:

1 Reword Hypotheses to make them more understandable when it comes to proving or disproving them.

2 Begin the designing of survey with a mixture of open and closed questions

3) Make sure that all questions asked in survey have some form of link to one of the hypotheses to make sure the results are relatable.

Progress made on each item:

1) Hypotheses reads much better and easier to understand.

2) Survey designed and piloted. Has been distributed and should be closed now.

3) Questions used are all suitable and relevant.

Progress made in today's meeting:

Proposed plan and action points for next meeting:

Action Point 1 – Remove subheadings throughout literature review and make it read much better. Needs to have a natural flow to it.

Action Point 2 – Find more links and connections throughout literature review for future referencing with survey results.

Action Point 3 – Discuss variables in 3.3 and choice of participants in 3.4.

Supervisor Comments:

A positive meeting where we went through all chapters to date and focused on some minor issues to fix and reword to make sure the dissertation report flows much better. Also, some detail to be added in elements of chapter 3. Survey should now be closed and process of data cleaning and analysis to begin.

Signed: (Supervisor) Date: 24/03/25

Student comments:

Signed: (Student) Date:

Appendix C: Meeting 3

South West College Undergraduate Degree Dissertation Supervision Record

SCHOOL OF Mathematics and Computing. Degree Title OU BSc Honours Computer Science Top Up

Name of student: Hugh Kelly

Date of supervisory meeting: 07/04/25

Personnel present: Michael Gillen and Hugh Kelly

Title of project: Enhancing User Experience Through AI (Artificial Intelligence)-Driven Personalised Recommendations in Streaming Services: A Comparative Study of Machine Learning Algorithms

Principal supervisor: Michael Gillen

Additional supervisors: N/A

Key aims set at last meeting:

1 Remove subheadings throughout literature review and make it read much better. Needs to have a natural flow to it.

2 Find more links and connections throughout literature review for future referencing with survey results.

3) Discuss variables in 3.3 and choice of participants in 3.4.

Progress made on each item:

1) Subheadings removed and reads more naturally

2) Still needs to be done

3) Discuss variables as not done yet

Progress made in today's meeting:

Data cleaning has taken place but for 2 questions they need to be cleaned deeper and maybe break into brackets for referencing.

Discussion on how to attack chapter 4 done with outlined plans for the week ahead.

Proposed plan and action points for next meeting:

Action Point 1 – Deeper dive into the 2 open questions

Action Point 2 – Write up and finish chapter 4 with results. Can mention briefly elements of Hypotheses but this is mainly for Chapter 5.

Action Point 3 –

Supervisor Comments:

.

Signed: (Supervisor) Date: 07/04/25

Student comments:

Signed: (Student) Date:

Appendix D: Ethics form

South West College

Student Research Ethics Application Form

South West College (SWC) is concerned to protect the dignity, rights, safety and well-being of all participants in any research study involving people. The avoidance of harm to research participants should therefore be a prime consideration for all SWC students.

SWC has developed research ethics review procedures that require students to complete an ethics approval application form prior to the commencement of any research project.

Please complete the questions below (type-written) and forward this form to your Dissertation Supervisor. Please use the guide / exemplar to help you. Once the Supervisor has approved and signed off the form, they will submit it to the College Research and Governance Committee for consideration as to i) proceed with the research, ii) resubmit the application for further review, or iii) consider a new or substantially changed project.

The approved form must be attached as an appendix to the final submitted dissertation.

Student name	Hugh Kelly
SWC email address	30006375@student.swc.ac.uk
Student number	30006375
Programme title	Bsc Honors in Computing Science (Top up)
Dissertation Supervisor name	Bronagh McNamee

Dissertation / project title	"Enhancing User Experience Through AI-Driven Personalised Recommendations in Streaming Services: A Comparative Study of Machine Learning Algorithms"
Proposed start date	January 25'
Proposed end date	May 25'

1. *Does the research project involve any of the following risk factors: *(Researchers should note that any study not deemed as low risk is unlikely to obtain a favourable ethical opinion to proceed, unless a particularly compelling case can be made.)*

	YES	NO
Research involving health sector organisations		X
Research involving children under 18		X
Adults with learning or other disabilities		X
Very elderly people		X
Other vulnerable groups		X
Research involving sensitive topics		X
Research involving defence organisations		X

Updated 13.08.24 / JK

SouthWest College

2. Provide a brief outline of the aims and objectives of the proposed research project.

The research aims to enhance user experience in streaming services through AI-driven personalized recommendations. Specifically, it seeks to:

- Investigate the role of AI in enhancing streaming service recommendations (e.g., Netflix, Spotify).
- Compare various machine learning algorithms for personalised recommendations, focusing on collaborative filtering, deep learning, and content-based filtering.
- Assess the Impact of Personalisation on User Engagement and Satisfaction, examining content consumption patterns.
- Assess the impact of NLP in content categorisation and recommendation.

