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Deep Learning Recommendation Model for Education Serious Games for Kids

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We are extremely thankful to our parents for their love, prayers, caring, and sacrifices for educating and preparing us for our future.

Thank you all for your confidence in us.

Dedication

From the bottom of my heart, and with love and sincerity, I would like to dedicate this thesis to everyone who was with me in my difficult times before the happy ones, in my weakness before my strength, and in every stage of my life...

*To the first woman of my life...To the fragrance and the wind of Heaven...To the moon that illuminated my days and my path... To the one who welcomes me with her smile and bid me farewell with her prayers... To the one who taught me to trust in Allah, because Hi is the only one who will never let me down if I get attached to Him... To the one who taught me and gave me love and affection, which was and will remain my source of strength for as long as I live...**My Mother, my love, and my role model**.*

*To my dear father... Whatever I try to give you, I will not fulfill your right so accept my love and appreciation and a kiss that I print it on your forehead ... To the best supporter, bond, and the secret of my happiness...**My darling Father**, all gratitude and respect to you.*

***My Sisters and My Brothers** ...Words are racing and competing to organize the contract of thanks and praise that all of you deserve ... I wish you all success and reimbursement in your studies and your lives ... all of you are my best cheerleaders ... I love you all. And also to everyone whom I love, to each member of my extended family, my teachers, and all my friends ...Thank you very much to all.*

*Finally, my graduation dream cames true, Thanks to **Allah** first, and to My beloved parents...My love for all of you cannot be quantified, May **Allah** the Almighty help you...Allah protects you all.*

"وَمَا تَوْفِيقِي إِلاَّ بِاللهِ عَلَيْهِ تَوَكَّلْتُ وَإِلَيْهِ أُنِيبُ" سورة هود، 56.

<< Hibat Errahmane >>

To my angel in life...To the meaning of love and to the meaning of tenderness and dedication...To the smile of life and the secret of existence...To whomever, her supplication was the secret of my success and tenderness Balm surgical to the most precious beloved.

To my loving mother.

To whom God Almighty has prestige and reverence... To the one who taught me the giving without waiting... To the one who holds his name with great pride … The harvest has come after a long wait I hope that God will extend in your life to see the fruits and your words will remain the stars guiding them today and tomorrow and to Forever

To my dear father.

***To my beloved brothers** on my way in this life...To*

For those who see optimism and happiness in their eyes... to the flame of intelligence who do not know the meaning of surrender to those who accompanied me since childhood, and you still accompany me until now

*My brother **Abdel-Razzak** and my little brother **Mohamed Zian**.*

To those whom I loved and loved me...To those whom I appreciate and respect them... To those who forgot me, and participated in my most beautiful moments ... and they were a help to me

To my colleagues and friends of my career.

<< Youssra >>

Abstract

The development in recent years of serious educational games has achieved great success because it has provided positive points for our children by developing themselves, training their characters, and honing their skills. In this context, we need to customize the game related to the child's profile, and we build on the strength of the recommendations system to create personalized recommendations for children during their play.

Traditional recommendation systems use a single criteria in the recommendation, while studies have shown that the recommendation to use multi-criteria is more accurate. There are many techniques used in the recommendation systems, and the technique that is based on collaborative filtering is the most widely used.

On the other hand, the use of deep learning in recommendation systems began to receive much attention lately. Nevertheless, there is still no attempt to use deep learning in multi-criteria recommendation systems in serious educational games.

In order to improve the efficacy of Multi-criteria recommendations system in Educational filed .We interesting to select the most performance functions and techniques for different steps of educational RS.

The experiments part showed the results obtains of our comparisons between single criteria recommendation systems and multi criteria RS. In the results section, prove this performance. This is evidence of the successful use of multi-criteria accurate technique and recommendation systems with deep learning therefore their dropping in the field of serious games.

Keywords: Serious games, Education, Recommendation system, Collaborative filtering, Multi-criteria, Deep learning.

ملخص

حقق تطور الألعاب التعليمية الجادة في السنوات الأخيرة نجاحًا كبيرًا لأنها قدمت نقاطًا إيجابية لأطفالنا من خلال تطوير أنفسهم وتدريب شخصياتهم وصقل مهاراتهم. في هذا السياق، نحتاج إلى تخصيص اللعبة المتعلقة بملف تعريف الطفل، ونبني على قوة نظام التوصيات لإنشاء توصيات مخصصة للأطفال أثناء لعبهم.

تستخدم أنظمة التوصية التقليدية معيارًا واحدًا في التوصية، بينما أظهرت الدراسات أن التوصية باستخدام معايير متعددة أكثر دقة. هناك العديد من التقنيات المستخدمة في أنظمة التوصية، والتقنية التي تعتمد على التصفية التعاونية هي الأكثر استخدامًا.

من ناحية أخرى، بدأ استخدام التعلم العميق في أنظمة التوصيات يحظى باهتمام كبير مؤخرًا. ومع ذلك، لا توجد حتى الآن أي محاولة لاستخدام التعلم العميق في أنظمة التوصية متعددة المعايير في الألعاب التعليمية الجادة.

من أجل تحسين فاعلية نظام التوصيات متعدد المعايير في المجال التربوي، نحن مهتمون باختيار وظائف وتقنيات الأداء الأكثر لخطوات مختلفة من RS التعليمية.

أظهر جزء التجارب النتائج التي تم الحصول عليها من مقارناتنا بين أنظمة توصية المعايير الفردية والمعايير المتعددة RS. في قسم النتائج، أثبت هذا الأداء. هذا دليل على الاستخدام الناجح لتقنية وأنظمة توصية متعددة المعايير دقيقة مع التعلم العميق لتطبيقها في مجال الألعاب الجادة.

الكلمات المفتاحية: الألعاب الجادة، التعليم، نظم التوصية، الترشيح التعاوني، المعايير المتعددة، التعلم العميق.

Résumé

Le développement ces dernières années de jeux éducatifs sérieux a connu un grand succès car il a fourni des points positifs à nos enfants en se développant, en formant leurs personnages et en perfectionnant leurs compétences. Dans ce contexte, nous devons personnaliser le jeu en fonction du profil de l'enfant, et nous nous appuyons sur la force du système de recommandations pour créer des recommandations personnalisées pour les enfants lors de leur jeu.

Les systèmes de recommandation traditionnels utilisent un seul critère dans la recommandation, tandis que des études ont montré que la recommandation d'utiliser des critères multiples est plus précise. De nombreuses techniques sont utilisées dans les systèmes de recommandation et la technique basée sur le filtrage collaboratif est la plus largement utilisée.

D'un autre côté, l'utilisation de l'apprentissage profond dans les systèmes de recommandation a commencé à recevoir beaucoup d'attention ces derniers temps. Néanmoins, il n'y a toujours pas de tentative d'utiliser l'apprentissage profond dans les systèmes de recommandation multicritères dans les jeux éducatifs sérieux.

Afin d'améliorer l'efficacité du système de recommandations multicritères dans le domaine éducatif, nous sommes intéressants de sélectionner les fonctions et techniques les plus performantes pour les différentes étapes de la RS éducative.

La partie expérimentation a montré les résultats obtenus de nos comparaisons entre les systèmes de recommandation monocritères et les RS multicritères. Dans la section des résultats, prouvez cette performance. Ceci est la preuve de l'utilisation réussie de systèmes de technique et de recommandation précis multicritères avec un apprentissage en profondeur pour leur application dans le domaine des jeux sérieux.

Mots-clés : Jeux sérieux, Éducation, Système de recommandation, Filtrage collaboratif, Multicritères, Apprentissage Profond.

Contents

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List of Abbreviations

CBF: Content Based Filtering.

CF: Collaborative Filtering.

CNN: Convolution Neural Network.

CV: Cross-Validation.

DL: Deep Learning.

DNNs: Deep Neural Networks.

ESG: Educational Serious Games.

FCP: Fraction of Concordant Pairs.

GBL: Game Based Learning.

KBF: Knowledge-Based Filtering.

KNN: Nearest Neighborhood.

LA: Learning Analytic.

MAE: Mean Absolute Error.

MAP: Mean Average Precision.

MCRSs: Multi-Criteria Recommendation Systems.

MF: Matrix Factorization.

ReLU: Rectified Linear Unit.

RMSE: Root Mean Square Error.

RSs: Recommendation Systems.

SG: Serious Games.

SVD: Singular Value Decomposition.

TBF: Trust-Based Filtering.

TEL: Technology Enhanced Learning.

General Introduction

1. Preface:

In view of developments today about the importance of education through play, we deal in particular with children from an early age, and we consider the goals and positive results presented, we mention: Learning to cooperate and respecting rights and others helps in the growth of memory, thinking, perception and imagination, acquires self-confidence and is easy to discover and test his capabilities it has a positive effect.

Encouraging children to play and explore helps them learn and develop their social and cultural abilities. We cannot ignore the importance of playing to expand their perceptions; the process of playing is a powerful and multifaceted learning experience. Subadrah Madhawa Nair and al (2014) believe that play includes exploration and linguistic experience, and through this research paper [1], which examined the comparison of pre-school children's education in the vocabulary of the Malaysian language between the traditional method and the method of play, was explained by a study for a period Six weeks. The results indicated that the use of the grea111tly game play method enhances vocabulary skill, unlike the regular method. The use of play-based learning can be determined especially for children, their ability to succeed, and supports the continuous development of problem solving, etc. … As Nintino Hussein, Al-Azhar and others (2018) mentioned, cognitive skills of children are still in the first stage of their inception and it is important Emphasizing the value of learning based on play during this developmental period [2].

Through current studies that indicate, that education through play is growing rapidly, especially in the field of academic research. Fadwa Al-Amarti and others (2014) see that in most of the previous surveys and references, serious games have different areas, including education, health, social welfare and culture …, in addition to proposing a classification of dangerous games applications that have been reviewed from the literature, and provide feedback derived from the design and develop successful serious games. We can maximize academic standards by having more than one teaching method. If an educational system that uses motivation and manipulation in play-based learning is envisioned [4], In his experimental studies of 47 works explaining, that serious games useful for learners to gain cognitive abilities were reported, the positive impact of learning increased.

Recently, serious games have been used as play-based learning tools and have proven effective in enhancing the learning process / approach. In the literature, many works examine the impact and impact of the use of serious games on an educational learning approach. “TEL” is one of them. No one child is alike. Each child learns differently, for these reasons.

Most adaptive learning solutions are intended to tell learners what to do next by automatically matching teaching materials with individual learner needs or to help learners decide what to do next by recommending them to different educational entities, based on their preferences [5].

To date, recent studies have worked on how to integrate analytical learning (LA) techniques into serious educational games to improve learner outcomes. Learning Analytics (LA) is a multidisciplinary field that includes machine learning, artificial intelligence, information retrieval, statistics, and visualization [6]. LA is also an area in which many related research areas converge on TEL. These include academic analyzes, procedural research, educational data mining, recommendation systems, and personalized adaptive learning. However, diagnosing children’s skills is an enabling mechanism to overcome potential errors during play.

Deep learning in recommendation systems is an emerging field of research, but it shows promising results. The strength of deep learning lies in its ability to represent the complex models that describe user behavior for the recommendation process and its ability to deal with disrupted data in large systems. YouTube and Microsoft, Spotify, recently revealed significant improvements through the use of deep learning in the recommendation engines used within their systems. Collaborative filtering is known to be one of the most successful recommendation methods, and based on the strength of the recommendation system for generating personalized recommendations for kids, which ensures better outcomes that correspond to the needs and interests of the kid.

2. Motivation & Problematique:

Most recent research into deep learning recommendation systems deals with models of traditional systems that use the single criteria for evaluation. According to the study conducted in this thesis, there is no work for a multi-criteria recommendation system that relies on deep learning. For these reasons, we have defended its use in the field of serious educational games. So to proposed a new model or to adapted, we need to take into consideration the following dimensions:

•What is being personalized? Content, resources, Learner, choice..!

•How? Type of learning (Mostly informal but some gaming may take place in formal settings).

•what? Personal characteristics of the learner: Demographic Prior knowledge.

•Who? Is doing the personalization.

•Learner Computer/gaming software and algorithms.

•How is personalization carried out?

•Cognitive-based and whole-person personalization.

•Impact/beneficiaries developers.

3. Our objective :

We seek to improve the efficacy of Multi-criteria recommendations system in Educational filed. We interesting to select the most performance functions and techniques for recommendations system with their different steps.

We explaining a personal recommendation model in educational serious games using recommendation system and multi-criteria rating system based on the interactions of kids, using collaborative filtering technique witch uses user ratings only for elements, in the field of early learning for children through education serious games. The main contributions and solutions that we presented in this research are summarized in the following points:

•Design a model for a multi-criteria recommendation system based on deep learning.

•Applied the model to a set of data for testing.

•Show the efficiency of the proposed model in improving the educational performance of the kid.

4. Structure of the Thesis:

In this stage, we present the rest of this thesis, which structured as follows:

In the next chapter we will take a look about the state of the art in technology enhanced learning and them aspects also knowledge of serious game in educations with different examples domains, therefore we mention especially of one most technique of RS witch is collaborative filtering and we give a simple example to understand them clearly a CF, also their limitations in this filed. More there, we depth explaining of the most technique and functions of Multi-criteria Recommendations system in the last we monition their integration of RS with deep learning. In the second chapter, we will present our methodology. We will start by explaining the proposed personal recommendations model in educations serious game, then we explain our methodology and how each step it work deeply. In the third chapter, we will describe the experiment steps and evaluation, then the obtained results. General conclusion, which draws the conclusion of thesis, as it, illustrates the main outcome of it and what more can be achieved in the future.

Chapter 01:

State of The Art

1. Introduction:

Recommendation systems are gaining increasing importance as applied in Education, especially in technology-enhanced learning (TEL) in order to personalize the profile of learners. Serious games are important TEL technologies that have proven useful in the last decade. This method of teaching is known as game-based education, a trend that is rapidly expanding in the light of prestigious primary schools, universities, and large corporations.

So in this chapter, we will present an overview of the related background knowledge about technology-enhanced learning (TEL), serious game concepts, recommendation systems techniques, with a large explications of Multi criteria rating, as well as its integrations with deep learning.

2. Technology-Enhanced Learning:

2.1. Definition:

Technology-enhanced learning is a broad field between formal and informal learning, in addition to supporting teaching through the use of technology in the classroom and the workplace, and covers almost all topics in our daily life. Since technology is used in different learning scenarios, recommendation systems have also been used to support different learning scenarios. Where its characteristics can be linked to the corresponding principles in education in order to facilitate learning [5].

From literature, Elizabeth FitzGerald et al [6], say that there is a need for ongoing evidence-informed research and design into both policy and practice in order to ensure that the best decisions are made to empower our learners and to ensure that personalized learning focuses on personal choice and personal control. In the case, the industries may be profit-driven rather than pedagogy, given the growing number of venture capitalists and large multinational companies such as Google that are now investing in this area significantly, there are concerns that educational principles may be reallocated to their own purposes - perhaps Driving it to profit instead of learning the origins of teaching.

However, while the idea of personalization might be appealing, the reality of its implementation is much more complex. Personalized learning has been reduced to the presentation of the same content in a different sequence for different students.

Perrotta and Williamson (2018) [7], point out that the algorithms behind learning analytics that personalization are in some cases might exacerbate rather than reduce educational inequality.

For this complex tasks, there in the references model of Chatti, M A Dyckhoff, et al[5], investigated the evolution of learning analytics in recent years and discuss a reference model that pointed the learning analytic concepts and methods are drawn from a variety of related research fields including academic analytics, action research, educational data mining, recommender systems, and personalized.

2.2. Dimensions of TEL:

We describe a reference model for learning analytic [5] based on four dimensions and identify various challenges and research opportunities in the area of LA about each:

1- Where (the area of study):

The challenge today is how to make students of these connected generations motivated to learning? Today students are living in the virtual world, they are smart and creative. For theme, traditional methods of learning are outdated and need to be aligned with technological evolutions.

So to respond to this problem we are interested in the field of a serious game and their integrations in the new way of learning in our schools today. Especially we intend to make evolutions less stressful and more fun by integrating learning games in the evolutions process. To personalize the skills of our kids. To acquire knowledge and skills through an artificial process. This will motivate the kids to learn to achieve the game and succeed in this new method to learn better.

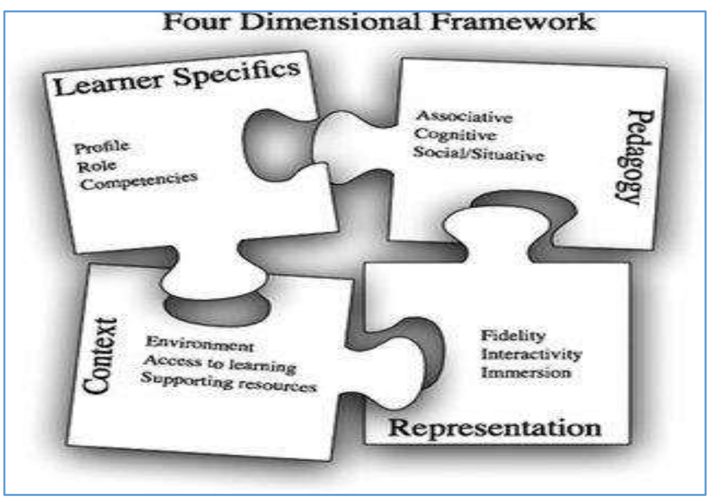


Figure 1.1: A new paradigm of Serious Game [8].

2- Depending –On:

Currently, many of the systems of technology-enhanced learning are data-rich, but information poor. Researchers need to find pedagogically useful, predictions, and recommendations by evaluating the quality of analytics results when our kids are practice so how can available data be converted into actionable knowledge to the kids? , and how can it become an empirical base for decision-making?

Learning analytics has attracted a great deal of attention in TEL in recent years as educational institutions and researchers are increasingly seeing the potential that LA has to support the learning process. LA approaches share a movement from data to analyze the profile of our kids when are playing.

So we aimed to get their attention and help to guide them for doing learning better, for this context we noted the researches of TEL(reference model) about the importance of learning analytic and they are investigating the connections between LA and these related field.

3- What?

Personalization occurs when ~~some~~ product, service, or resource has an element of individualized adjustment, such that we receive a different experience, based upon information about us as end-users [9].From litterateur (Brown et al. 2006). An oft-cited example is the recommender system on the Amazon retail website: we are typically shown other products we may be interested in, based on our past shopping history or that of others who have bought or viewed the same product as us [10].

In the same context but for learners, personalization means adjusting the learning experience, for example, by showing the learner resources based on age, ability, prior knowledge or personal relevance or giving adaptive quizzes that get harder as more questions are answered correctly ~~a base~~ with their gender or errors ~~makes~~ or timeout ..., to get more information we can see that in the study of (FitzGerald et al. 2017) [11].

4- How?

Personalized, context-aware recommendation mechanisms to support the information need of knowledge when the kid's interaction with the game. From K. Schoefeggera ~~et~~ al,2010)[12], this research work presented an approach for user modeling for personalized recommendations in Work-integrated learning based on an example with collaborative tagging systems and include a deeper investigation of the mapping between KIE of work-integrated learning systems incorporating topics that emerge from the usage of the system and the user’s ’real knowledge’.

In the same concept, this study adopts existing recommendation mechanisms and develops new recommendation mechanisms in order to provide the kids with personalized, context-aware recommendations based on the topics they are dealing with and have dealt with and the corresponding knowledge levels. The goal is to be able to provide that support the users in extending their knowledge and improving their levels where necessary and ~~appropriate~~.

~~On~~ based on the techniques of recommendations system, we recommended a help or voice, technical video…..etc, to take full advantage of correctly learning of our kids.

In the end, we can summarize the last points that were mentioned in the following chart on Figure (1.2).

