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AIRA: An Intelligent Recommendation Agent Application for Movies

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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

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I. INTRODUCTION

The growing amount of online data has resulted in a hard and time-consuming browsing process despite its invaluable nature as a source of knowledge [1]. An intelligent recommendation agent refers to a system specifically developed to offer personalized ideas or recommendations to users, taking into account their tastes, behaviors, and other pertinent data. The primary objective of this platform is to facilitate users in exploring novel products, services, or content that are to their interests and requirements. The recommendation agent utilizes sophisticated algorithms and machine learning methodologies to examine extensive datasets, including user profiles, historical actions, item attributes, and input from other users. The data above forecasts what a user may prefer or see as valuable. The recommendations may take on diverse formats, encompassing suggestions for products, films, music, news articles, or even connections with friends on social networking platforms [1]. Social media platforms like Facebook, Instagram, LinkedIn, and Twitter enable the construction of virtual networks and communities, thereby facilitating user exchange of ideas, thoughts, movies, images, and information. The advancement of technology has facilitated the expansion of firms and products'

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reach to a wider audience for marketing and advertising, as well as the gathering of public feedback [2]. Recommendation systems play a crucial role in aiding users in discovering and choosing products, such as books, films, and restaurants, from a broad and diverse range of available possibilities. Recommendation systems for films have a comparable challenge, as individuals possess diverse expectations, and it is unfeasible to evaluate a film only based on the annotations offered by other users. The movie recommendation system offers users a convenient and personalized experience, allowing them to navigate the system and access films that align with their preferences. [2].

In the expansive realm of the Internet, characterized by a multitude of alternatives and an abundance of information, individuals sometimes find themselves inundated and overwhelmed by the sheer volume of available resources. The abundance of options presented with each click rendered the task of identifying the significant elements challenging. The issue of information overload has become increasingly prevalent. Recommendation systems are of paramount importance in addressing the issues associated with information overload by efficiently filtering, prioritizing, and providing relevant information. In the realm of digital technology, it is explained that these systems operate as custodians, tirelessly sifting through the vast expanse of continuously generated content to offer consumers personalized recommendations [1,2].

The prediction algorithms employed in recommendation systems exhibit a range of distinct traits and possess diverse potentials. A range of recommendation strategies are employed in the field, including content-based, collaborative filtering-based, knowledge-based, hybrid, computational intelligence-based, social network-based, and context awareness-based approaches. The techniques encompass several methodologies, including but not limited to the research of user preferences, employment of similarity measures, utilization of Bayesian methods, implementation of artificial neural networks, application of clustering techniques, utilization of genetic algorithms, adoption of fuzzy set theory, employment of social network analysis, utilization of trust-based frameworks, and consideration of contextual information. These strategies aim to enhance the accuracy, coverage, and user experience of recommendations [1,2,3,4,5].

A recommendation system is an algorithmic system that utilizes data to generate personalized recommendations for consumers across various resources, including books, movies, and songs. Generally, movie recommendation systems employ predictive algorithms to anticipate a user's preferred films by analyzing their traits and previously provided data. Recommendation systems are advantageous for enterprises that gather extensive client data and aim to provide optimal recommendations. When developing a movie recommendation system, various elements can be considered, such as the film's genre, cast, plot, and directorial credentials. The systems can suggest films by considering a single attribute or a combination of two or more attributes. A recommendation engine employs multiple algorithms to process data and subsequently suggests the most pertinent products to consumers. When a user visits a movie website, the website will not own any preexisting user data. In such cases, users have the option to do a search based on their personal preference for movie genres or directors in order to obtain a similar recommendation [3].