The research aims to either prove or disprove the following relevant hypotheses:

- AI-driven personalised recommendations significantly enhance user engagement and satisfaction compared to non-personalised or generic recommendation systems in streaming services.
- The integration of NLP in AI-driven recommendation systems significantly improves the accuracy of recommendations by effectively categorising and interpreting textual metadata.
- AI-driven personalised recommendations lead to higher user engagement, measured by increased watch time and reduced churn rates, compared to non-personalised recommendations.

3. Describe the proposed research design. Include the types of data to be collected from participants (e.g. observation of people, interviews or survey questionnaires / participant numbers / types of people to be interviewed, such as their job role or occupation).

Research Design: This study will employ a quantitative research method using surveys distributed via email. The surveys will gather insights into user engagement, satisfaction, and the quality of AI-driven recommendations in streaming services like Netflix, Spotify, and YouTube. The data collected will be used to objectively assess the effectiveness of personalized recommendations.

Data Collection:

Participants: The survey will target students and staff aged 18 and older from a local FE College, allowing for a diverse range of perspectives.

Procedure: Participants will complete an online survey that includes multiple-choice and open-ended questions about their experiences with personalized recommendations. The

Updated 13.08.24 / JK

survey will also include questions on user engagement, content consumption patterns, and satisfaction with recommendations.
Research design will be methodologically sound and ethically justified and there will be no conflicts of interest.

4. Does the proposed research contain any potentially contentious issues that might affect the physical, psychological or emotional wellbeing of the research participants? If so, provide full details.

Despite research involving examining AI-driven algorithms for content recommendations, the ethical concerns primarily relate to data privacy and the potential for biased or harmful recommendations. These risks will be mitigated by ensuring transparency, obtaining informed consent where necessary, and following ethical guidelines in data handling and AI model selection. It is also important to note that in the Microsoft form, , participants will be fully informed about the study's purpose, procedures, risks, and benefits.
Participants can withdraw at any time without penalty.

5. How do you intend to gain consent of individuals who will participate in the research?

The study complies with institutional and national ethical guidelines, including GDPR. All data will be handled strictly in accordance with GDPR laws. Participants personal data will be kept confidential and stored securely on OneDrive with strong authentication, this data will be solely used for the purposes of this research and deleted afterwards, no identifiable information will be collected except for age (for demographic purposes). Participants will be informed about the nature of the study, their role, and how their personal data will be managed. Consent will be obtained through an initial statement on the survey platform (Microsoft Forms), stating that by proceeding, participants consent to the use of their data for research purposes.
A consent statement will be included at the start of the survey, and participants will be asked to confirm their understanding that their data will be used and that their participants are aged 18 or older before proceeding. Signed consent forms are not required, but participants must consent digitally before taking part in the survey.

6. Describe how you will maintain the confidentiality of the research data collected. Include how you intend to store the data.

Anonymity will be gained by not asking for personal identifiers such as name, or address to ensure each participant cannot be identified in the results. The only personal identifiers which are being collected is age which is necessary for the study. To further minimise the risk of breaching confidentiality, responses will be aggregated.
All data will be stored securely without personalised identifiers to maintain confidentiality throughout the primary research phase. The survey responses will be password protected on OneDrive and only accessible by the researcher and the dissertation supervisor. Data will only be used for research purposes and will not be shared with any third parties.

Declaring the use of generative AI in assessment

South West College's Plagiarism Policy states that students should take care to ensure that all assessed work presented is their own, and they must fully acknowledge the work and opinions of others through proper referencing and citation. Students should also ensure

Updated 13.08.24 / JK

that the use of AI tools is authorised for use in their assessment as practices may differ across modules and courses of study.

The College states that any unauthorised use of plagiarism or academic malpractice will be investigated in line with the processes outlined in the College's Plagiarism Policy.

Declaration by Student:

I confirm that the project will be conducted in compliance with the research description / protocol and in accordance with the College's requirements on recording and reporting:

Student signature: Hugh Kelly   Date: 27/01/2025

Declaration by Dissertation Supervisor:

I confirm that this project is viable and is of research or educational merit and that all risks and ethical and procedural implications have been considered.

Dissertation Supervisor signature: Bronagh McNamee Date:27/01/2025

Please note that the Dissertation Supervisor will retain this form for the duration of the student research project. The form may need to be accessed for ethics auditing purposes during this period.

Once completed and signed, the Dissertation Supervisor will forward this form to Julie Kelly julie.kelly@swc.ac.uk who will present it to the College Research and Governance Committee for consideration of approval to commence research.

