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Factors Influencing YouTube as a Learning Tool and Its Influence on Academic Achievement in a Bilingual Environment Using Extended Information Adoption Model (IAM) with ML Prediction—Jordan Case Study

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Abstract: YouTube usage as a learning tool is evident among students. Hence, the goal of this study is to examine the various factors that influence the use of YouTube as a learning tool, which influences academic achievement in a bilingual academic context. Using survey data from 704 YouTube users from Jordan's bilingual academic institutes, the research model was empirically validated. Using Amos 20, structural equation modeling (SEM) was performed to assess the study hypotheses. SEM permits concurrent checking of the direct and indirect effects of all hypotheses. Confirmatory factor analysis (CFA) was used to validate the instrument items' properties in addition to machine learning methods: ANN, SMO, the bagging reduced error pruning tree (RepTree), and random forest. The empirical results offer several key findings: academic achievement (AA) is influenced by the information adoption (IA) of YouTube as a learning tool. Information adoption (IA) is influenced by information usefulness (IU). Source credibility (SC) and information quality (IQ) both influence information usefulness (IU), while information language (IL) does not. Information quality (IQ) is influenced by intrinsic, contextual, and accessibility information quality. This study adds to the literature by empirically testing and theorizing the effects of YouTube as a learning tool on the academic achievement of Jordanian university students who are studying in bilingual surroundings.

Keywords: YouTube; information adoption model; education; learning; e-learning

1. Introduction

Many students as well as practitioners, researchers, and teachers resort to using YouTube as a learning tool, and many educational and training institutes offer their educational materials through YouTube. YouTube as a platform is available to everyone and anyone. Knowledge seekers may use such a platform to educate themselves as an alternative to face-to-face lectures for many reasons: availability, ease of use, etc., and, in fact, many will adopt such a source as an alternative. The question is what are the factors that influence such adoption of YouTube as a learning tool? This research adopted an expanded information adoption model (IAM) to study this case and used academic achievement as a motivation since [1] studied the factors influencing students' web-based learning performance during the COVID-19 pandemic. That study stressed the influence of learning anxiety, attitude, and motivation on web-based learning, and found that motivation is the essential factor.

YouTube has many advantages: visual and auditory facilitation of knowledge transfer, it accommodates learning pace, and can be used as a complementary learning resource for educators. YouTube allows interactivity among users [2], enhances the understanding of course content, meets learners' expectation, encourages self-directed learning, and provides a free source of learning, and users can create, share, comment, and develop their own YouTube content with lifelong learning [3].

The objective of this research is to study the influence of YouTube as a learning tool on academic achievement within the scope of the extended information adoption model that includes information usefulness (credibility, language), quality (intrinsic, contextual, accessibility), and adoption perspectives. Furthermore, the research was conducted in a bilingual academic environment.

The motivation of this research is the following: YouTube is used as a learning tool in many fields from accounting in [4] to anatomy, as in [5]. In fact, according to [6], a study conducted by [5] "examined the application of YouTube videos in an anatomy course and found that 98% of the students utilized YouTube as an online information resource and 92% agreed that the tutorial videos on YouTube were helpful". As such, the previous study only reflects the importance of and motivation to conduct this research. The credibility of knowledge sought from YouTube is very important [7], in fact some students rely on YouTube as source of information [8–10], while others try to measure the cognition value of YouTube education videos [11].

The importance of this research stems from the above findings. Teachers, practitioners, and researchers can use the findings of this research as a support. Teachers can learn more about delivering knowledge by learning from popular YouTube teachers. Educational institutes may share knowledge from each other. Publishing houses may accommodate students' needs by providing YouTube channels just as in e-textbooks [12]. Researchers and practitioners can even develop web services [13].

The current study makes a significant contribution by examining a proposed model that includes five independent factors, three intermediate factors, four moderating factors, and one dependent factor. As a result, the research attempted to take a comprehensive look at the influencing factors of YouTube. However, to the best of the researchers' knowledge, no research was found to include all of these factors within one research scope of YouTube, nor has the proposed model been examined in the bilingual context.

The empirical results offer several key findings. Academic achievement (AA) is influenced by information adoption (IA) of YouTube as a learning tool. Information adoption (IA) is influenced by information usefulness (IU). Source credibility (SC) and information quality (IQ) both influence information usefulness (IU), while information language (IL) does not. Information quality (IQ) is influenced by the quality of intrinsic, contextual, and accessible information.

Section 1 of this research paper is a review of the literature that supports the model developed for this study. Following that, the theoretical framework of the model is explained, as well as the development of the hypotheses. After that, the survey design and methodology are explained. Then data analysis, including a descriptive analysis, SEM analysis validation, and prediction, is presented. Following that, there is a discussion of the theoretical and practical implications. Subsequently, the limitations and future research directions are discussed.

2. Literature Review

The study of information adoption is not new; many researchers have studied the idea using many models, frameworks, and theories. The authors of [14] studied the adoption of mobile learning in higher education using task-technology fit (TTF). The author of [15] studied users' information adoption intention in online health communities using the elaboration likelihood model (ELM). The authors of [16] studied mobile messaging applications' (MMAs) information adoption using the information adoption model (IAM). The authors of [17] used the IAM to discover the characteristics that influence health information on social media adoption. The authors of [18] studied the adoption of AI in the m-banking arena using task-technology fit (TTF) and stimulus–organism–response (SOR) theory. The authors of [19] studied the behavior of customers towards the usage of social media for purchasing decisions using the technology acceptance model (TAM). The research found that usefulness is the most influential factor. The authors of [20] studied the adoption of mobile payment technology using the TAM and prospect theory. The authors of [21] studied YouTube adoption and its influence on destination visits in India. The study was conducted using the IAM. The authors of [21] found "comprehensiveness, relevance, timeliness, source expertise and attitude as the most significant predictors of a traveler's destination visit intention through YouTube channel adoption". Furthermore, in [22] the researchers studied agricultural learning and development in new media's usability and effectiveness. In [23] the researchers explored the use of social media sites for health professionals' engagement and productivity in public sector hospitals. In [24] the researchers studied the continuous intention to use mobile on the adoption hotel reservation on travel websites.

As for using YouTube as a learning tool, learning, by definition, is "an activity that individuals engage in with the goal of improving their understanding of an issue and/or their ability to solve problems in life, work and/or study" [25].

The authors of [6] studied the use of YouTube as a learning tool or resource. The study used *social cognitive theory* (person, environment, and behavior) and included influencing factors such as prior experience, using YouTube as a learning resource, the sociability of YouTube, attitude, and the learning outcome expectation.

To analyze the gap in the field for this research, several published researches were reviewed and was found as follows: Some studies focused on the characteristics of educational content [26–28], while others [6] considered the social cognitive perspective; [2] considered the technology–user–environment perspective, and [3] considered the self-directed learning perspective. The author of [28] studied the attitudes, experiences, and perceptions of undergraduate students related to YouTube as an information source to support their studying. The author of [29] studied the impact of social media on adolescents' abilities, attitudes, communication, education, interactions, personal conduct, social behavior, and skills in Sri Lanka. The source found that YouTube was the most preferred social media (99.23%) among adolescents, and that education was the second preference. The author of [4] studied the effectiveness of podcasting in higher education within financial accounting and found that student performance increased when using video. The authors of [30] studied the impact of social media on academic performance: the researchers found that social media, especially YouTube, is very popular among students as a learning tool. The authors of [31] studied YouTube stickiness within needs, personal, and environment perspective. The study used two theories: Uses and Gratifications Theory (UGT) and social cognitive theory (SCT). The study was conducted in Chinese within a bilingual environment. Hence, the next section presents the theoretical framework of this research and the hypotheses development.

3. Theoretical Framework and Hypotheses Development

The proposed model in Figure 1 is based on the information adoption model (IAM). The IAM, as stated by [32], "can explain how individuals adopt information and thus change their intentions and behaviors within the computer-mediated communication platforms". The IAM is based on both the TAM and the dual-process model of informational influence, i.e., the elaboration likelihood model (ELM). According to the same source, while quoting others, the TAM's explanatory power is constrained and concentrates both information systems and the individual usage of a computer while neglecting the social processes.

