Journal of Informatics and Web Engineering

Vol. 2 No. 2 (September 2023) eISSN: 2821-370X

AIRA: An Intelligent Recommendation Agent Application for Movies

Ayesha Anees Zaveri[1*], Ramsha Mashood [2], Sarama Shehmir[3], Misbah Parveen[4], Naveera Sami[5] & Mobeen Nazar[6]

[1,6]Malaysian Institute of Information Technology-Universiti of Kuala Lumpur, 1016, Jln Sultan Ismail, Bandar Wawasan, 50250 Kuala Lumpur, Malaysia
[2,4] Bahria University Karachi, 13 National Stadium Rd, Karsaz Faisal Cantonment, Karachi, Pakistan
[3] Toronto Metropolitan University, 350 Victoria St, Toronto, ON M5B 2K3, Canada
[5] NED University of Engineering and Technology, Service Rd, Karachi, Pakistan
**corresponding author: (ayeshazaveri1988@gmail.com; ORCiD: 0009-0007-7230-1696)*

Abstract - An intelligent Recommendation App has been developed to assist caregivers. This project's primary objective is to assist parents in determining whether a particular movie/cartoon/drama is adequate for their children by providing ratings that will assist them in identifying age-appropriate content. This application will provide reliable evaluations, reviews, and recommendations to parents. Each rating and review are based on fundamental, essential child development principles. Intelligent Recommendation Agent aids families in making intelligent media selections. It provides the most extensive and reliable database of learning ratings, age recommendations, and content evaluations for films, television series, and dramas. In addition, there will be a list of abusive words from the content with its subtitles so that parents can identify appropriate content for children. By limiting their child's exposure to violent acts, parents can play a positive role in their child's life by using this application. Movies with positive role models can also have a positive effect on children.

Keywords— Intelligent Recommendation, Media, Technology, Review, Rating, Age-appropriate

Received: 08 June 2023; Accepted: 17 July 2023; Published: 16 September 2023

I. INTRODUCTION

Due to the explosion of online data, searching the web is now a laborious and time-consuming operation, despite the fact that it is a priceless information resource [1]. An intelligent recommendation agent is a system designed to provide personalized suggestions or recommendations to users based on their preferences, behaviors, and other relevant data. It aims to help users discover new products, services, or content that align with their interests and needs. The recommendation agent leverages advanced algorithms and machine learning techniques to analyze large amounts of data, such as user profiles, past behavior, item characteristics, and feedback from other users. This data is used to predict the items a user might like or find useful. The recommendations can be in various forms, including product recommendations, movie recommendations, music suggestions, news articles, or even friends to connect with on social media platforms [1]. By creating virtual networks and communities, social media such as Facebook, Instagram, LinkedIn, and Twitter facilitate sharing ideas, thoughts, videos, photos, and information. This has enabled companies and products to reach a broader audience for marketing and advertising purposes and to collect public feedback [2].

Journal of Informatics and Web Engineering
https://doi.org/10.33093/jiwe.2023.2.2.6

Published by MMU Press. URL: https://journals.mmupress.com/jiwe

Recommendation systems assist users in locating and selecting items, such as books, movies, and restaurants, from the vast array of options available. Movie recommendation systems face a similar issue, as people have varying expectations, and it is not possible to observe a film based on the annotations provided by other users. A movie recommendation system provides the user with convenience and customization, enabling him to progress through the system and view movies that suit his preferences [2].

On the vast Internet landscape, where endless options and information abound, we are overwhelmed with the provided information. Every click led to a flood of choices, making finding what truly mattered to us difficult. The problem of information overload had become all too familiar. The recommendation systems help to filter, prioritize, and efficiently deliver relevant information, alleviating the burden of information overload. In the digital realm, it explains that these systems acted as guardians, tirelessly searching through the vast sea of dynamically generated content to provide users with personalized recommendations [1],[2].

There are various characteristics and potentials of different prediction techniques in recommendation systems. Various recommendation techniques are used, like content-based, collaborative filtering-based, knowledge-based, hybrid, computational intelligence-based, social network-based, and context awareness-based recommendation techniques. The techniques include approaches such as analyzing user preferences, similarity measures, Bayesian methods, artificial neural networks, clustering, genetic algorithms, fuzzy set theory, social network analysis, trust-based frameworks, and considering contextual information. These techniques aim to improve recommendation accuracy, coverage, and user experience [3],[4],[5].

A recommendation system is a data-driven system that provides personalized recommendations to users for various resources, including but not limited to books, movies, and songs. Typically, movie recommendation systems anticipate a user's favorite movies based on the characteristics and previously provided data. Such recommendation systems are helpful for businesses that collect data from many clients and want to deliver the best recommendations available. Several factors can be considered when designing a movie recommendation system, including the movie's genre, cast, plot, and directorial credits. The systems can propose movies based on a single attribute or a combination of two or more. A recommendation engine uses several algorithms to filter data and then recommends the most relevant items to consumers. If a user initiates a visit to a movie website for the first time, the website will lack any prior record of the user. In such instances, the user may search based on their preferred movie genre or director to receive a comparable recommendation [3].

Machine learning has experienced significant growth and advancement due to the rising need for automated solutions utilizing machines. In contemporary times, with the proliferation of electronic commerce on the World Wide Web, the prevalence of online shopping and entertainment has reached unprecedented heights. It is anticipated that online activities will become the new norm in the forthcoming decade. Consider the scenario where one engages in online shopping through platforms such as Amazon.com, which boasts a vast inventory of one million products, and other e-commerce websites like Flipkart. Online platforms such as Netflix and Hotstar offer a vast collection of over 10 million movies and series for viewers. A search query may be executed if one desires a particular item from Amazon. However, what is the recommended course of action for procuring other items? [3]

Finding search results that are comparable or superior in quality can be likened to searching for a golden tree amidst a dense forest of trees. One may become disoriented and unable to navigate their way out of the jungle [4]. Recommendation systems can assist in this regard. The utilization of recommender systems is advantageous in such platforms. The Recommendation System is crucial in serving as a navigational aid within Amazon, Netflix, and other e-commerce platforms. Without a recommendation system, one would have to rely on a database and exercise caution in determining their search criteria. The potential impact of reduced consumer engagement, such as decreased product purchases or viewership, on Amazon and Netflix could be significant. Hence, corporations will require it more in the forthcoming years than any other resource. Hence, we decided to acquire knowledge of recommender systems and elevate our understanding to a higher level.