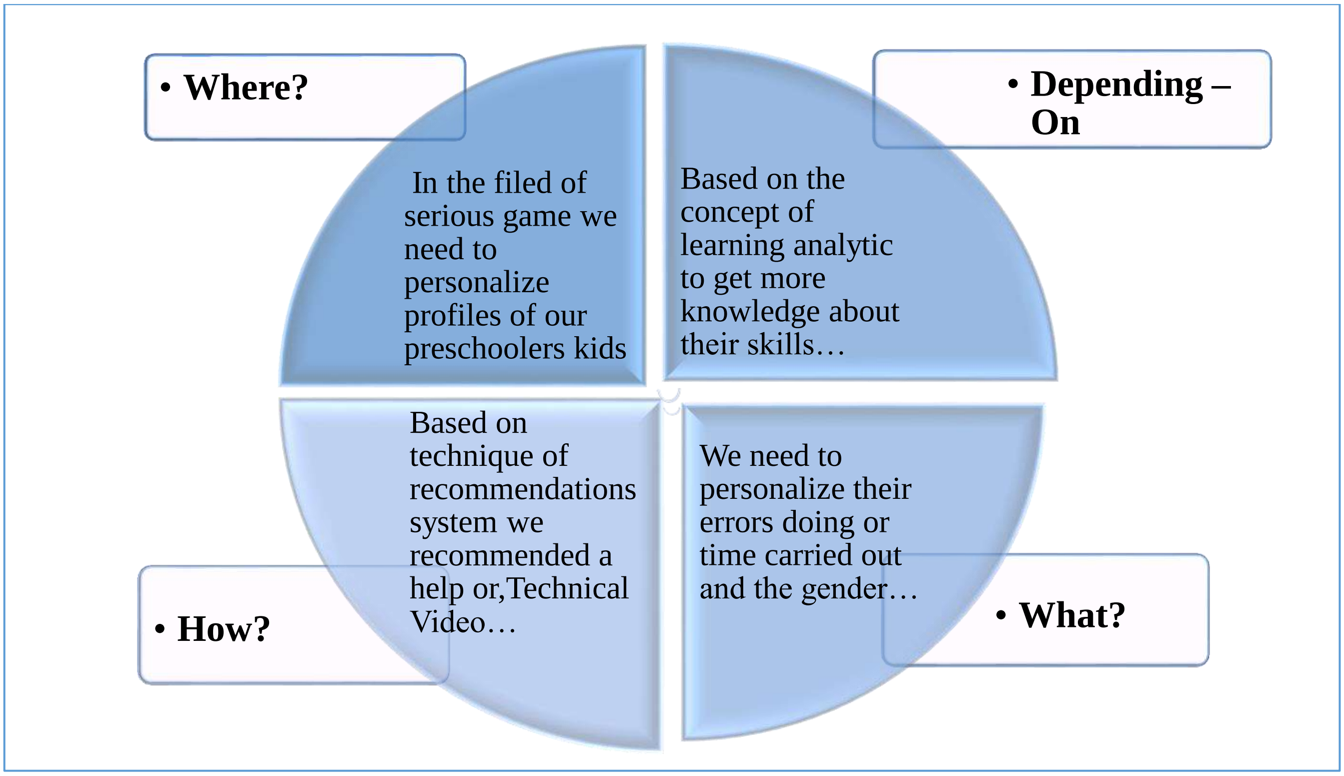


Figure 1.2: Chart summarize our dimension of TEL in our work.

3. Serious Game:

The field of serious games has been growing rapidly for over a decade. To have a closer look at the trend of research in this domain~~. Firstly~~, we need ~~what the mean~~ of serious games ~~also~~ digital games. There are several perspectives of defining serious games; we carried out a survey of published articles related to ~~serious games.~~

As seen from the academia and the industry. For example, they ~~are believed as~~ ‘serious game’ often varies depending on who uses it and in what context [13].

For Zyda (2005),a serious game is "a mental contest played on a computer, according to specific rules and uses entertainment for purposes related to the areas of company executive training, education, health, public policy, and communication strategy” [14]. Also, defines serious games as an application with three components: experience, entertainment, and multimedia [3], as shown in the diagram of figure (1.3). The diagram demonstrates also the differences between serious games and several terminologies such as training simulation, computer games, and sports.

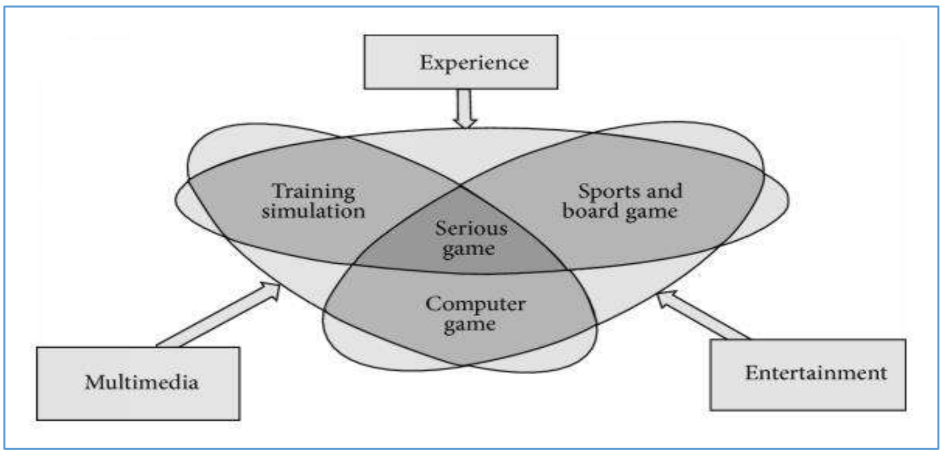


Figure 1.3 Definition of Serious Game [3].

Recently, digital games and simulations have gained popularity as the most powerful and highly engaging learning environment even though the production of these serious games require complex and dynamic constructs with appropriate designs of multimodal context and engaging interactions, as well as productive pedagogical strategies to preserve the efficacy of learning. Therefore, serious games are digital applications prepared for training and education, where the primary function is to give knowledge, train, inform, memorize, and teach end-users.

Additionally, about report of (SERIOUS GAMES MARKET - GROWTH, TRENDS, and FORECASTS 2020 - 2025) which says that the governments of the world are encouraging the adoption of serious games for the learning and education application.

For instance, in September 2019, The University of Canterbury, New Zealand, announced to invest over USD 4.5 million along with USD 3.2 million from the government for the research on its new Applied Immersive Gaming Initiative. [15].The initiative is aimed at providing assistance to tackle tasks that might otherwise be boring or difficult, and one example of the theme, the companies such as Grandel Games ~~has~~ developed a serious game that achieves behavioral change.

For instance, ~~it is one of the games - 'Garfield's Count Me In'~~ is designed for students in primary education ~~allow~~ them to do repetitive math exercises.

3.1. Applications of SG in Education:

Nevertheless, it might be risky to claim ~~that~~ digital games. They may well prove to be an important teaching tool, however, should be combined with other tools and methods to achieve the desired result. Serious games can find applications in many different areas regarding learning, training, attitude change, etc :

- Health – healthcare.
- Military Games.
- Government – policy games.
- Company and enterprise management training games.
- Education.

Now we will show some examples of serious game in educational filed:

Example 01: **Pulse.**

In this video game, future nurses can practice all they have learned in their theoretical classes and gain experience handling real situations. The goal of the players is to identify each patient's problem, giving priority to the most serious cases, and applying the appropriate measures depending on each person's condition [16].

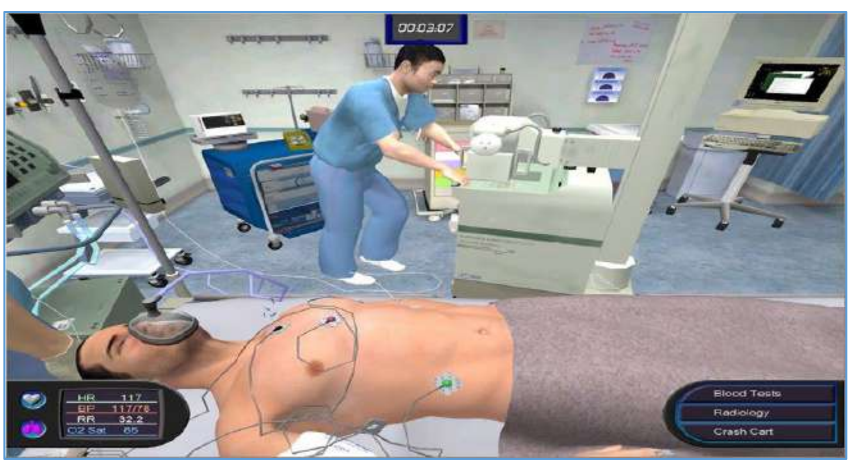


Figure1.4: Pulse Game [16].

Example 02: **Food Force.**

As for the Food Force game, in particular, the aim was to investigate its effectiveness in knowledge acquisition and the understanding of the procedures required for sending humanitarian aid to areas in a state of emergency worldwide. To get more information read their article [17].

Figure1.5: Food Force Game [17].

Example 03: **Duolingo.**

Duolingo, while users learn English, Spanish, French, or German, they receive points, go up to the next level, lose lives, or outdo their friends and relations. Each lesson they learn has a reward. It is one of the most successful applications when it comes to using gamification elements for learning [18].

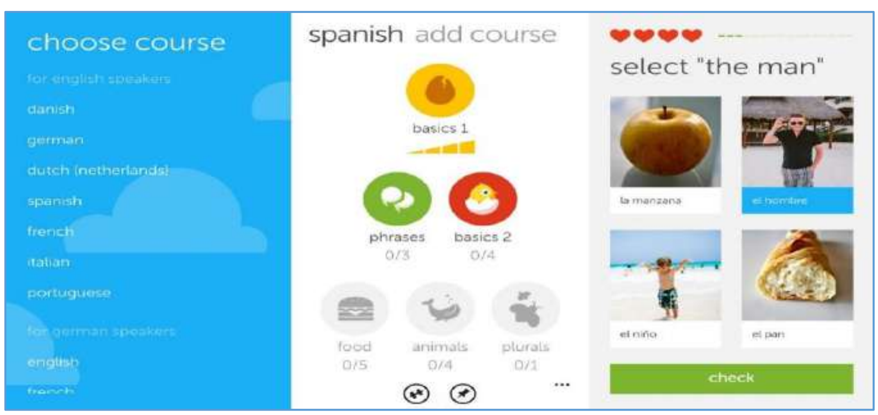


Figure1.6: Duolingo Game [18].

3.2. Success of SG:

Digital games allow training to take place in a safe environment without risks of injury or expensive equipment. They are actually a simulation of real-world events and processes. According to Corti (2006) [17].

The reasons why game-based learning (GBL) is so popular are becoming much more well-known as we have seen, they improve student engagement and motivation, they afford direct practice without risk, and they facilitate the memorization and retention of knowledge.

While serious games have been around for centuries (let's not forget that ever since we were ~~small~~ we've all been learning as we play), the social and technological changes of recent years are extending game-based learning to the four corners of the planet. Serious games have become one of the most practical and effective teaching tools in the world today.

4. Recommendation Systems:

With the growing number of students in the classroom and the switch to online environments, instructors are beginning to integrate collaborative learning approaches in the classroom. Students are overwhelmed by the amount of available information! It is often challenging to select the most appropriate sources of information. A promising way to deal with this challenge and enhance social interaction in collaborative learning environments is by introducing recommender systems.

4.1. What is RS:

Recommender systems (RS) are software tools and techniques that can recommend items users might have a need for or could use [19]. Also, for ~~them~~ (Wang, P ~~et~~ al), [20] ~~that~~ the recommendation systems help the users ~~to~~ choose objects they can find useful or of their interest. RS is the system that has, as a principal task, to choose certain objects that meet the users requirements [19], these objects can be any kind of information or articles, such as books, movies, songs, Web pages, blogs, etc….

The recommendation system needs to know as much of the user as possible in order to make a personal recommendation. Therefore, any recommendation system includes three phases that Information collection phase, a learning stage, and a prediction / recommendation.

The first phase relies ~~about~~ users describing the user's profiles and representing their interests and behavior .This information includes intellectual capabilities and interaction with the system. Typically, a user profile is used to retrieve the information needed to build a user form, either explicitly or implicitly.

The next phase in the analysis of information includes the application of algorithms and learning techniques and the exploitation of the personal characteristics of the user that were gathered in the information gathering stage. In the last step, the system predicts or recommends items that the user might prefer. Based on the data collected in the previously information gathering stage, which can be memory-based or model-based, or directly do so. Figure (1.7) highlights the stages of the recommendation.

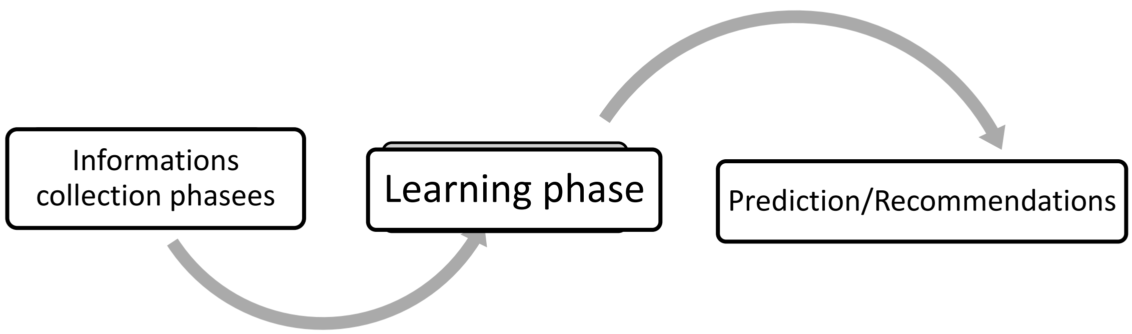


Figure 1.7: Phases of Recommendation Systems.

4.2. Recommendation System Techniques:

Among the stages of the recommendation systems, the proposed model predicts the user's choices or recommends the elements that the user would most likely prefer. In order to obtain a good and useful recommendation for its individual users, it is imperative to use effective and accurate recommendation techniques, and this explains the importance of understanding the features and capabilities of the various recommendation techniques. Figure (1.8) shows the most important techniques of recommendation systems.

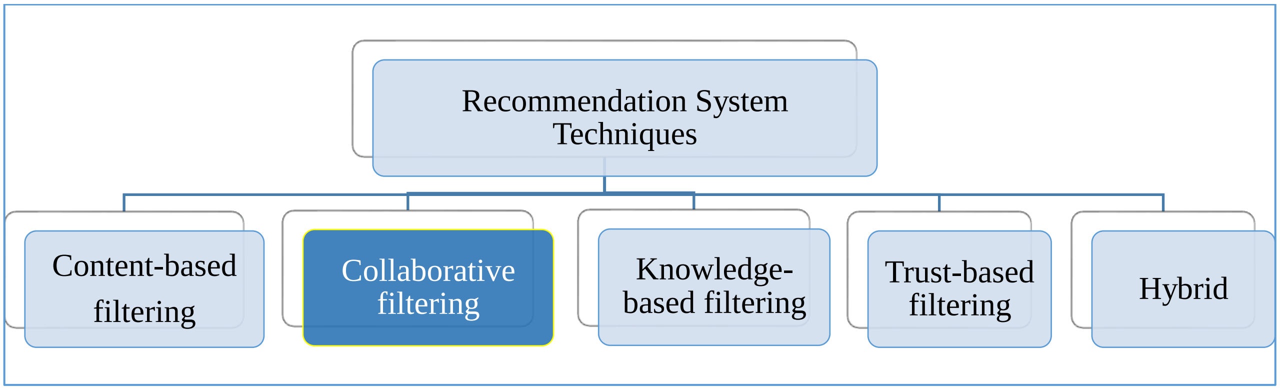


Figure1.8: Recommendation System Techniques.

4.2.1. Collaborative Filtering RS:

Collaborative filtering technology is the most common and used technique for building recommendation systems. It gives the results of the recommendation, the most accurate and independent of the field, ~~meaning~~ that you do not need information about the field in which it is applied, and this technology does not need information about users or elements but rather expectation and recommendation are made, based on user reviews of the items only. Through the following figure (1.9), the concept is simplified for us more.

Figure 1.9: Simple Example of CF[1].

As for the following Figure (1.10), it shows classifications of CF techniques as being either memory-based or Model-based:

[1] https://spatnaik77.files.wordpress.com/2013/07/user-user1.jpg

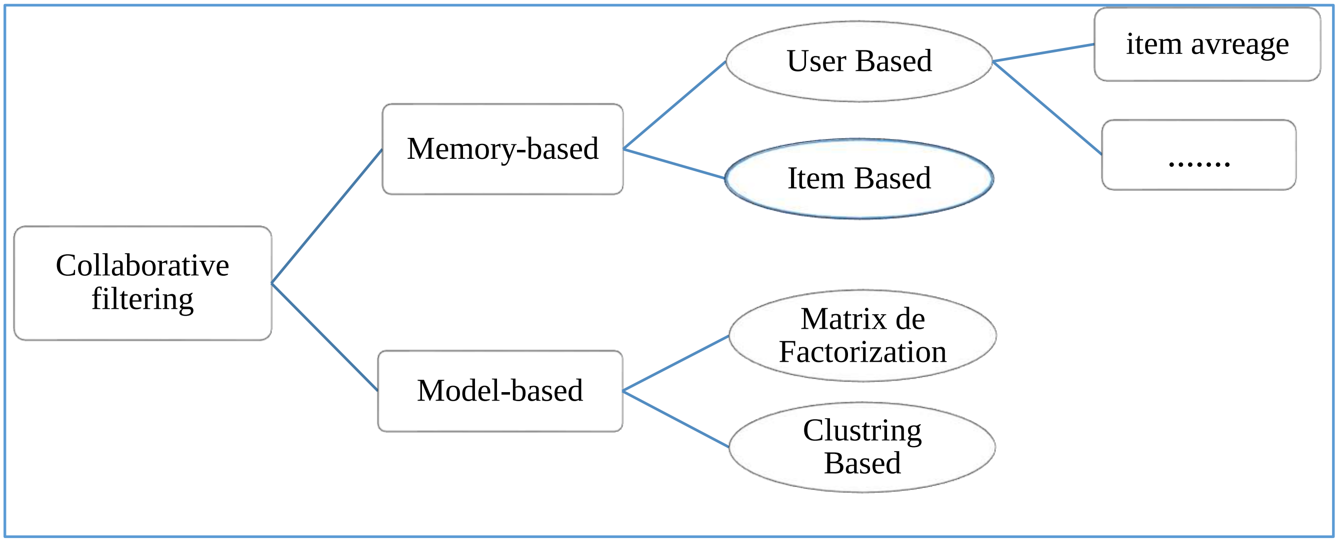
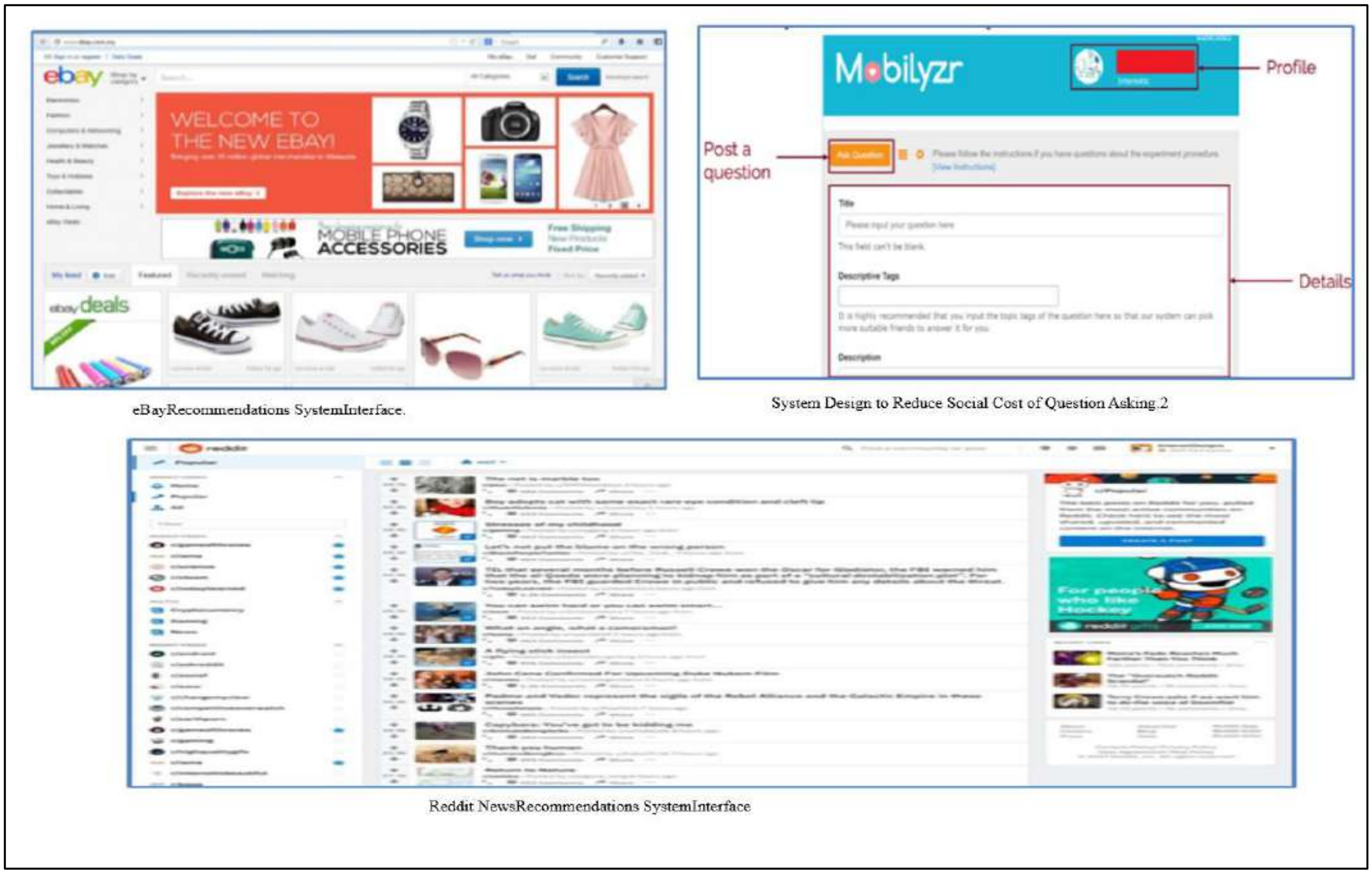


Figure1.10: Classification of CF Functions.

