How do Students Perceive Artificial Intelligence in YouTube Educational Videos Selection? A Case Study of Al Ain City

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Abstract—This research focused on the students' perceptions of the role of Artificial Intelligence in the educational content recommendation system by using the SEM- Artificial Neural Network approach. Data obtained from structured surveys indicated that Artificial Intelligence plays a significant role in the educational content recommendation process. Most relationships proposed in the conceptual model remained significant, with p values as strong as p> 0.000. Further, the IPMA and ANN also revealed in-depth results. Thus, this research concludes that the video recommendation system is helping young students to search for and find the educational content they want. Besides, this system also provides them with a searching facility with fewer efforts, adding more value to YouTube as one of the most prominent digital platforms today.

Keywords—artificial intelligence, matrix factorization, users' metadata, United Arab Emirates, education

1 Introduction

Social Media platforms, from Facebook to Twitter to Reedit and others, are important in our day-to-day communication, information, and entertainment. These digital platforms play a crucial role in sustaining our daily life activities in the better possible manner. Taking specifically abbot the role of social media in education, learners consider social networks as a great way to advance their personal learning experiences. For this purpose, today, both teachers and students prefer these platforms as an important source of education. According to Dijck and Poell [1], we cannot deny the existence of social media transforming and improving our lives. Although a common perception about social media is its role in communication and entertainment, education is another major function of the relevant networks. Especially after the Covid-19 outbreak, the rapid transition from formal learning to online learning further magnified the importance of these networks. As a result, several institutions across the globe incorporated online learning as part of the crisis management system. They encouraged their students to search for additional sources that could help them in their educational journey [2]. As noted by Salim and Hafedh [3], starting from the primary level to Doctorate level university education, social networks are enriched platforms to utilize new ways to search for e educational content, gather information, and share with others. Recent statistics also show that 96% of students worldwide use social media for education and information purposes, indicating the role of digital technology in facilitating the young generation. It is also notable that social networks provide academic help and information about careers, internships, and even useful suggestions for selecting college and university majors. Moreover, collaborative learning and teamwork, gathering information about educational opportunities, etc., are part of the students' social [4], [5]Similarly, as one of the most influential social networking platforms, YouTube has brought a great revolution in education as a popular video-sharing website [6], [7]. YouTube is closely related to education and learning, which has improved its quality and content during the past few years [8]. As noted by Koto [9], YouTube is now the world's second-largest search engine and second most visited social networking platform. With a daily watch time of over one billion hours. Evidence also indicates that YouTube has the potential to engage the audience once logged in for more the four hours. Especially regarding the quality of content, YouTube has introduced new features and incorporated intelligent systems to enhance the users' video-watching experiences [11]. For instance, YouTube integrated Artificial Intelligence to recommend and deliver content as YouTube algorithms give special consideration to the other channels offering similar content [10]. This video recommendation system is one of the most powerful use cases of Machine Learning that young students encounter while searching for the required content. This AI also monitors one's average time spent per day on YouTube, which further helps the content managers and creators improve or alter their content's quality accordingly [12].

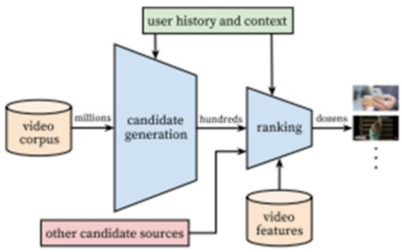

Fig. 1. Video recommendation algorithms [10]

Further Covington and their collegaues [13] highlighted the role of AI algorithms on YouTube. As noted, there are two primary neural networks currently working on YouTube. One of them uses filters to evaluate the best matching options according to the users' previous search. Second, the neural network scores each video based on its relevance and uniqueness in meeting users' needs as also mentioned by Grieves and their colleagues Thus, these neural networks widely facilitate young students to search for the educational content they need and the suitable recommendation and facility to choose and watch the quality content to gratify their academic needs [14].

Therefore, this research also focused on the students' perceptions of the role of Artificial Intelligence in the educational content recommendation system [15], [16]. The researchers focused on YouTube due to its growing importance in the United Arab Emirates, especially after the Covid-19 pandemic. It is also notable that, despite YouTube being widely used in the United Arab Emirates, there is yet no study that has assessed students' perceptions about the availability of the educational content and the role of Artificial Intelligence in its relevance. Thus, the existing gap in the current literature also highlights the need and significance of the current research. Thus, this study is based on four primary sections per the formal research requirements. Further, the researchers will conclude this article with suitable recommendations for further research investigations.