Figure 1. Proposed model based on expanded IAM.

The ELM, on the other hand, can be used to describe the attitude change from and articulate the process underlying the effectiveness of persuasive communication since the ELM is used to explain how the recipients are affected by message information [33]. Hence, Sussman and Siegal in 2003 developed the IAM, which was published in [34]. The original IAM is composed of two independent variables, argument quality and source credibility, one intermediate variable, information usefulness, and one dependent variable, information adoption, as can be seen in [34]. Argument quality is "the persuasiveness of arguments within an informational message". [35] and has four dimensions: accuracy, comprehensiveness, relevance, and timeliness [35]. According to [35], source credibility is "the extent to which a message source is perceived to be believable, competent and trustworthy by the recipients". "Argument quality and source credibility are the two most cited central and peripheral signals" [35].

The proposed model in Figure 1 is composed of independent, intermediate, dependent, and moderating variables. The independent variables are source credibility (SC), information language (IL), intrinsic information quality (IIQ), contextual information quality (CIQ), and accessibility information quality (AIQ). The intermediate variables are information usefulness (IU), information quality (IQ), and information adoption (IA). The dependent variable is academic achievement (AA). The moderating variables are age, gender, education level, and previous experience.

Furthermore, the original IAM model was expanded to include IL, IIQ, CIQ, AIQ, AA, and the moderating variables. The IL was adopted based on the work of [35–39]. The IQ was expanded with IIQ, CIQ, and AIQ based on the work of [34,35,40]. The variable AA was adopted based on the work of [8–10,34,35,41,42]. In addition, the model was expanded with moderating variables adopted from [6,43–53]. Furthermore, the model was analyzed, validated, and verified using structural equation modeling (SEM) and confirmatory factor analysis (CFA).

3.1. Hypotheses Development

Source credibility was investigated based on its influence on behavior, perception, and usefulness according to [35] referencing others, i.e., [34,54–57]. Founded on the previous, the following hypothesis is stated.

Hypothesis 1 (H1). *Source credibility (SC) will positively influence information usefulness (IU).*

For information language (IL), the language here refers to the mother language of the receiving end whether the communicated information is written or spoken. There are many studies that have investigated such a factor [35–39]. Based on the previous, the following hypothesis is stated.

Hypothesis 2 (H2). *Information language (IL) will positively influence information usefulness (IU).*

According to [40] "information quality refers to users' subjective judgment of whether the information characteristics meet their own needs and intended use" [40]. "Information quality is an important variable for the success of an information system model and is defined as the fitness of information characteristics for information users" [40] based on [58].

Different studies have measured information quality with different key measures in [59]; the measures were "accessibility, comprehensibility, credibility, and usefulness". In addition, [60] included accessible, contextual, expressive and intrinsic", while [7] identified the key measures of information quality as "comprehensiveness, correctness, relativities, and timeliness". Furthermore, [61] explained that "comprehensiveness and relevance are two key determinants of information quality". According to [40], information quality is influenced by three factors: intrinsic, contextual, and accessibility information quality. Intrinsic information quality (IIQ) "refers to the quality dimensions originated from the data in its own independent of the user's perspective and context". Contextual information quality (CIQ) focuses on the aspect of information quality within the context of the task at hand. Accessibility information quality (AIQ) refers to the quality aspects concerned with accessing distributed information. [40]. Furthermore, according to [34,35,40], the quality influences the usefulness. Hence, the following four hypotheses are developed.

Hypothesis 3 (H3). *Intrinsic information quality (IIQ) will positively influence information quality (IQ).*

Hypothesis 4 (H4). *Contextual information quality (CIQ) will positively influence information quality (IQ).*

Hypothesis 5 (H5). *Accessibility information quality (AIQ) will positively influence information quality (IQ).*

Hypothesis 6 (H6). *Information quality (IQ) will positively influence information usefulness (IU).*

Using the elaboration likelihood model (ELM) in [62], discussed that information usefulness (IU) positively influences information adoption and stated that information usefulness (IU) in this research refers to the degree to which users believe that the information in YouTube can have a positive impact on their study/work. The influence of usefulness and adoption in the study that used the IAM is evident in [16]. Furthermore, other studies concluded the same, ref. [34,35] showed the relation between usefulness and adoption. Based on the previous, the following hypothesis is postulated.

Hypothesis 7 (H7). *Information usefulness (IU) will positively influence information adoption (IA).*

"Academic performance is defined as students' ability to carry out academic tasks, and it measures their achievement across different academic subjects using objective measures such as final course grades and grading point average" [8]. The adoption of ICT influencing academic achievement was researched by [8,10,34,35,41,42,63], and even in medicine as in [9]. Hence, the following hypothesis is suggested.

Hypothesis 8 (H8). *Information adoption (IA) will positively influence academic achievement (AA).*

3.2. Hypotheses Related to Moderating Factors

This study includes four moderating factors in addition to the nine main factors. According to the model, the moderating factors are age, gender, education level, and previous experience. The expansion of the hypotheses on moderation factors is based on the work of [6,45–53].

3.2.1. Hypothesis Related to Age

There are two aspects to age as a moderating factor. One could argue that older people are less accepting of modern technology, whereas younger generations are. On the other hand, older generations may be more willing to accept YouTube because they value such sources more. Many studies, including [47,50–53], used age as a moderating factor. As a result, the following hypothesis is conceived based on the preceding.

Hypothesis 9 (H9). *Age has a significant moderating effect on information adoption (IA) towards YouTube.*

3.2.2. Hypothesis Related to Gender

Another moderating factor that may influence information adoption (IA) suggested by UTAUT is gender. Gender was used as a moderator in many studies [43,44,47–50,53,64]. As a result, the following hypothesis is proposed.

Hypothesis 10 (H10). *Gender has a significant moderating effect on information adoption (IA) towards YouTube.*

3.2.3. Hypothesis Related to Education Level

This study adopts [46,52,65] to suggest the education level of the student (BSc, Master's, or Ph.D.). As a result, the following hypothesis is developed.

Hypothesis 11 (H11). *Education level has a significant moderating effect on information adoption (IA) towards YouTube.*

3.2.4. Hypothesis Related to Previous Experience

Previous experience was used in the research [6] as part of the behavior demonstrated by the student towards using YouTube as a learning tool. Researchers categorized previous experience as weak, good, or excellent. Hence, the following hypothesis is developed based on [6].

Hypothesis 12 (H12). *Previous experience has a significant moderating effect on information adoption (IA) of YouTube as learning tool.*

4. Research Methods

For this study to reach its goal of examining the overall effect on the AA of students employing YouTube as learning tool, it examines the effect of the independent variables source credibility (SC) and information language (IL) on the intermediate variable information usefulness (IU), the effect of the independent variables intrinsic information quality (IIQ), contextual information quality (CIQ), and accessibility information quality (AIQ) on information quality (IQ), and the effect of the intermediate variable information quality (IQ) on information usefulness (IU). In turn, we studied the effect of the intermediate variable information adoption (IA) on academic achievement (AA). Furthermore, the study investigated the moderating role of age, gender, education level, and previous experience on information adoption (IA).

As previous investigation on this topic was incomplete, the researchers, after an extensive research study stage, put forward the model introduced in Figure 1, along with the proposed hypotheses above. Furthermore, a questionnaire was utilized and tested, and then, from a sample of convenience, data were accumulated from 704 participants. To clarify and explain the survey design and methods of this research in detail, the following three sections are presented.

4.1. Research Context

Many people consider YouTube to be a source of knowledge. As a result, the key questions are what factors influence students' information usefulness (IU) in using YouTube as a source of information, and how the entire operation affects academic achievement (AA) while using YouTube. This study was carried out as follows.