Recommendation systems are primarily employed to aid consumers in obtaining personalized outcomes based on their preferences. One potential application of machine learning algorithms is using recommendation systems as a filtering mechanism to identify the optimal outcome from a pool of projected outcomes. Films can be categorized according to their genres, such as thriller, animation, comedy, action, drama, etc. An alternative approach to classifying films is using metadata, including but not limited to the cast, year of release, language, or director. Currently, most online video-streaming platforms offer a variety of comparable television programs and films to users through the utilization of their prior search terms and viewing history. The primary objective of constructing a Movie Recommendation System is to ensure its dependability and effectiveness in delivering precise user recommendations based on their

preferences. The recommendation can be of several types: data collection, pre-processing, feature extraction, model training, recommendation generation, evaluation, and refinement. Typically, Recommendation Systems are categorized into three distinct types: Collaborative or User Filtering, Content-Based Filtering, and Hybrid Filtering [5],[6],[7].

The primary objective of this application is to ensure that the needs of children are prioritized whenever the media and technology sectors develop and market their products. These industries need to be held accountable by implementing transparent policies and regulations. This research advocates on behalf of children on a wide variety of problems, including the educational impact of technology, preserving children's privacy when they use the internet, and improving the influence of media on child health and development. This application will assist parents in browsing content that is suitable for their children's ages. The results of psychological studies have shown that children are negatively affected by watching violent content on television. This application will give parents reliable ratings, reviews, and recommendations. Each of the evaluations and reviews is founded on significant and fundamental aspects of how children grow and develop. Therefore, this app will suggest movies, dramas, and cartoons for parents to watch with their children. This application has been developed as a remedy for the problem so that parents can play a constructive part in their children's lives by reducing the likelihood of their children being exposed to violent acts. [5],[6],[7].

II. LITERATURE REVIEW

In the 21st century, internet e-commerce is becoming increasingly prevalent. The online retail and entertainment industries are thriving. Online Everything will become the new standard in the future years. Imagine purchasing online at Amazon.com. They offer more than sixty million products for sale, the same as Flipkart and other e-commerce websites. The entertainment websites of Netflix, Amazon Prime, and Hotstar offer over 10 million films and television series. If the user finds something specific on these websites, it can effortlessly search. However, what about the remaining products? If the users are looking for a comparable or superior product, more than search results may be required. Also, if the user seeks globally, it will be similar to looking for a golden tree in a forest. The user will become hopelessly disoriented and never find the way home. In this situation, recommendation systems become the ally. The Recommendation System is essential for Amazon, Netflix, and other systems. Without Recommendation Systems, many E-commerce and Entertainment websites will resemble databases, and the user must be sure of its search criteria. It would be a significant loss for these companies if no one purchased their products or watched their movies. Similarly, it will harm users if they cannot obtain the required product [8].

The significance of recommendation systems is rising in the fast-paced contemporary society. Individuals are frequently constrained by time due to the numerous tasks they must complete within a 24-hour day. Hence, recommendation systems are significant as they aid individuals in making appropriate decisions while conserving their cognitive resources.

The fundamental objective of a recommendation system is to identify and retrieve content that is captivating to a specific user. In addition, the process entails several variables to generate customized compilations of pertinent and captivating material tailored to each user's unique preferences. Recommendation systems are algorithms based on Artificial Intelligence that scan through a vast array of options and generate a personalized list of items that are pertinent and engaging to an individual. The findings mentioned above are derived from an individual's profile, their search and browsing history, the viewing habits of individuals with comparable characteristics and demographics, and the probability of the individual viewing said films. The abovementioned task is accomplished using predictive modeling and heuristics, utilizing the available data. Therefore, incorporating a Recommendation System into various websites is necessary for both the industry and the end user [8].

Recommendation systems provide customized recommendations based on the user's profile and past actions. Internet companies like Amazon, Netflix, and YouTube use recommendation systems extensively. Recommendation systems assist users in locating and selecting items (e.g., books, movies, restaurants) from the vast collection on the Internet or other electronic information sources. In addition to many items and a description of the user's requirements, they provide the user with a small subset of items that are well-suited to the description. Similarly, a movie recommendation system provides convenience and customization that enables the user to interact with the system more effectively and watch the movies that best suit his requirements [9].

A. Types of Recommender Systems

When applied to recommender systems, machine learning algorithms often fall into one of two groups: content-based systems, collaborative filtering systems and hybrid filtering. All these methodologies are used in today's recommender systems as shown in Figure 1 [10].

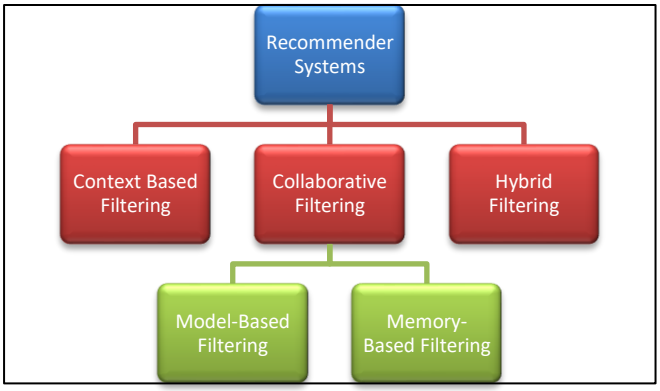

Figure 1. Types of Recommender System

i. Content-based filtering recommender systems

Content-based filtering, another technique, focuses on the intrinsic qualities of the items themselves. It was like having a personal curator who understood user tastes and preferences, sifting through the vast collection of digital content to present her with tailored recommendations as shown in Figure 2 [11].

This defines a detailed profile for content and then creates data connection matrices, allowing them to calculate firm developmental patterns based on some prevalent connections between similar products and user preferences.

This system utilizes both keywords and user profiles. The products are described with keywords, and a user's profile indicates the type of item that the user prefers. The algorithms used in these systems will assist in predicting the future by recommending similar items to those that a user previously enjoyed (or is currently examining). After comparing the previously rated items, the best-matching items are proposed as recommendations.

As these systems are based on observing user behavior, estimates are derived by analyzing past consumer adoptions and their similarities to those of other users. This strategy involves accumulating large amounts of data and reducing the information volume; it clusters users based on firm characteristics such as demographic data and developmental patterns.

ii. Collaborative filtering recommender systems

As shown in Figure 2, Collaborative filtering, one of the techniques, analyzes the preferences and behaviors of like-minded individuals to generate recommendations. It was similar to a classified club, where members shared their insights to help each other discover hidden gems. The information is filtered through the recommendations of others. It is based on the assumption that individuals who previously concurred on evaluating particular items will likely continue to do so in the future.