2 Review of literature

2.1 Covid-19 and elearning

During the Covid-19 pandemic, a greater transition from traditional learning to online learning took place [17]. As a result, several pedagogical approaches were designed and adopted as the aim was to familiarize the students with new learning platforms and patterns, as eLearning was the need of the day [18] For example, Muhammad and Srinivasan presented with constructivist approach to learning, leading to deeper engagement in the learning process among students [19]. As noted by Greaves and their colleagues [20], despite the uncertainty and inconvenience were prevailing, institutions provided the students with remote learning as a strong substitution to keep the students motivated and attentive towards their educational matters [21], [22] It is notable that, online learning was an only possible option to the students as suspending their education could further undermine their academic cycle, delaying their educational journey, and further decreasing career-making opportunities [17]. Additionally, despite there were several technical, and assessment challenges, eLearning remained as a significant option for the students across the globe [23].

Artificial Intelligence and Users' Metadata. According to Collins and their collegaues [24], today, Artificial Intelligence is helping to create better metadata in less time with minimum effort. Despite the countless benefits of high-quality metadata, adding and keeping it in records is difficult and time-consuming. Notably, a human cannot save and analyze millions of texts, videos, and images to select the relevant keywords. However, the recent developments in Machine Learning and Artificial Intelligence are helping to minimize human efforts and produce constructive results [25]. In this regard, Islam and their collegaues [26] highlighted the types of Artificial Intelligence used in the metadata creation process. First, it involves Natural Language Processing, which functions similarly to how the human brain works. Natural Language Processing looks for the images, audio files, and patterns in the text. Second, AI uses Statistical Learning which depends on different statistical models to search for the important information from large data sets. The third system involves Neural Networks that find the patterns through information carried out by neural networks. According to Informatica [27], these neural networks are designed to work like human brain neurons. Finally, the AI system uses Deep Learning and further extracts meaning from the layers of information.

X. Liu and their colleagues [28] described four systems used by Artificial Intelligence to create metadata and add it to the images, text, video, and other files. For example, search engines now categorize files like MP4, MP3, PNG, JPEG, etc. These search engines have an AI-enabled system that instantly recognizes and categorizes the file accordingly. [29] further cited an example of Artificial Intelligence in analyzing the video files. An AI-enabled system analyzes video files through images, content, and texts. Another example can be taken from the face recognition system during office meetings. Even it also enables to find the YouTube users' exact moment when a certain research technique is discussed [30], [31].

H1: Artificial Intelligence has a significant impact on users' metadata

Collaborative Filtering and Users' Metadata. Collaborative filtering is an important part of an AI-enabled online system that recommends the most relevant content according to users' needs. Existing literature describes two primary senses of collaborative filtering, including general and narrow ones [13]. Narrow one involves a collaborative filtering process as making an automated prediction about the user's interest by collecting their search keywords, data, and information. The basic assumption of collaborative filtering is that if a person has the same opinion as to the other person, the first individual will be more likely to have a similar opinion to the second person [32]. Here Sultana [33] further cited an example of the types of YouTube videos that a person is more likely to watch. AI-enabled system on YouTube further predicts the person's interest and recommends the videos similar to their search and keywords they used. However, it is notable that these predictions vary according to every user yet are gleaned from several users. According to Deldjoo and their collegaues [34], collaborative filtering involves filtering information using methods involving different agents such as data sources and viewpoints. These methods can be applied to different types of data depending on the type of online platform and the user requirements.

Seo and their collegaues [35] further highlighted the importance of collaborative filtering in the YouTube video recommendation system. A recommendation system is a part of our everyday internet surfing activities. However, when it is to the YouTube video recommendation system, collaborative filtering prefers relevance and suitability. YouTube contains unique algorithms designed to evaluate users' interests, suggest content, and retain their interest until the end [36]. Thus, collaborative filtering further involves content-based, hybrid, and collaborative filtering that further magnifies the importance of AI-enabled video recommendation systems on YouTube [37].

H2: Users' metadata has a significant impact on **Collaborative Filtering**

Users' Metadata and Matrix Factorization. According to Kula [38], matrix factorization is a collaborative filtering system mainly used for content recommendation. These matrix factorization algorithms function by decomposing the "user-content exposure matrix" into two lower-dimensional rectangle matrices. This method of content recommendation system became popular during the prize challenge by Netflix due to its effectiveness. As noted by Fernandez and Cantador [39], matrix factorization generates latent features while comparing two distinct entities. For this purpose, users' metadata helps the matrix factorization to identify and differentiate between what different users search for and prefer to watch. For instance, the users giving ratings or likes/dislikes to a video helps the matrix factorization to determine which video is preferred by the users and what to recommend them accordingly.

However, since not all the users give ratings to content, sometimes it is hard for the system to determine the users' metadata. As a result, the absence of rating leads to missing data causing a sparse matrix. Hence, absent ratings are 0 and cannot multiply with the other values. When users respond, the matrix factorization helps recommend content similar to users' interactions and preferences [40]. As argued by Fernandez and their collegaues [41], the core idea behind matrix factorization is to represent items and users in a lower latent space. Since the first origin of matrix factorization, experts have proposed several approaches, most of which have proved highly beneficial for both the users and the content providers. Thus, today's video content providing websites such as Netflix, YouTube, Hulu, Amazon prime, and others pay special consideration to matrix factorization. These platforms have improved Artificial Intelligence-based systems, which further adds more value to their value and popularity among the users [42].