4.2. Measurement Items

The construct information quality (IQ) was measured by 3 items, clarity, high quality, and understandability, as recommended by [16,35]. The mediating variable information adoption (IA) was measured using the 5 items ease of understanding, effectiveness of explaining, motivation towards the topic, following their method, and contributed knowledge as recommended by [66]. The mediating variable information usefulness (IU) was measured using the 3 items volubility, informativeness, and helpfulness as recommended by [35]. The construct information language (IL) was measured, as suggested by [35], by 7 items: preferred reading language of newspapers, books, magazines, watching TV, and YouTube. The construct source credibility (SC) was measured by adopting 6 items from [35,66,67], believability, factuality, credibility, trustworthiness, comprehensibility, knowledgeability, and expertise. The construct intrinsic information quality (IIQ) was measured using 5 items suggested by [40,67], including believability, accuracy, and objectivity. The construct contextual information quality (CIQ) was measured using 16 items suggested by [40,68,69], including concise ability, verifiability, representational consistency, understandability, adequateness of information, reputation, and completeness of information. The construct accessibility information quality (AIQ) was measured using 11 items suggested by [40] including availability, relevance including clarity, applicability, strength, accessibility with readiness and ease, and response time. The construct academic achievement (AA) was evaluated by 7 items adopted from [69–71].

4.3. Participants and Procedure

A quantifiable method was employed with an investigative and explanatory design. A survey form was utilized to gather data. The purpose was to validate the conceptual model of the research and examine the research hypotheses. The target population of this study consisted of all students that follow the YouTube platform in Jordanian universities, which is a bilingual education environment. A web link to the survey was sent to potential respondents in the period between 15 and 30 March 2022. To make sure students would answer, we asked faculties and colleagues to distribute the survey through e-groups (Facebook, WhatsApp). The survey was prepared in both Arabic and English languages, and 704 social media users were sampled to collect the data, after removing contaminated survey. The content of the questionnaire (constructs and measures) was developed and adopted from prior pertinent studies [16,34,35,40,66–71] using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Table A1 in Appendix A, encapsulates the constructs and items used to measure the constructs and mediating factors. The questionnaire included 65 self-reported items related to nine constructs to prove twelve hypotheses.

To validate the construct, the questionnaire content was modified to accommodate Jordanian bilingual education culture, based on the results of a pilot study and feedback from six professional academician faculty members in this field. The survey instrument was reviewed by a panel of six academician faculty members in the areas of information technology, e-learning, and education to guarantee face validity. Subsequently, various items were amended, and the modified survey was used for pilot testing on college students in Jordan. Indeed, a pretest was conducted with twenty-five students to check the comprehensibility of the questions. Some amendments were made, resulting in a clear and comprehensible survey questionnaire.

As shown in Table 1, the demographic profile of the respondents for this research exhibited that they were typically females in gender, between 18 years old and less than 34 years old in age, the majority held bachelor's and master's degrees in education level, and had excellent previous experience in using YouTube.

Table 1. Description of the respondents' demographic profiles.

Category	Category	Frequency	Percentage %
Gender	Male	293	41.6
	Female	411	58.4
	Total	704	100
Age (Year)	18 to less than 34	496	70.5
	34 to less than 44	175	24.9
	44 to less than 54	20	2.8
	54 to less than 64	10	1.4
	64 and over	3	0.4
	Total	704	100
Education level	Bachelor	350	49.7
	Master	339	48.2
	PhD	15	2.1
	Total	704	100
Previous experience	Low	186	26.4
	Good	237	33.7
	Excellent	281	39.9
	Total	704	100

5. Data Analysis and Results

In this section, the statistical results are presented. First, the descriptive analysis is presented to show the demography of the respondents. Second, the structural equation model (SEM) analysis will be presented to validate and verify the study hypothesis with the measurement model and structural model. Third, the effect of the moderating factors is analyzed, and fourth, machine learning techniques used to validate and predict the different factors are presented.

5.1. Descriptive Analysis

The mean and standard deviation were estimated to describe the responses and thus the attitude of the respondents toward each question asked in the survey. While the mean represents the data's central tendency, the standard deviation measures their dispersion and provides an index of the data's spread or variability [72,73]. In other words, a small standard deviation for a set of values indicates that these values are clustered closely around or close to the mean; a large standard deviation indicates the opposite. The level of each item was determined by the following (1)

$$\text{Level} = \frac{\text{highestpointinLikertscale} - \text{lowestpointinLikertscale}}{\text{thenumberofthelevelsused}} = \frac{5-1}{5} = 0.80 \quad (1)$$

Hence, producing the following lookup Table 2 of values.

Table 2. Level lookup table of value and ranges.

Range	Level
1–1.80	very low
1.81–2.60	low
2.61–3.40	moderate
3.41–4.20	high
4.21–5	very high

As presented in Table 3, the data analysis results show that all research variables were ranked from "moderate" to "very high". The independent variables contextual information quality (CIQ) and accessibility information quality (AIQ) and the mediating variable information usefulness (IU) all ranked as "very high", while five other variables ranked as "high", namely: the independent variables source credibility (SC) and intrinsic information quality (IIQ), the mediating variables information quality (IQ) and information adoption (IA), and the dependent variable academic achievement (AA). On the other hand, the independent variable information language (IL) ranked as "moderate". As such, this reflects the respondents' feelings regarding the importance of some variables. Accessibility information quality (AIQ) ranked the highest with a mean (4.3102) that reflects that AIQ is more important than the other factors. AIQ was followed by CIQ and AIU.

Table 3. Overall mean and standard deviation of the study's variables.

Type of Variable	Variables	Mean	SD	Level	Order
Independent Variables	Source Credibility (SC)	4.1638	0.70222	High	4
	Information Language (IL)	3.1055	0.48915	Moderate	5
	Intrinsic Information Quality (IIQ)	4.1719	0.95858	High	3
	Contextual Information Quality (CIQ)	4.2198	0.98594	Very high	2
	Accessibility Information Quality (AIQ)	4.3102	0.82849	Very high	1
Mediating Variables	Information Quality (IQ)	4.1146	1.06993	High	3
	Information Usefulness (IU)	4.2098	1.10506	Very high	1
	Information Adoption (IA)	4.1634	1.07376	High	2
Dependent Variable	Academic Achievement (AA)	4.1396	1.14964	High	-

Table 4 exhibits the mean, standard deviation, level, and scores the order for each item belonging to a construct. The highest item in the construct source credibility (SC) is SC3, which directly asks the credibility question. The highest item in the construct information language (IL) was LI3, which asks the respondents about their reading language. The highest item in the construct intrinsic information quality (IIQ) was IIQ5, which asks the responders about the impartially of the YouTube channels utilized by the responder. The highest item in the construct contextual information quality (CIQ) was CIQ5, which asks the responders about the clarity and easiness to understand the topic. The highest item in the construct accessibility information quality (AIQ) was AIQ1, which asks the responders about the availability 24/7 of the channel. The highest item in the construct information usefulness (IU) was IU1, which asks the responders about the evaluability of information provided by YouTube channels. The highest item in the construct information quality (IQ) was IQ1, which asks the responders about the high-quality information. The highest item in the construct Information adoption (IA) was IA1, which asks the responders about the easiness to understand the topic through YouTube. The highest item in the construct academic achievement (AA) was AA1, which asked the responders about how useful YouTube was to the student.

Table 4. Mean and standard deviation of the study's variables.