Machine learning has witnessed substantial progress and development due to the increasing demand for automated solutions employing machines. Today, characterized by the widespread adoption of electronic commerce on the Internet, the popularity of online buying and leisure has attained unparalleled levels. There is an expectation that online activities will become the prevailing standard in the upcoming decade. This study examines the hypothetical situation in which individuals participate in online buying activities on popular e-commerce platforms such as Amazon.com, renowned for its extensive selection of one million products, and similar websites like Flipkart. Online streaming platforms, such as Netflix and Hotstar, provide an extensive repertoire of more than 10 million films and shows to cater to consumers' preferences. If an individual wants to obtain a specific item from Amazon, they may initiate a search query. [3].

The task of locating search results of equivalent or greater quality might be metaphorically compared to the challenge of finding a golden tree within a densely populated forest. Individuals may experience disorientation and a loss of navigational abilities within the forest [4]. Recommendation systems have the potential to assist in this context. The utilization of recommender systems confers several advantages within such platforms. The Recommendation System is crucial in functioning as a navigational assistant within prominent e-commerce platforms such as Amazon and Netflix. Individuals must depend on a database and practice prudence without a recommendation system when establishing their search parameters. The potential ramifications of less customer involvement on Amazon and Netflix could be substantial, characterized by a decline in product acquisitions or viewership. Therefore, corporations will likely need it more in the upcoming years than any other resource. Consequently, we decided to acquire expertise in recommender systems and enhance our comprehension to an advanced level.

Recommendation systems are predominantly utilized to assist clients in acquiring personalized results depending on their interests. One conceivable utilization of machine learning algorithms involves employing recommendation systems as a filtering technique to discern the most advantageous result from a set of expected outcomes. Films can be classified based on distinct genres, encompassing categories such as thriller, animation, comedy, action, drama, and others. An alternate methodology for categorizing films involves the utilization of metadata, encompassing several factors such as the cast, release year, language, and director, among others. Most online video-streaming platforms provide consumers with a diverse range of comparable television programs and films by leveraging their previous search queries and viewing patterns. The main goal of developing a Movie Recommendation System is to establish its reliability and efficacy in providing accurate user recommendations according to their tastes. Various recommendations can be made, including data gathering, pre-processing, feature extraction, model training, suggestion creation, evaluation, and refining. Recommendation Systems are commonly classified into three major categories: Collaborative or User Filtering, Content-Based Filtering, and Hybrid Filtering [5,6,7].

This application's main aim is to prioritize children's requirements throughout the development and marketing of products within the media and technology industries. It is imperative to ensure accountability within these industries by implementing clear policies and regulations. This study argues for the rights and well-being of children by addressing a range of issues, such as the educational implications of technology, safeguarding children's privacy in online environments, and enhancing the impact of media on child health and development. This application aims to facilitate parents in accessing age-appropriate content for their children. The empirical findings from psychology research indicate that exposure to violent television programming adversely affects youngsters. This program will provide parents with dependable ratings, evaluations, and suggestions. Every assessment and appraisal are based on essential and fundamental factors about the growth and development of youngsters.

Consequently, this application will propose a selection of films, television series, and animated programs for parents to share viewing experiences with their children. This program has been designed to address the issue, enabling parents to actively engage in their children's lives and mitigate the risk of their children's exposure to acts of violence. The user provided a list of numbers: [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 primary goal of a recommendation system is to effectively discern and retrieve engaging content tailored to an individual user's preferences. Furthermore, the procedure involves multiple variables to provide personalized compilations of relevant and engaging content that are specifically matched to each user's individual interests. Recommendation systems are algorithmic models rooted in the field of Artificial Intelligence. These systems employ advanced computational techniques to analyze various alternatives and produce a tailored compilation of relevant and captivating items for a certain user. The conclusions above are based on an individual's profile, including their search, and browsing history, and the viewing patterns of individuals with similar features and demographics. Additionally, the likelihood of the individual viewing the stated films is considered. The objective above is achieved using predictive modeling and heuristics, employing the existing data. Hence, integrating a Recommendation System into diverse websites is vital for the industry and the end consumer [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].