Now we will look at some examples ~~shows~~ in the figure 1.11 to illustrate the various uses of the collaborative filtering technique in different domains such as economic or promotional fields.

~~e~~Bay[21], is an example of e-commerce recommendation engine .The interaction Profile feature at eBay.com™ (www.ebay.com) allows both buyers and sellers such that consists of a satisfaction rating as well as a specific comment about the other customer ,the Feedback is used to provide a recommender system for purchasers, Personal Shopper: ~~The personal shopper~~ feature of eBay allows customers to indicate items they are interested in purchasing. Also for the second examples, GroupLens is Usenet's collaborative filtering of news is an experimental success based on client / server architecture, and through the research paper of (joseph A et al), the effect of providing predictions for new users more quickly by providing general averages so that the user categorizes enough articles to link[21] .



eBayRecommendations SystemInterface.

System Design to Reduce Social Cost of Question Asking 2

Reddit NewsRecommendations SystemInterface

Figure 1.11: Examples of CF techniques.

Therefore, Reddit [22], is an example of filtering system that provides news recommendations to members who post content such as links, text posts, and images. Posts are organized by topic into panels created by the user called "subreddits", such as news, politics, science, ….etc, and in the end the result appears at the top of the page that contained more votes and posts by registered users.

4.3. Limitations of CF:

Several recommendation systems have some problems which are the challenges for research work [23]. The collaborative filtering systems provide a powerful predictive for recommender systems and require the least information at the same time, despite his success he has a few limitations in some particular situations and some of his problems shown as follows:

Cold-start problem: This is one of the major problems that reduce the performance of the recommendation system. The profile of such a new user or item will be empty since he has not rated any item; hence, his taste is not known to the system. [24].The Cold start problem refers to the situation when a new user or item just enters the system.

Three kinds of cold start problems are new user problems, new item problem, and new system problem~~s~~. In such cases, it is really very difficult to provide recommendations as in the case of a new user, there is very little information about the user that is available and, also for a new item [23].

Data sparsity problem: Data sparsity always leads to coverage problems~~,~~ the generation of weak recommendations~~,~~ when new items are added to the system, they need to be rated by a substantial number of users before they could be recommended to users who have similar tastes with the ones rated them. The new item problem does not limit the content-based recommendation, because the recommendation of an item is based on its discrete set of descriptive qualities rather than its ratings [25].

Scalability: This is another problem associated with recommendation algorithms because computation normally grows linearly with the number of users and items, .For example, with tens of millions of customers O(M) and millions of items O(N), a CF algorithm with the complexity of (n) is already too large. As well, many systems need to react immediately to online requirements and make recommendations for all users regardless of their purchases and rating history, which demands higher scalability of a CF system [23].

4.4. Multi-criteria Recommendation Systems:

Most of the traditional recommendation systems work on single rating systems that indicate the extent to which a specific user likes a particular item, meaning that the user evaluates the item by a single value, which represents the general rating. A number of applications, recommenders are often interested in predicting the ratings of all the elements as closely as possible.

Multi-criteria recommendation systems are still in the mature stages. Therefore, the recommendation techniques are expanded to include multiple criteria that contain ~~in addition to the~~ general classification because they depend on a set of additional information about the user's preferences that are represented in many important aspects / components of the element that can help improve the performance and accuracy of the recommendations system. In this context, we summarized most of the recommendation systems techniques ~~are~~ based on the chapter 24 in handbook (multi-criteria recommendations system) [26], also their various stages with specifying the nature of their types~~, this is represented~~ in the following figure (1.12).

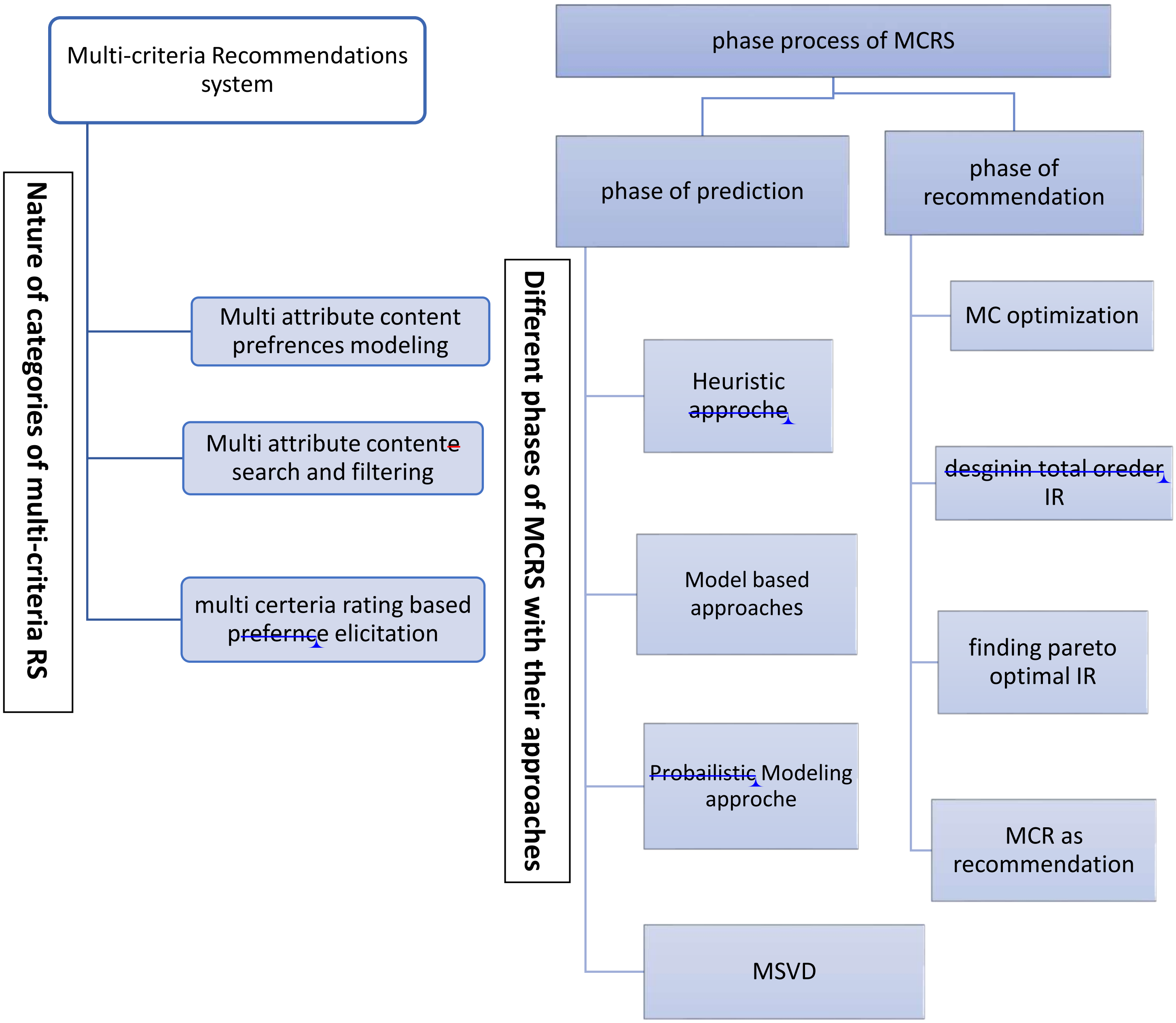


Figure 1.12: Chart Summarizes different approaches and categories of MCRS.

~~With depth more,~~ we will describe below in the approaches of multi-criteria ratings /single criterion rating in the similarity computation and how to ~~calculating~~ similarity using multidimensional distance metrics[26], ~~all this we summarize~~ in the table (1.1) below. Notes:

- Where $\boldsymbol{\omega}_{\boldsymbol{k}}$ is the weight ~~of the weight~~ of the similarity for r_k.
- Where $\boldsymbol{I}(\boldsymbol{u}, \boldsymbol{u}')$ represents a set of items that both of users u and u' have rated.

<table>
<tr><th colspan="2">Survey Algorithms for multi criteria rating recommendation</th></tr>
<tr><th colspan="2">Heuristic approaches</th></tr>
<tr><th>Single criterion rating</th><th>Multi criteria rating</th></tr>
<tr><td rowspan="3">

• Cosine based:

$$\text{cosin similarity: sim(ui, uk)} = \frac{\text{ri}.rk}{|\text{ri}|.|\text{rk}|} = \frac{\sum_{j=1}^{m} rij.rkj}{\sqrt{\sum_{j=1}^{m} rij}\sqrt{\sum_{j=1}^{m} rkj}} \quad (1-1)$$

</td><td>

• Average similarity:

$$\text{sim}_{\text{avg}}(\text{u}, \text{u'}) \quad \frac{1}{\text{n}+1}\sum_{\text{k}=0}^{\text{n}} \text{sim}_{\text{k}}(\text{u}, \text{u'}) \quad (1-2)$$

</td></tr>
<tr><td>

• Worst case:

$$\text{sim}_{\text{worst}}(\text{u}, \text{u'}) \min_{\text{k}=0,1,2,..,\text{n}} \text{sim}_{\text{k}}(\text{u}, \text{u'}) \quad (1-3)$$

</td></tr>
<tr><td>

• Aggregate similarity:

$$\text{sim}_{\text{agg}}(\text{u}, \text{u'}) \quad \sum_{\text{k}=0}^{\text{n}} \omega_{\text{k}} \text{sim}_{\text{k}}(\text{u}, \text{u'})$$

</td></tr>
<tr><th colspan="2">Model-based approaches</th></tr>
<tr><td></td><td>

Aggregations function approaches: this pproach assumes the existence of an aggregate nction ***f*** which represents: $= f(r_1, \ldots, r_k)$ (1-5)

</td></tr>
</table>

Table 1.1: Different functions and techniques of two approaches for MCRS.

4.5. Recommendation Systems in Education:

There are several uses of RS in education, the most reported is helping on academic choices, or , research document complementary materials, also ~~there are more,~~ areas of education enhanced by RS is the e-learning education through web platforms. Moreover, most of the existing recommendation approaches do not consider differences in the learner profile.

So in this context ~~we based on the paper of~~ mapping study [27], to get more knowledge of studies to improve the available knowledge of implementing and deploying models of RS within the educational context. witch support~~ing~~ a systematic mapping study~~, a~~ total of 44 research papers have been selected, reviewed and analyzed from an initial set of 1181 papers, table(1.2) below illustrate the results ~~obtains~~ in their study.

Research question	Criteria	Options	Number of studies With percentage (%)	
RQ1. What are the educational areas covered by RS?	C1. Areas in education	– Academic choices – Learning activities – Learning resources – Academic performance – Vocational and educational training – e-learning	Studies	Percentage
			72	163,69%
RQ2. What are the approaches used to generate recommendations within the educational context?	C2. RS approach	– Collaborative filtering – Content based – Hybrid approach – Knowledge based – Other	59	99,99%
RQ3. Which platform is used for the recommender system deployment?	C3. RS Development	-Desktop based – Web based – Mobile based – Conceptual model	44	99,99%
RQ4. Which evaluation or validation strategies are applied to recommendation systems?	C4. RS empirical validation	– Survey – Case Study – Experiment – None	44	100%
RQ5. What are the challenges addressed by adopting a recommendation	C5. Issues addressed by the RS	– Availability of information & content sharing	65	147,73%

system in the educational context?		– Personalized recommendations – Prediction accuracy & efficiency – Improve educational practices		

Table 1.2: Results of paper mapping study.

In these papers [27], the recommendation targets a general specific educational context, to engage students through the instructional recommendation in a ~~novel~~ way, so the actual issues in RS are how to improve the personalization recommendation system.

We can also see the percentage obtained through the study shown in the table for the collaborative filtering technique~~. It is as follows:~~ 29.55% of approximately 13 research papers. In contrast, it shows the lack of integration of these technologies within the educational context especially of educational games, which is one of the previously studied issues.

Therefore, in this context, from the idea to enhance the RS model ~~.We~~ seek to improve the integration and personalized of educational games~~. On~~ ~~the~~ one hand, in the other hand, we need to combine with other algorithm of~~ intelligence artificial~~ ~~for~~ order to improve the ~~efficacy~~ of multi criteria ~~in~~ uses and test the systems using performance metrics such as recall and precision.

5. Recommendation Systems with Deep Learning:

In recent decades, the development of artificial intelligence technology has witnessed great success in many application areas such as computer vision, object recognition, and automatic control. In addition, researchers define artificial intelligence as "the study and design of intelligent systems that absorb their environment and take actions that increase their chances of success" [28].

Deep learning is a signification feature of the development of artificial neural networks and is a class of machine learning, Which is able to experience, learn and develop itself without human intervention, so it simulates the way the human brain works and its ability to solve complex tasks ~~theses.~~

In this context, Deep learning is adopted to enhance ~~we need~~ to customize the game related to the child's profile. Additionally, we build on the strength of the recommendations system to create personalized recommendations for kids during their play.

Deep neural networks (DNN) is one of the most popular deep learning algorithms, and it has had many notable successes in this field~~,~~ this was achieved thanks to advances in deep learning in trapping items and partying users. Our work will be around the personalized profile of our kids. We will talk about the most popular learning algorithms in ~~the~~ field.

5.1. Uses of RS:

Recent year~~'s~~ showed~~. Growing~~ research activity in the application of deep learning within the recommendation systems. ~~Where he found a large number of recommendations based on deep learning~~, which gave promising results improvements in this area. Regarding the beneficial aspects~~.~~

The researchers used different neuronal network structures such as deep neuronal networks, convolution neural networks, and automatic encoders~~. In~~ improving the performance of traditional recommendation systems. One of the most prominent examples is Netflix, who won the Netflix Progress Award in 2007. It was a model by integrating the Restricted Boltzmann Machine, and SVD single value differentiation and the merging performance was better than that of single value differentiation alone [28].

- Deep neural networks with several layers have recently become a highly successful and popular research topic in machine learning due to their excellent performance in many benchmark problems and applications.

The figure (1.13) below shows the example of YouTube represents one of the largest scale and most industrial recommendation systems in existence. The first network generates the nominations while the second network arranges them (see the figure that illustrates the general structure of the model.) In this model, the candidate videos are chosen using a neural network based on collaborative filtering technology, and then these videos are arranged by taking advantage of their features using a network Neurological.

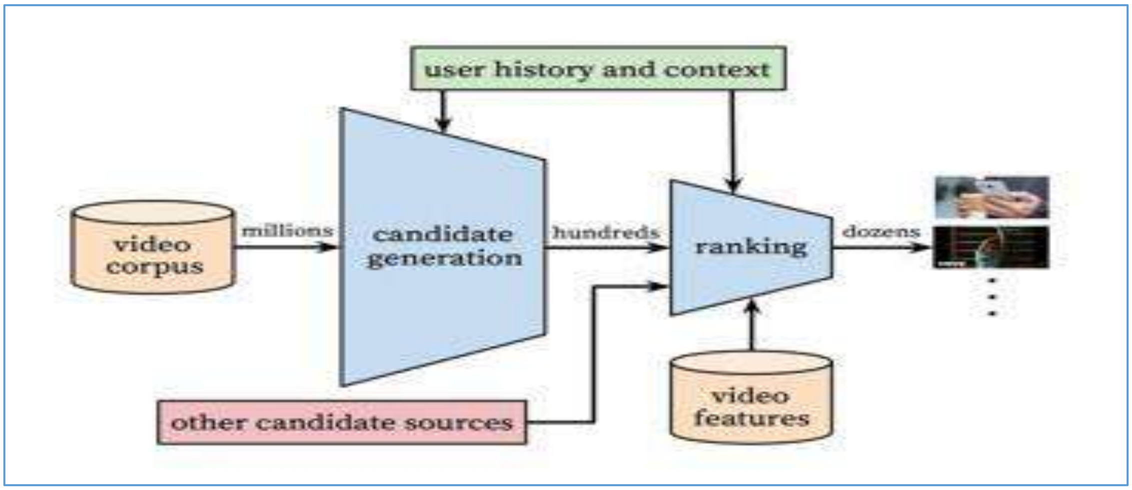


Figure1.13: The structure of the two-stage recommendation system relies on deep learning of the video's recommendation for you tube [28].

- A convolution neural network (CNN) is a different type of multi-layered perception that is commonly used in computer vision. CNN is also commonly used to model user-profiles and item descriptions for the recommendation. They were used to directly model the interaction between users and object features in recommendation systems. More specifically, a special case of NCF using the matrix factor and CNN was proposed, where the model used the general matrix factor to model the interactions of latent traits using a linear core and a CNN to learn the interaction function from data using a nonlinear kernel. Trials with a public dataset, Movielens, showed that the proposed model was superior when compared to the state of the art technology.

6. Conclusion:

In this chapter, we introduced the background of the topics related to our research. The chapter consists of the general overview of LA and their dimension related ~~in~~ the area of educational serious game, then we identifie~~r~~ basic of a serious game and different technique of RS with some of the examples of collaborative filtering technique, we precise more ~~explain~~ detailed ~~of~~ multi criteria RS approaches and techniques. Furthermore, we identif~~y~~ an overview study of RS in educational filed .Finally; the chapter gives little introductions of deep learning and also the uses examples of integrations the RS with deep learning.

Chapter 02:

Our Methodology

1. Introduction:

This chapter contains the explanation of our methodology that we have counted on. In the first section, we will present the personal recommendation model in educational serious games and how we can personalize an ESG. In addition, in the second section, we are going to describe our proposed model and illustrative process of modeling data and of the proposed help recommendations for personalization ESG, and the proposed recommendation methods in our work. Next, in the third section, we will show the strategy of comparative study between the proposed models of the single-criterion rating systems and multi-criteria rating systems. Finally, the conclusion of this chapter.

2. Personal Recommendation Model in Educational Serious Games:

Educational serious games (ESG) present potent tools for technology-enhanced learning, which proposes the use of game rules, player experiences, and cultural roles to shape kids' knowledge and behavior. ~~And~~ in order to improve the learning outcomes for all learners and especially those who are in an early stage of education (in preschoolers), we need to personalize the game elements.

Playing with games is the work of our kids, where we can work to take advantage of this point as a positive one to harness the energy, motivation, and sheer potential of their game-play and direct them toward learning, and we can give kids tools to become high scorers and winners in real life [28].