Source Credibility (SC)	**Mean**	**SD**	**Level**	**Order**
SC1:	3.85	0.535	High	5
SC2:	4.15	0.780	High	4
SC3:	4.40	0.868	Very high	1
SC4:	4.15	0.840	High	4
SC5:	4.21	0.805	Very high	3
SC6:	4.23	0.813	Very high	2
Information Language (IL)	Mean	SD	Level	Order
IL1:	3.08	0.491	Moderate	5
IL2:	3.15	0.620	Moderate	4
IL3:	3.71	1.035	High	1
IL4:	2.42	0.741	Low	7
IL5:	2.49	0.860	Low	6
IL6:	3.70	0.627	High	2
IL7:	3.19	0.586	Moderate	3
Intrinsic Information Quality (IIQ)	Mean	SD	Level	Order
IIQ1:	4.27	1.172	Very high	2
IIQ2:	4.14	0.830	High	4
IIQ3:	3.97	1.098	High	5
IIQ4:	4.20	0.823	High	3
IIQ5:	4.28	1.192	Very high	1
Contextual Information Quality (CIQ)	Mean	SD	Level	Order
CIQ1:	4.35	0.590	Very high	2
CIQ2:	4.29	1.189	Very high	4
CIQ3:	4.26	1.187	Very high	5
CIQ4:	4.00	1.101	High	10
CIQ5:	4.49	0.825	Very high	1
CIQ6:	4.29	1.156	Very high	4
CIQ7:	4.18	0.787	High	8
CIQ8:	4.31	1.176	Very high	3
CIQ9:	4.22	0.770	Very high	7
CIQ10:	4.31	1.172	Very high	3

Table 4. *Cont.*

Source Credibility (SC)	**Mean**	**SD**	**Level**	**Order**
CIQ11:	4.00	1.065	High	10
CIQ12:	3.98	1.069	High	11
CIQ13:	4.28	1.194	Very high	5
CIQ14:	4.25	1.188	Very high	6
CIQ15:	4.05	1.123	High	9
CIQ16:	4.26	1.177	Very high	5
Accessibility Information Quality (AIQ)	Mean	SD	Level	Order
AIQ1:	4.71	0.499	Very high	1
AIQ2:	4.69	0.530	Very high	2
AIQ3:	4.32	1.172	Very high	6
AIQ4:	4.22	1.162	Very high	7
AIQ5:	4.05	0.717	High	9
AIQ6:	4.09	1.103	High	8
AIQ7:	4.48	0.816	Very high	3
AIQ8:	4.03	1.078	High	10
AIQ9:	4.43	0.908	Very high	5
AIQ10:	3.96	1.073	High	11
AIQ11:	4.44	0.888	Very high	4
Information Usefulness (IU)	Mean	SD	Level	Order
IU1:	4.33	1.168	Very high	1
IU2:	4.00	1.073	High	3
IU3:	4.30	1.158	Very high	2
Information Quality (IQ)	Mean	SD	Level	Order
IQ1:	4.30	1.159	Very high	1
IQ2:	4.04	1.079	High	2
IQ3:	4.01	1.067	High	3
Information Adoption (IA)	Mean	SD	Level	Order
IA1:	4.30	1.143	Very high	1
IA2:	4.09	1.087	High	5
IA3:	4.11	1.099	High	4
IA4:	4.22	1.154	Very high	2
IA5:	4.10	1.104	High	3
Academic Achievement (AA)	Mean	SD	Level	Order
AA1:	4.34	1.175	Very high	1
AA2:	3.98	1.089	High	6
AA3:	4.31	1.188	Very high	2
AA4:	4.21	1.192	Very high	4
AA5:	4.03	1.112	High	5
AA6:	4.22	1.171	Very high	3
AA7:	3.87	1.439	High	7

5.2. SEM Analysis

In this section, the SEM analysis was utilized to test the research hypotheses. The paper presents a measurement model using confirmatory factor analysis (CFA) first, the second to be used is the structural model, and the third are the moderation effects.

5.2.1. Measurement Model

CFA was used to evaluate the properties of the instrument items. In fact, the measurement model signifies how hypothetical constructs are measured in terms of the observed variables and personifies the validity and reliability of the observed variables' responses for the latent variables as in [74–77]. Table 5 presents the factor loadings, Cronbach alpha, composite reliability, and average variance extracted (AVE) for the variables. All the indicators of the factor loadings exceeded 0.50, except for certain items, specifically: IL3 = 0.110, and IL6 = 0.044. The aforementioned items were eliminated, thus constituting evidence of convergent validity as in [74,78]. While the measurement reached convergent validity at the item level because all the factor loadings were above 0.50, all the composite reliability values exceeded 0.60, demonstrating a high level of internal consistency for the latent variables. Additionally, since each value of AVE exceeded 0.50, as in [74,79], the convergent validity was proved.

Table 5. Properties of the final measurement model.

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance	Cronbach Alpha	Composite Reliability *	AVE **
Source Credibility (SC)					0.952	0.97	0.98
SC1	0.722	***	0.521	0.137			
SC2	0.855	0.074	0.911	0.054			
SC3	0.842	0.083	0.708	0.219			
SC4	0.930	0.080	0.865	0.094			
SC5	0.908	0.077	0.824	0.114			
SC6	0.845	0.077	0.893	0.071			
Information Language (IL)					0.895	0.95	0.96
IL1	0.577	***	0.333	0.160			
IL2	0.668	0.101	0.446	0.213			
IL4	0.920	0.137	0.846	0.084			
IL5	0.874	0.165	0.950	0.037			
IL7	0.708	0.098	0.501	0.171			
Intrinsic Information Quality (IIQ)					0.958	0.95	0.96
IIQ1	0.878	***	0.956	0.061			
IIQ2	0.778	0.018	0.606	0.271			
IIQ3	0.838	0.014	0.879	0.145			
IIQ4	0.856	0.015	0.733	0.180			
IIQ5	0.848	0.015	0.899	0.144			
Contextual Information Quality (CIQ)					0.989	0.65	0.99
CIQ1	0.508	***	0.248	0.263			
CIQ2	0.875	0.261	0.950	0.070			
CIQ3	0.871	0.260	0.942	0.081			
CIQ4	0.814	0.232	0.835	0.200			
CIQ5	0.870	0.180	0.940	0.040			
CIQ6	0.878	0.254	0.957	0.057			
CIQ7	0.829	0.156	0.687	0.193			
CIQ8	0.882	0.259	0.963	0.050			
CIQ9	0.853	0.155	0.728	0.161			
CIQ10	0.884	0.259	0.967	0.045			

Table 5. *Cont.*

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance	Cronbach Alpha	Composite Reliability *	AVE **
CIQ11	0.918	0.225	0.843	0.178			
CIQ12	0.822	0.226	0.849	0.172			
CIQ13	0.877	0.262	0.955	0.065			
CIQ14	0.877	0.261	0.954	0.065			
CIQ15	0.822	0.238	0.850	0.189			
CIQ16	0.876	0.259	0.952	0.066			
Accessibility Information Quality (AIQ)					0.973	0.94	0.98
AIQ1	0.846	***	0.716	0.071			
AIQ2	0.816	0.037	0.666	0.094			
AIQ3	0.877	0.068	0.955	0.062			
AIQ4	0.853	0.070	0.908	0.124			
AIQ5	0.719	0.053	0.517	0.248			
AIQ6	0.831	0.068	0.867	0.162			
AIQ7	0.853	0.049	0.909	0.060			
AIQ8	0.828	0.067	0.862	0.161			
AIQ9	0.878	0.060	0.771	0.188			
AIQ10	0.832	0.066	0.868	0.151			
AIQ11	0.809	0.056	0.827	0.136			
Information Usefulness (IU)					0.974	0.96	0.90
IU1	0.887	***	0.974	0.036			
IU2	0.922	0.015	0.849	0.173			
IU3	0.885	0.009	0.970	0.041			
Information Quality (IQ)					0.969	0.96	0.89
IQ1	0.924	***	0.854	0.195			
IQ2	0.877	0.017	0.955	0.052			
IQ3	0.880	0.017	0.960	0.046			
Information Adoption (IA)					0.979	0.97	0.98
IA1	0.920	***	0.846	0.201			
IA2	0.876	0.018	0.952	0.057			
IA3	0.881	0.018	0.963	0.045			
IA4	0.899	0.024	0.808	0.255			
IA5	0.880	0.018	0.960	0.049			
Academic Achievement (AA)					0.985	0.96	0.97
AA1	0.878	***	0.957	0.060			
AA2	0.843	0.014	0.889	0.132			
AA3	0.877	0.012	0.954	0.065			
AA4	0.847	0.015	0.897	0.146			
AA5	0.930	0.015	0.866	0.166			
AA6	0.844	0.015	0.890	0.150			
AA7	0.862	0.016	0.925	0.154			

* Utilizing Fronell and Larcker's [80] formula of CR and ** AVE, *** null value.