H3: Users' metadata has a significant impact on Matrix Factorization

Deep Learning Architecture and Users' Metadata. The deep learning paradigm has gained much attention during the last few years due to its utmost significance in the Machine Learning community. Deep learning has also become one of the most preferred computational methods in Machine Learning (ML) that has brought outstanding results regarding different cognitive tasks, beating and even matching those provided by the human brain [43]. Czum [44] noted that, one of the basic features of Deep Learning is its ability to learn and assess a massive amount of data. As a result, Deep Learning has grown and improved the conventional data learning techniques. From simple website product recommendation systems to robotics, bioinformatics, cyber security, and information control, Deep Learning is an integral part of the internet system across the globe. However, [44] argued that despite much work on the Deep Learning Architecture, a little focus is given to its ability to use the metadata and highlight its role in the content recommendation system. As noted by Arora and their collegaues [45], the expanding role of Deep Learning is widely adopted for video recommendation, text mining, multimedia concept retrieval, spam detection, and others. Regardless of the availability of several other Machine Learning approaches, Deep Learning is the most preferred one for the relevant purposes. Deep Learning is also known as Representational Learning (RL) due to its wider applicability and significance. Consequently, existing literature on both distributed and deep learning is due to potential growth in data availability and users' increased interest in adopting the intelligent system for improved human-computer experiences [46].

H4: Users' metadata has a significant impact on Deep Learning Architecture

YouTube Video Recommendation System. According to Deldjoo and their collegaues [34], every major social networking platform recommends its content based on several factors. This suggested content is based on an automated recommendation system that is user-centric and relevant to what an individual is searching for. As affirmed by [29], this automated recommendation system uses the details regarding how similar the individuals interacted with the service to make it more personalized. This makes the search and recommendation system smoother and saves consumers time searching for the most relevant content.

Zhou and their collegaues [47] further argued that recommendation systems are usually built on the principle that they should help find the users what they want to watch. For example, YouTube users experience exposure to the recommendation system in two places. First, it appears on the homepage, where they have a mix of content based on subscription, past viewing, and the latest news. These recommendations also appear in the "up next" panel while watching any videos. As a result, it is hard for the user's to watch just one video as the recommendation system appeals to them to watch more. As of today, the recommendation system drives a large audience, and it adds more value to the incorporation of Artificial Intelligence.

Further, Elahi and their collegaues [48] argued that the goal of the recommendation system is to provide the users with high-quality content by minimizing their efforts to search for it. YouTube tries to anticipate what a user would like to see next based on what they have already watched. For this purpose, YouTube takes signals from users' behaviour, including watch time, keywords, genre, and others. Specifically, YouTube measures valued watch time by using structured surveys to rate a video on a scale from one to ten [49].

Thus, every traffic source is different but depends on external factors, personalization, and performance. The YouTube recommendation system is still evolving and improving its services for users. Now, the YouTube recommendation system not only suggests content but also keeps strict control over content that violates the YouTube community guidelines [50]. The relevant platform does this by using certain classifiers to identify whether the video is borderline or authoritative with the help of human evaluators placed worldwide. Notably, since 2011, YouTube has had strict control over recommending poor quality content. In 2015, the automated system also demoted sensational content from the homepage. Later, in 2016 YouTube further added strict control over its content that could harm the minors [45].

H5a: Collaborative Filtering has a significant impact on YouTube Video Selection
H5b: Matrix Factorization has a significant impact on YouTube Video Selection
H5c: Deep Learning Architecture has a significant impact on YouTube Video Selection

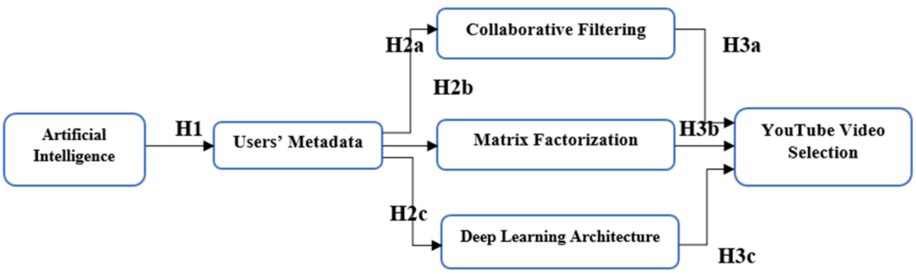

Fig. 2. Conceptual model of current research

3 Research methods

Current research involves cross-sectional design as the relevant studies are based on a brief time frame, with greater generalizability [51]. Moreover, the researcher applied structured questionnaires, whose items were adopted from existing studies cited in Table 1 below. The questionnaires are designed using a five-point Likert scale (strongly agree, agree, neutral, disagree, strongly disagree). Further, the researchers used Structural Equation Modelling (SEM) to examine the explanatory model proposed in the current research, as suggested by Dermawan and their collegaues [52]. The researchers used IBM Amos and Statistical Package for Social Sciences Ver 64 bit for the data analysis.