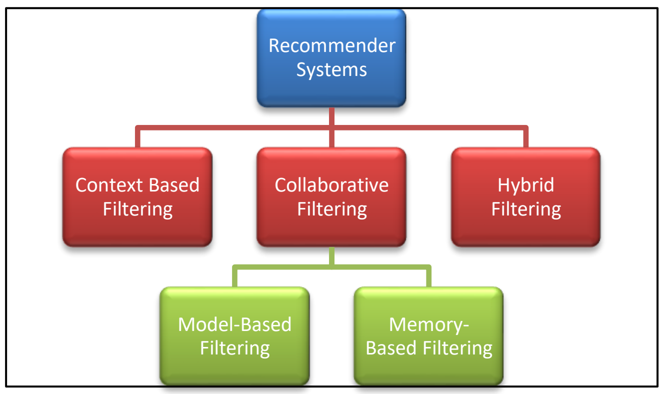

Figure 1. Types of Recommender System

i. Content-based filtering recommender systems

Content-based filtering is a methodology that prioritizes the intrinsic attributes of the entities being examined. The experience resembled that of having an individual curator who possessed an understanding of the user's tastes and preferences. This curator would then sift through a massive collection of digital information and provide the user with personalized recommendations, as depicted in Figure 2 [11]. This approach establishes a comprehensive content profile and subsequently generates data connection matrices, enabling the calculation of firm-developing patterns by leveraging prominent links between comparable products and customer preferences.

The method employs a combination of keywords and user profiles. The products are delineated by utilizing specific phrases, while a user's profile indicates the preferred category of items. The algorithms employed in these systems facilitate predicting future outcomes by suggesting products comparable to previously enjoyed or presently being examined by users. Recommendations are generated by comparing previously rated things and identifying the best-matching ones. These systems rely on observing user behavior to provide estimates obtained through analyzing previous consumer adoptions and their resemblances to those of other users. This approach entails the collection of substantial quantities of data and subsequent reduction of information volume. It involves grouping users according to company 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 like 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 assumes that individuals who previously concurred on evaluating 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].