Office use only

South West College Research & Governance Committee

- The application must be considered by the Research & Governance Committee in accordance with the requirements of the College

- The Research & Governance Committee should write to the Dissertation Supervisor indicating the outcome of its review

- Depending upon the outcome of the Research & Governance Committee review, the Dissertation Supervisor should arrange for the student to i) proceed with the research, ii) resubmit the application for further review, or iii) consider a new or substantially changed project

- The Research & Governance Committee should retain a complete set of original forms.

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Research and Governance Committee Approval

The South West College Research and Governance Committee has considered this research study application and given the nature of the study and ethical considerations permits / rejects (delete as applicable) this dissertation research to proceed.

Chair of Research and Governance Committee

Signed.......... _Paul Mc Gowan_   Dated.......27.01.25

Appendix E: Chi-square table

	Somewhat Dissatisfied	Neutral	Somewhat Satisfied	Very Satisfied	Row Total
Always	0.01	0.01	1	1	2.02
Often	3	2	20	2	27
Sometimes	1	9	14	1	25
Rarely	1	3	0.01	0.01	4.02
Column Total	5.01	14.01	35.01	4.01	58.04
Expected Frequencies	Somewhat Dissatisfied	Neutral	Somewhat Satisfied	Very Satisfied	
Always	0.174365955	0.487598	1.218473467	0.139562371	
Often	2.330634045	6.517402	16.28652653	1.865437629	
Sometimes	2.157994487	6.034631	15.08011716	1.727257064	
Rarely	0.347005513	0.970369	2.424882839	0.277742936	
Chi-Square Contributions	Somewhat Dissatisfied	Neutral	Somewhat Satisfied	Very Satisfied	
Always	0.154939461	0.467803	0.039172503	5.30481755	
Often	0.192244159	3.131143	0.846705107	0.009706586	
Sometimes	0.6213877	1.457158	0.077363662	0.306209683	
Rarely	1.228804105	4.245194	2.404924079	0.258102981	
Chi-Square Value	20.74567595				
Degrees of Freedom	9				
p-Value	0.0138				

Appendix F: Blank Questionnaire

Personalised recommendations in streaming services.

By participating in this survey, you confirm that you are at least 18 years old and consent to your responses being used for primary research. Anonymity is ensured as no personal identifiers, such as names or addresses, are collected. The only personal information gathered is age, which is necessary for the study. You can withdraw from the survey at any time.

1. What is your age group? *

  ○ 18-24

  ○ 25-34

  ○ 35-44

  ○ 45-54

  ○ 55+

2. Which streaming services do you use the most? (select all that apply) *

  ☐ Netflix

  ☐ YouTube

  ☐ Spotify

  ☐ Disney+

  ☐ Amazon Prime Video

  ☐ None

  ☐ Other

3. How often do you use streaming services? *

○ Daily

○ A few times a week

○ Once a week

○ A few times a month

○ Less than once a month

4. When choosing what to watch or listen to, how much do you rely on recommendations such as "Recommended for You" or "Top Picks" from the platform? *

○ Always

○ Often

○ Sometimes

○ Rarely

○ Never

5. Do you feel that the recommendations improve your overall experience on the platform? *

○ Yes, significantly

○ Yes, somewhat

○ No, doesn't make a difference

○ No, I don't find them helpful

6. How satisfied are you with the recommendations you receive? *

○ Very satisfied

○ Somewhat satisfied

○ Neutral

○ Somewhat dissatisfied

○ Very dissatisfied

7. Do you prefer watching/listening to recommended content or searching manually? *

○ Mostly rely on recommendations

○ A mix of recommendations and manual search

○ Mostly search manually

8. How often do you watch/listen to content suggested by the platform's recommendation system? *

○ Always

○ Often

○ Sometimes

○ Rarely

○ Never

9. Have **AI-driven** recommendations increased the time you spend on a streaming platform? *

○ Yes, I spend more time on the platform because of recommendations

○ No, my viewing/listening habits are unaffected by recommendations

10. In what ways, if any, have AI-driven recommendations influenced your decision to subscribe or remain subscribed to a streaming service? *

Enter your answer

11. Have you ever switched to another platform because of poor recommendations? *

○ Yes

○ No

12. How likely are you to cancel a streaming subscription if the recommendations no longer match your interests? *

○ Very likely

○ Somewhat likely

○ Neither likely nor unlikely

○ Somewhat unlikely

○ Highly unlikely

13. Do you feel that streaming services provide content recommendations that align with your interests? *

○ Yes, most recommendations match my interests

○ Sometimes, but not consistently

○ No, recommendations are often unrelated to my interests

14. Have you noticed that AI-generated recommendations improve over time as you engage with the platform (e.g., liking, rating, searching)? *

○ Yes, recommendations have become more accurate over time

○ Somewhat, but not significantly

○ No, recommendations remain the same regardless of my activity

15. How do you feel AI-powered recommendations impact your overall streaming experience? *

Enter your answer