The educational games have behavioral, social, and cultural rewards. They contain activities that are performed for education and self-amusement to motivate kids to engage in the classroom, give parents and teachers better tools to guide and reward them, and get kids to bring their full selves to the pursuit of learning. Added to that, they can show them the ways how education can be a joyful experience, and the kids can be inspired by blurring the boundaries between formal and informal learning to learn in wide, long, and deep ways.

Therefore, we can count on their power in enhancing and ensuring a meaningful education and in developing the capabilities and skills of the kids at the same time.

We need to personalize the game-related on the interaction of kids and their profiles to guide ~~the kids~~ in how to play and deal with the game and to develop meaningful assessments to ~~they are achieving~~ their aims. In this context, our work is based on the power of the recommendation systems to present a novel model for design, build, and develop personal recommendations in educational serious games for kids.

In our proposed model, personalization is taking place within the games themselves by using a multi-level of recommendations, where it is all about collecting information on kids' interaction, feedback, and preferences while playing, then using those data to adapt the personal recommendations, which fit them and make the interactions more ~~enjoy~~.

Generally, for personalizing an ESG ~~we based on the dimensions of TEL as illustrated in Figure (1.2) to presents~~ the analysis dimensions for personalization educational serious games. Where it can be simplified in the following Figure (2.1) Analysis Dimensions of the Proposed Model ~~for~~ Personalize ESG for defining the core elements of our model.

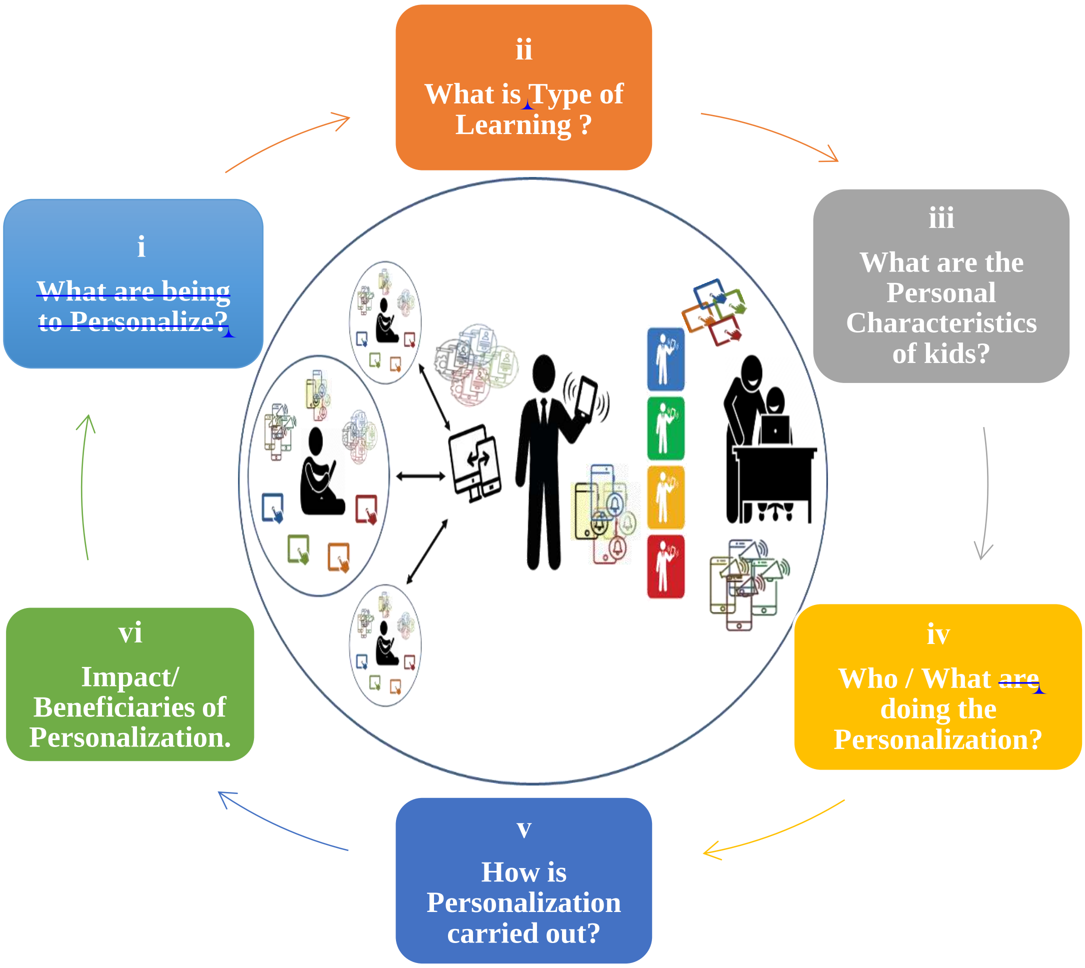


Figure 2.1: Analysis Dimensions of the Proposed Model for Personalize ESG.

Dimension **i**: Understanding what is going to personalized in ESG:

What ~~are being to personalize?~~

A key factor that determines the success of personalization in ESG, is a good understanding of what the personalize is ~~being~~. Therefore, we are going to determine and specify what will be personalized in the game like the content of the game, playing style, learner, skill level, resources, game feedbacks, choices, help, user interface, and activities to empower the kids to achieve the objective of the educational game.

Dimension **ii**: Defining Type of Learning:

What is the type of learning ~~using~~?

We have to define the type of learning where most games use Informal learning, but also the Formal setting is used in some places, to make the education simply and joyfully and to ensure ~~his~~ success for kids.

Dimension **iii**: Personal characteristics of kids:

What are the personal characteristics of kids?

Which is an essential part to define the fit personal recommendation for a kid which is based on their personal characteristic like: demographic (e.g. age, gender, maturation, language, cultural background...), prior knowledge, prior skills, the personal interests, and the preferred mode of learning to them (with others, or on an individual basis).

Dimension **iv**: Who / what ~~are~~ doing the personalization ?

We are going to specify ~~how is~~ the generator of this personalization ~~if~~ computer/system designers, learners/kids, educators, mentors, or gaming software and algorithms.

Dimension **v**: How is personalization carried out ?

The recommendation system is the best tool for personalizing the ESG ~~for generating and carrying~~ out help recommendations for a suitable education ~~for the kids~~ based on their profiles and interactions with the game.

Dimension **vi**: Impacts and beneficiaries of the personalization:

The most beneficial in this case ~~are~~ the learners/kids to help ~~them~~ ~~to~~ learn easily and ~~funnier~~ and at the same time facilitate to the parents and teachers to guide their kids during their education, and finally, it influences in the commercial entities (developers of systems and games).

3. Our Proposed Model:

In this section, we are going to present and to describe the process of the proposed recommendation model for personalizing educational serious games for preschool kids and the needs of our model.

Firstly, we start by tackling about modeling of the data that we can use ~~it~~. Secondly, we are going to ~~showing~~ and ~~explaining~~ the process of delivering personal recommendations and display them with deep details.

3.1. Modeling Data:

We were centered on the semantic model of [29] and the general framework of [30] to ~~defining~~ the main e~~lement~~s of our model, where each of them is ~~presenting~~ as follows:

- Kids Information: can rely on these questions to allow~~s~~ ~~obtaining and describe the kids' information~~: "what is the general information of kids we need ~~it~~?", "what do we need ~~it~~ from the interaction of kids with the game?".

In general, the kid can be represented by a set of simple and complex features where this general information can ~~obtain~~ by profiles of kids in the case of tablets applications this means that the game application is available for everyone, or in the case of integrating the teacher in the process collect the information that can add more confidence in explicit and implicit information.

Like: codes of kids, names of the kids, gender, age, language, favorite color,...

In addition, we can ~~be used~~ the information obtained from the interactions of kids during the playing of a game to estimate ~~the fit help~~ for kids, where those pieces of information are representing in: number of correct actions (NCA), number of actions by the player (NAP), number of drag not completed (NDNC), number of wrong actions (NWA), navigation skill (NS), analysis skill (AS), activity time (AT), player activity time (PAT), automatic play skill (APS), weight skill (WSk), skill level activity ratting level ratting (LRi), general rating players (PGR), time (T).

- Help Recommendation: "in which level of recommendation we can recommend help to kids?", "what we need to recommend to kids to help them?".

The help recommendations focus on those issues that the kids will ~~found~~ in interaction with the game in order to help them attend their goals, therefore we proposed a multi-level of recommendation based on the general evaluation for the kids in real-time, after *k* activity, after each level, in ~~the start~~ of the game, or in the end as ~~showing~~ in the following Figure (2.2) with more clarification architecture of the multi-level.

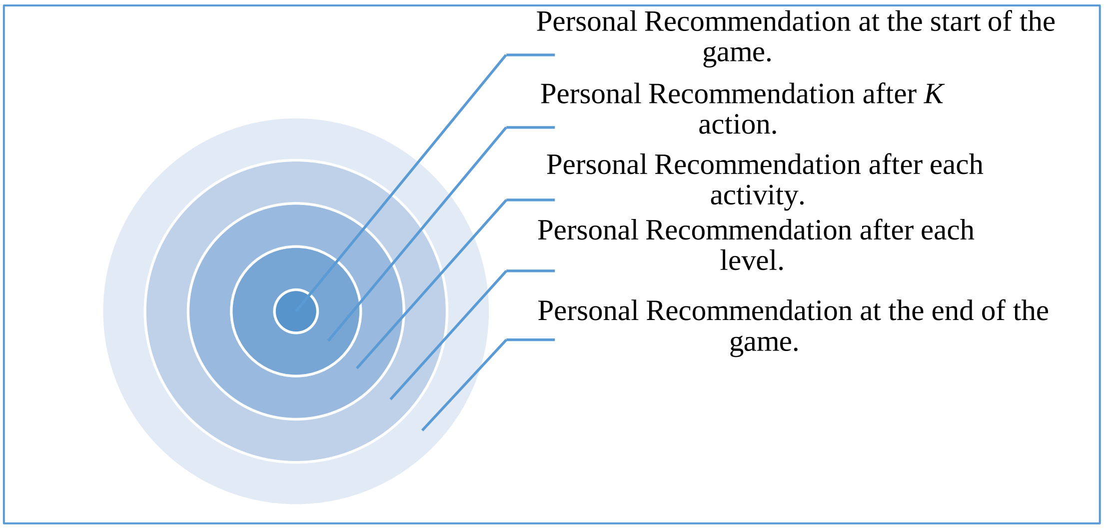


Figure 2.2: Multi-Level of Personal Recommendation.

Moreover, there are several categories of recommendation that the system can be ~~recommend~~ for helping the kids at any level:

- Play Next Level (L+1): at each level, we order to further develop the kid's abilities and competencies by increasing educational values.

- Play Low Level (L-1): by noting that the lower level competencies are still not absorbed and not acquired, we need to take into consideration the previous competence.

- Replay Current Level (RCL): by noting a large number of errors at this level, it means that the desired efficiency has not been acquired yet.

- Voice Motivation (VMo): audio messages work to motivate more kids when playing in the game so that they do not become frustrated, especially if the solution is incorrect or if it requires a lot of time to implement the specified tasks in order to attract the child's attention, motivate and encourage him and make him separate between the wrong action and the correct action, for example: Excellent, Right, Good, Cool, Wrong done, Try again, Focus well, Fantastique.

- Technical Video (TeV) or Taking a Quiz (TQ): providing help for kids how to use ~~play in~~ tablets (present for example method of how to move an object in tablet) or a video explaining how to approach the game, its objective, and how to play the game, or recommend to him a video or quiz before moving to the next activities in order to prepare them and help them.

- Learning Styles (LS): suggests a way of learning the contents or the appropriate alternative content, which applies best to the kid's preferred way of learning (read/write, visual, auditory, or kinesthetic).

- Game Style (GS): in order to attract the kid's attention and help him increase his focus, and this ensures good interaction while playing (user interface, colors, lighting, line type, font size, music, visual effects, pictures, animation of the game elements,...).

- Notification to Educator or Parent (NoE / NoP): in order to follow their kid and follow the way he plays, and to ensure that he has a good educational ~~medium~~ that helps him learn.
- Accessibility (Ac): deals with accessibility issues, such as recommending an alternative format that matches the kid accessibility preferences.
- Scrutability (Sc): promotes self-reflection by telling the kid what the system knows about ~~her~~.

After we presented and illustrated the basic elements of our proposed recommendation model for personalizing the educational serious games. Now, we are going to explain the mechanism of the general process of the help recommendation for personalized ESG in our model and when can be with details, as ~~showing~~ in the Figure (2.3) which summarized all the proposed process.

We start by the first level of recommendation which based on the personal recommendation at ~~the start of the game, in initial of the game~~ ~~generally we~~ get the basic characteristics of kids (name, age, gender, favorite color, ...) by two different ways, either through the input formula where each kid enters his basic personal information in the first use of the game (explicit information), or through the information stored in the game database that was obtained from their profiles through the first use (implicit information) then we use that information (data) in the personalization ~~as~~ like ~~for~~ personalizing the user interface to kids, display the toy in the kid's favorite color, or ~~sent~~ a welcome voice by using the name of kid (voice motivation),... All these help recommendations ensure a good, enjoyable interaction for the kid with the game during the playing which leads to a meaningful, useful, and enjoyable education.

Then for the rest of the levels of the help recommendation which based on the personal recommendation after k action or after each activity or after each level, we propose that each game ~~have~~ a fixed number of actions for achieving and realizing a specific activity, and also has a fixed number of activities to realize a specific concept and each level contain one concept, where in the end a game has a certain number of levels to achieve its main goal. ~~Where~~ the help recommendation is effected and recommend it after each overall evaluation (after each level, after each activity, real time) for the kids in a different case by using a set of parameters. And finally, for the help recommendation in the end of game we use the general rating of the kid to help the teachers and the parents (sent a notification, mail, or results of quiz,..) to know the level of knowledge and education that the kid acquired during the use of the game and the extent of the benefit from playing.

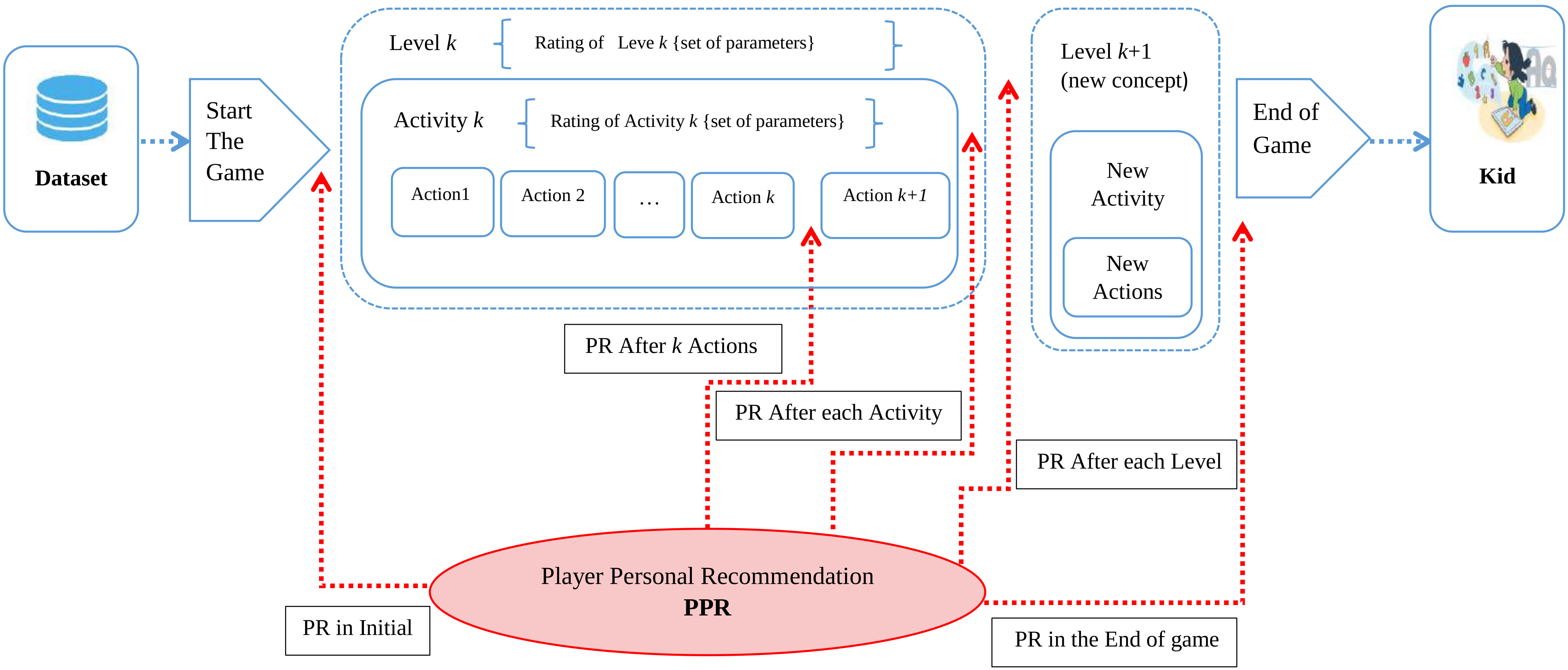


Figure 2.3: States of Personal Recommendations in ESG for kids.

3.2. Proposed Recommendation Methods:

"What recommendation methods can we use?, what ratings our system estimate to kid for giving ~~to~~ him a help?" .

To realize and generate the recommendation in our model for personalizing the game-related with the interaction of kids ~~we are based on~~ the power of the single-criterion ratings recommender systems (SRS), multi-criteria ratings recommender systems (MCRS), and deep neural network (DNN) in the prediction ratings of kids to providing the optimal recommendation to them.

Whereas, we conducted a comparative study in the both cases of a single rating recommender system and a multi-criteria rating recommender system to present who is more effective than the other ~~is~~.

In the case of single-criterion recommendation, we are going to gather the single collaborative filtering technique and deep learning in order to effectively improve the performance of our model [35] and also on the other side, we are fusing the DNN and matrix factorization (MF) in the single-criterion recommendation, to combine the non-linearity of DNN and linearity of MF in the single-criterion RS for modeling kid-help latent structures [33].

Additionally, in the case of the multi-criteria recommendation, we will do the same as in a single rating case, where we are going to combine the deep learning and multi-criteria collaborative filtering and also, we are going to ~~fusing~~ DNN and MF in a multi-criteria recommendation system for the same goal to improve the strengths of both techniques [35].

In this part, we will explain the proposed process of recommendation systems that we used to recommend help to the kids in our model, by basing on the two phases: the prediction phase and the recommendation phase.

3.2.1. Single Rating Recommendation Systems:

The majority of traditional recommendation systems operate on single-criteria rating systems that indicate how much a given user liked a particular item in total and in other sense; the opinion of the user about this item, i.e., the user evaluates the item by a single value (representing the overall rating)[19].

The single-rating recommendation systems operated in a two-dimensional space of which in our case represent kids and the help recommended($Kids \times Helps$).

The utility of helps to kids is generally represented in single-rating systems by the overall rating, where the utility function $\boldsymbol{R}$ can be defined as follows [19]:

$$R: (Kids\ \times\ Helps) : k \times h\ \rightarrow \boldsymbol{r_0} \qquad (2-1)$$

Where r_0 is the overall rating values.

For more understanding, we have a simple ~~instance~~ of our proposed model, where provides our recommender system with a single rating (between 1 and 5) for each help recommendation based on kids' interactions in the game.

~~Assume~~, that we have five kids $(k_1, \ldots, k_5)$ and four help recommendation $(hr_1, \ldots, hr_4)$ proposed in our model like (learning styles, game style, technical video, and voice motivation), as Figure (2.4) illustrates this simple example.

Let's suppose that this recommendation system needs to estimate how much the target kid k_1 would need to the help recommendation hr_4, and we suppose that the system knows all other ratings from different kids to different help recommendations as indicated in Figure (2.4).

Then, using the traditional collaborative filtering with a single-rating approach for finding the kids that are closest to k_1 and that have a need to the help recommendation hr_4.

According to our example, the kids k_2 and k_3 seem to be perfect matches for kid k_1 because they both gave exactly the same rate for different help recommendations

Since both k_2 and k_3 rate help recommendation hr_4 as 4, the value of target rating $R(k_1, hr_4)$ will be predicted as 4.