The collaborative filtering recommender system is used to design the AIRA application. This is a movie recommendation system for Android users that recommends movies and searches for content based on user-provided data. A user can manually select his preferences from a list of attributes [12].

Collaborative approaches can be classified into two distinct categories: memory-based and model-based approaches [12].

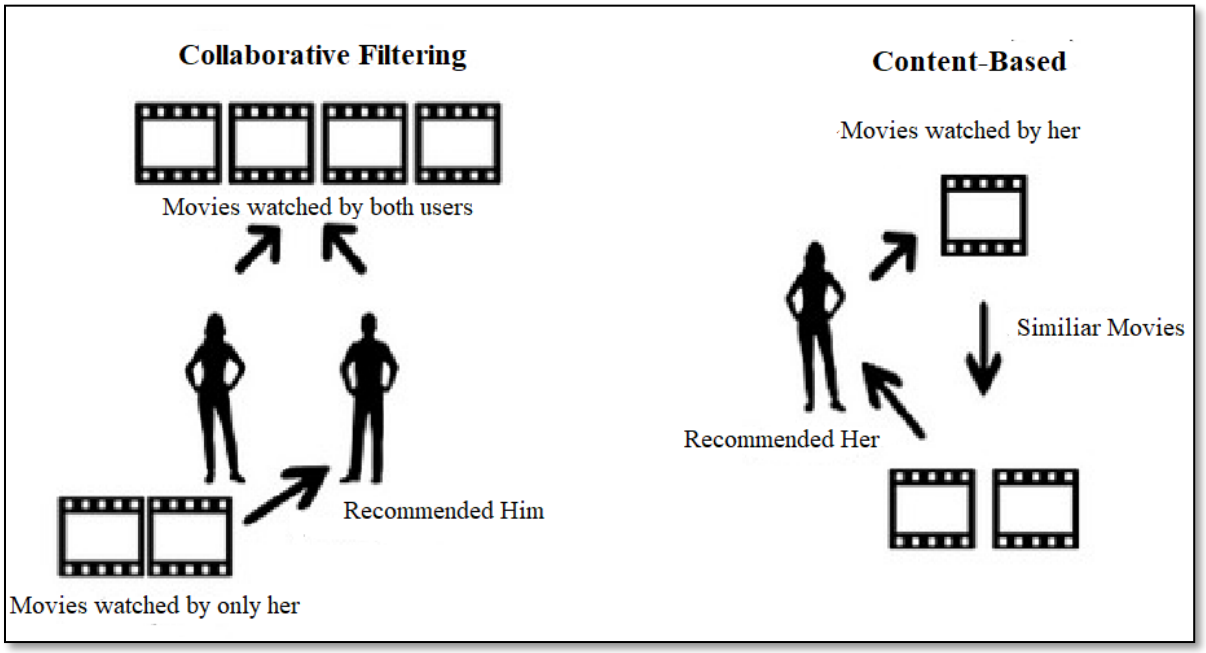

Figure 2. Collaborative Versus Content Filtering

a. Memory-Based Filtering

Collaborative filtering techniques that rely on memory-based approaches suggest novel items based on the preferences of the surrounding community. The utility matrix is utilized directly for prediction. The initial stage of this methodology involves constructing a model. As mentioned earlier, the model can be expressed as a mathematical function that accepts the utility matrix as its input [13].

Memory-based collaborative techniques can be further classified into two distinct types: user-based collaborative filtering and item-based collaborative filtering. The user-based approach involves determining the rating of a new item by identifying other users within the user's neighborhood who have previously rated the same item. If a novel item garners favorable evaluations from the user community, said item is suggested to the user [13].

b. Model-Based Filtering

Model-based methodologies operate under the assumption of a foundational "generative" model that elucidates the user-item interactions, intending to uncover this model to facilitate novel predictions [14].

Model-based methodologies obviate the need to incorporate the user profile of a novel user into the utility matrix before generating predictions. It is possible to provide suggestions to individuals not included in the model. The utilization of model-based systems is more efficient in the context of group recommendations. The pre-existing model can expeditiously suggest a set of items. The efficacy of this methodology is predominantly contingent upon the effectiveness of the foundational machine learning algorithm employed in constructing the model. By utilizing dimensionality reduction techniques and model learning techniques, model-based approaches can address conventional challenges of recommender systems, such as sparsity and scalability [14].

iii. Hybrid Filtering

A hybrid recommender system integrates multiple recommendation techniques to generate output. Compared to collaborative or content-based systems, hybrid recommender systems typically provide more accurate recommendations. In collaborative filtering, this is due to a lack of information about domain dependencies, whereas in content-based systems, this is due to a lack of information about user preferences. It is combining both results in an increase in shared knowledge, which contributes to improved recommendations. The increase in knowledge makes it

especially promising to investigate new methods for extending the underlying collaborative filtering algorithms with content data and content-based algorithms with user behavior data [15].

B. Machine Learning

Machine Learning is also used for movie recommender systems. It discusses the limitations of existing systems that focus on promoting their content, neglecting user preferences. This system implements an Item-Based Collaborative Filtering system with a KNN algorithm in a web-based application, providing recommendations for all movies. The user interface is evaluated, and improvements are suggested, such as adding a virtual guide. The system performs well for popular movies but less so for less popular ones. The author suggests enhancing the system with a content-based approach and creating a hybrid system for more balanced recommendations. The author also learns Python and backend development to implement the project successfully [15].

C. Blockchain

A digitalized, decentralized, and publicly accessible ledger of all cryptocurrency transactions is known as a blockchain. Blockchain is causing sectors to change profoundly by opening the door to novel business procedures. Its transformative influence can be seen in domains as diverse as banking and finance, trading, manufacturing, the management of supply chains, healthcare, and even governance. As a result of the utilization of Blockchain in the inter-IOT communication system, it is possible to achieve security and privacy considerations—Blockchain with the Internet of Things (BIOT). The merging of blockchain technology with the Internet of Things enables the creation of modern decentralized systems. Decentralization, scalability, and security may all be improved with the help of the BIOT models, which can be utilized in various fields, including e-commerce. In light of this research, a creative and cutting-edge investigation into Blockchain and recommendation algorithms is required. By integrating smart contracts with the primary blockchain protocol, we intend to construct a reliable and secure system by leveraging blockchain technology's benefits, enabling secure multiparty computation. Integrating recommendation algorithms and blockchain technology enables online activities to maintain a higher level of confidentiality and security. Enterprises can use intelligent contract systems to collaborate on creating a secure database and host a continuously updated model using a system currently in construction [16].