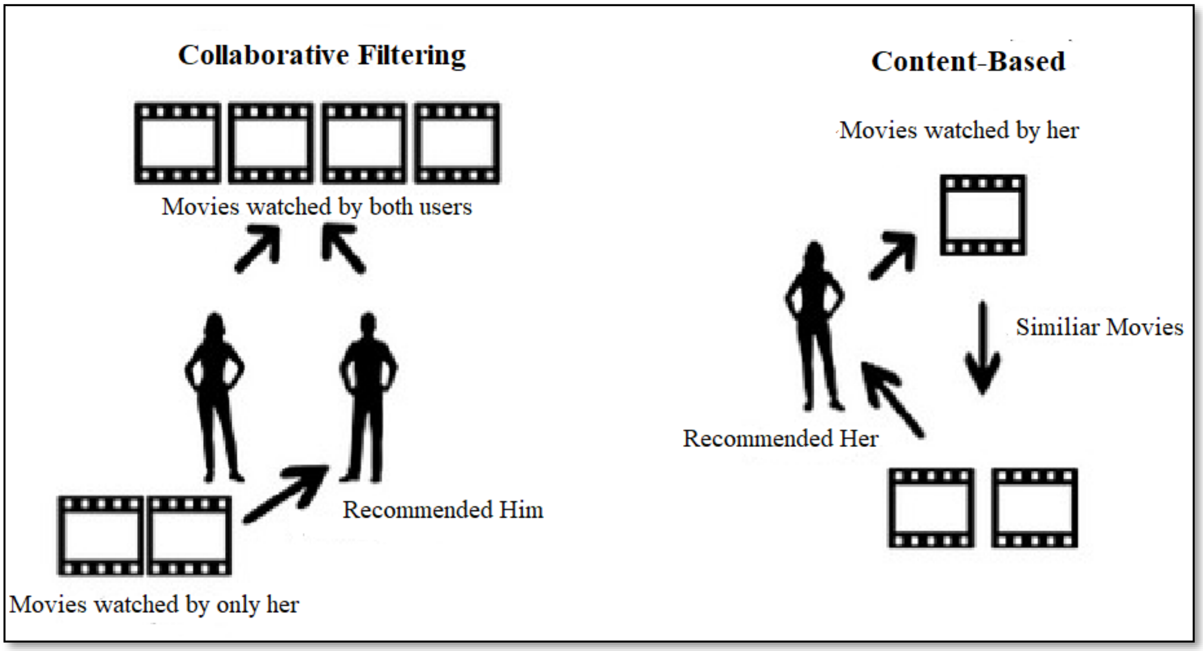

Figure 2: Collaborative Versus Content Filtering

a. Memory-Based Filtering

Memory-based collaborative filtering algorithms are utilized to recommend new goods by considering the preferences of the neighboring community. The utility matrix is employed explicitly to make predictions. The first step of this process entails the construction of a model. As previously stated, the model can be represented as a mathematical function that inputs the utility matrix [13].

Memory-based collaborative approaches can be categorized into two separate types: user-based collaborative filtering and item-based collaborative filtering. The user-based technique entails assessing the rating of a novel item by identifying other users within the user's neighborhood who have previously rated the identical item. If a newly introduced product receives positive feedback from the user community, it is recommended to the user [13].

b. Model-Based Filtering

Model-based techniques are predicated on the underlying premise of a fundamental "generative" model that elucidates the interactions between users and items. The primary objective of these methodologies is to identify and understand this model, enabling innovative prediction generation [14].

Model-based techniques eliminate the necessity of integrating the user profile of a new user into the utility matrix before generating forecasts. It is conceivable to offer recommendations to individuals who need to be more encompassed within the model. The efficiency of group recommendations is enhanced when employing model-based solutions. The existing model can efficiently propose a collection of objects. The usefulness of this methodology primarily depends on the performance of the fundamental machine learning algorithm used to build the model. Model-based approaches can tackle common issues encountered in recommender systems, such as sparsity and scalability, by employing dimensionality reduction and model learning techniques [14].

iii. Hybrid Filtering

A hybrid recommender system is designed to incorporate and combine various recommendation approaches to produce recommendations. In contrast to collaborative or content-based systems, hybrid recommender systems generally offer recommendations of higher accuracy. This occurrence in collaborative filtering can be attributed to a need for more knowledge of domain dependencies. Conversely, in content-based systems, the absence of information pertains to user preferences. Integrating both outcomes lead to a rise in collective knowledge, enhancing the quality of suggestions. The investigation of novel ways for enhancing the underlying collaborative filtering algorithms with content data and content-based algorithms with user behavior data is particularly promising, given the rise in knowledge [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

"Blockchain" is a digitalized, decentralized, publicly available ledger that records all cryptocurrency transactions. The advent of blockchain technology has brought about significant transformations in various sectors since it enables the implementation of innovative business processes. The disruptive impact of this phenomenon is seen in various sectors, including banking and finance, trading, manufacturing, supply chain management, healthcare, and governance. Integrating Blockchain technology into the inter-IoT communication system enhances security and privacy measures. This amalgamation, referred to as Blockchain with the Internet of Things (BIoT), offers the potential to address security and privacy concerns effectively. Integrating blockchain technology with the Internet of Things facilitates the development of contemporary decentralized systems. Utilizing BIOT models in diverse domains, such as e-commerce, could enhance decentralization, scalability, and security. Given the findings of this study, there is a need for a scholarly and innovative exploration of Blockchain technology and recommendation algorithms. We aim to establish a robust and trustworthy system by including smart contracts in the core blockchain protocol. This integration aims to capitalize on blockchain technology's advantages, facilitating secure multiparty computation. The integration of recommendation algorithms and blockchain technology facilitates the preservation of enhanced levels of confidentiality and security in online activities. Enterprises can utilize intelligent contract systems to collaborate on establishing a secure database and host a consistently updated model. This is achieved through the utilization of a system that is presently under development [16].