Target Kid

Kids most similar to K_1

	Help Recommendation ***HR₁***	Help Recommendation ***HR₂***	Help Recommendation ***HR₃***	Help Recommendation ***HR₄***
Kid ***K₁***	4 4	2	5	**?**
Kid ***K₂***	4	2	5	4
Kid ***K₃***	4	2	5	4
Kid ***K₄***	3	3	4	5
Kid ***K₅***	3	3	4	5

Ratings to be predicted

Ratings to be used in prediction

Figure 2.4: Personal Help Recommendation using a Single-Criteria setting.

The following Figure (2.5) shows the two phase's prediction and recommendation used in the proposed single models. As we have mentioned previously that, the case of single RSs has two models: the first proposed model depends on using DNN with the single collaborative filtering to predict the overall ratings for the kids, whereas the second proposed model based on the fusing of DNN and MF with the single CF.

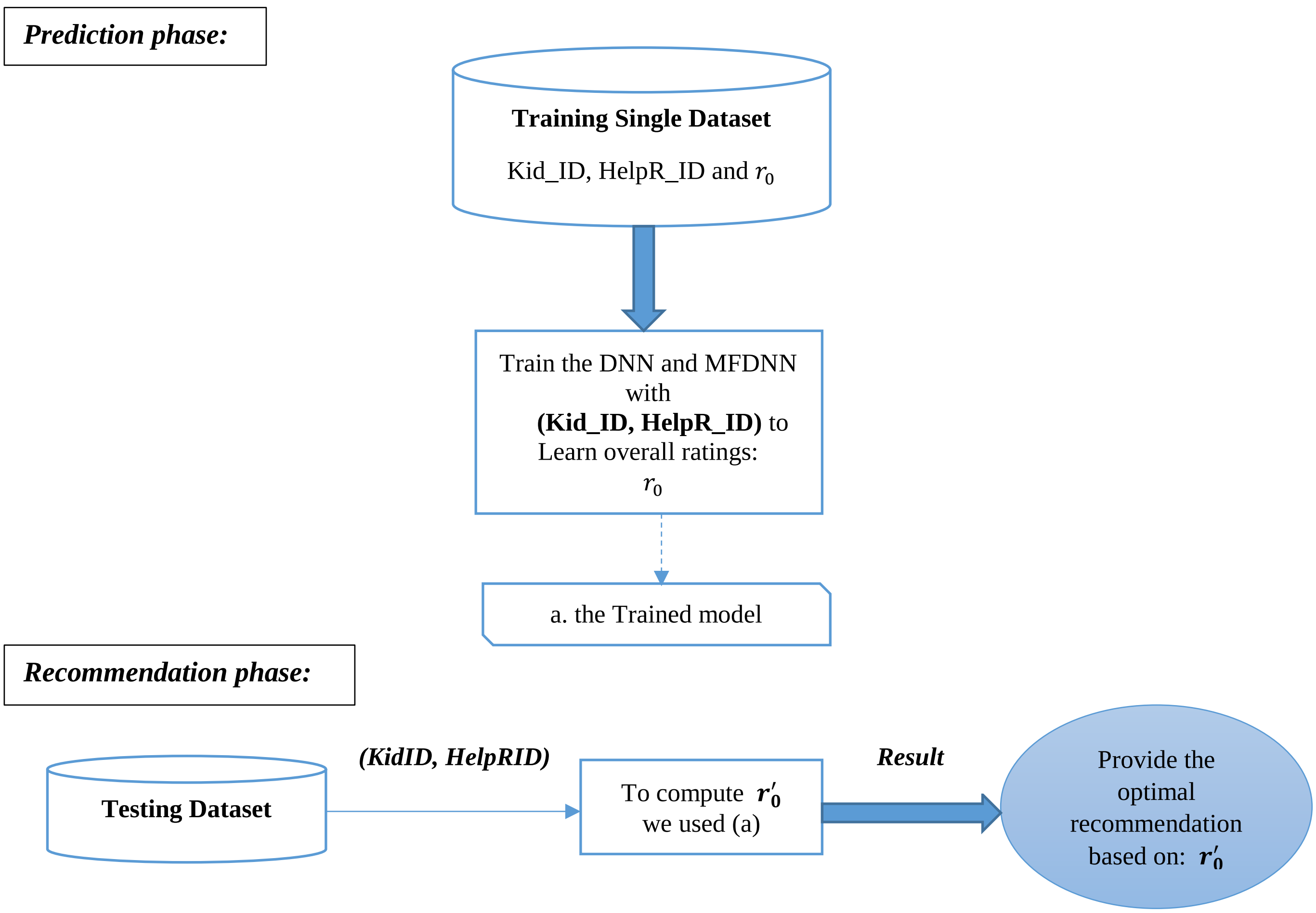


Figure 2.5: The framework of the Prediction and the Recommendation Phase of single-criteria models.

-Prediction phase:

We concentrate on pure collaborative filtering technique in all our models for this we use only the kid ID or the help recommendation ID as a feature [32]. Still, with such a generic feature representation, we can solve the cold start problem in our models with easy modification ~~which~~ content features to represent kids and help recommendations.

Therefore, we use the embedding layer above the input layer for converter the IDs into a dense valued and low dimensional vector, which initialized with random values that are adjusted to minimize the loss function during the training.

*The single DNN architecture shown the Figure (2.6.a), where the input layer has the input vector $\boldsymbol{i}$:

$$i = Concatenate(\, k_{emb}\,, h_{emb}) = \begin{bmatrix} k_{emb} \\ h_{emb} \end{bmatrix} \qquad (2-2)$$

where : k_{emb} and h_{emb} are kid and help recommendation embedding vectors.

Followed by a number of hidden layers, then we choose the most efficient and popular activation function, which is the Rectified Linear Units (**ReLU**) [33], described as follows:

$$ReLU(z) = \max(z, 0) \qquad (2-3)$$

Where the output of each hidden layer serves as the input of the next one; the output of a hidden layer l is formulated in the relationship as:

$$h_l = ReLU(W_l h_{l-1} + b_l) \qquad (2-4)$$

where: W_l and b_l are the weight matrix and bias vector for the layer l and $h_1 = i$.

In the output layer, we predict the kid overall ratings using equation (2-5), (2-6):

$$y_{kh} = ReLU(W_L h_{L-1} + b_L) \qquad (2-5)$$

$$r_0 = y_{kh} \qquad (2-6)$$

where L is the number of layers.

* The Figure (2.6.b) showing The single MFDNN architecture, In this model, we will combine DNN that kids a nonlinear kernel to learn the interaction function from data, and MF that applies a linear kernel to model the latent feature interactions.

And to ensue more flexibility in the combination of DNN and MF, we use different embeddings layer.

-In the input layer of MF, the input vector $\boldsymbol{i}$ is given by:

$$i = (k_{emb} \odot h_{emb}) \qquad (2-7)$$

where k_{emb} and h_{emb} are kid and help recommendation embedding vectors and $\odot$ is the element-wise product of vectors.

And the equation (2-8) formulate the output layer:

$$y_{kh} = a_{out}(w^T(k_{emb} \odot h_{emb})) \qquad (2-8)$$

where a_{out} and w denote the activation function and weights of the output layer.

-And concerning the DNN, it is the same as in the first model where the output layer is defined by equation (2-5).

- Use the concatenating of the last hidden layer to combine them. o^D denotes the output layer of the DNN as in:

$$o^D = ReLU\left(W_L\left(ReLU\left(W_{L-1}\left(\dots ReLU\left(W_2\begin{bmatrix}k^D_{emb}\\ h^D_{emb}\end{bmatrix} + b_2\right)\dots\right) + b_{L-1}\right)\right) + b_L\right) \quad (2-9)$$

where k^D_{emb} and h^D_{emb} are kid and help recommendation embedding vectors of DNN respectively.

And o^M denotes the output layer of the MF as in:

$$o^M = (k^F_{emb} \odot h^F_{emb}) \qquad (2-10)$$

where k^F_{emb} and h^F_{emb} are kid and help recommendation embedding vectors of MF respectively.

Finally, in the output layer of the model we predict the kid overall ratings by using equation (2-11), (2-12):

$$y_{kh} = ReLU\left(W\begin{bmatrix}o^D\\ o^M\end{bmatrix} + b\right) \qquad (2-11)$$

$$r_0 = y_{kh} \qquad (2-12)$$

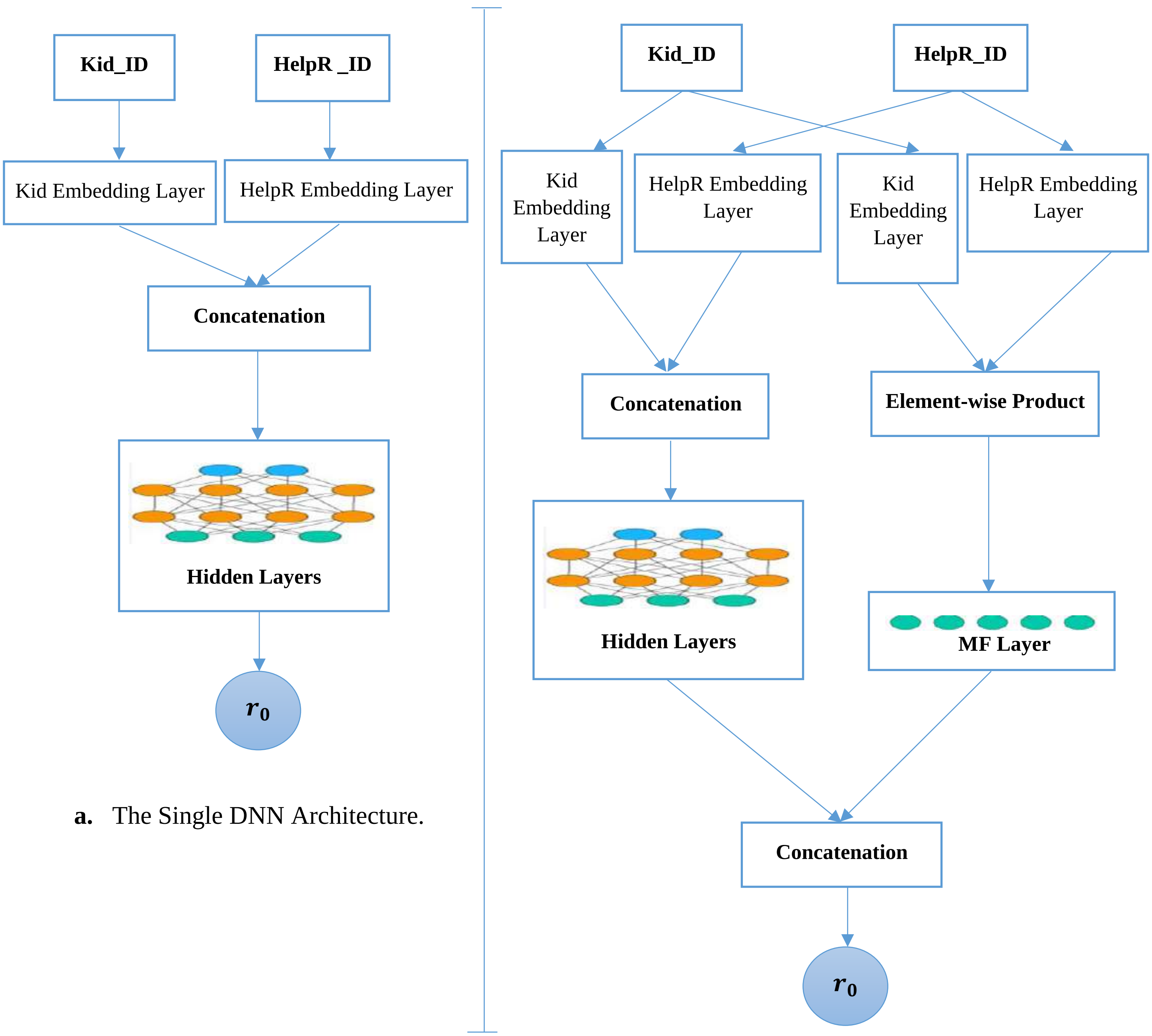
And we adopted in all proposed models on the most famous loss function **MAE** and used also **Adam** optimizer [34].

-Recommendation phase:

After ~~the train~~ each of models, now we can use the two models to predict the kid overall rating on the help recommendations that he has not rated yet.

Step (1): Compute overall ratings: First, we get the kid ID and help recommendation ID pairs and feed them as the inputs to the single DNN and the single MFDNN, and then we predict the overall ratings r_0' .

Step (2): Provide recommendations: Finally, we recommend the optimal items to the kid basing on the overall ratingr_0' .



a. The Single DNN Architecture.

b. The Single MFDNN Architecture.

Figure 2.6: Architecture of the Single-Criteria Models.

3.2.2. Multi-Criteria Recommendation Systems:

The goal of Multi-criteria recommendation systems in our case is to find the most beneficial help recommendations for each kid, as in the case of single-ratings recommender systems. Therefore, the RS must be able to predict the overall rating of each help recommendation for each kid, so ultimately the kids can be compared based on their overall ratings, and thus recommend the best help recommendations to the kids.

The difference between single-rating and multi-criteria rating recommendation systems is that the latter has detailed kid needs and preferences to several criteria that express the kid's needs for the help recommendation in detail and more information about kids and the help recommendations to be used in the recommendation process.

More formally, the general form of the utility function formulation of the multi-criteria recommendation system can be represented either with or without overall ratings as follows [19]:

$$R: (Kids \times Helps) \rightarrow r_0 \times r_1 \times \ldots \times r_k \qquad (2-13)$$

$$or \qquad R: (Kids \times Helps) \rightarrow r_1 \times \ldots \times r_k \qquad (2-14)$$

Where $\boldsymbol{r_0}$ is the overall rating values, $\boldsymbol{k}$ is the number of multi-criteria and $\boldsymbol{r_i}$ represents the possible rating values for each individual criterion $\boldsymbol{i}$ $(\boldsymbol{i} = \mathbf{1}, \ldots, \boldsymbol{k})$.

Now let's look at the same scenario as above but from multi-criteria recommendation systems. Let us assume that we have the same five kids $(k_1, \ldots, k_5)$ and the four help recommendations $(hr_1, \ldots, hr_4)$. Also, the rating $R(k_1, hr_4)$ is unknown and needs to be predicted, and as indicated in Figure (2.7), all other overall ratings of different kids to different help recommendations are known and are exactly the same as before in Figure (2.4).

Besides, we assume that the system is also calculated ~~for~~ each kid their interactions with the game to provide the help recommendation on four specific criteria, which are: number of correct actions, number of actions by kid, number of drag not completed, number of wrong actions, and activity time. Finally, the overall rating that is in this stage is a simple average of the four individual criteria ratings.

Following the idea of the collaborative filtering approach, in order to predict $R(k_1, hr_4)$ the recommender system should find the kids that are closest to kid k_1 and that have the help recommendation hr_4, look at Figure (2.7).

However, all the additional information that is available in the form of multi-criteria ratings shows that kids k_2 and k_3 are quite different in their interactions with the game from kid k_1 even though their overall ratings for each help recommendation completely identical.

In particular, the kid k_1 has a less number of actions and correct action and drag not ~~complete thane~~ the kid k_2 and k_3, and on the contrary, k_1 has a high number of wrong actions and high activity time ~~thane~~ the k_2 and k_3. Therefore, in recommender systems that are based on single-criteria ratings, this information would be hidden in the overall rating, which this aggregation can lead to inaccurate insights about the true similarity between kid interactions (as in this example).

The kids $k_4$and k_5 seem to be much better resemble k_1 in this example not only in their overall ratings are similar, but also in their total interactions for different help recommendation aspects were very similar as well. Since both $k_4$and k_5 rated help recommendation hr_4 as 5, so the value of target rating $R(k_1, hr_4)$ would be predicted as 5. This result is very different from the one obtained in a single-criteria rating system.

	Help Recommendation ***HR₁***	Help Recommendation ***HR₂***	Help Recommendation ***HR₃***	Help Recommendation ***HR₄***
Kid ***K₁***	$4_{3,3,3,5,5}$	$2_{1,1,2,2,4}$	$5_{5,5,5,5,5}$	?
Kid ***K₂***	$4_{4,4,4,4,4}$	$2_{1,4,2,2,1}$	$5_{5,5,5,5,5}$	4
Kid ***K₃***	$4_{4,4,4,4,4}$	$2_{1,4,2,2,1}$	$5_{5,5,5,5,5}$	4
Kid ***K₄***	$3_{2,2,3,5,5}$	$3_{2,2,3,5,5}$	$4_{4,4,4,4,4}$	5
Kid ***K₅***	$3_{2,2,3,5,5}$	$3_{2,2,3,5,5}$	$4_{4,4,4,4,4}$	5

Target Kid

Ratings to be predicted

Kids most similar to K_1

Ratings to be used in prediction

Figure 2.7: Personal Help Recommendation using a Multi-Criteria setting.

We based on the aggregation function-based [31] for building a multi-criteria recommendation system in our model to personalized the educational serious game, as shown in the Figure (2.8) it requires ~~on~~ three important steps as the following:

1- Predicting unknown k multi-criteria ratings using any recommendation technique.

2- Learn the aggregation function f using statistical or machine learning techniques.

3- Predict unknown overall ratings using f and the predicted multi-criteria ratings.

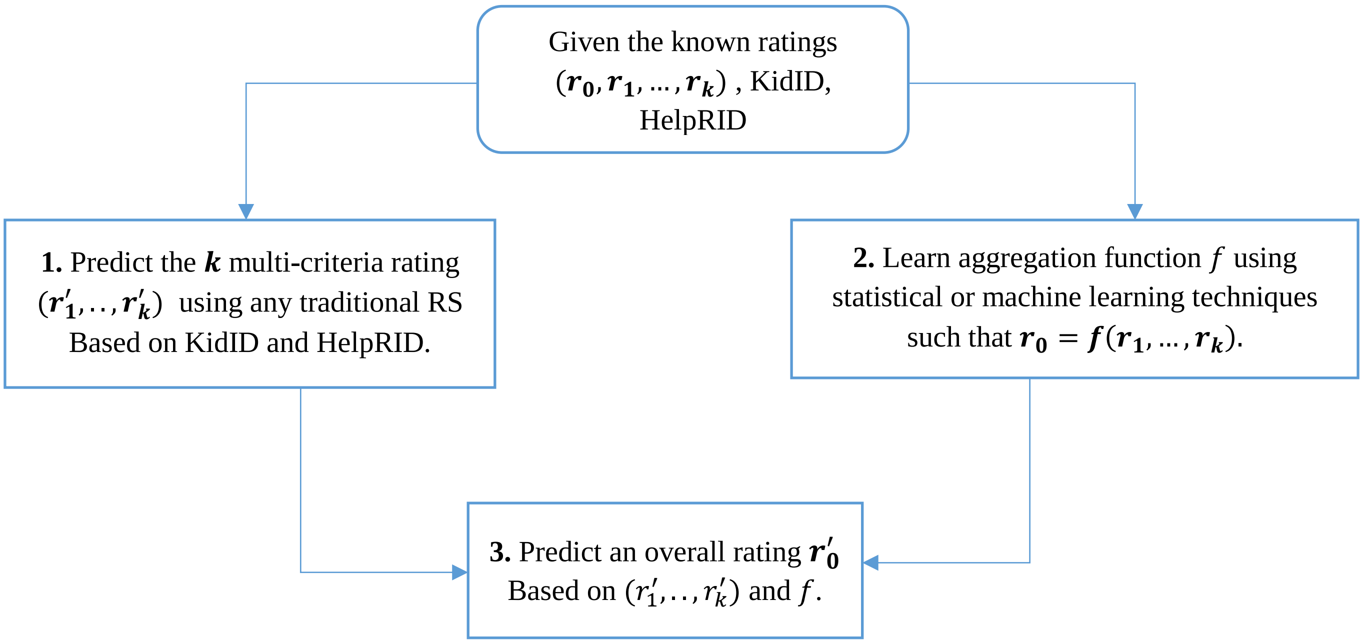


Figure 2.8: Operation principal of the aggregation function-based approach.