D. K-Means Clustering

Another research recommendation system combines improved K-means clustering with genetic algorithms. The system addresses the challenge of sparse data and the increasing number of movies and users by employing principal component analysis (PCA) for data reduction and dense clustering. The experimental results on the Movielens dataset demonstrate that the proposed approach achieves high accuracy and generates reliable and personalized movie recommendations compared to existing methods. Future work includes addressing higher dimensionality and sparsity, exploring more effective data reduction algorithms, and incorporating additional useful features for improved personalization. The scalability and reliability of movie recommendations based on the number of clusters will also be investigated [16].

E. K- Clique Clustering

Improving accuracy is also focused in some research on movie recommendation systems by introducing the k-clique methodology, originally used in social network analysis. Collaborative filtering methods are commonly used but lack accuracy. The proposed algorithm combines the k-clique method with other techniques to enhance recommendation accuracy. Experimental results using MovieLens data show that the proposed methods outperform other approaches. The maximal clique method, introduced in a movie recommendation system, proves effective. The k-clique method is further enhanced, leading to improved accuracy. The study suggests future research on reducing computation time for k-clique methods and incorporating data mining techniques for increased effectiveness [17].

III. EXISTING SYSTEMS

Today, the development of recommendation programs is a significant testing ground that attracts scientists and researchers from all over the globe. In addition to songs, movies, books, details, and marketing products, promotional systems have been utilized in numerous other contexts. A collaborative filtering algorithm is one of the most popular self-paced strategies for seeking the most substantial users to elevate objects carefully. The essential techniques to construct a movie recommendation engine are collaborative filtering (CF) and alternating squares (ALS) of rules. One of the matrix models used to solve a linked CF is a set of rules whose values are included in the user's list of matrix objects. As there is a need to analyze the ALS algorithm by choosing completely specified parameters, it may be easier to develop a raw movie recommendation engine. This research suggested a movie-sponsored movie recommendation machine at some point. This analysis modifies the efficacy of the RS solid structure by modifying the parameters of all algorithms. Drawing conclusions based on the selection of all algorithm parameters can also affect the overall performance of the film recommendation engine based on the results. Unfamiliar metrics such as execution time, root mean square errors of the standard prediction, and the degree to which the most effective translation has evolved led to the conclusion of the version analysis. Gender, emotion, and age recognition are used to segment customers. Image analysis determines gender, emotion, and age. This classification is added to the existing database for customer segmentation. Following consumer segmentation, we recommend movies based on segmentation and develop chatbots accordingly. It accepts both login and image inputs. It caters to the interests of the logged-in user and the actual individual using the computer or smart television. It also includes a chatbot that can answer any user's queries [30].

Data-driven business models, such as recommender systems (Netflix, Pandora) and targeted advertising (Facebook, Google), rely solely on consumer data and information about individuals' preferences and behavioral patterns. This dependency effectively opens the door to the age-old conflict between privacy and convenience. Because customers expect the rendered goods to be content-relevant to their specific requirements, service providers must exploit user data to some degree. Simultaneously, the increasing number of data collection and data use breaches has caused public hostility towards the tech sector; a recent example is the $170 million fine imposed on Google and YouTube Kids in September 2019 for violating federal requirements for child privacy protection [29]. Homomorphic encryption provides a solution to this pressing issue: the fully homomorphic encryption (FHE) scheme can be used to construct a private recommender system in which user data is not exposed to service providers in their raw form, and only "masked" data are sent to providers for recommendation inference. In this project, we develop a general architecture for an FHE-backed recommender that can be applied to various applications, using YouTube Kid as a proof of concept.

This research proposed a private video recommendation system suitable for platforms like YouTube Kids to achieve this. Based on fully homomorphic encryption, this system would enable the platform to provide personalized recommendations to minors without disclosing their private data. In this article, we briefly describe our system's motivation and construction. The research discusses such a system's originality, validity, practicability, and significance [18].

As a result of the rise of online shopping, recommender systems have become indispensable tools for consumers who are looking for guidance regarding the finest products to buy [18,19,20]. A recommender system sifts through information to make an educated guess as to what a user prefers and then customizes its recommendations to meet the requirements or fulfill the goals of a particular user. On the other hand, because there is so much information available online, the demand for recommendation systems has increased significantly [21].

The smart e-Tourism recommenders focus on their application specifically in the field of tourism. It aims to explore how recommender systems can enhance the tourism experience for individuals. It specifically examined the previous research publication in Artificial Intelligence journals and conferences. This search allowed the authors to gather relevant information about the advancements and progress in the field of tourism recommendation systems. It specifically focuses on content-based (CB), collaborative (CL), and demographic-based (DM) systems. CB systems calculate the similarity between users and items based on their preferences and features. CL systems recommend items based on the preferences of similar users, while DM systems rely on demographic data to provide recommendations. The passage also mentions the drawbacks of each approach, such as data sparsity and the "grey sheep" problem in CL systems. The combination of different techniques is a common practice, and hybrid systems can integrate these techniques in various ways [22].

AI techniques in e-Tourism recommenders include knowledge representation, semantic similarity measures, autonomous agents, approximate reasoning, clustering, and optimization. Guidelines include using both web and mobile versions, leveraging social network data, incorporating contextual recommendations, and employing semantic representations for precise recommendations [23].

Also, these systems play a crucial role in addressing the information overload problem and enhancing customer relationships. With diverse techniques and software, these systems have found applications in e-government, e-business, e-commerce, e-library, e-learning, e-tourism, e-resource services, and e-group activities [23].

The movie recommendation system, MOVREC, utilizes collaborative filtering and user ratings to suggest movies tailored to individual preferences. Using the K-means algorithm, the system efficiently provides personalized recommendations, allowing users to easily find movies of their choice. The research methodology involved the use of the K-means algorithm for clustering in a movie recommendation system. Data attributes such as genre, actor, director, year, and rating are weighted and matched to generate personalized recommendations. Challenges include user satisfaction and diversity, which are addressed through simplicity, extensive data collection, and algorithm optimization [24].

There is another movie recommendation system that combines collaborative filtering approaches with content-based information. The system aims to recommend a list of movies to users based on their preferences and incorporates user ratings, reviews, and emotions. In recent years, emotion has been a hot topic due to the critical stress caused by the pandemic and its aftermath. Emotions play a crucial role in our daily lives, particularly when it comes to the protection of children. It can indirectly affect their performance, activity, and mind from different perspectives [35]. The recommendation system is applied in various domains, including OTT platforms, search engines, articles, music, and videos. The proposed method utilizes collaborative filtering, content-based, and hybrid recommendation approaches. Distance measures such as Euclidean distance, Manhattan distance, and Hamming distance are employed to calculate the similarity between movies. The system utilizes metadata and applies algorithms such as singular value decomposition and user-based cosine similarity for personalized movie recommendations which improve the accuracy as compared to other methods [24].