Table 1. Sources of the survey items

S/R.	Constructs	Source
1.	Artificial Intelligence	[53]–[55]
2.	YouTube Educational Videos	[56]–[58]
3.	Matrix Factorization	[59], [60]
4.	Deep Learning Architecture	[13], [61], [62]
5.	YouTube Video Selection	[9], [63]–[65]

Study Population and Sampling. The population of current research involves students from Al-Ain university, United Arab Emirates. However, as per the research criteria, the researchers randomly selected a sample of n= 400 students from the Al-Ain University having a relevant YouTube usage. Notably, selecting n= 400 participants is justified according to two established criteria. First, Sabri and their collegaues [66] recommend that the studies applying Structural Equation Modeling (SEM) contain a minimum sample size of n= 200 participants. Second, the researchers used G*Power analysis to determine the suitable sample size, as also suggested by [67].

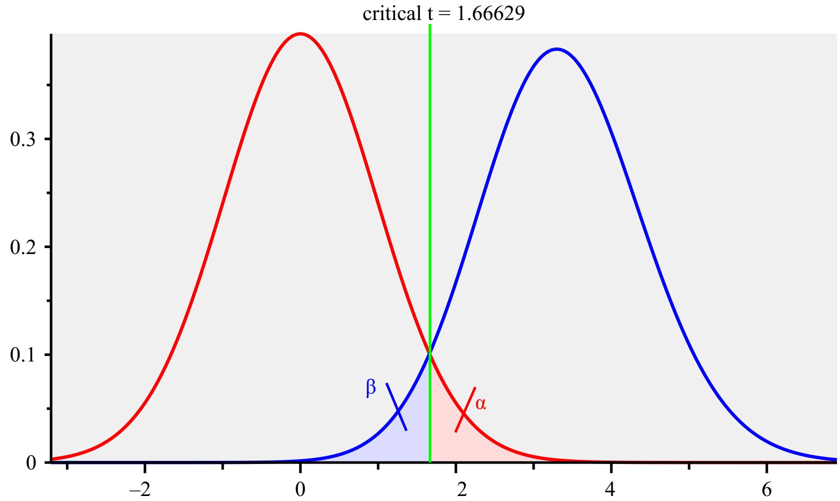

Fig. 3. Central and non-central data distribution

Figure 3 indicates the central and non-central data distribution to indicate the ideal sample size. Thus the G*Power analysis revealed a suitable sample size for the current research would be a minimum of *n*= 74 participants with a critical *t* value of 1.66 and the total effect size at 015. Hence, it is found that the selected sample size for the current research is ideal. Notably, the researchers used a convenient sampling method for the participants' selection. The basic study requirement was to select the students having some experience with YouTube educational content selection and exposure. According to Tahedoost [68], despite some limitations and criticism regarding the convenient sampling technique, it is one of the widely preferred methods among social sciences researchers.

Informed Consent & Response Rate. Informed consent is one of the most important ethical considerations in research as it provides the participants with the details about the study, its relevance, generalizability, and significance for society [69]. Thus, the current research also involved informed consent as the researchers provided the respondents with all the details regarding the current research. Besides, the researchers also provided the respondents with n autonomy to quit survey filling whenever they wanted. The researcher ensured that the respondents could quit, and they will not be obligated to justify or mention the reason behind their decision. Finally, after the data gathering, the researchers received a response rate of 98.0% as n= 8 or 2% of the questionnaires were missing or wrongly filled by the participants.

4 Data analysis and findings

Measurement Model Analysis. The researchers first conducted the concurrent validity analysis to examine the measurement model. According to Sarstedy and their collegaues [70], convergent validity helps examine the research items' internal consistency by calculating Average Variance Extracted, Factor Loading, Composite Reliability, and Cronbach Alpha values. Thus, first, the researchers calculated the Factor Loading and Average Variance Extracted. Here, most Factor Loading values are greater than the threshold value of 0.5. However, the items whose values are below 0.5 will be removed while determining the goodness of fit. Besides, all the Average Variance Extracted values are also found to exceed the threshold value of 0.5, ranging from .734 to .870.

Further, calculating the Cronbach Alpha and Composite Reliability values also ensured the construct reliability of the measurement model. As Cronbach Alpha values range from .718 to .801, and Composite Reliability values range from .708 to .791. Thus, it is affirmed that the measurement model is internally consistent (See Table 2).