Additionally, as seen in Table 6, to provide discriminant validity [75], intercorrelations between constructs–pairs are less than the square root of the AVE estimates. Subsequently, the measurement results indicated that this study had adequate levels of convergent and discriminant validity. According to Table 6, the least correlated constructs are SC and IL with (0.714), while the most correlated were SC with AIQ, SC with IQ, and SC with IA (0.900, 0.923, 0.921), respectively. Other correlations were above 0.800 and below 0.900. Hence, there is a high correlation between the source credibility (SC) and information quality (IQ) and information adoption (IA). On the other hand, the least correlated according to this research finding is credibility with information language (IL).

Table 6. Correlations of constructs.

Constructs	SC	IL	IIQ	CIQ	AIQ	IU	IQ	IA	AA
SC	0.98								
IL	0.714	0.97							
IIQ	0.836	0.815	0.97						
CIQ	0.888	0.821	0.888	0.99					
AIQ	0.900	0.820	0.887	0.883	0.98				
IU	0.871	0.899	0.877	0.878	0.876	0.95			
IQ	0.923	0.843	0.854	0.836	0.847	0.843	0.94		
IA	0.921	0.819	0.853	0.834	0.846	0.850	0.885	0.98	
AA	0.881	0.879	0.878	0.871	0.879	0.873	0.857	0.859	0.98

Note: Diagonal elements are square roots of the average variance extracted for each of the ten constructs. Off diagonal elements are the correlations between constructs.

5.2.2. Structural Model

Structural equation modeling (SEM) using Amos 20 was performed to test the study hypotheses. SEM allows simultaneous testing of all hypotheses including direct effects. The results of the direct effects indicate that while source credibility (SC) impacted information usefulness (IU), information language (IL) did not. Consequently, while H1 was accepted, H2 was not supported. Moreover, intrinsic information quality (IIQ), contextual information quality (CIQ), and accessibility information quality (AIQ) impacted information quality (IQ); thus, H3, H4, and H5 were supported. The results found that information quality (IQ) impacted information usefulness (IU), and the latter had an effect on information adoption (IA), and, in turn, on academic achievement (AA); consequently H6, H7, and H8 were supported.

Moreover, the coefficient of determination (R^2) for the research endogenous variables IQ, IU, IA, and AA were 0.929, 0.922, 0.945, and 0.928, respectively, which suggests that the research model does account for the variation. Table 7 below presents an abstract of the tested hypotheses.

Table 7. Summary of the results for the research theoretical model.

Research Proposed Paths	Coefficient Value	t-Value	*p*-Value	Empirical Evidence
H1: SC → IU	0.233	16.344	0.000	Supported
H2: IL → IU	0.009	0.507	0.612	Not supported
H3: IIQ → IQ	0.084	7.720	0.000	Supported
H4: CIQ → IQ	1.012	95.741	0.000	Supported
H5: AIQ → IQ	0.053	4.215	0.000	Supported
H6: IQ → IU	0.861	89.513	0.000	Supported
H7: IU → IA	0.952	109.907	0.000	Supported
H8: IA → AA	1.041	95.116	0.000	Supported

To reflect the results shown in Tables 3 and 7 onto the proposed model, Figure 2 was developed to show with a graph and numbers the results of this research. The figure shows the mean and standard deviation for each construct. Moreover, it reflects the value of coefficient of determination (R^2) for each intermediate construct and the coefficient value for each relation.

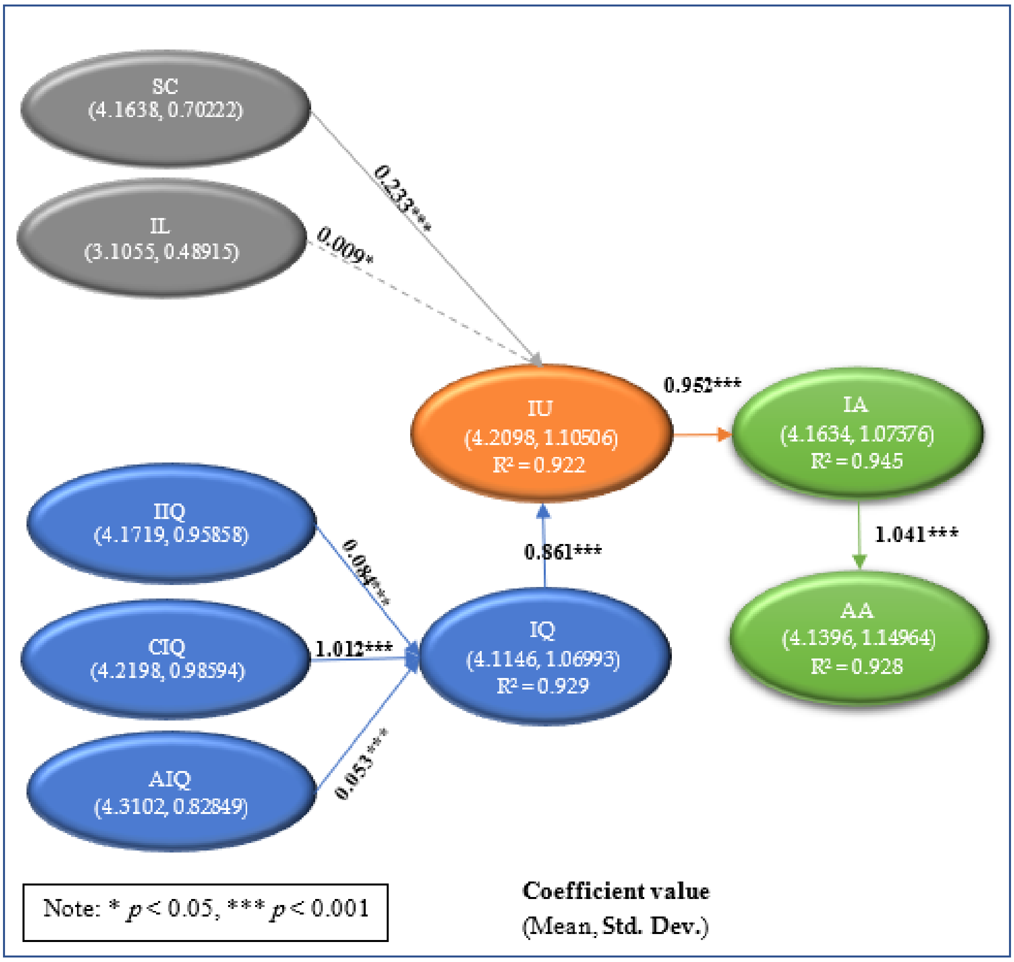

Figure 2. Proposed model with results' coefficient value, mean, and Std. Dev. reflected.

5.3. Moderation Effects

Hypotheses H9, H10, H11, and H12 argued that there is a significant difference in the respondents' information adoption (IA) due to age, gender, education level, and previous experience. An independent samples *t*-test was utilized in order to explore if there were any significant differences in the respondents' information adoption (IA) that can be attributed to gender. Additionally, the ANOVA test was employed to examine if there were any significant differences in the respondents' information adoption that could be attributed to age, education level, and previous experience. The results of the *t*-test, displayed in Table 8, indicate that there is a significant difference in the information adoption that can be attributed to gender, that goes for males more than females.

Table 8. The *t*-test of the respondents' information adoption (IA) attributed to gender.

Variable	Male			Female			*T*	df	Sig.
	N	Mean	Std. Dev.	N	Mean	Std. Dev.			
Information adoption	293	4.8498	0.39219	411	3.6740	1.13601	19.423	537.458	0.000

In addition, the outcomes of the ANOVA test, presented in Table 9, indicate that there is a significant difference in the respondents' information adoption (IA) supportive of age, education level, and previous experience.

Table 9. ANOVA analysis of respondents' information adoption (IA) attributed to age, education level, and previous experience.