D. K-Means Clustering

A proposed research recommendation system integrates enhanced K-means clustering with evolutionary algorithms. The system effectively tackles the issue of limited data availability and the growing volume of films and users by utilizing principal component analysis (PCA) for data reduction and dense clustering techniques. The experimental findings obtained from the analysis of the MovieLens dataset provide evidence that the proposed methodology attains a notable level of precision and produces dependable and tailored movie suggestions compared to pre-existing techniques. Future research should tackle the challenges posed by increasing dimensionality and sparsity in the data. Additionally, there is a need to investigate more efficient data reduction methods that can enhance the system's performance. Furthermore, it is important to consider incorporating additional relevant features to enhance the level of personalization further. The investigation will also examine the scalability and reliability of movie recommendations about the number of clusters [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

The development of recommendation systems has emerged as a significant domain for scholarly investigation, capturing the interest of academics and researchers on a global scale. Promotional systems have been utilized in diverse contexts, including promoting songs, films, books, marketing objects, and other information dissemination and communication modes. The collaborative filtering algorithm is widely acknowledged as a prominent self-paced approach for identifying significant users and enhancing object precision. Two primary methodologies are employed in constructing a movie recommendation system: collaborative filtering (CF) and alternating least squares (ALS) of rules. One of the matrix models employed for solving a linked computational fluid dynamics problem comprises a set of rules whose values are integrated into the user's matrix object list. To thoroughly assess the ALS algorithm, it would be beneficial to develop a basic movie recommendation system by meticulously choosing well-defined criteria. This paper presents a proposal for developing a movie recommendation system funded by movie businesses. This analysis aims to optimize the efficiency of the RS solid structure by modifying the parameters of all algorithms. The overall performance of the film recommendation engine can be significantly influenced by the careful selection of algorithm parameters, thereby affecting the interpretation of the obtained results. The determination of the conclusion in the version analysis was made by evaluating many previously unknown metrics. These metrics encompassed factors such as execution time, root mean square errors in standard prediction, and the degree of modifications observed in the most effective translation. Customer segmentation is enhanced by employing gender, mood, and age identification techniques. Image analysis is employed to determine the gender, emotional state, and age of individuals. Incorporating this categorization aims to augment the customer segmentation within the existing database. Following the completion of the consumer segmentation analysis, it is suggested that a film recommendation system be implemented, considering the identified categories.

Additionally, customized chatbots will be developed to cater to these specific segments. The system can accept both login credentials and photo inputs. The system caters to the preferences of the authenticated user and the specific individual utilizing the computer or smart television. Furthermore, the system integrates a chatbot to respond to user inquiries (30).

Data-driven business models, such as those observed in recommender systems like Netflix and Pandora and targeted advertising platforms like Facebook and Google, rely extensively on consumer data to analyze individuals' preferences and behavioral patterns. The interconnectedness above effectively contributes to the enduring contradiction between privacy and convenience. In order to fulfill client demands for personalized products, service providers must employ user data to a certain degree. Simultaneously, the IT industry has seen increasing public hostility due to the rising instances of data collection and data usage breaches. An illustrative example of this phenomenon occurred in September 2019 when Google and YouTube Kids were subjected to a substantial penalty of $170 million for violating federal regulations pertaining to protecting children's privacy [29]. Homomorphic encryption presents a feasible answer to this pressing issue. The fully homomorphic encryption (FHE) technique enables the development of a confidential recommender system that effectively protects user data from being disclosed to service providers in its original form.

In contrast, solely "masked" data is transmitted to service providers for recommendation inference. This project aims to develop a comprehensive framework for a recommender system supported by fully homomorphic encryption (FHE). This framework will be designed to be applicable across various applications. The proof of concept for this framework is exemplified by its implementation in the context of YouTube Kid.