Table 2. Convergent validity analysis

Variables	Items	FL	AVE	CA	CR
Artificial Intelligence	AI1	.422	.740	.718	.753
	AI2	.542			
	AI3	.938			
Users' Metadata	UMT1	.719	.795	.782	.756
	UMT2	.866			
	UMT3	.801			
Collaborative Filtering	CFG1	.806	.870	.742	.708
	CFG2	.240			
	CFG3	.934			
Matrix Factorization	MTN1	.744	.734	733	.790
	MTN2	.415			
	MTN3	.725			
Deep Learning Architecture	DLA1	.770	.744	.801	.762
	DLA2	–.002			
	DLA3	–.166			
YouTube Video Selection	YTS1	.699	.816	793	.791
	YTS2	.934			
	YTS3	.403			

Notes: AI is artificial intelligence, UMT is users' metadata, CFG is collaborative filtering, MTN is matrix factorization, DLA is deep learning architecture, and YTS is YouTube video selection.

Discriminant Validity. After analyzing the convergent validity, the researchers examined the discriminant validity. According to Alacron and their collegaues [71], two criteria are important two assess the discriminant validity, including Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio. Thus, the researchers first used Fornell-Larcker Criterion and calculated the square of all the Average Variance Extracted values. Results revealed that all the squares of AVE values are greater than the correlation values given in Table 3 below. Further, regarding the Heterotrait-Monotrait Ratio, the research manually calculated the average of all the variables and applied the relevant formula See Table 4). The calculation revealed the HTMT value at –.49, smaller than the threshold value of 0.9 as suggested by Suhr [72]. Thus, the findings of both criteria revealed that the discriminant validity is also established.

Table 3. Fornell-larcker criterion

	AI	UMT	CFG	MTN	DLA	YES
AI	**.547**					
UMT	.067	**.632**				
CFG	.429	.139	**.756**			
MTN	.246	–.005	.267	**.538**		
DLA	–.010	.322	.059	–.187	**.553**	
YES	.583	–.016	.301	.475	–.089	**.665**

Notes: AI is artificial intelligence, UMT is users' metadata, CFG is collaborative filtering, MTN is matrix factorization, DLA is deep learning architecture, and YTS is YouTube video selection.

Table 4. Heterotrait-monotrait ratio

	AI	UMT	CFG	MTN	DLA	YTS
AI						
UMT	–.021					
CFG	–.287	–.110				
MTN	–.665	–.016	.077			
DLA	–.174	–.306	–.018	.252		
YES	–.356	.046	–.086	–.055	.071	

Notes: AI is artificial intelligence, UMT is users' metadata, CFG is collaborative filtering, MTN is matrix factorization, DLA is deep learning architecture, and YTS is YouTube video selection.

Model Fit. Finally, the researcher assessed the Goodness of Fit to examine whether and to what extent which observations accurately fit the data distribution as suggested by Narsky [73]. Thus, the model fit analysis revealed the chi-square value at $x2$ = 1.347 (47) with the probability value at .000. Further, the results also revealed the Standardized Root Mean Square (RMSEA0 value at .013, lower than the threshold value of 0.9. Thus, the goodness of fit is affirmed in Figure 3.

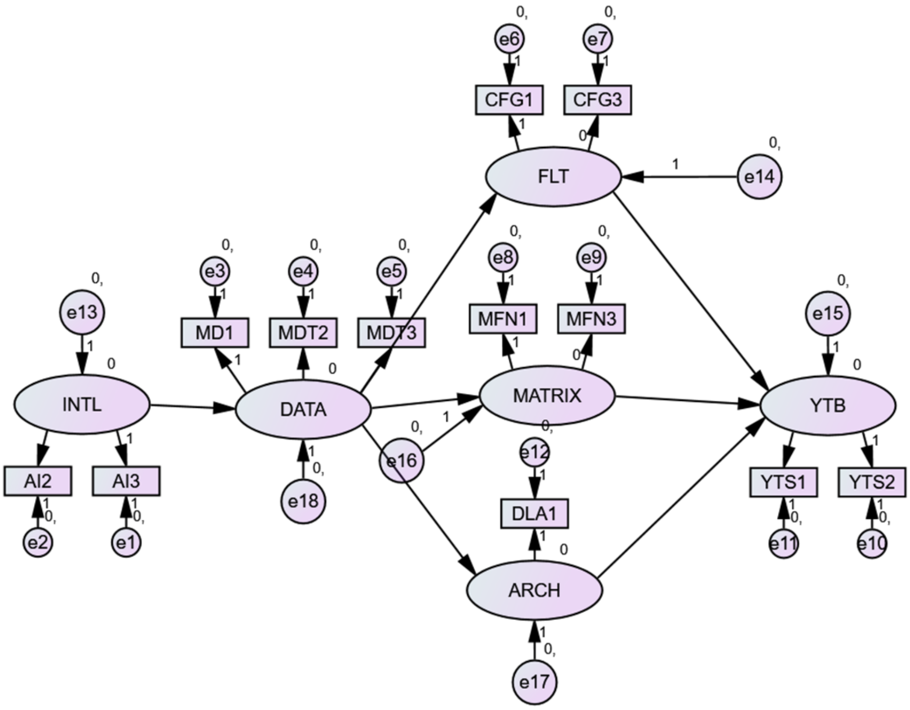

Fig. 4. Goodness of fit

Coefficients of Determination R^2. According to Azman and their collegaues [74], coefficients of determination *R2* helps to determine the predictive power of the latent variables. Besides, it also assesses the extent to which the independent variable is causing variance in the dependent variable(s) [75]. Thus, the coefficients of determination *R2* in the current study revealed that all the R2 values are fundamental and are considered strong ranging from .301 to .756. Table 5 summarizes the results of the coefficients of determination *R2*.