Variable		Sum of Squares	Df	Mean Square	F	Sig.
Information adoption attributed to age.	Between Groups	524.371	4	131.093	320.216	0.000
	Within Groups	286.163	699	0.409		
	Total	810.534	703			
Information adoption attributed to education level	Between Groups	262.877	2	131.438	168.241	0.000
	Within Groups	547.658	701	0.781		
	Total	810.534	703			
Information adoption attributed to previous experience	Between Groups	416.788	2	208.394	371.011	0.000
	Within Groups	393.746	701	0.562		
	Total	810.534	703			

However, Table 10 provides the statistical significance of the differences between each pair of groups for age. As observed in Table 10, the five groupings (i.e., 18 to less than 34, 34 to less than 44, 44 to less than 54, 54 to less than 64, and 64 and over) were statistically different from one another.

Table 10. Multiple comparisons analysis of the information adoption (IA) attributed to age.

(I) Age	(J) Age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
18 to less than 34	34 to less than 44	2.00912 *	0.05626	0.000	1.8553	2.1630
	44 to less than 54	0.31540	0.14593	0.196	−0.0837	0.7145
	54 to less than 64	0.23540	0.20436	0.779	−0.3235	0.7943
	64 and over	0.07540	0.37052	1.000	−0.9379	1.0888
34 to less than 44	18 to less than 34	−2.00912 *	0.05626	0.000	−2.1630	−1.8553
	44 to less than 54	−1.69371 *	0.15103	0.000	−2.1068	−1.2807
	54 to less than 64	−1.77371 *	0.20803	0.000	−2.3427	−1.2048
	64 and over	−1.93371 *	0.37256	0.000	−2.9526	−0.9148
44 to less than 54	18 to less than 34	−0.31540	0.14593	0.196	−0.7145	0.0837
	34 to less than 44	1.69371 *	0.15103	0.000	1.2807	2.1068
	54 to less than 64	−0.08000	0.24781	0.998	−0.7577	0.5977
	64 and over	−0.24000	0.39615	0.974	−1.3234	0.8434
54 to less than 64	18 to less than 34	−0.23540	0.20436	0.779	−0.7943	0.3235
	34 to less than 44	1.77371 *	0.20803	0.000	1.2048	2.3427
	44 to less than 54	0.08000	0.24781	0.998	−0.5977	0.7577
	64 and over	−0.16000	0.42119	0.996	−1.3119	0.9919
64 and over	18 to less than 34	−0.07540	0.37052	1.000	−1.0888	0.9379
	34 to less than 44	1.93371 *	0.37256	0.000	0.9148	2.9526
	44 to less than 54	0.24000	0.39615	0.974	−0.8434	1.3234
	54 to less than 64	0.16000	0.42119	0.996	−0.9919	1.3119

* The mean difference is significant at the 0.05 level.

Table 11 shows the statistical significance of the differences between each pair of groups for education level. The three groups (i.e., bachelor, master, and PhD) were statistically different from each other.

Table 11. Multiple comparisons analysis of the information adoption (IA) attributed to education.

(I) Education Level	(J) Education Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Bachelor	Master	1.23413 *	0.06736	0.000	1.0759	1.3923
	PhD	0.40629	0.23306	0.190	−0.1411	0.9537
Master	Bachelor	−1.23413 *	0.06736	0.000	−1.3923	−1.0759
	PhD	−0.82785	0.23321	0.001	−1.3756	−0.2801
PhD	Bachelor	−0.40629	0.23306	0.190	−0.9537	0.1411
	Master	0.82785 *	0.23321	0.001	0.2801	1.3756

* The mean difference is significant at the 0.05 level.

Table 12 presents the statistical significance of the differences between each pair of groups for previous experience. The three groups (i.e., low, good, and excellent) were statistically different from one another.

Table 12. Multiple comparisons analysis of the information adoption attributed to previous experience.

(I) Previous Experience	(J) Previous Experience	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Low	Good	1.18695 *	0.07342	0.000	1.0145	1.3594
	Excellent	−0.59948 *	0.07084	0.000	−0.7659	−0.4331
Good	Low	−1.18695 *	0.07342	0.000	−1.3594	−1.0145
	Excellent	−1.78642 *	0.06610	0.000	−1.9417	−1.6312
Excellent	Low	0.59948 *	0.07084	0.000	0.4331	0.7659
	Good	1.78642 *	0.06610	0.000	1.6312	1.9417

* The mean difference is significant at the 0.05 level.

This section presented the moderation effects reflected in H9, H10, H11, and H12. The hypothesis H10 pertaining to gender was validated using a *t*-test. Additionally, ANOVA analysis and multiple comparison analysis validated the influence of age (H9), education level (H11), and previous experience (H12) on information adoption (IA).

5.4. Machine Learning Techniques' Validation and Predictions

The study evaluates five machine learning (ML) classification techniques, which take inherited information from a dataset's input and convert it into a desired output pattern [81]. The five ML models utilized to create and assess models for the YouTube dataset application were ANN [82], linear regression [83], SMO [84], bagging using the REFTree model [85], and random forest [86]. The back-propagation approach is used by the ANN to estimate the error values between the prediction and actual output values. The error is then used to change the weights and bias settings of the ANN architecture, bringing the predicted and real values closer together. The linear regression model is a polynomial function with weighted coefficients for the predictor factors and an outcome that is target dependent. The training phase updates the coefficients of the linear function from the training dataset. The SMO updates the weighted vectors of the SVM model using the sequential minimal optimization algorithm. From a random sampling of the objects and characteristics in the training set, the bagging technique builds several REFTree models, with the average value of the trees providing the final predicted value. The random forest (RF) is a decision tree (DT) model with a random sampling of training data items and random attribute subsets for each subtree. The model's final output is represented by the average value of the DT trees.

5.5. Validation and Predictions

This study aimed to investigate the various factors that have an impact on the adoption of YouTube as a learning tool, which affirmably influences AA in a bilingual academic environment. The factors most likely connect the quality of the YouTube resource and the perceived information in achieving high-quality scores in academic environments. Consequently, intelligent approaches have to be utilized to predict the perceiving information quality from a different perspective. This study conducted several experiments using supervised ML techniques to validate the information quality learned using YouTube as a learning tool. As shown in Figure 3, the proposed model comprises four dataset models that are considered as the input to ML techniques. These models are: (1) Model 1, which has three inputs that are SC, IL, and IQ as independent variables and IU as a dependent variable, (2) Model 2, which also contains three factors that are IIQ, CIQ, and AIQ to predict IQ as a dependent variable, and (3) Model 3 and Model 4, each of which has one input and dependent variable, IU to IA and IA to AA, respectively. The experimental results are shown in Figure 4 using R^2 and Mean Square Error (MSE) as evaluation metrics. The R^2 and MSE values are displayed on the *y*-axis, while the models are depicted on the *x*-axis. The R^2 indicates how the independent values are anticipated to affect the dependent variable (target). The MSE measures the average difference between a model's evaluated and actual output values.

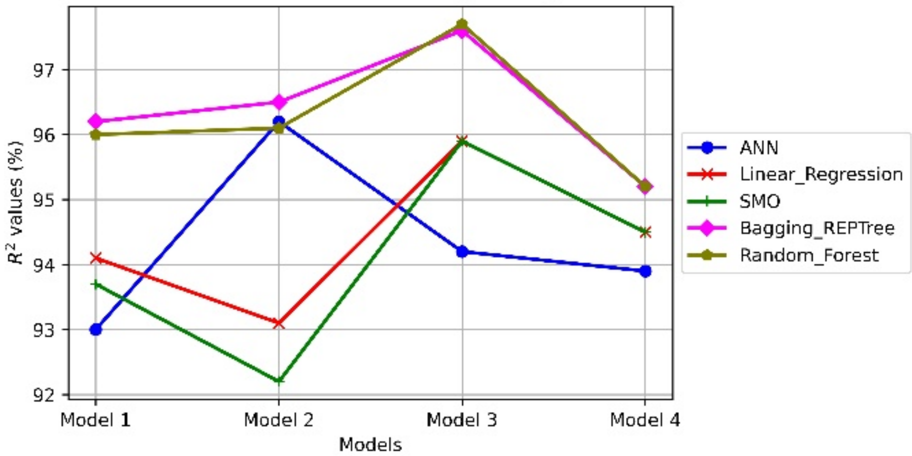

Figure 3. The R^2 results of using ML techniques on YouTube dataset.