User experience has been a special focus in another recommendation system. From various techniques, it highlights collaborative approach relies on user ratings and behavior to make recommendations, while the content-based approach focuses on movie properties. The demographic approach considers user demographic information, and the hybrid approach combines multiple techniques. This research suggests prospects, such as emotion-based recommendations and incorporating time constraints. The effectiveness of ensemble learning in collaborative approaches is highlighted. The overall goal is to improve the accuracy and efficiency of movie recommendation systems, ultimately enhancing the customer experience and benefiting companies [25].

Some movie recommendation schemes have worked on improving scalability and practical usage feedback in movie recommendation systems. It introduces a high-efficient recommendation algorithm that utilizes users' profile attributes to partition them into clusters. Each cluster is represented by a virtual opinion leader, reducing the dimensionality of the user-item matrix. The proposed Weighted Slope One-VU method is then applied to the virtual opinion leader-item matrix to generate recommendations. The algorithm achieves comparable performance to traditional clustering-based collaborative filtering (CF) schemes but with significantly reduced time complexity. Furthermore, a real personalized web-based movie recommendation system called MovieWatch is developed and deployed to collect user feedback and evaluate the proposed algorithm. The system utilizes K-means clustering and the Weighted Slope One-VU algorithm. Experimental results on the MovieLens dataset show promising performance. Future improvements include incorporating the latest films and optimizing the selection of virtual users to enhance recommendation accuracy [25].

Some of the movie recommendation applications are Netflix, Rotten Tomatoes and IMDb. “Netflix” basically asks user to rate films to determine which film user will want to see next. Netflix is the world's most popular streaming entertainment service, with 208 million paid subscribers in over 190 countries watching TV series, documentaries, and feature films in a wide range of disciplines and languages. Members can watch as much as they want, whenever and wherever they want, on any screen connected to the internet. Members can play, pause, and resume viewing without commercial interruptions or obligations [25]. For "Rotten Tomatoes" to discover the best movies, users only need to specify the types of films they enjoy, the actors they want to see, and other preferences. "Mobile Internet device" IMDb is an online database containing all information about movies, television shows, and video games. IMDb automatically suggests films identical to the one the user searched for.

IV. METHODOLOGY

A recommender system is a type of filtration system. The system's algorithm can identify specific user preferences by utilizing massive data sets. Once it has determined what users enjoy, it can suggest new, relevant content. Moreover,

this holds for everything from romantic companions to movies and music. Netflix, YouTube, Tinder, and Amazon are examples of companies that employ recommender systems. The systems allure users with pertinent recommendations based on their selections [26].

AIRA application is designed by using Collaborative filtering recommender system. To make recommendations, collaborative filtering considers the similarities between users and items. In other words, the algorithm continually identifies user relationships and generates recommendations. The algorithm discovers embeddings between users without requiring feature tuning. Matrix factorization is the most prevalent method for identifying the embeddings or features that comprise a user's interest [26].

This filtration approach considers both the user's behavior and the comparison and contrast of that behavior with the behavior of other users already included in the database. All users' activity is considered fundamental by this algorithm. The primary distinction between content-based filtering and collaborative filtering is that the latter considers all users' interactions with the things being filtered.

There are many different approaches to putting collaborative filtering into practice. The fact that multiple users' data influences the recommendations made by collaborative filtering is, however, the most crucial concept to comprehend. Thus, the modeling process does not rely on the data from a single user alone [27].

As shown in Figure 3, this research also uses keyword-based recommendation technique. It has been demonstrated that recommender systems are valuable instruments for providing appropriate user recommendations. In the past decade, the number of consumers, services, and online data has increased dramatically, posing a challenge for recommender systems regarding extensive data analysis. As a result, traditional service recommendation systems frequently experience scalability and efficiency issues when processing or analyzing such massive amounts of data. In addition, most existing recommender systems present the same ratings and rankings of items to various users without taking into account the preferences of diverse users and therefore fail to meet the personalized needs of users. This initiative proposes a Keyword-based Recommendation method in response to the issues above. It seeks to present a personalized recommendation list and effectively recommend the most relevant items to users. Specifically, keywords are used to signify users' preferences, and a user-based Collaborative Filtering algorithm is implemented to generate appropriate recommendations [28].

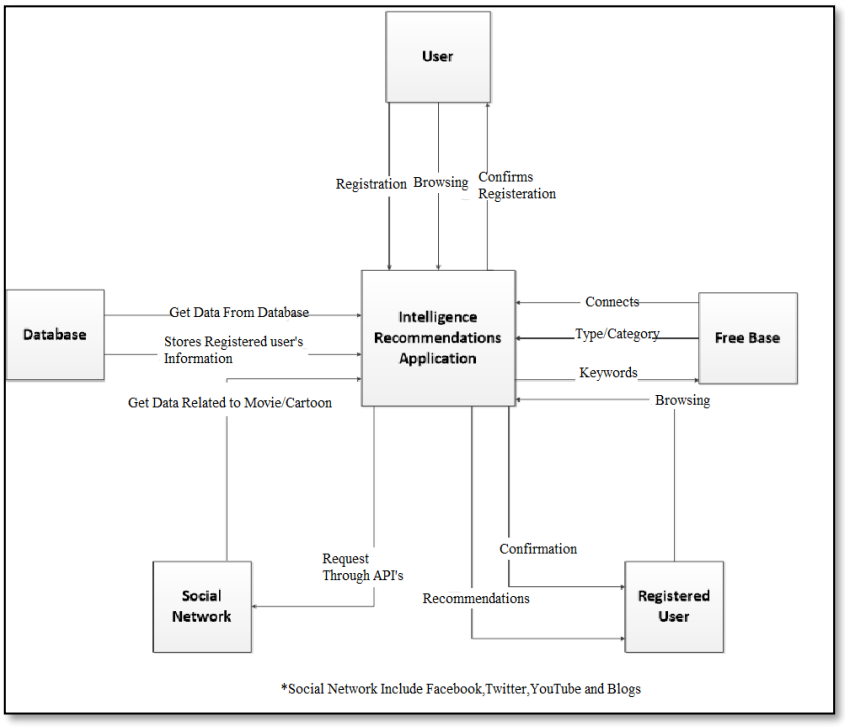

Figure 3. Context Diagram

A. Algorithm:

Algorithm: Age-Appropriate and Filtered Content Selection

Input: Age (x), Content (y)
Output: Age-appropriate and filtered content

Step 1:
User selects age (x) and corresponding content (y)