In the first proposed model of this case, we are going to predict the multi-criteria ratings by using the DNN technique in the first step, and in the second step using two different ~~technique~~ DNN and linear regression for learning the aggregation function. And for the second proposed model, we use a fused model of DNN and MF to predict the criteria ratings as the first step, while in the second step we use the same techniques for learning the aggregation function as in the first model. As illustrated in Figure (2.9) the prediction and recommendation phase of the two models.

-Prediction phase:

1-Predict Criteria Ratings:

As shown in Figure (2.10) and (2.11) architecture of the two criteria rating models, to predict the multi-criteria rating we use the same architecture formulas of the two single models ~~has~~ illustrated above, where the one difference between the criteria rating models and the singles models is in the output layer; in the single models we have one output which the overall rating while in the criteria rating we have k output.

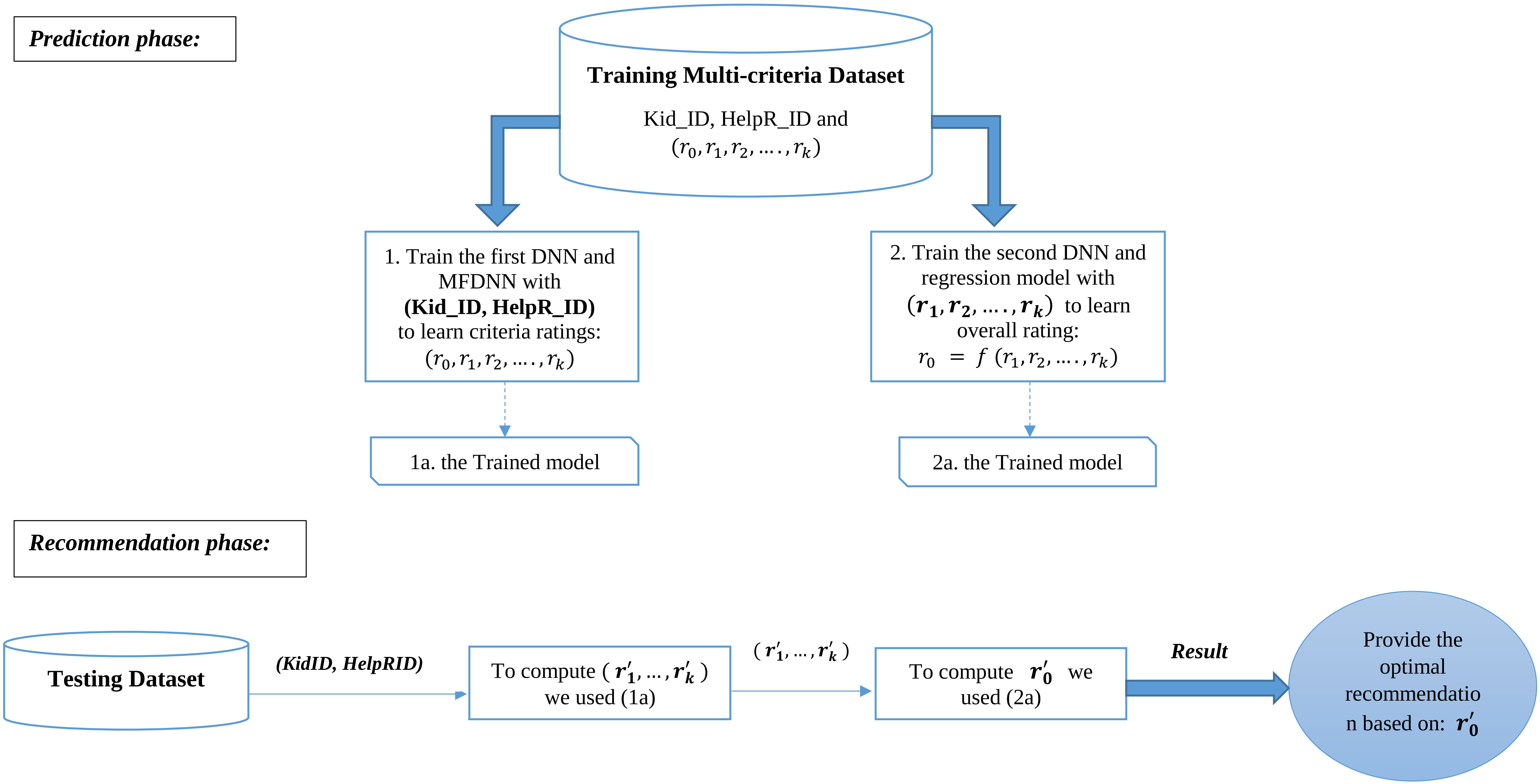


Figure 2.9: The framework of the Prediction and the Recommendation Phase to multi-criteria models.

The output layer of the criteria rating with DNN using (2-5) and the following equation (2-15):

$$[r_1, r_2, \dots, r_k]^T = y_{kh} \qquad (2-15)$$

and for the criteria rating with MFDNN using (2-11) and (2-15).

2-Predict Overall Ratings:

In this step, we are going to find the aggregation function with learning the relationship between the overall rating r_0 and the criteria ratings $(r_1, \dots, r_k)$ by using DNN and Linear regression model, as shown in Figure (2.10) and (2.11).

Overall ratings DNN: in the input layer, the input vector is the criteria ratings $(r_1, \dots, r_k)$ for kid k and help recommendation h, we normalize the continuous features $(r_1, \dots, r_k)$. The normalization of a sample r_i is calculated as:

$$z_i = \frac{r_i - m}{s} \qquad (2-16)$$

Where m is the mean of the training samples, and s is the standard deviation of the training samples. So the input vector i becomes as:

$$i = [z_1, z_2, \dots, z_k]^T \qquad (2-17)$$

Then, followed by a number of dense ReLU layers, the output of the hidden layer is given again by equation (2-4).

In the output layer, we predict the overall rating r_0 in equation (2-15), where:

$$r_0 = y_{kh} \qquad (2-18)$$

Linear regression model [31]: we ~~be~~ normalize the criteria rating $(r_1, \dots, r_k)$ as above ~~first for~~ estimate the regression function Lr in equation (2-19):

$$r_0 = Lr(r_1, \dots, r_k) = \beta_0 + \beta_1 r_1 + \dots + \beta_k r_k + \varepsilon \qquad (2-19)$$

Where $\beta_0, \beta_1, \dots, \beta_k$ are the regression coefficients, and ε is the random error.

-Recommendation:

After the ~~train~~ of the models, where each part of each model was trained separately without knowing each other, now we can use the models to predict the kid overall rating on the help recommendations that he has not rated yet.

Step (1): Compute criteria ratings: First, we get the kid ID and help recommendations ID pairs and feed them as inputs to the Criteria Ratings DNN and MFDNN, and then we predict the criteria ratings $(r'_1, r'_2, \dots, r'_k)$.

Step (2): Compute overall ratings: In this step, we normalize the criteria ratings $(r_1', r_2', \dots, r_k')$ computed in step (1), feed them as inputs to the Overall Rating DNN and Linear regression model, and then predict the overall ratings r_0' .

Step (3): Provide recommendations: Finally, we recommend the optimal items to the kid using the overall rating r_0' as in single rating recommender systems.

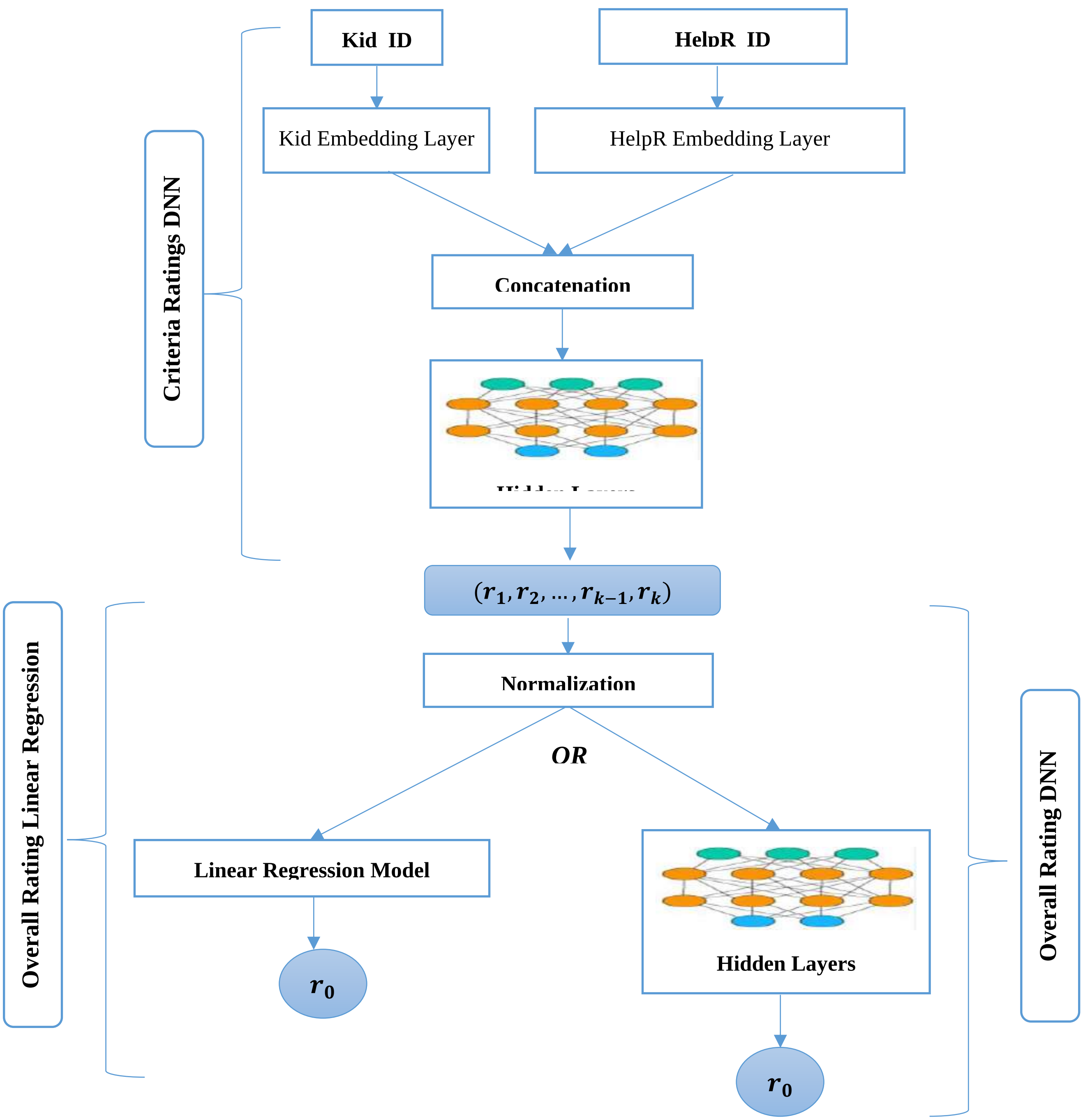


Figure 2.10: Multi-Criteria DNN Recommendation System Architecture.

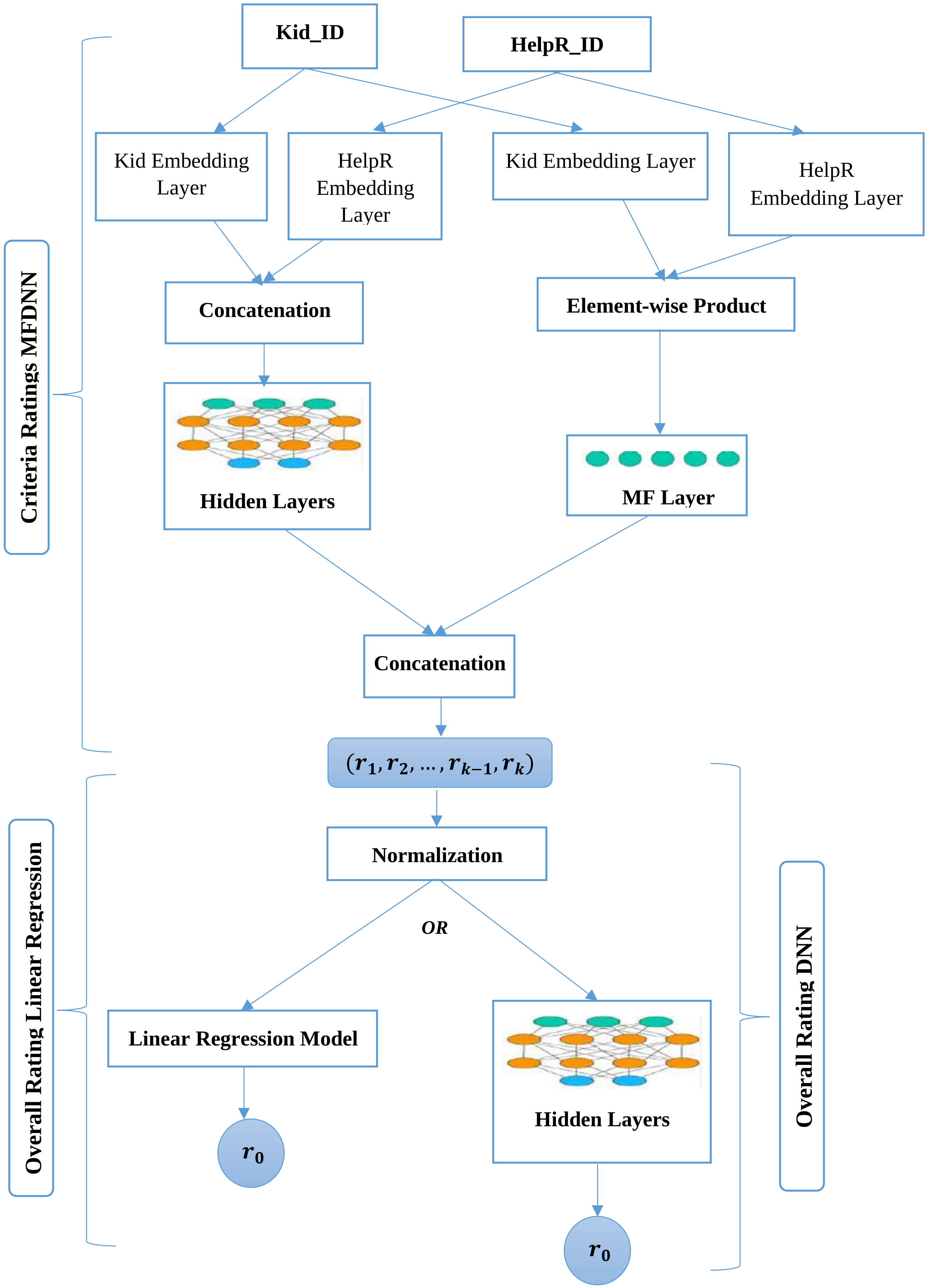


Figure 2.11: Multi-Criteria MFDNN Recommendation System Architecture.

4. Strategy of Comparative Study:

The main contribution of our work is to rely on the power of the recommendation systems techniques in order to personalize the educational serious games for kids based on their interactions. Therefore, we have done a comparative study between the multiple models of single-criteria and multi-criteria recommendation systems in several different stages, where this comparative study will help us to use more performance models to recommend their personalization faster. Through this comparative study allowed us to ask different following questions: -What are the most important methods used by RS?

-What methods are used to generate recommendations within the personalization of ESG?

In the first stage: "what is the single model more ~~performance~~ to make personalization in ESG?", we will compare single-criteria RSs models in the first one used DNN without matrix factorization (MF) and in the second with MF to predict the help recommendations for kids, and present who ~~is~~ more performance.

And in the second stage: "what is the multi-criteria model more ~~performance~~ to make personalization in ESG? ", in the case of multi-criteria RSs we depended on the aggregation function-based approach which ~~contain~~ three steps; in the step of prediction the criteria ratings used DNN in the first model and MFDNN in the other one, wherein the second step of prediction the overall rating used DNN and linear regression model, and in the last step, we based on the prediction of the overall to recommend the most appropriate help recommendation to kids, to compare ~~who is the model more efficacy~~ than the other.

And in the final stage, “How different kinds of split data help to improve the performance of the model?”, we are going to test how cross-validation can impact on the performance of models.

5. Conclusion:

In this chapter, we presented our novel recommendation model for the personalization of the educational serious games and ~~his~~ core elements and the processes of the help recommendation system in our proposed model. And also, this chapter contains the strategy of our comparative study of the most efficient method among the two methods with single-criteria and multi-criteria recommendation systems.

Chapter 03:

Experiments

&

Results Discussions

1. Introduction:

To achieve our goal, we focus in this chapter on the experiments and discuss the obtained results. In the first section, we present the description of the datasets used for doing the experiments and the tests. Also, the second section consists of the summary of the evaluation metrics used for evaluating the effectiveness of the proposed models, and in the third section, we are going to present the method we use to split data. Where in the fourth section we will present all experiments that we proposed in the previous chapter. Finally, we will discuss the obtained results to improve the models.

2. The Experimental Datasets:

We would ~~liked~~ to use a real dataset in educational serious games as we described in the previous chapter in our experiments, but we could not get it due to the current situation and the health measures imposed on us by the Coronavirus pandemic, we were not able to collect the real data that we wanted to collect through real kids playing with different educational serious games. Therefore, we turned to do our experiments by using two other databases that are very well known in multi-criteria recommendation systems from two different domains: a hotel and a movie recommendation domain where users rate hotels and movies respectively by using a multi-criteria rating technique; These databases are datasets provided by the TripAdvisor site and MoviesData.

2.1. TripAdvisor Dataset:

TripAdvisor[2] is the largest and most popular website in the world for evaluating and providing reviews to hotels, restaurants, tourist destinations, and other travel-related services that help the traveler to determine how to travel and to express their view.

This dataset is a multi-criteria rating dataset used for recommendation systems, which contains users' ratings for hotels based on seven criteria ratings (aspects, or attributes) of hotels [36,37,38]. Figure (3.1) shows an example of a multi-criteria rating for a hotel in TripAdvisor.

For extract~~,~~ this dataset we used web crawling procedure to review~~s~~ data for TripAdvisor by Wang ~~et~~ al [39], downloaded from this link[3] .

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[2] https://www.tripadvisor.com/
[3] http://times.cs.uiuc.edu/~wang296/Data/

Where the dataset includes these aspects: *Service* aspect rating, *Business Service* aspect rating, *Cleanliness* aspect rating, *Check-in/Check-out* aspect rating, *Value* aspect rating, *Rooms* aspect rating, *Location* aspect rating, and *Overall rating*.

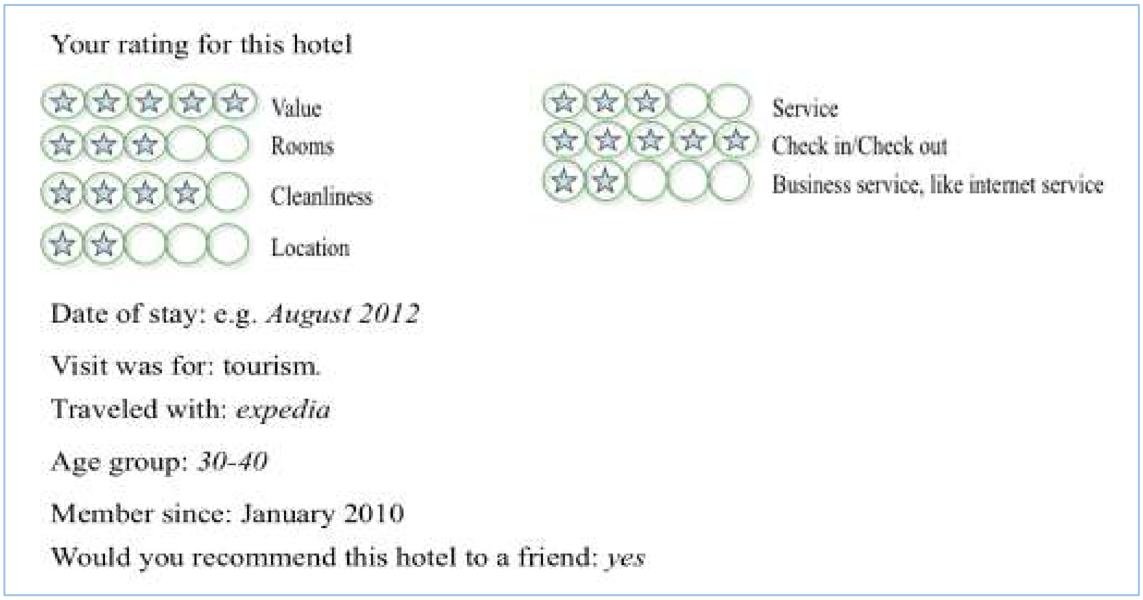

Figure 3.1: Example of multi-criteria rating for a hotel in TripAdvisor.