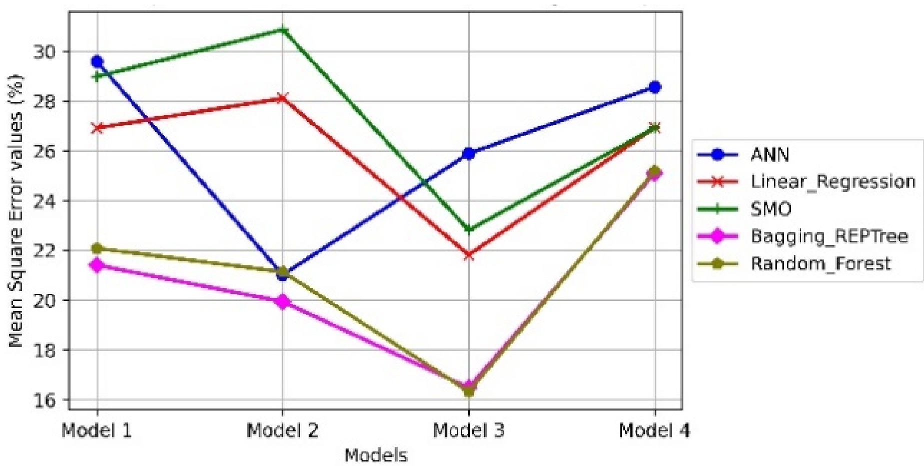

Figure 4. The MSE results of using ML techniques on YouTube dataset.

When compared to other ML techniques, the random forest and bagging REPTree ML models, as shown in Figure 3, give remarkable results reaching up to approximately 98%. This suggests that the tree-based models are more correlated to the target labels. Despite the strong performance of tree-based models, the other ML approaches produce reasonable outcomes of approximately 92%. These findings provide evidence about the effectiveness of ML to predict the information quality (IQ) when depending on the YouTube learning tool. Furthermore, Figure 4 ensures the effectiveness of the tree-based models that accomplish low MSE values flanked by the target and the actual values of the model.

6. Discussion and Conclusions

As people shift towards using YouTube as a learning tool with academic achievement (AA) as an incentive, many practical and theoretical implications arise from such a change.

In general, according to Table 3 and reflected in Figure 2, the most influential factors in the proposed model were the independent variables contextual information quality (CIQ) and accessibility information quality (AIQ), and the mediating variable information usefulness (IU), while five other variables ranked as "high", namely: the independent variables source credibility (SC) and intrinsic information quality (IIQ), the mediating variables information quality (IQ) and information adoption (IA), and the dependent variable academic achievement (AA). On the other hand, the independent variable information language (IL) ranked as "moderate". In layman's terms, the respondents ranked contextual and accessibility qualities and usefulness as more important than information language. In fact, when examining Table 4, some items in the IL variable ranked as low (IL4, Il5) pertaining to TV language, while IL3 and IL6 ranked high pertaining to magazines and YouTube language, which reflected that the respondents did not rank Arabic speaking TV shows, while they ranked as "high" Arabic speaking YouTube and magazines. Furthermore, IL1 and IL2, which pertain to Arabic newspapers and books, were ranked as moderate. All other constructs were ranked as "high" and "very high".

6.1. Theoretical Contribution

The results of this research can be used by many: educational institutes, teachers, publishers, researchers, and students. YouTube is used as a learning tool by many prestigious educational institutes such as MIT and Berkley, which is a wake-up call for other educational institutes. As such, this makes YouTube an established venue. Competition among educational YouTubers is the way to perfection, which is reflected in the number of views. Publishers in the future may accompany each published book with a YouTube video, much like PowerPoint slides. Based on the findings of this research, students value the credibility of the source very much. Hence, the publisher's YouTube channels will be more attractive to students than others. Content quality and accuracy are much needed aspects on YouTube, where source credibility is an essential factor. As the number of views on YouTube may work as a source of income, YouTubers may pay more attention to their delivery style.

Information language (IL) is an important factor. As a result, many may deliver knowledge to knowledge seekers via YouTube. Still, according to this research, such a hypothesis was not supported. In fact, the research indicated, in Table 6, that SC correlated the least with IL, and correlated the highest with AIQ, IQ, and IA. Hence, there is a high correlation between SC, IQ, and IA. On the other hand, the least correlated, according to this research finding, is the credibility with IL.

The H1 hypothesis, which reflects the impact of SC positively influencing IU is supported, hence agreeing with the findings of [35] as well as [34,54,55,57]. SC ranked as "high" in Table 3.

The H2 hypothesis, which reflects the impact of information language (IL) positively influencing information usefulness (IU) was not supported, hence disagreeing with the findings of [35–39]. IL ranked as "moderate" in Table 3.

The H3–H5 hypotheses, which reflect the impact of IIQ, CIQ, and AIQ positively influencing IQ, were supported, hence agreeing with the findings of [34,35,40]. AIQ and CIQ ranked as "very high", while IIQ ranked as "high" according to Table 3.

The H6 hypothesis, which reflects the impact of information quality (IQ) positively influencing information usefulness (IU), was supported, hence agreeing with the findings of [34,35,40]. IQ ranked as "high" in Table 3

The H7 hypothesis, which reflects the impact of information usefulness positively influencing information adoption (IA), was supported, hence agreeing with the findings of [16,34,35]. IU ranked as "very high" in Table 3.

The H8 hypothesis, which reflects the impact of information adoption (IA) positively influencing academic achievement (AA), was supported, hence agreeing with the findings of [4,8–10,34,35,41,42]. IA and AA both ranked as "high" according to Table 3.

As for the moderating variables, age, gender, education level, and previous experience, these are shown in hypotheses H9–H12. There is a significant difference in the information adoption (IA) that can be credited to gender, that goes for males more than females. This research used a *t*-test in Table 8, and the results, shown in Table 8, agreed with the findings from [47–50,53,64]. There is a significant difference in the information adoption that can be attributed to age. This research used the ANOVA test, shown in Table 9, and multiple comparisons analysis, shown in Table 10; the results agreed with the findings from [47,50–52,63]. There is a significant difference in the information adoption that can be credited to age and education level. This research used multiple comparisons analysis, shown in Table 11, and the results agreed with the findings from [46,52,65]. There is a significant difference in the information adoption that can be credited to previous experience. This research used multiple comparisons analysis, shown in Table 12, and the results agreed with the findings from [6].

The model was validated using ML techniques by comparing MSE, and R^2 from SEM results, with ML results. Hence, the model can predict the value with high accuracy, 98%, when using random forest and bagging REPTree. The other models' accuracy reached 92%.

6.2. Practical Implications

Teachers are challenged as they are no longer the only source of delivering knowledge to students. There are hundreds, if not thousands, of sources on YouTube. Such a challenge is not only for teachers but also educational institutes as well as libraries. Hence, the educational institutes are challenged to produce YouTube channels that deliver educational materials. Many educational institutes have taken major steps towards such a goal, while other educational institutes are delaying the inevitable or burying their heads in the sand. The quality of the presentation, as shown previously, is very important.

Teachers are challenged in their delivery of knowledge methods. The number of views is a reflection of the teacher's performance as is the like/dislike button; therefore, teachers must prepare and plan their lessons. Moreover, the credibility of the source is very important, as shown previously, which influences the information usefulness. Furthermore, the credentials of the presenter are very important.

The positive influence of Information usefulness (IU) on information adoption (IA) is very important, as shown previously; hence, the material delivered to students should reflect this.

Students are adopting information for the purpose of academic achievement, which is evident from previous research; hence, the goal of any YouTube film should be to be clear and to the point.