Table 5. Coefficients of determination R^2

Latent Variables	R^2	Strength
Artificial Intelligence	.583	Fundamental
Users' Metadata	.756	Fundamental
Collaborative Filtering	.301	Fundamental
Matrix Factorization	.475	Fundamental
DeepLearning Architecture	.489	Fundamental

Hypotheses Testing. The researchers further conducted the Path Analysis to examine the structural relationships proposed in the conceptual model of the current study as suggested by. For the relevant purpose, the researcher used IBM Amos Version 23. Thus, results indicated that the relationship proposed between Artificial Intelligence and Users' Metadata remained significant, with the path value at .649 and the significance value at p> 0.000. Moreover, the relationships proposed between Users Metadata, Collaborative Filtering (H2a), Matrix Factorization (H2b), and Deep Learning Architecture (H2c) also remained significant with the path values at .362, .242, 1.066 (respectively) along with the same significance values at p> 0.000. Additionally, in the H3a, H3b, and H3c, the researchers proposed significant relationships between YouTube Video Suggestion, Collaborative Filtering, Matrix Factorization, and Deep Learning Architecture. Notably, the relationships between Collaborative Filtering and YouTube Video Selection and Matric Factorization and YouTube Video Selection remained insignificant, with the path values at .038, –.131 and significance values at p> 668, p> .570 (respectively). However, the relationship between Deep Learning Architecture and YouTube Video Selection remained significant, with the path value at 1.648 and the significance value at p> 0.000. Thus, path analysis revealed a majority of structural relations as significantly approved, as also shown in Table 6 below:

Table 6. Analysis of the structural model (hypotheses testing)

Hyp.	Relationships	Path	t-value	Sign
H1	AI>UMT	.649	13.405	***
H2a	UMT>CFG	.362	5.608	***
H2b	UMT>MTN	.242	5.178	***
H2c	UMT>DLA	1.066	10.202	***
H3a	CFG>YTS	.038	.430	.668
H3b	MTN>YTS	–.131	–.568	.570
H3c	DLA>YTS	1.648	13.392	***

Notes: AI is artificial intelligence, UMT is users' metadata, CFG is collaborative filtering, MTN is matrix factorization, DLA is deep learning architecture, and YTS is YouTube video selection.

Importance of performance map analysis

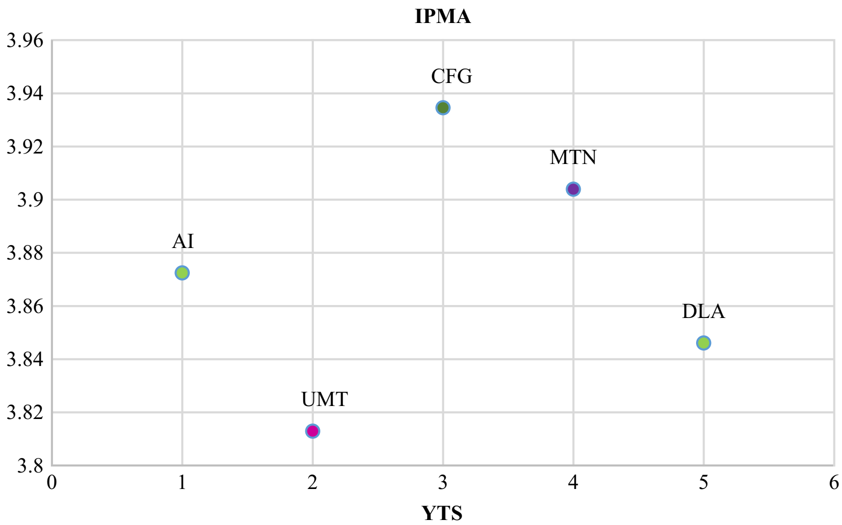

Fig. 5. Importance of performance map analysis

This research also involves Importance Performance Map Analysis (IPMA) as an important part of studies having Structural Equation Modelling (SEM). We examined the strength of endogenous variables. As shown in Figure 5, Collaborative Filtering remained the strongest linked variable (M= 3.93) with the exogenous variable "YouTbe Video Selection." Followed by Matrix Factorization (M= 3.90), Artificial Intelligencereamined the third-highest ranked variable (M= 3.87). Further, Deep Learning Architecture remained the fifth most strongly associated variable (3.84), while Users' Metadata remained the lowest variable (M= 3.81).