Step 2:
If (x <= 17) and (y is the input searched content list from external HTML page) then
Display top ten searched (x) and (y) with details
Else
Display the output content sorted by (x)

Step 3:
If (x is equal to the searched age (x) and content (y)) then
Select age-appropriate content

Else
Break

End Algorithm

Algorithm: Search Based Content Recommendation

Input: Content Name
Output: Ten content names with rating and details

Step 1:
Take input (content Name) from the user

Step 2:
For Integer i = 0 to 9 do
If (searched keyword or input id matches URL content id) then
Get ten input content names with references and display them
Else
Return

Step 3:
If one content from the list is selected, then
Load next activity and display content picture, rating, recommendation, and storyline
Else
Go to next activity

Step 4:
If the top activity from Step 3 is "List of abusive words" then
Show a list of abusive words with their occurrence frequency

Step 5:
If the top activity from Step 3 is "See More Details" then
Show user details

Step 6:
End Algorithm

B. Equations

i. Rating (R)

We've used the same rating pattern that most rating websites use for their Top listed content filtering, but we've adapted it to our application and configured it to filter the top 10 most-searched content as shown in (1).

$$\text{Rating (R)} = (v \div (v+m)) \times R + (m \div (v+m)) \times C \quad (1)$$

Where:

R = average for the content (mean) = (Rating)

v = number of votes for the content = (votes)

m = minimum votes required to be listed in the Top 10

C = the mean vote across the whole evaluation

C. Conditions

Conditions are shown in Table 1.

Table 1: Conditions

Age-Appropriate	
PG	Parental Guidance Suggested—Some Material May Not Be Suitable for Children
PG-13	Parents Strongly Cautioned—Some Material May Be Inappropriate for Children Under 13
R	Restricted—Under 17 Requires Accompanying Parent or Adult Guardian
NC-17	No One 17 and Under Admitted

V. RESULTS AND DISCUSSIONS

As shown in figure 4, Recommender Systems provide personalized support for sifting through large quantities of data, aiding users in making product decisions that match their tastes and preferences. Most previous research on recommender systems has focused on traditional users, i.e., adults who can provide explicit feedback, compose reviews, or purchase items themselves. However, children's attention and interaction patterns differ significantly from those of adults [28].

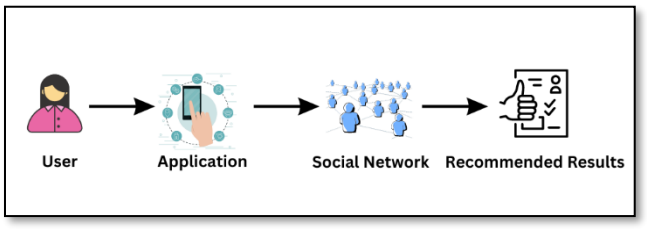

Figure 4. AIRA- An Intelligent Recommendation System

A. Reviewing Phase

In this application model, attributes determine the content's outcome.

1. Rating
2. Age-Appropriate
3. List of abusive words from the subtitle
4. Recommendation technique

The research determines that the most appropriate movie recommendations for children should be based on the films' ratings; therefore, we have given the rating attribute greater weight. These evaluations have been obtained from www.imdb.com, which may have the most extensive collection of films with user ratings from around the globe.

An additional key parameter in this application model is a list of abusive words extracted from subtitles, which retrieves another parameter containing age-appropriate recommendations for children. In our work, it is presumed that if a list of abusive words contains fewer than ten words and is average or mediocre for a child of the appropriate age, it will be marked as "Highly Recommended." If a list of abusive words contains more than twenty words and is moderate or fair in intensity, it will be marked as "Recommended." If a list of abusive words contains more than thirty words and is extreme or liberal for a child of the appropriate age, it will be marked as "Not Recommended." Users typically want their children to watch a decent movie that is age-appropriate, and a higher rating ensures that our predicted movie content is among those that are liked by many users and must be suitable for their children.

B. Approach

A few options are available to users when they log into AIRA. The user can search for a particular movie or other content, such as dramas or serials. The user can select or enter values for various properties from the most recent interfaces they visited on the search page. Database's search is based on the user's input, and a selection of relevant movie content is then prepared.

Movies included in the array are those for which even one search attribute value matches the user's input searched value. A counter is then used to determine the number of movies in the array. The application presents a list of items sorted by age-appropriateness if the counter value is less than or equal to ten. It will be listed as "Highly Recommended" if the number of offensive words is less than ten and is ordinary or mediocre for the target child. The list will be marked "Recommended" if the number of offensive words exceeds twenty and is moderate or fair. It will be marked as "Not Recommended" if the quantity of harsh words is more significant than thirty and they are too extreme or liberal for the child's age [29,30,31].

C. Survey

To design a best-practice application, this research used a rigorous procedure to construct survey questions to assess critical areas for parents in Karachi and beyond, which included questions and measurements covering various topics.68% of parents backed our proposal. They require such an application to seek healthy and educational materials for their children as shown in Figure 5.

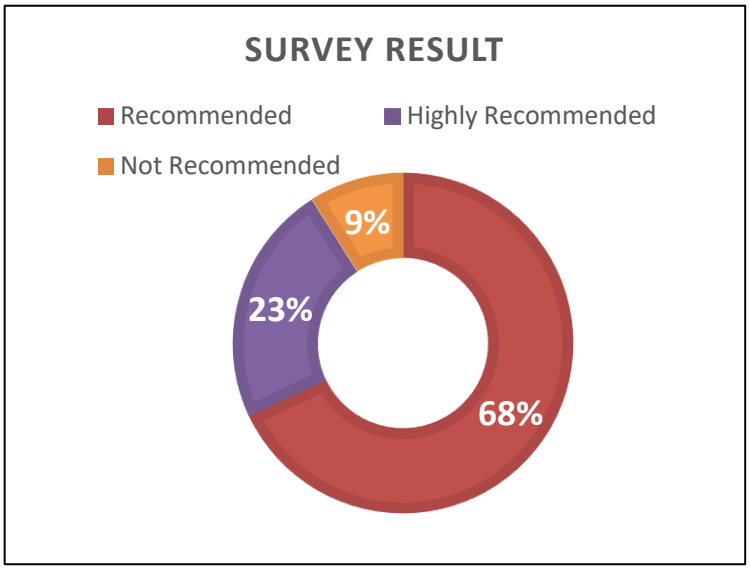

Figure 5. AIRA- Survey

D. Evaluation Matrix

If the intensity of the abusive language is less than or equal to ten and is average or subpar, then it is recommended. If the intensity of the abusive language is greater than or equal to twenty and is mild or moderate, then it is recommended [32]. If the intensity of the abusive language exceeds thirty and is Extreme, then it is Not Recommended, as shown in Table 2.