This study presents a novel approach to developing a personalized video recommendation system specifically designed for sites like YouTube Kids. This method, built upon the principles of completely homomorphic encryption, would provide personalized suggestions to individuals under the age of majority while safeguarding the confidentiality of their private information. This article provides a concise overview of the rationale and development of our system. The study examines the system's originality, validity, practicability, and relevance [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 tourism. It aims to explore how recommender systems can enhance the tourism experience for individuals. It specifically examined the previous research publications in Artificial Intelligence journals and conferences. This search allowed the authors to gather relevant information about the advancements and progress in 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 similar users' preferences, 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. Combining 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 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 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 find movies of their choice easily. The research methodology involved using 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, addressed through simplicity, extensive data collection, and algorithm optimization [24].

There exists an alternative movie recommendation system that integrates collaborative filtering methodologies with content-based data. The system's primary objective is to provide users personalized movie recommendations by considering their tastes and including user ratings, reviews, and emotional responses. In recent years, there has been a significant focus on emotion, mostly driven by the substantial stress induced by the epidemic and its subsequent consequences. Emotions are vital in our daily existence, specifically in safeguarding children. Several perspectives suggest it can impact individuals' performance, activity, and cognitive functioning [35]. Using recommendation systems is prevalent throughout several domains, encompassing OTT platforms, search engines, publications, music, and videos. The suggested method incorporates collaborative filtering, content-based, and hybrid recommendation methodologies. Distance measurements, such as Euclidean distance, Manhattan distance, and Hamming distance, are utilized to compute movie similarity. The system employs metadata and algorithms such as singular value decomposition and user-based cosine similarity to provide personalized movie suggestions, resulting in enhanced accuracy compared to alternative approaches [24].

The prioritization of user experience has been a particular area of emphasis in different recommendation systems. The collaborative approach emphasizes the utilization of user ratings and behavior as a basis for generating suggestions, whereas the content-based approach centers on the characteristics and attributes of movies. The demographic approach considers user demographic information, while the hybrid approach integrates many techniques. This study proposes potential avenues for exploration, such as implementing emotion-based suggestions and integrating time limits. The efficacy of ensemble learning within collaborative methodologies is emphasized. The primary objective is to enhance the precision and effectiveness of movie recommendation systems, thereby augmenting the consumer experience and yielding advantages for organizations [25].

Certain movie recommendation schemes have focused on enhancing the scalability and practicality of feedback in movie recommendation systems. This paper presents a recommendation system that effectively utilizes users' profile information to partition them into clusters. The user-item matrix is reduced in dimensionality by assigning a virtual opinion leader to represent each cluster. The Weighted Slope One-VU approach is subsequently utilized to generate recommendations by applying it to the virtual opinion leader-item matrix. The technique performs similarly to conventional clustering-based collaborative filtering (CF) methods while exhibiting dramatically decreased time complexity. In addition, a web-based movie recommendation system known as MovieWatch has been created and implemented to gather user feedback and assess the effectiveness of the suggested algorithm. The system employs the K-means clustering technique and the Weighted Slope One-VU algorithm. The experimental findings obtained from the analysis of the MovieLens dataset exhibit encouraging levels of performance. Potential enhancements are integrating contemporary films and refining virtual user selection to augment the precision of recommendations [25].

Several popular movie suggestion services include Netflix, Rotten Tomatoes, and IMDb. Netflix utilizes a user rating system to ascertain user preferences and recommend films that align with their preferences. Netflix, a globally recognized streaming entertainment platform, boasts 208 million paid users across more than 190 countries. These subscribers engage with diverse content, including television series, documentaries, and feature films, spanning various subject areas and linguistic backgrounds. Members can access unlimited content at their convenience, without any restrictions on time or location, using any internet-connected device. According to a study by [25], individuals can engage in activities such as playing, pausing, and resuming their viewing experience without interruptions or obligations from commercial content. For "Rotten Tomatoes" to identify the most exceptional films, users only need to indicate their preferred genres, desired performers, and other relevant preferences. The term "mobile Internet device" refers to a portable electronic gadget enabling users to access the Internet while moving. IMDb is an internet-based repository encompassing comprehensive data on films, television series, and video games. IMDb employs an automated algorithm to generate film recommendations that closely match the film queried by the user.