Artificial neural network analysis

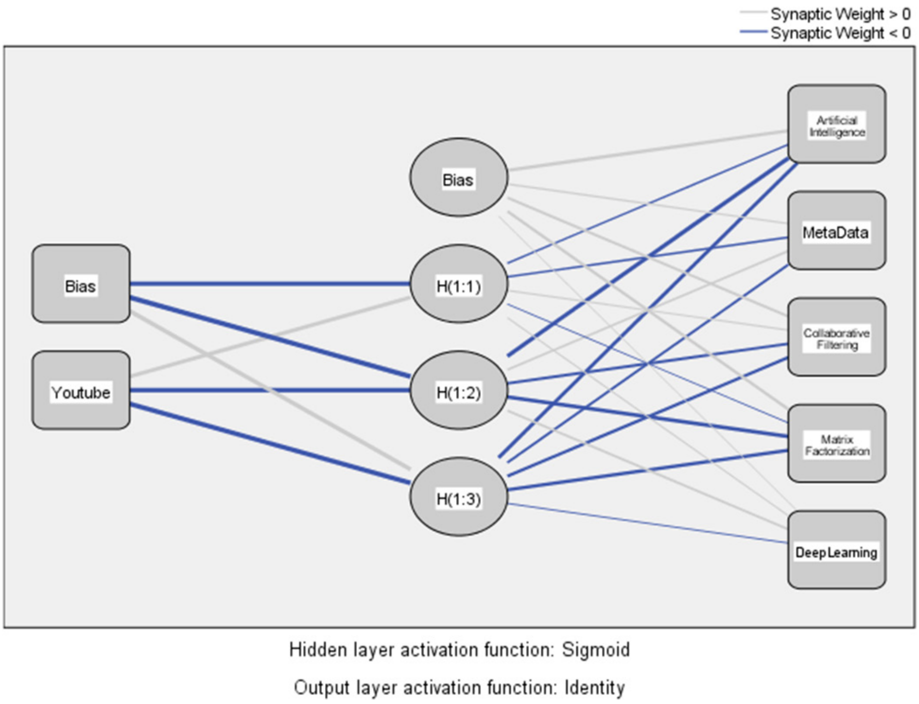

Fig. 6. Artificial neural network (ANN) analysis

According to Zamaniyan and their collegaues [76], Artificial Neural Network (ANN) is one of the most significant techniques in Machine Learning (ML) that help to determine how a human brain works. Thus, the current research also involves the relevant technique by keeping the significance of Artificial Neural Network Analysis (ANN). The researchers selected Artificial Intelligence, Users' Metadata, Collaborative Filtering, Matrix Factorization, Deep Learning Architecture, and YouTube Video Selection for the Artificial Neural Network (ANN). As shown in Figure 6, with the sum of square regarding Training value at 578.076 and Testing value at 237.818, we found 81.7% of Average Overall Relative Error in Training and 82.5% in Testing. Hence, there is an overall accuracy of 19.3% (Training) and 17.5?% (Testing).

5 Discussion on results

When YouTube recommendation works at their best, it helps users find and experience the best content. In educational realms, the role of the YouTube recommendation system not only suggests content but also inspires teachers, students, and even parents to consider and reconsider social networking platforms for learning purposes [77]. For Davidson and their collegaues [32], YouTube recommendations for the educational content mean diving into online lectures and tutorials that help students solve their educational problems and get support in the best possible manner. Notably, the YouTube recommendation system is based on the simple principle of helping users find what they want to watch and value. This video recommendation system shows a mixture of several personalized subscriptions, the latest news, and recommendations. Besides, the “Up Next” panel is another significant feature that indicates what the users’ are currently watching and what the AI system thinks the users must be interested in [1], [3], [16], [26], [34], [78].

Similarly, current research also investigated the role of the YouTube recommendation system in helping students find relevant educational content. As noted by June and their collegaues [79], greater advancements in information and educational technologies have effectively improved the students’ learning experiences. Today when children are growing with new media, they are also learning to gain maximum benefits from it, thus, leading to positive impacts on your academic journey. Talking specifically about the study results, the researchers found a greater consistency with the studies conducted in other regions witnessing the role and importance of AI-enabled video recommendation systems on YouTube.

First, the researchers proposed a significant relationship between Artificial Intelligence and Users’ Metadata. Thus proposition remained significant, with the *p*-value at p> 0.000 indicating a greater relevance to the study conducted by Tsay and their collegaues [29]. As Tsay and their colleagues also argued, despite the online networks being a collection of several systems, Artificial Intelligence adds a different value to them. Collecting users’ metadata, recognizing their needs, and suggesting relevant content are primary functions of AI, especially on the major websites that prefer user-centric approaches. Further, the relationships were also proposed between Users’ Metadata, Collaborative Filtering, Matrix Factorization, and Deep Learning Architecture (H2a, H2b, and H2c).