Table 2. Evaluation Matrix

Intensity	**Weight**		
	If Abusive words <=10	**If Abusive words >=20**	**If Abusive words >=30**
Ordinary	Highly Recommended		
Mediocre	Highly Recommended		
Moderate		Recommended	
Fair		Recommended	
Extreme			Not Recommended

E. Recommendation Details

- This research conducted survey on a group of married individuals to assign attributes weights and importance, and based on the results, the attributes were ranked.
- The proposed application has been evaluated with a small group of users, and a positive response has been observed. This application has been kept simple and cooperative.
- To precisely recommend content to the user, we have utilized an external J-Soup library and a filter.
- In addition to searching accessible online movie databases for information, this application retrieved data that was beneficial for this proposed application, such as sub-scene for subtitles, IMBD for rating, and common-sense media for age-appropriateness.
- This research included search-based content in our database regardless of language, allowing users from all over Pakistan to utilize our application.

F. Data Set

Inspired by Semantic Web research and collaborative data communities such as Wikipedia, Freebase is a practical, scalable, graph-shaped database of structured generic human knowledge. Freebase enables public read and write access for research through an HTTP-based graph-query API, the creation and maintenance of structured data, and application development. Freebase data are licensed under extremely permissive terms (e.g., Creative Commons, GFDL).

Freebase was a large collaborative knowledge base, with the majority of its data contributed by community members. It was an online compilation of structured data from numerous sources, including user-submitted contributions to a wiki. Freebase sought to establish a global resource that improved people's (and machines') access to shared information. It was created by the American software firm Metaweb and began operating publicly in March 2007. Google acquired Metaweb in a private transaction announced on July 16, 2010. Freebase is a contributor to Google's Knowledge Graph. Freebase data was available for commercial and non-commercial use under a Creative Commons Attribution License, and programmers had access to an open API, an RDF endpoint, and a database extract. Google announced on December 16, 2014, that it would close down Freebase over the next six months and assist with migrating its data to Wikidata. Google officially announced the Knowledge Graph API on December 16, 2015, intended to supplant the Freebase API. On May 2, 2016, Freebase.com was officially wound down. Google has made

Graphd and MQL, the graph database and JSON-based query language developed by Metaweb for Freebase, available on GitHub under the Apache 2.0 license. Graphd was released as open-source on September 8, 2018. MQL was released as open-source on August 4, 2020 [33].

VII. CONCLUSION AND FUTURE WORK

In conclusion, recommendation systems are intelligent agents that provide personalized suggestions to users based on their preferences and behaviors. They utilize advanced algorithms and machine learning techniques to analyze data and generate predictions about items that users might be interested in. These systems play a crucial role in addressing information overload and enhancing customer relationships in various domains, including e-commerce, tourism, and movie recommendations. Different recommendation techniques, such as collaborative filtering, content-based filtering, and demographic-based systems, offer unique advantages and face specific challenges. Hybrid approaches that combine multiple techniques are commonly used to improve recommendation accuracy and coverage. Research efforts focus on improving the accuracy, scalability, and practical usage feedback of recommendation systems. Techniques like K-means clustering, genetic algorithms, and K-clique methods have been explored to enhance the performance and personalization of movie recommendation systems [34].

This research determined that the most appropriate recommendations can be made for children, and we have proposed an Android-based application called AIRA, which is a recommendation system. The application is founded on a collective filtering approach that utilizes user-provided content, analyses it, and then recommends content that is pertinent to the user at that time.

Future work in the field includes incorporating the latest content, optimizing recommendation algorithms, addressing data sparsity and dimensionality, exploring new data reduction techniques, and incorporating additional user features. The goal is to provide accurate and efficient recommendations that enhance user satisfaction and overall user experience [35].

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers who have provided valuable suggestions to improve the article.

REFERENCES

[1] S. Rana Federal Trade Commission, “Netflix EDA + Movie Recommendation System”, 2021. https://www.kaggle.com/code/shivanirana63/netflix-eda-movie-recommendation-system.

[2] Inbotics, Machine Learning, “Age and Gender Based Movie Recommendation System Using Facial Recognition”, 2022. https://www.projectwale.com/2022/07/09/age-and-gender-based-movie-recommendation-system-using-facial-recognition/

[3] A. Satuse, O. Bhalerao, P. Pawar, H. Thorat and D. S. Hirolikar, “Intelligent Movie Recommendation System Using Ai and Ml,” Journal of Emerging Technologies and Innovative Research, vol. 9, no. 2, 2022.

[4] J. Lu, D. Wu, M. Mao, W. Wang and G. Zhang, “Recommender system application developments: a survey. Decision support systems”, vol. 74, pp. 12-32, 2015.

[5] J. Zhang, Y. Wang, Z. Yuan and Q. Jin, “Personalized real-time movie recommendation system: Practical prototype and evaluation”, Tsinghua Science and Technology, vol. 25, pp. 180-191, 2020.

[6] Great Learning Team., “Excerpts from a Masterclass on Movie Recommendation System”, 2022. https://www.mygreatlearning.com/blog/masterclass-on-movie-recommendation-system/

[7] M. Kumar, D. K. Yadav, A. Singh and V. K. Gupta, “A movie recommender system: Movrec,” International Journal of Computer Applications, vol. 124, 2015.

[8] D. S. Hirolikar, A. Satuse, O. Bhalerao, P. Pawar and H. Thorat, “Intelligent Movie Recommendation System Using AI and ML,” International Journal for Research in Applied Science & Engineering Technology (IJRASET), vol. 10, no. 5, 2022.

[9] G. Geetha, M. Safa, C. Fancy and D. Saranya., “A hybrid approach using collaborative filtering and content-based filtering for recommender system,” Journal of Physics: Conference Series, vol. 1000, 2018.

[10] B. Rocca., “Introduction to recommender systems, Towards Data Science”, 2019. https://towardsdatascience.com/introduction-to-recommender-systems-6c66cf15ada

[11] Z. Wang, X. Yu, N. Feng and Z. Wang, "An improved collaborative movie recommendation system using computational intelligence," Journal of Visual Languages & Computing, vol. 25, no. 6, pp. 667-675, 2014.