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 considering 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].

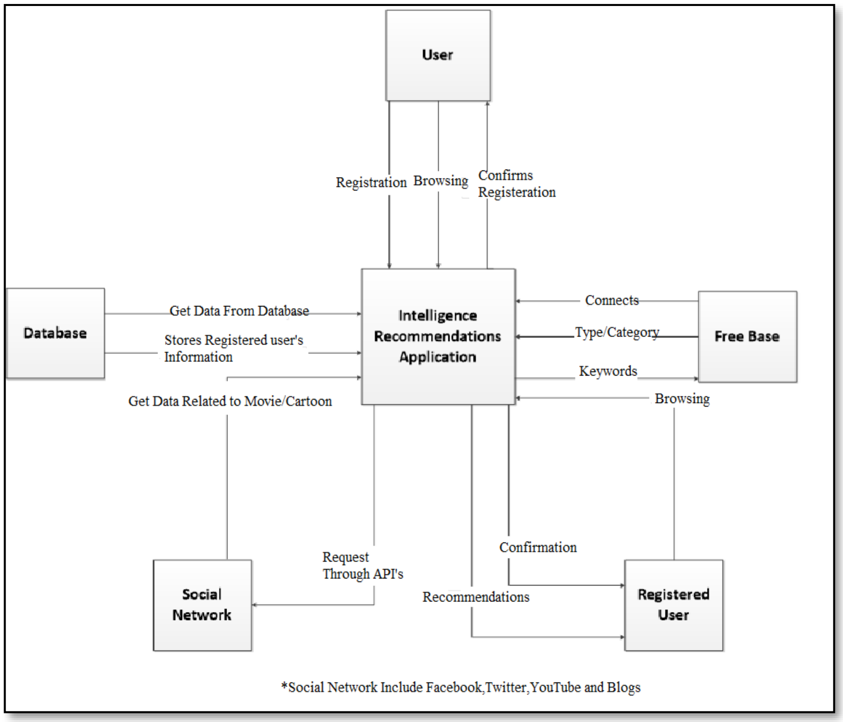

Figure 3: Context Diagram

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).

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

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].

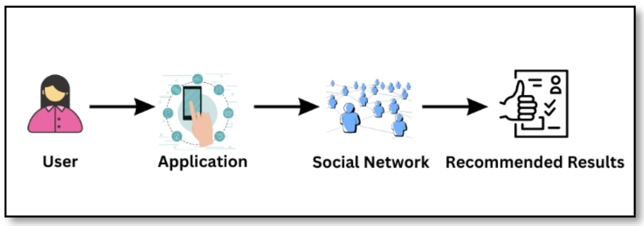

Figure 4: AIRA- An Intelligent Recommendation System

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.