Ratings range from 0 to 5 stars, and -1 indicates this aspect rating is missing in the original Html file. As shown in the Table (3.1) statistics of the TripAdvisor dataset. Similarly, Table (3.2) presents a simple example of the obtained data. Where, we can calculate the sparsity of dataset as the following [35]:

$$Sparsity = 1 - density \qquad (3-1)$$

$$Density = \frac{Number\ of\ ratings}{Number\ of\ users\ \times Number\ of\ \ Hotels} \qquad (3-2)$$

Field Description	Value
Number of Hotels	2,724
Number of Users	80,120
Number of Ratings	101,530
The Sparsity of Dataset (%)	99.95%

Table 3.1: The statistics of the TripAdvisor dataset.

User ID	Hotel ID	Overall	Service	Business Service	Cleanliness	Check in/ Check out	Value	Rooms	Location
user_1	hotel_875	5	5	5	5	5	5	5	5
user_2	hotel_1892	2	1	1	3	3	4	3	5
user_3	hotel_563	3	4	3	2	3	4	1	4
user_4	hotel_59	4	4	4	4	4	4	4	4
user_5	hotel_214	2	2	2	2	2	2	2	2
user_6	hotel_633	3	2	5	4	4	2	3	1
user_7	hotel_1436	3	1	4	3	2	5	3	5
user_8	hotel_2484	3	-1	5	3	5	4	5	3
user_9	hotel_1887	4	4	4	4	4	4	4	4
user_10	hotel_2153	5	5	5	5	5	5	5	5
user_11	hotel_1979	2	5	-1	3	2	2	1	4
user_12	hotel_1641	3	1	4	3	5	2	2	4

Table 3.2: Simple Dataset for TripAdvisor.

2.2. Movies Dataset:

Movies Data is a multi-criteria database, where contains extensive collections of information on movies. And available on the GitHub[4] website, ~~which movies were ratings~~ by users based on four different criteria (criteria1, criteria2, criteria3, criteria4) and overall rating [35].

Ratings for each criterion range from 1 to 13. Shown in the Table (3.3) statistics of the Movies dataset, and Table (3.4) present a simple example of her data.

Field Description	Value
Number of Movies	976
Number of Users	6,087
Number of Ratings	62,156
The Sparsity of Dataset	98.95%

Table 3.3: The statistics of Movies dataset.

[4] https://github.com/an888ha/multi_criteria_recommender_system/blob/master/data_movies.txt

User ID	Movie ID	Overall	Criteria_1	Criteria_2	Criteria_3	Criteria_4
user_1	movie_26	8	6	6	8	12
user_2	movie_132	10	9	11	10	9
user_3	movie_180	7	6	10	9	8
user_4	movie_59	5	6	6	6	5
user_5	movie_214	10	10	11	10	9
user_6	movie_633	12	11	12	12	12
user_7	movie_1436	11	9	13	11	13
user_8	movie_329	11	12	12	10	12
user_9	movie_1887	9	9	12	9	8
user_10	movie_191	10	12	8	8	10
user_11	movie_1979	12	13	12	11	9
user_12	movie _211	13	13	13	13	13

Table 3.4: Simple Dataset for Movies.

3. Evaluation Metrics:

The evaluation processes are an essential part in implementing, improving, and in evaluating the accuracy and acceptability of the recommendation systems. The formers have been used to measure the prediction and recommendation accuracy of RSs by estimating how well the systems can predict [35,36].

Generally, according to Erdt et al. [40], can be as classified as the techniques for evaluating RSs into three types: Offline experiments, User studies, and Real-life testing.

*Offline experiments: (also called dataset driven evaluation) use two kinds of datasets consisting of user interaction to simulate the interaction between users and system, and to evaluate recommender systems because they are ~~no~~ required with the real users, which are the Natural/Historical datasets or the Synthetic datasets [40], as like Yahoo! Movie, Netflix Price, Movie Lens, and Pinterest. And usually, this evaluation comes to be before the online evaluation.

*User studies: is a technique typically measure user satisfaction through explicit ratings. Where a group of real users use the systems in a particular place for a given period and gave their responses about the efficiency of the systems using the highest ratings and most effective [40].

*Real-life Testing: (also known as online evaluation) measures the users' reactions to the recommendations presented. Where these real users interact with the system directly and naturally, and they use it for an extended period and express their feelings about the systems [40].

Mainly, the metrics used for estimating the prediction accuracy and quality of the proposed methods are:

-**Mean Absolute Error** (**MAE**): is the most popular and commonly used. It was used to estimate the average absolute differences between the predicted and the actual ratings [19].It is computed as follows:

$$MAE = \frac{1}{|S|} \sum_{u,i} | r_{ui} - p_{ui} | \qquad (3-3)$$

Where p_{ui} is the predicted rating for user u on item i , and S is the set of the ratings.

-**Root Mean Square Error** (**RMSE**): is another metric for measuring prediction accuracy that is related to MAE, where there is more emphasis on the larger absolute error and the lower [19].As shown in equation (3-4):

$$RMSE = \sqrt{\frac{1}{|S|} \sum_{u,i} (r_{ui} - p_{ui})^2} \qquad (3-4)$$

-**Precision:** is the percentage of the fraction of recommended items that are actually relevant to the user [19]. With proposing k more appropriate item to the user, as expressed in equation (3-5):

$$precision = \frac{1}{|U|} \sum_{u} \frac{|\{relevant\ and\ recommended\ items\ in\ top\ K\}|}{|\{total\ recommended\ items\ in\ top\ K\}|} \qquad (3-5)$$

Where U is the set of the users.

-**Mean Average Precision (MAP):** is the average precision on all the users [19].

-**Recall:** can be defined as the percentage of the fraction of recovered relevant items [19]. With proposing k more appropriate item to a user as shown in equation (3-6):

$$recall = \frac{1}{|U|} \sum_{u} \frac{|\{relevant\ and\ recommended\ items\ in\ top\ K\}|}{|\{\ relevant\ items\}|} \qquad (3-6)$$

-F-measure (F_β): is combined with two measures precision and recall in equation (3-7) [19].

$$F_\beta = \frac{(1+\beta^2) \times precision \times recall}{\beta^2 \times precision + recall} \qquad (3-7)$$

In the case of $\beta = 1$, equation (3-8) denote F_1:

$$F_1 = \frac{2 \times (precision \times recall)}{precision + recall} \qquad (3-8)$$

And in the case of $\beta = 2$, F_2 denoted in equation (3-9):

$$F_2 = \frac{5 \times (precision \times recall)}{(4 \times \ precision) + recall} \qquad (3-9)$$

-Fraction of Concordant Pairs (FCP): in equation (3-10), it was also used to ensure the correct measurement of the ranking accuracy when a pair of valuations that are considered compatible if the correct and estimated values are in the same direction. The n_c represents the number of concordant pairs, and n_d is the corresponding number of discordant pairs calculated. As given in equation (3-11) and (3-12) [19].

$$FCP = \frac{n_c}{n_c + n_d} \qquad (3-10)$$

$$n_c = \sum_{u \in U} |(i,j)| \{ \hat{r}_{ui} > \hat{r}_{uj} \ and \ r_{ui} > r_{uj} \} \qquad (3-11)$$

$$n_d = \sum_{u \in U} |(i,j)| \{ \hat{r}_{ui} > \hat{r}_{uj} \ and \ r_{ui} \leq r_{uj} \} \qquad (3-12)$$

4. Splitting Dataset into Training, Validation, and Testing set:

Testing process aims to evaluate and to measure the quality of the recommendation systems and their ability to predict users' ratings of various items. Cross-validation is the most popular testing technique within the field of data mining, machine learning, recommendation systems ... etc, to evaluate predictive models and to help the developers in testing the built models [41].

The main principle of this technique is partitioning the original dataset into; a training set to train the model, and a test set to evaluate it.

In *k*-fold cross-validation, the original data is divided into *k* equal size sub-data, where only one sub-data is used in the testing of the model as validation data, and the remaining *k-1* sub-data is used in the training of the model as training data.

The process of cross-validation is then repeated k times, as each k subs-data is only used once as the validation data. The k results from the folds can then be averaged to produce a single estimation, as shown in Figure (3.2).

In our tests, we used $k = 10$ where we repeated the process 10 times and split the data randomly into 10% testing set and 90% training set.

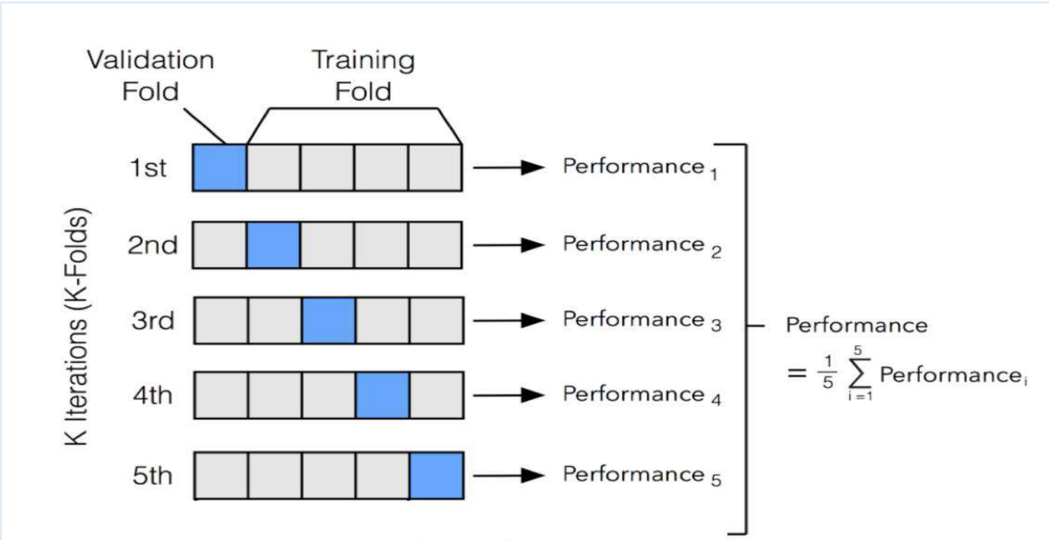

Figure 3.2: Process of K-fold Cross-Validation where k=5.

5. Experiments and Results:

In this section, we conduct experiments with the aim of answering the comparative study questions in the previous chapter.

For implementing our deep learning models, we used Python as a programming language and based on Keras and TensorFlow libraries as backend in addition to some other Python libraries and we trained on Google Colaboratoey.

5.1. The First Experiment:

"Performance Comparison of Single Models"

The first experiment was conducted to compare the two proposed single-criteria recommendation models by using TripAdvisor and Movies datasets, it was carried out ten times by initialized the k-fold cross-validation using k=10. We randomly initialized both of DNNs parameters by using a normal distribution with a mean of 0.0 and a standard deviation of 0.01. We experimented with a number of optimizers (Adam, Adamax, RMSprop) with a 0.001 learning rate.

For TripAdvisor dataset, in SingelDNN, we used batch size of 256 and set epochs to 2. We set each of user and hotel embedding vector size to 64, and we selected the [128,64,32,16,8] as hidden layers. And in SingelMFDNN, we tried to find the optimal MF user and hotel embedding vector size and we set it to 16, and the same DNN of the SingelDNN.

And for Movies dataset, we used batch size of 128 and set epochs to 5. We set each of user and movie embedding vector size to 128, and we selected the [256, 128, 64, 32, 16, 8] hidden layers ~~this all~~ for the DNN to SingelDNN and SingelMFDNN, and about the MF embedding vector size, we set it to 32. And in the output layer of all models, there is one neuron, which is the overall rating.

Experimental results of different optimizers shown in the following table (3.5). After the results of our experiment using different optimizers, we noticed that Adam provides us with elaborate results based on the value of evaluation metrics RMSE which is better whenever it low.

Dataset	Optimizers	SingelDNN	SingelMFDNN
TripAdvisor	Adam	0.6100 ± 0.0047	0.6099 ± 0.0045
	Adamax	0.6190 ± 0.0058	0.6142 ± 0.0099
	RMSprop	0.6164 ± 0.0050	0.6153 ± 0.0053
MoviesData	Adam	3.0921 ± 0.0623	3.0244 ± 0.0617
	Adamax	3.1574 ± 0.0472	3.0506 ± 0.0502
	RMSprop	3.4719 ± 0.1529	3.2574 ± 0.8024

Table 3.5: Optimizers Results for Single Models.

The following table (3.6) presents the results obtained from the experiment of comparison performance.

Dataset	Evalu M	SingelDNN	SingelMFDNN
TripAdvisor	RMSE	0.6100 ± 0.0047	0.6099 ± 0.0045
	MAE	0.3594 ± 0.0068	0.3584 ± 0.0062
	Precision@10	0.8200 ± 0.0047	0.8210 ± 0.0042
	Recall@10	0.8749 ± 0.0622	0.8794 ± 0.0722
MoviesData	RMSE	3.0921 ± 0.0623	3.0244 ± 0.0617
	MAE	2.2193 ± 0.0320	2.1973 ± 0.0406
	Precision@10	0.9280 ± 0.2255	0.9290 ± 0.0068
	Recall@10	0.9081 ± 0.0067	0.9091 ± 0.0076

Table 3.6: Evaluation Results for Single Models.

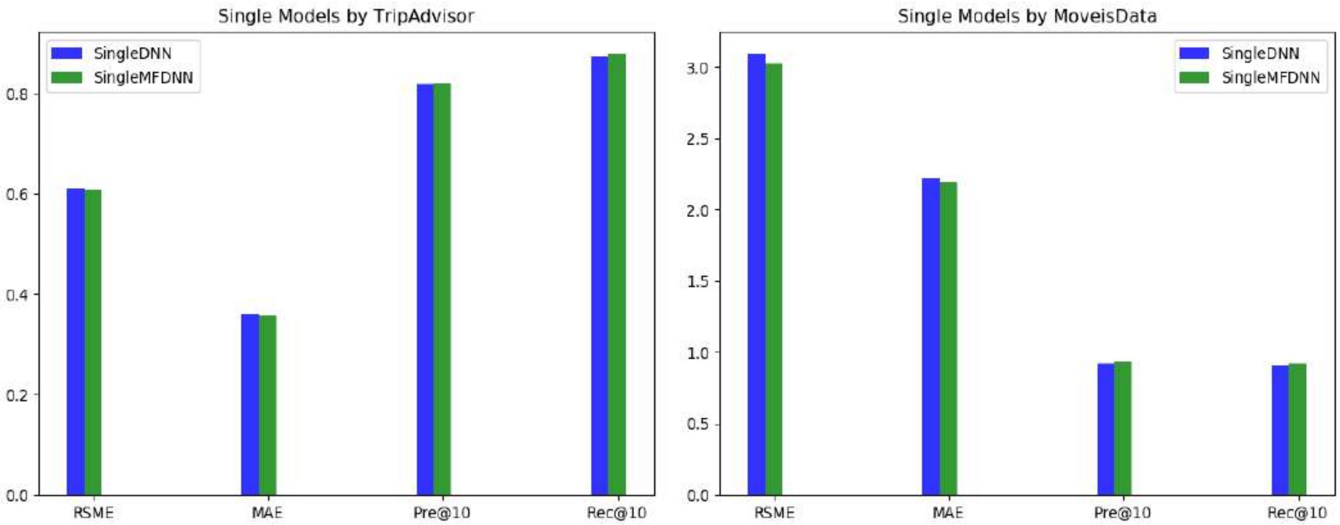

Figure 3.3: Comparative results of Single Models.

Through the results of the experiment, we note that the results of the single-criterion recommendation model with the fusing of DNN and matrix factorization are better than the results obtained in the single-criterion recommendation only with DNN; so the SingelMFDNN is outperformed than the other . ~~Where RMSE and MAE the lower the better,~~ while ~~Precision@10 and Recall@10 the higher the better.~~

5.2. The Second Experiment:

“Performance Comparison of Multi-Criteria Models.”

In this section, we compare ~~among~~ the proposed multi-criteria models. This experiment uses the same general parameters like in the previous experiment. We conducted several experiments to find the optimal parameters as follow.

a-Prediction Criteria ratings:

with DNN: For TripAdvisor dataset, we used batch size of 512 and set epochs to 2. We set each of user and item embedding vector size to 128, and we selected the [256,128, 64, 32,16, 8] hidden layers. For Movies dataset, we used batch size of 128 and set epochs to 5. We set each of user and item embedding vector size to 64, and we selected the [128, 64, 32, 16, 8] hidden layers.

with MFDNN: For MF, we tried to find the optimal embedding vector size for TripAdvisor dataset, we set user and item embedding vector size to 16, and for Movies dataset, we set them to 32.~~And~~ concerning the DNN, it is the same as above.

The output layer of those models, in TripAdvisor dataset there are 7 neurons which are equal to the number of the criteria, and 4 neurons for Movies dataset.

b- Prediction Overall ratings:

with DNN: for TripAdvisor dataset, we set the epochs to 50, and we selected the [128, 64, 32,16, 8] hidden layers, And for Movies dataset, we set the epochs to 25 and we used [64,32,16,8] hidden layers while for both we set the batch size to 512. And finally, the output layer of both datasets there is 1 neuron which is the overall rating.

And also table (3.7) ~~emphasize~~ that Adam optimizer's results are more ameliorated in Multi-Criteria Models.

		Criteria Rating with MFDNN		Criteria Rating with DNN	
Dataset	Optimizers	Overall rating with DNN	Overall rating with L reg	Overall rating with DNN	Overall rating with L reg
TripAdvisor	Adam	0.6051 ±0.0046	0.6186 ±0.0065	0.6158 ±0.1641	0.6313 ±0.1373
	Adamax	0.6433 ±0.0172	0.6807 ±0.0100	0.7585± 0.0674	0.7763 ±0.1659
	RMSprop	0.6616 ±0.0375	0.6858 ±0.0457	0.7596 ±0.1706	0.7565 ±0.1565
MoviesData	Adam	3.0055 ±0.0529	3.0240 ±0.0385	3.0126 ±0.6171	3.0207 ±0.3598
	Adamax	4.5080 ±2.8501	3.6629 ±1.6851	3.1775 ±2.0240	3.1243 ±0.0726
	RMSprop	4.4094 ±2.4863	3.1184 ±0.1887	3.2556 ±0.2716	3.4185 ±0.6547

Table 3.7: Optimizers Results for Multi-Criteria Models.

The results illustrated in the table (3.8) below demonstrate the comparison ~~among~~ the multi-criteria models using RMSE, MAE, Precision@10, Recall@10 evaluation metrics. We can see that criteria rating with MFDNN and overall rating with DNN model achieves the best performance on both datasets, significantly outperforming each model on all the evaluation metrics.

		Criteria Rating with MFDNN		Criteria Rating with DNN	
Dataset	Evalu M	Overall rating with DNN	Overall rating with reg	Overall rating with DNN	Overall rating with L reg
TripAdvisor	RMSE	0.6051 ± 0.0046	0.6186 ± 0.0065	0.6158 ± 0.1641	0.6313 ± 0.1373
	MAE	0.3561 ± 0.0140	0.3612 ± 0.0107	0.3734 ± 0.1844	0.3801 ± 0.1572
	Precision@10	0.8300 ± 0.0042	0.8299 ± 0.0042	0.8289 ± 0.2519	0.8217 ± 0.2440
	Recall@10	0.8801 ± 0.0721	0.8795 ± 0.0722	0.8775 ± 0.2756	0.8742 ± 0.2916
MoviesData	RMSE	3.0055 ± 0.0529	3.0240 ± 0.0385	3.0126 ± 0.6171	3.0207 ± 0.3598
	MAE	2.0943 ± 0.0565	2.1006 ± 0.0456	2.1305 ± 0.5412	2.1322 ± 0.5138
	Precision@10	0.9381 ± 0.0058	0.9299 ± 0.0058	0.9290 ± 0.0099	0.9205 ± 0.0083
	Recall@10	0.9098 ± 0.0070	0.9097 ± 0.0076	0.9095 ± 0.0080	0.9094 ± 0.0083

Table 3.8: Evaluation Results for Multi-Criteria Models.