[12] P. Vilakone, D. S. Park, K. Xinchang and F. Hao, "An efficient movie recommendation algorithm based on improved k-clique", Human-centric Computing and Information Sciences, vol. 8, pp. 1-15, 2018.

[13] S. Sumathi and M. Suriya, "Certain Investigations on Cognitive based Movie Recommendation system using Pairwise Cosine Similarity", International Conference on Advanced Computing and Communication Systems (IEEE), vol. 1, pp. 2139-2143, 2023.

[14] N. Sharma and M. Dutta, "Movie Recommendation Systems: a brief overview", International Conference on Computer and Communications Management, vol. 8, pp. 59-62, 2020.

[15] K. Duay, "Personalized web-based application for movie recommendations", 2015.

[16] D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," Journal of Big Data, vol. 9, 2022.

[17] T. Y. Yeh and R. Kashef, "Trust-Based Collaborative Filtering Recommendation Systems on the Blockchain", Advances in Internet of Things, vol. 10, pp. 37-56, 2020.

[18] F. Ricci, L. Rokach and B. Shapira, "Introduction to Recommender Systems", Springer, 2011.

[19] S. S. Lakshmi, and A. T., "Lakshmi, Recommendation Systems: Issues and Challenges," International Journal of Computer Science and Information Technologies, vol. 5, pp. 5771-5772, 2014.

[20] M. N. Moreno, S. Segrera, V. F. Lopez and M. D. Muñoz, "Web Mining Based Framework for Solving Usual Problems in Recommender Systems. A Case Study for Movies", Elsevier, 2015.

[21] J. Lu, D. S Wu, M. S. Mao, W. Wang and G. Q. Zhang, "Recommender System Application Developments: A Survey", Decision Support Systems, vol. 74, pp. 12-32, 2015.

[22] N. Severt, "An Introduction to Recommender Systems (+9 Easy Examples)", 2023. https://www.iteratorshq.com/blog/an-introduction-recommender-systems-9-easy-examples/

[23] P. Kumar, "Netflix Movie Recommendation — Using Collaborative Filtering", Towards Data Science, 2020.

[24] S. Das, "Create Your Own Movie Movie Recommendation System", 2022. https://www.analyticsvidhya.com/blog/2020/11/create-your-own-movie-movie-recommendation-system/.

[25] B. V. Savadekar, B. G. Pramod, "Towards Keyword Based Recommendation System," International Journal of Science and Research (IJSR), vol. 3, no. 11, pp. 1318-1323, 2014.

[26] Y. Deldjoo, C. Fra, M. Valla, F. Garzotto and P. Cremonesi, "Enhancing Children's Experience with Recommendation Systems", Conference: Workshop on Children and Recommender Systems, vol 11, 2017.

[27] J. Beel, S. Langer, G. M. Kapitsaki and B. Gipp, "Mind-Map based User Modelling and Research Paper Recommendations", International Conference on User Modeling, Adaptation, and Personalization, 2014.

[28] A. Pham, M. Samragh, S. Wagh, and E. Wenger, "Private Movie Recommendations for Children. Protecting Privacy through Homomorphic Encryption", pp. 163-167, 2021.

[29] Federal Trade Commission, "FTC. Google and YouTube Will Pay Record $170 Million for Alleged Violations of Children's Privacy Law", 2019. https://www.ftc.gov/news-events/news/press-releases/2019/09/google-youtube-will-pay-record-170-million-alleged-violations-childrens-privacy-law

[30] J. Borràs, A. Moreno and A. Valls, "Intelligent tourism recommender systems: A survey. Expert systems with applications", vol. 41, no. 16, pp. 7370-7389, 2014.

[31] F. O. Isinkaye, Y. O. Folajimi and B. A. Ojokoh, "Recommendation systems: Principles, methods, and evaluation," Egyptian Informatics Journal, vol 16, pp. 261-273, 2015. https://doi.org/10.1016/j.eij.2015.06.005

[32] F. H. Zeya, S. O. Mustafa, M. B. Hasan and A. A. Zaveri, "Light house-An intelligent recommendation software agent", 2012.

[33] K. Bollacker, R. Cook and P. Tufts, "Freebase: A shared database of structured general human knowledge", AAAI Conference on Artificial Intelligence, vol. 7, pp. 1962-1963, 2007.

[34] M. Shafiq, H. Ng, T. T. V. Yap, V. T. Goh, "Performance of Sentiment Classifiers on Tweets of Different Clothing Brands," Journal of Informatics and Web Engineering, vol. 1, no. 1, pp. 16 – 22, 2022.

[35] Y. Lim, K. W. Ng, P. Naveen, S. C. Haw, "Emotion Recognition by Facial Expression and Voice: Review and Analysis," Journal of Informatics and Web Engineering, Vol. 1 No. 2, pp. 45 – 54, 2022.

APPENDIX

Questionnaire:

To design a best-practice application, this research used a rigorous procedure to construct survey questions to assess critical areas for parents in Karachi and beyond, which included questions and measurements covering various topics.

Link: https://forms.gle/zjtrQc8grL71qFW4A

Questionnaire for Intelligent Recommending Agent App

Instructions: Please read the questions carefully and tick one of the options beside each question. Please make sure that you have answered all questions.

1. What is the age of your child?

- 1-5 year
- 6-10 years
- 11-15 years
- 16-20 years
- More than 20 years

2. How often does your child watch TV shows?

- Extremely often
- Very often
- Moderately often
- Slightly often
- Not at all often

3. What is favorite TV show of your child?

4. Which type of Cartoons they watch?

- Action
- Drama
- Adventure
- Horror
- Don't Know

5. What behavior does your child have after watching TV drama, movie or cartoon?

- Aggressive
- Sleepy
- Sweet
- Dramatic
- Don't know

No.	Question	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
6	Do you accompany your child while watching TV?					
7	Did you notice any change in behavior of your child after watching TV?					
8	Cartoons, Drama, movie takes your child away from play and exercise activities?					
9	Cartoons, Drama, movie can also contribute to eating disorder in your child?					
10	Does your child live in an imaginative world after watching cartoons, movie?					
11	Does your child imitate the violence they see on TV?					
12	Do you find any benefit for your child after watching cartoons, drama, movie or other?					
13	How confident are you that your child watching informative show?					
14	Do you select cartoon, drama or movie for your child?					
15	What do you think would be of any help you to recommend (TV series cartoon, movies) the best for your child a/c to his or her age?					
16	Is this application easy to use?					

COMMENTS Any suggestion would you like to share for this application

Almost 68% of parents support our idea. They require such an application to seek healthy and educational materials for their children.