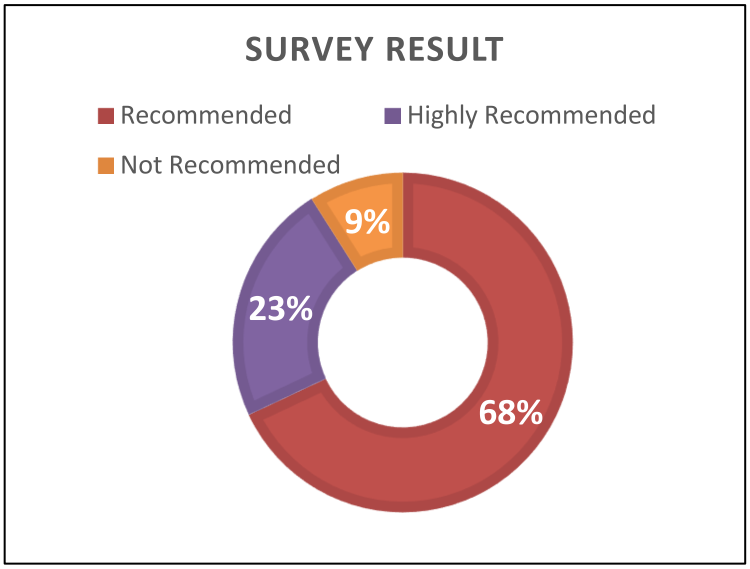

Figure 5: AIRA- Survey

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 substantial collaborative knowledge base that relied heavily on contributions from members of the community for most of its data. The online collection consisted of organized data from multiple sources, encompassing user-submitted contributions to a wiki and other relevant information. The primary objective of Freebase was to create a comprehensive worldwide repository that enhanced the accessibility of shared knowledge for individuals and automated systems. The platform was developed by Metaweb, a prominent American software company, and was officially launched to the public in March 2007. On July 16, 2010, Google announced the acquisition of Metaweb in a private transaction. Freebase is a prominent contributor to the Knowledge Graph, an integral component of Google's information retrieval system. The Freebase dataset was made accessible for commercial and non-commercial use according to the Creative Commons Attribution Licence terms.

Additionally, programmers were granted access to an open Application Programming Interface (API), a Resource Description Framework (RDF) endpoint, and a database extract. On December 16, 2014, Google announced the discontinuation of Freebase within six months. Additionally, Google expressed its commitment to facilitating the transfer of Freebase's data to Wikidata. On December 16, 2015, Google made an official announcement regarding introducing the Knowledge Graph API, intending to replace the Freebase API. The official winding down of Freebase.com took place on May 2, 2016. Google has released Graphd and MQL, the graph database and JSON-based query language created by Metaweb for Freebase, on GitHub with the Apache 2.0 license. The open-source version of Graphd was made publicly available on September 8, 2018. The open-source version of MQL was made available to the public 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].

REFERENCES

[1] S. Rana Federal Trade Commission, "Netflix EDA + Movie Recommendation System", Accessed: 2021. [Online]. Available: 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", Accessed: 2022. [Online]. Available: 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, 2022.

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

[5] J. Zhang, Y. Wang, Z. Yuan, & Q. Jin., "Personalized real-time movie recommendation system: Practical prototype and evaluation", Tsinghua Science and Technology, vol. 25, pp. 180-191, 2019.

[6] Great Learning Team., "Excerpts from a Masterclass on Movie Recommendation System", Accessed: Aug 22, 2022. [Online]. Available: https://www.mygreatlearning.com/blog/masterclass-on-movie-recommendation-system/

[7] M. Kumar, D. K. Yadav, A. Singh, & 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, 2022.

[9] G. Geetha, M. Safa, C. Fancy, & 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", Accessed: June 3, 2019. [Online]. Available: 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, 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 Dutta., "Movie Recommendation Systems: a brief overview". International Conference on Computer and Communications Management, vol 08, 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, 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)”, Accessed: 2023. [Online]. Available: 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”, Accessed: August 2022. [Online]. Available: https://www.analyticsvidhya.com/blog/2020/11/create-your-own-movie-movie-recommendation - system/, Analytics Vidhya

[25] B. V. Savadekar, B. G. Pramod., “Towards Keyword Based Recommendation System”, International Journal of Science and Research (IJSR), vol. 3, 2014.

[26] Y. Deldjoo, C. Frà, C. Frà, M. Valla, M. Valla, P. Cremonesi 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, S. Langer, G. M. Kapitsaki, 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”, Accessed: 2019. [Online]. Available: 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, & A. Valls., “Intelligent tourism recommender systems: A survey. Expert systems with applications”, vol. 41(16), pp. 7370-7389, 2014.

[31] F.O. Isinkaye, Y.O. Folajimi, B.A. Ojokoh., “Recommendation systems: Principles, methods, and evaluation”, Egyptian Informatics Journal, vol 16, pp. 261-273, 2015.

[32] F. H. Zeya, S.O. Mustafa, 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, 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.