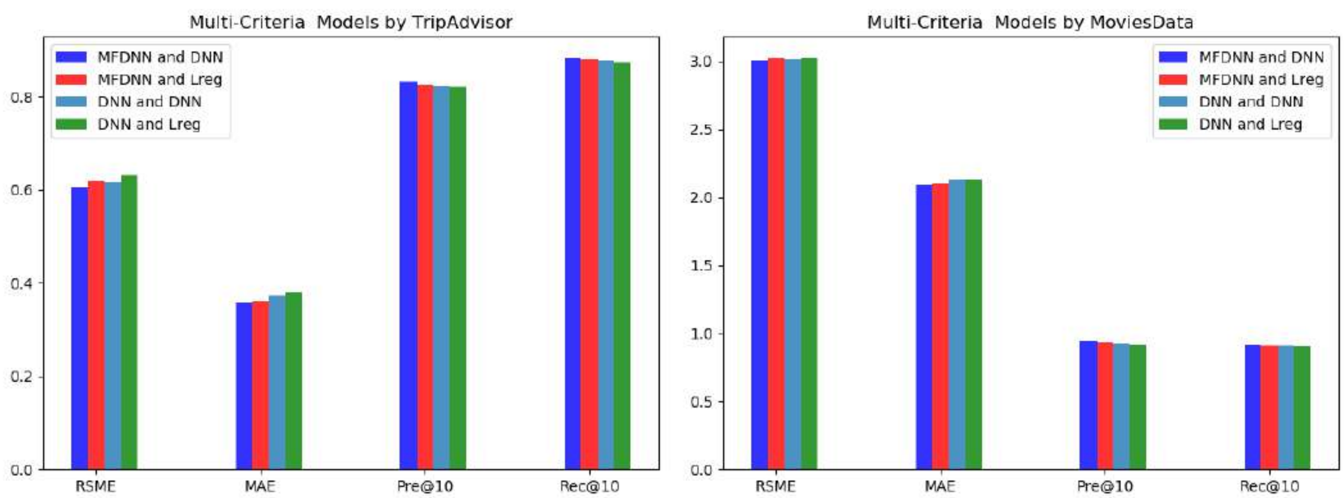

Figure 3.4: Comparative results for Multi-Criteria Models.

At the end of each experiment, we found that there is only one model, which is better. In the first SingelMFDNN is better and criteria rating with MFDNN and overall rating with DNN model in the second. Comparing those better models, multi-criteria recommendation is the best.

5.3. The Third Experiment:

"How different kinds of split data help to improve the performance of the model?"

In the last experiment, we based on the different value of k-folds cross validation where we used k=3, k=5 and k=10 to see the effect of the different division of dataset in the performance of the model. when k=3 it is divided into 75% for training set and 35% for testing set, k=5 we have 80%training set and 20%for testing set, and in case of k=10 90% training and 10% testing. Added to that we compared all single and multi-criteria models as proposed previously, and also the traditional single rating recommendation system such as SVD [42] that represents the matrix factorization, SlopeOne [43] that represents the slopeone-based RS, K Nearest Neighbors (KNN) with Baseline [44],using RMSE, MAE, Precision@10, Recall@10,F1,F2 evaluation metrics. ~~Where RMSE and MAE the lower the better while Precision@10,Recall@10,F1 and F2 the higher the better.~~

		TripAdvisor Dataset			Movies Dataset		
Evaluation M	**Models**	**k=3**	**k=5**	**k=10**	**k=3**	**k=5**	**k=10**
RMSE	MC:DNN and DNN	0.6372 ± 0.0052	0.6140 ± 0.0052	0.6158 ± 0.1641	3.0389 ± 0.0144	3.0149±0.5241	3.0126 ± 0.4171
	MC:DNN and Lreg	0.7878 ±0.0559	0.6908 ± 0.0721	0.6313 ± 0.1373	3.0366 ± 0.0050	3.0519 ± 2.8756	3.0207 ± 0.3598
	MC:MFDNN and DNN	0.6126 ± 0.0038	0.6139 ± 0.0024	0.6051 ± 0.0046	3.0188 ± 0.0119	3.0043 ± 0.0288	3.0055 ± 0.0529
	MC: MFDNN and Lreg	0.6429 ± 0.0110	0.6147 ± 0.0122	06186± 0.0065	3.0343 ± 0.0101	3.0308 ±0.0357	3.0240± 0.0385
	SingelDNN	0.6101 ± 0.0027	0.6097 ± 0.0030	0.6100±0.0047	3.0847±0.0333	3.0773±0.0318	3.0921±0.0623
	SingelMFDNN	0.6089 ± 0.0028	0.6099 ± 0.0034	0.6099± 0.0045	3.0320±0.0029	3.0202±0.0228	3.0244±0.0617
	SVD	0.6188± 0.0021	0.6181 ± 0.0031	0.6189± 0.0052	3.9679±0.0085	3.9600±0.0227	3.2550±0.0381
	SlopeOne	0.6197±0.0026	0.6197 ± 0.0033	0.6970±0.0096	3.5232±0.0260	3.5225±0.0346	3.5214±0.0413
	KNN Baseline	0.6190± 0.0034	0.6170 ± 0.0045	0.6593±0.0073	3.9685±0.0067	3.9592±0.0236	3.5938±0.0491
MAE	MC:DNN and DNN	0.4489 ± 0.0085	0.3761 ± 0.0157	0.3734±0.1844	2.2072±0.0049	2.1291 ± 0.6947	2.1305 ± 0.5412
	MC:DNN and Lreg	0.5545 ±0.0660	0.5255 ± 0.1042	0.3801±0.1572	2.2090±0.0049	2.1525 ± 2.9423	2.1322 ± 0.5138
	MC:MFDNN and DNN	0.3665 ± 0.0031	0.3729 ± 0.0124	0.3561±0.0140	2.2002 ± 0.0130	2.1030 ± 0.0280	2.0943 ± 0.0565
	MC: MFDNN and Lreg	0.4582 ± 0.0206	0.4756 ± 0.0218	0.3612±0.0107	2.2063 ± 0.0058	2.2024 ± 0.0230	2.1006 ± 0.0456
	SingelDNN	0.3610 ± 0.0020	0.3589 ± 0.0044	0.3594±0.0068	2.2098±0.0210	2.2005±0.0190	2.2193±0.0320
	SingelMFDNN	0.3600 ± 0.0055	0.3580 ± 0.0059	0.3584±0.0062	2.2092±0.0101	2.1882±0.0286	2.1973±0.0406
	SVD	0.4068 ± 0.0026	0.4042 ± 0.0037	0.4070±0.0026	2.2556±0.0143	2.2501±0.0239	2.2454±0.0393
	SlopeOne	0.3620±0.0029	0.3602 ± 0.0041	0.3602±0.0029	2.8395±0.0190	2.8381±0.0308	2.3872±0.0469
	KNN Baseline	0.4166± 0.0045	0.4002 ± 0.0010	0.3485±0.0039	2.2528±0.0138	2.2442±0.0251	2.2385±0.0399
Precision@10	MC:DNN and DNN	0.8199± 0.0028	0.8200 ± 0.0032	0.8289±0.2519	0.9328 ±0.0032	0.9283 ± 0.0045	0.9290 ± 0.0099
	MC:DNN and Lreg	0.5965 ± 0.1125	0.7012 ± 0.1705	0.8217±0.2440	0.9301 ±0.0016	0.9283 ± 0.0045	0.9205 ± 0.0083
	MC:MFDNN and DNN	0.8199 ± 0.0028	0.8200 ± 0.0033	0.8300±0.0042	0.9389± 0.0005	0.9284 ± 0.0037	0.9381 ± 0.0058
	MC: MFDNN and Lreg	0.8199 ± 0.0029	0.8200 ± 0.0050	0.8299±0.0042	0.9360± 0.0005	0.9283± 0.0038	0.9299 ± 0.0058
	SingelDNN	0.8120 ± 0.0030	0.8200 ± 0.0030	0.8200±0.0047	0.9294±0.0003	0.9282±0.0040	0.9280±0.2255
	SingelMFDNN	0.8199 ± 0.0028	0.8201 ± 0.0032	0.8210±0.0042	0.9301±0.0011	0.9281±0.0020	0.9290±0.0068
	SVD	0.8020 ± 0.0032	0.8101 ± 0.0010	0.8199±0.0032	0.9248±0.0004	0.9145±0.0038	0.9246±0.0077
	SlopeOne	0.8002± 0.0030	0.8121 ± 0.0030	0.8190±0.0028	0.9151±0.0011	0.9150±0.0030	0.9151±0.0036

	KNN Baseline	0.8000 ± 0.0045	0.7002 ± 0.0010	0.8145±0.0017	0.9247±0.0003	0.9245±0.0037	0.9145±0.0017
Recall@10	MC:DNN and DNN	0.8752 ± 0.0661	0.8792 ± 0.0721	0.8775±0.2756	0.9080 ± 0.0051	0.9091± 0.0052	0.9095 ± 0.0080
	MC:DNN and Lreg	0.6149 ± 0.1366	0.7332 ± 0.1985	0.8742±0.2916	0.9080 ± 0.0051	0.9092± 0.0052	0.9094 ± 0.0083
	MC:MFDNN and DNN	0.8752 ± 0.0661	0.8793 ± 0.0722	0.8801±0.0721	0.9087 ± 0.0041	0.9097 ± 0.0050	0.9098 ± 0.0070
	MC: MFDNN and Lreg	0.8753 ± 0.0663	0.8793 ± 0.0710	0.8795±0.0722	0.9082 ± 0.0039	0.9093 ± 0.0050	0.9097 ± 0.0076
	SingelDNN	0.8743 ± 0.0620	0.8795 ± 0.0730	0.8749±0.0622	0.9076±0.0035	0.9075±0.0040	0.9081±0.0067
	SingelMFDNN	0.8754 ± 0.0663	0.8794 ± 0.0722	0.8794±0.00722	0.9079±0.0042	0.9090±0.0052	0.9091±0.0076
	SVD	0.8134± 0.0117	0.8649 ± 0.0672	0.8547±0.0763	0.9034±0.0043	0.9032±0.0035	0.9033±0.0059
	SlopeOne	0.7318 ± 0.0813	0.8659 ± 0.0642	0.8574±0.0466	0.9072±0.0042	0.9070±0.0050	0.9072±0.0061
	KNN Baseline	0.8598±0.0102	0.6450 ± 0.0652	0.8032±0.0153	0.9034±0.0040	0.9033±0.0045	0.9032±0.0053
F1	MC:DNN and DNN	0.8456 ± 0.0318	0.8473 ± 0.0346	0. 8472±0.2570	0.9188± 0.0020	0.9186 ± 0.0018	0.9186 ± 0.0044
	MC:DNN and Lreg	0.6053 ± 0.1240	0.7160 ± 0.1817	0.8403±0.2690	0.9188± 0.0020	0.9186 ± 0.0002	0.9185 ± 0.0044
	MC:MFDNN and DNN	0.8455 ± 0.0318	0.8473 ± 0.0347	0.8498±0.0347	0.9189± 0.0050	0.9189 ± 0.0021	0.9288 ± 0.0043
	MC: MFDNN and Lreg	0.8456 ± 0.0319	0.8474 ± 0.0347	0.8473±0.0347	0.9189± 0.0050	0.9188 ± 0.0019	0.9196 ± 0.0045
	SingelDNN	0.8475 ± 0.0105	0.8475 ± 0.0355	0.8424±0.0292	0.9186±0.0021	0.9124±0.0018	0.9182±0.0042
	SingelMFDNN	0.8457 ± 0.0319	0.8474 ± 0.0347	0.8470±0.0347	0.9187±0.0020	0.9185±0.0020	0.9184±0.0046
	SVD	0.7902 ± 0.0100	0.8157 ± 0.0457	0.8357±0.0219	0.9119±0.0022	0.9088±0.0023	0.9179±0.0039
	SlopeOne	0.7476 ± 0.0204	0.8177 ± 0.0457	0.8347±0.0219	0.9111±0.0021	0.9110±0.0022	0.9111±0.0021
	KNN Baseline	0.7900 ±0.0080	0.8215 ± 0.0154	0.8108±0.0110	0.9109±0.0022	0.9088±0.0020	0.9108±0.0010
F2	MC:DNN and DNN	0.8628 ± 0.0517	0.8658 ± 0.0563	0.8715±0.2674	0.9123±0.0016	0.9132 ± 0.0046	0.9124 ± 0.0063
	MC:DNN and Lreg	0.6110 ± 0.1314	0.7260 ± 0.1910	0.86640±0.2818	0.9123 ±0.0016	0.9130 ±0.0036	0.9120 ± 0.0065
	MC:MFDNN and DNN	0.8628 ±0.0516	0.8659 ± 0.0564	0.8759±0.056	0.9127 ± 0.0033	0.9133± 0.0036	0.9234 ± 0.0056
	MC: MFDNN and Lreg	0.8629 ± 0.0518	0.8659 ± 0.0562	0.8659±0.0564	0.9127 ± 0.0033	0.9131±0.0036	0.9132 ± 0.0061
	SingelDNN	0.8605 ± 0.0158	0.8650 ± 0.0569	0.8560±0.0522	0.9120±0.0029	0.9118±0.0031	0.9122±0.0055
	SingelMFDNN	0.8629 ± 0.0518	0.8669 ± 0.0564	0.8660±0.2564	0.9122±0.0034	0.9127±0.0036	0.9128±0.0059
	SVD	0.8102 ± 0.0210	0.8608 ± 0.0620	0.8526±0.0518	0.9107±0.0034	0.9054±0.0034	0.9085±0.0043
	SlopeOne	0.8004 ± 0.0193	0.8599 ± 0.0980	0.8529±0.0518	0.9087±0.0033	0.9086±0.0037	0.9057±0.0037
	KNN Baseline	0.8100±0.0020	0.8612 ± 0.0703	0.8099±0.0127	0.9105±0.0035	0.9054±0.0030	0.9055±0.0027

Table 3.9: Comparison Results of the third experiment.

According to the results, we find that there is a difference in the values of results depending on different values of k. This is because of the different in statistics and sparsity of the datasets, where sparsity of TripAdvisor is 99.95% and for MoviesData is 98.95%. Which are both important in the performance of the model. Moreover, the multi-criteria recommendation system, which uses the fusing of deep learning and matrix factorization for predicting the criteria ratings, and for the prediction of overall using the deep learning.

6. Conclusion:

In the last chapter, we present all the experiment of our comparative study in order to realize and generate the recommendation in our proposed model that personalizes the educational serious games for kids based on their interactions with the game. Starting from the presentation of datasets that we used. They are TripAdvisor and MoviesData them moving to the evaluation of the metrics then also presenting the technique that we used for splitting data. At the ~~and~~ we represent all the results of the experiment which allow us to know that the multi-criteria recommendation models are outperformed than the singles. And in the multi-criteria models the multi-criteria recommendation models which use the fusing of deep learning and matrix factorization for predicting the criteria ratings, and for the prediction of overall using the deep learning is better.

General Conclusion
And
Future work

In this thesis, we presented a reference study for the latest works dealing with recommendation systems and its various applications in the field of education and definition in the field of serious games, then we moved to study deep learning and its most important techniques. We found that deep learning has not yet been used in multi-criteria recommendation systems in the area of educational serious games ~~for personalizing~~ games for preschool kids based on their interaction. All deep learning attempts were limited to using traditional single criteria recommendation systems in different fields of marketing and others. We seek to improve the efficacy of the multi-criteria recommendation systems in the education field. Then, we suggested our recommendation model based on multi-criteria collaborative filtering that combines with deep learning techniques.

Our model gets the kids' interactions and the help recommendation and ~~use~~ them as an input to the first deep neural network to predict the multi-criteria ratings, which are used to predict the overall rating in the second DNN.

Finally, we reviewed the obtained results and all the used materials starting by the datasets which are TripAdvisor and MoviesData, and the evaluation metrics that we used to evaluate the accuracy of the model. The obtained results were promising which are shown in the part of the experiments.

Future work:

With the circumstances that we went through in the Coronavirus pandemic, we did not reach the results that we ~~hoped to.~~ In the other hand we hope to get better performance of our model as a follow-up in the future, we aim to achieve several ideas that can enhance our model:

1- It was our desire to use a real database in our domain, which is a real data of educational serious games. And we also wanted to use the fourth experiment for studying the performance of data sparsity and time for models “Does the sparsity of data affect the error value (RMSE) of the model?” to support our comparative study.

2- Our model is easy, fast, and general for implementation, Therefore, we can try to enhance and to improve the performance by using different recommendation system techniques like Content-Based technique, and with using other deep learning methods more complex and sophisticated such as Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) or other feature representation.

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Annex

Glossary of Games/ Serious Games Terminology:

Terms	Abbreviations	Clarifications
Mastery Learning	**ML**	Mastery learning is a method of instruction where the focus is on the role of feedback in learning. Furthermore, mastery learning refers to a category of instructional methods which establishes a level of performance that all students must. Learn more in: master before moving on to the next unit (Slavin, 1987) http://www.nyu.edu/classes/keefer/waoe/motamediv.htm
Learning Analytics	**LA**	Learning analytics is both an academic field and commercial marketplace which have taken rapid shape over the last decade. As a research and teaching field, Learning Analytics sits at the convergence of **Learning** (e.g. educational research, learning and assessment sciences, educational technology), **Analytics** (e.g. statistics, visualization, computer/data sciences, artificial intelligence). Learn more in: https://www.solaresearch.org/about/what-is-learning-analytics/
Technology-Enhanced Learning	**TEL**	The application of information and communication technologies to teaching and **learning** for the purpose of motivating and engaging the learner. Learn more in: Adaptable Learning Theory Framework for Technology-Enhanced Learning
Game Based Learning	**GBL**	One of the most engaging things in a video game is the learning curve or how players learn little by little to handle characters and environments. Learn more in: games-acronyms-dictionary/

Educational Entertainment	**EE**	A combination of entertainment with education: any type of entertainment aimed at entertaining and being educative. Learn more in: Playing for Better or for Worse?: Health and Social Outcomes with Electronic Gaming
Simulations Games	**SG**	They are edutainment applications that deploy interactive, 3D game technology to provide content that simulates real world scenarios and produces learning outcomes., allow learners to experience situations that are impossible in the real world for reasons of safety, cost, and time Learn more in: Context-Free Educational Games: Open-Source and Flexible
Video games	**VG**	That were designed to achieve certain learning results.[Learn more in: A Systematic Review of Video Games for Second Language Acquisition
Games	**G**	Games designed for a primary goal other than pure entertainment. designed for a primary purpose other than pure entertainment, for example, for education. Learn more in: Enhancing Life Skills of Children and Adolescents With Autism Spectrum Disorder and Intellectual Disabilities Through Technological Supports: A Selective Overview
Educational Games	**EG**	Educational games that are created in the context of game-based learning aiming to support the learners' achievement of specific learning outcomes. Learn more in: Game Mechanics Supporting a Learning and Playful Experience in Educational Escape Games
Digital Games	**DG**	Simulations, virtual environments and mixed reality/media that provide opportunities to educate or train through responsive narrative/story, gameplay or encounters. Learn more in: Using Video Gameplay to Measure Achievement for Students with Disabilities: A New Perspective to Grading and Achievement Reporting

Computer Games	**CG**	Designed for a purpose beyond pure entertainment. They use the motivation levers of game design and game media to enhance the motivation of participants to engage in complex or boring tasks. Learn more in: Foreign Languages Learning: From the E-Book to i TV-Assisted Learning
Game-Based Environment	**GBE**	Where the primary intention is not the entertainment of the player, but the attainment of some other objective which may be related to investigation or players' progress towards an objective of some real-world importance. Learn more in: Gamification
Gamification	**Gamify**	Gamification is the application of game principles to different business areas such as marketing, human resources, knowledge management, sales, project management and training. Learn more in: https://www.interactidesign.org/literature/topics/gamification