The student's age, gender, education level, and previous experience must be considered when presenting education materials on YouTube. In live lectures, a teacher can assess the audience and calibrate their presentation to the age, gender, education level, and previous experience, while such an option is not available on YouTube; therefore, the teacher must accommodate a rainbow of options. As such, meticulous preparation and planning is needed so that students with less experience can be accommodated as can older generations and females.

The proposed model can be used by teachers, educational institutes, researchers, and practitioners to create YouTube content that meets the needs of students and increases the sharing intent.

As such, teachers should be equipped with better cameras, better sound systems, a smart pad/phone, internet service provider and electronic pen and board. Long gone are the days of a regular pen and board. All this equipment will entail financial burdens on the teacher/institute, further added to by the demands from the teacher/institute for smart gadgets and the IoT. In addition, there is a need for training to deal with such technologies. In fact, the classroom environment will need to change to accommodate such a demand for YouTube as a learning tool.

6.3. Limitations and Future Research

In this study the researchers faced two main limitations. First was the lack of access to YouTube statistics to compare with the research questionnaire responses. Such studies and statistics are not available through YouTube itself. Second, due to the COVID-19 pandemic, lockdowns, and social distancing, face to face interviews and direct watching of respondents was not possible.

Still, this research drew the attention of the researchers to several factors that are very interesting to pursue for future research. Shortness and ease of explanation are also two important factors that leaners look for in educational YouTube content with animation that draws learners to YouTube over another provider. As stated by an interviewee, it must be "short and sweet". Hence, the question of the length of videos is that shorter YouTube videos are more attractive than longer ones. Moreover, the quality of the production of the YouTube film is important.

Does showing the teacher's face affect the number of views? Seeing the presenter of the education material may affect the understanding of the lesson, and the teaching manner and use of animation, pen and paper, and board in the presentation are other factors that need to be investigated.

Do teachers' accents affect the views of an educational YouTube? Accent when spoken in English or Arabic is another factor that influences the number of views. Some accents are more popular than others, for example, the Egyptian accent in Arabic is well understood due to TV shows and movies; hence, it is better understood than other Arabic accents. Furthermore, American and British accents are more popular than other English-speaking countries. A suggestion for future research is to investigate whether AI can be involved in changing the accents of the speaker to make the accent more understandable.

In addition, as future work, the ML methods can be developed further to predict the information adoption (IA) of YouTube as a learning tool and its influence on academic achievement (AA). Furthermore, this can be expanded to include the proposed model and other constructs.

6.4. Conclusions

In conclusion, this research was set up to investigate the various factors that influence the use of YouTube as a learning tool, which influences academic achievement in a bilingual academic context. A model was suggested, and hypotheses were developed. The hypotheses were tested using SEM, CFA, and ML methods. The results showed that academic achievement (AA) is influenced by information adoption (IA) of YouTube as a learning tool. Information adoption (IA) was influenced by information usefulness (IU). Source credibility (SC) and information quality (IQ) both influence information usefulness (IU), while information language (IL) does not. Information quality (IQ) is influenced by the intrinsic, contextual, and accessibility information quality. Two interesting findings that we can conclude with are: first, the respondents ranked contextual and accessibility qualities and usefulness as more important than information language. The second, there is a significant difference in the information adoption (IA) that can be credited to age, gender, education level, and previous experience. As such, all previously mentioned factors must be considered for a YouTube educational film.

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Appendix A

Table A1. Constructs and items.

Construct/Item		Source
	Gender 1. Male 2. Female	
	Age 1. 18 to less than 34 2. 34 to less than 44 3. 44 to less than 54 4. 54 to less than 64 5. More than 64	
	Educational Level 1. BSC 2. Master 3. PhD	
	Previous experience 1. Weak 2. Good 3. Excellent	
Information Quality (IQ)	IQ1. I think the YouTube channel I follow provide high quality information IQ2. I think the YouTube channel I follow provide clear information IQ3. I think the YouTube channel I follow provide understandable information	[16,40]
Information Adoption (IA)	IA1. The YouTube channel I follow made it easy for me to understand the topic. IA2. The YouTube channel I follow have enhanced my effectiveness in understanding the topic. IA3. The YouTube channel I follow have motivated me to understand the topic. IA4. I will follow the method taught in the YouTube channel I follow to understand the topic. IA5. The YouTube channel I follow contributed to my knowledge about the topic	[16,34,35,66]
Information Usefulness (IU)	IU1 The topic-related information at the YouTube channel I follow is valuable. IU2 The topic-related information at the YouTube channel I follow is informative. IU3 The topic-related information at the YouTube channel I follow is helpful.	[34,35]
Information language (IL)	IL1 The newspapers that I read are always in Arabic. IL2 Most of the books that I read are in Arabic. IL3 The magazines that I read are always in Arabic. IL4 Most of my favorite shows on TV are in Arabic. IL5 I prefer to watch Arabic –language TV over any other language I may speak. IL6 I prefer to watch Arabic –language YouTube over any other language I may speak. IL7 I don't mind watching YouTube with Arabic subtitle.	[35]

Table A1. *Cont.*

Construct/Item		Source
Source credibility (SC)	SC1 The information in the YouTube channel I follow is believable SC2 The information in the YouTube channel I follow is factual SC3 The information in the YouTube channel I follow is credible SC4 The information in the YouTube channel I follow is trustworthy SC5 The information in the YouTube channel I follow is Knowledgeable. SC6 The information in the YouTube channel I follow is Expert.	[35,66]
Intrinsic Information Quality (IIQ)	IIQ1. The YouTube channel I follow produces correct information. IIQ2. There are few errors in the information I obtain from the YouTube channel I follow. IIQ3. ACCU3: The information provided by the YouTube channel I follow is accurate. IIQ4. The YouTube channel I follow is objective. IIQ5. The YouTube channel I follow provides impartial view of the topic.	[40,67,68]
Contextual Information Quality (CIQ)	CIQ1. The YouTube channel I follow is concise. CIQ2. The YouTube channel I follow allows me to verify their results. CIQ3. The YouTube channel I follow provides me with resources to verify their work. CIQ4. The YouTube channel I follow allows me to access their sources. CIQ5. The YouTube channel I follow is clear and easy to understand. CIQ6. The YouTube channel I follow is presented consistently. CIQ7. The YouTube channel I follow is formatted concisely. CIQ8. The YouTube channel I follow has clear meaning. CIQ9. The YouTube channel I follow is easy to comprehend. CIQ10. The YouTube channel I follow provides enough information. CIQ11. The YouTube channel I follow provides me with adequate amount of information. CIQ12. The YouTube channel I follow has good reputation among my peers. CIQ13. The YouTube channel I follow has good reputation among my teachers. CIQ14. The YouTube channel I follow provides me with a complete set of information. CIQ15. The YouTube channel I follow produces comprehensive information. CIQ16. The YouTube channel I follow provides me with all the information I need.	[40]
Accessibility information quality (AIQ)	AIQ1. The YouTube channel I follow is available 24/7. AIQ2. The information in the YouTube channel I follow is relevant. AIQ3. The information in the YouTube channel I follow is clear. AIQ4. The information in the YouTube channel I follow is applicable. AIQ5. The information in the YouTube channel I follow is strong. AIQ6. The YouTube channel I follow allows information to be readily accessible to me. AIQ7. The YouTube channel I follow makes information very accessible. AIQ8. The YouTube channel I follow makes information easy to access. AIQ9. It takes too long for the YouTube channel I follow to respond to my requests (RC). AIQ10. The YouTube channel I follow provides information in a timely fashion. AIQ11. The YouTube channel I follow returns answers to my requests quickly.	[40,69]
Academic achievement (AA)	AA1. YouTube are useful to me as a student. AA2. YouTube have a positive impact on my Academic Achievement. AA3. YouTube help me to achieve my academic goals. AA4. The use of YouTube helps to improve my contact with my colleagues and teachers as well as my performances academic. AA5. Skills and knowledge obtained during studying YouTube are very important to my performance and academic achievement. AA6. I know the most important concepts and facts relating to YouTube communications have improved. AA7. The study of topics related to YouTube has a positive impact on my life in the future.	[69,70] Adopted from [71]

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