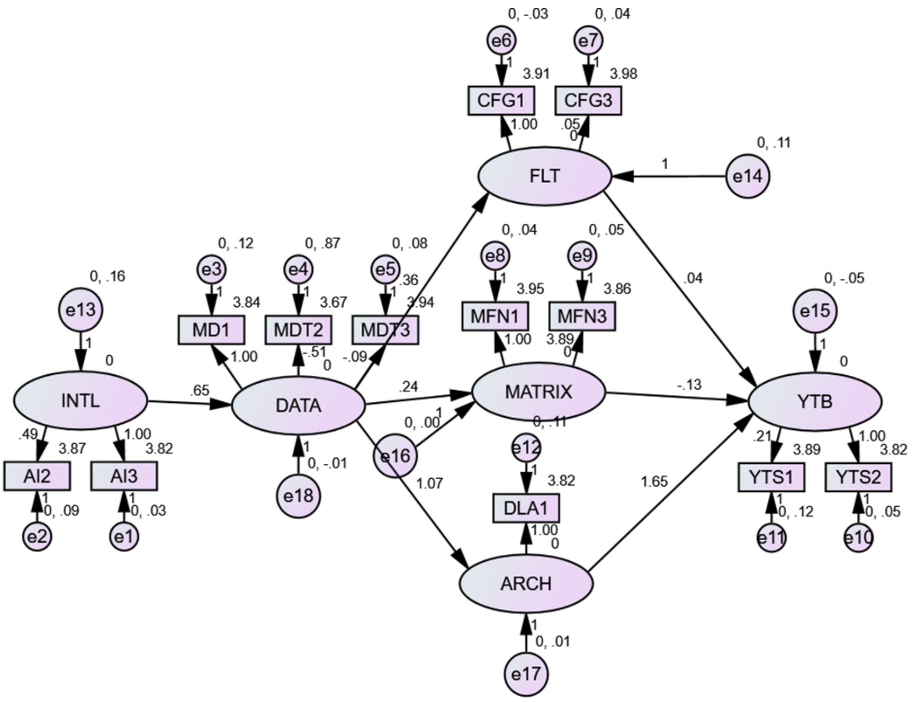

Fig. 7. Path analysis of structural relationships

Data gathered from n= 394 participants revealed a strong, significant impact of users' metadata on collaborative filtering, matrix factorization, and deep learning architecture showing a greater consistency with the existing literature regarding the features of AI-enabled content recommendation systems [80]. As noted by Ji Liu and their colegaues [81], YouTube has greatly controlled the content recommendation and selection process after incorporating a smart system. Users find it easy to search for the content they need. It also increases their exposure to more relevant content, which is one of the leading reasons behind YouTube as one of the most prominent social networking platforms today [82]. However, the proposed relationships between collaborative filtering and YouTube content selection and matrix factorization and content selection remained insignificant, as stated in the H3a and H3b of the study. The apparent reason behind these rejected hypotheses seemed to be participants' disagreement with the statements proposing collaborative filtering and matrix factorization as helping them to find any relevant YouTube-based educational content. Yet the relationship assumed between deep learning architecture and YouTube video selection remained significant, with the significance value as strong as $p< 0.000$. This significant relationship further indicated a stronger consistency with the study [49]. As Li and their colleagues also argued, Google Brain runs the recommendation system of YouTube, further open-sourced by Google as TensorFlow. As a result, the recommendation system is more vigilant and efficient enough to keep the users' data under consideration while also helping them find and select the most suitable content they want.

Thus, the results provided an overall reflection of the role and significance of the YouTube recommendation system, particularly for the students. These findings also provided an idea behind incorporating digital learning platforms in education, indicating the importance of modern rends in educational arenas [33], [83]–[87].

6 Conclusion

The recommendation system is an integral part of YouTube and has been successful in the context of the current study goals and objectives. An explanatory model is proposed in this research based on the existing literature that is empirically tested to affirm the proposed relationships further. The current study witnessed how algorithmic systems on YouTube are helping young Emirati students to find relevant and useful content. As a result, current research also magnified the importance and influence of YouTube as one of the most preferred social networking platforms among the young generation. Additionally, the system's ability to gather the users' preferences and demographical information also seemed dominant while seeking to recommend the most relevant content. Thus, it is concluded that the video recommendation system is helping young students to search for and find the educational content they want. Besides, this system also provides them with a searching facility with less effort, adding more value to YouTube as one of the most prominent digital platforms today.

Study Limitations and Recommendations. Although the current study adds to the existing literature, it has some limitations. First, this research is done in the United Arab Emirates, which questions the generalizability of results in other countries. Second, this study has two rejected hypotheses that further require more studies to examine their status in other scenarios. Finally, the third limitation involves selecting only YouTube when many other video platforms offer educational content to the students. However, the researchers recommend more studies especially addressing the role of Artificial Intelligence in ensuring content relevancy, to examine further the users' perceptions about intelligent systems and their advantages.

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