# مجلة بحوث الأعمال

https://abs.journals.ekb.eg

المعهد العالى للإدارة وتكنولوجيا المعلومات بكفرالشيخ

العدد: الأول

المجلد: الاول

يوليو ٢٠٢٤

# Factors Affecting the Adoption of Artificial Intelligence in the Lebanese Education Sector

**Dr/ Soumaya Kaakour**

Assistant Professor at Beirut Arab University, Beirut, Lebanon

Marketing specialist at Planforge consultancy

## Abstract

The education sector is leveraging cutting-edge technologies like artificial intelligence (AI) to provide better service and experience for students. These technological advancements transformed education into smart education, hence unlocking pristine avenues for research. This research examined the relationship between the factors that could affect the adoption of artificial intelligence in the Lebanese education sector. 300 respondents have been collected by using online survey form. Data has been analyzed, the findings indicated that the following factors (perceived curiosity, electronic word-of -mouth, self-efficiency, privacy and security, and awareness) have positive relationship toward the adoption of artificial intelligence in the Lebanese education sector. This study adds to existing theoretical knowledge of artificial intelligence in the education sector solutions where policymakers could use the findings to regulate the adoption toward artificial intelligence in the Lebanese education sector. Finally, conclusions and future research will be presented in this paper.

**Keywords**: Perceived curiosity, electronic word-of-mouth, self- efficiency, privacy and security, awareness, Adoption toward Artificial intelligence.

**المستخلص:**

القطاع التعليمي يستخدم أحدث التقنيات مثل الذكاء الاصطناعي (AI) لتقديم خدمات وتجارب أفضل للطلاب. هذه التطورات التكنولوجية حولت التعليم إلى تعليم ذكي، مما فتح آفاقًا جديدة للبحث. هذه الدراسة قامت بفحص العلاقة بين العوامل التي قد تؤثر على تبني الذكاء الاصطناعي في قطاع التعليم اللبناني. تم جمع ٣٠٠ استجابة باستخدام استمارة استبيان عبر الإنترنت. تم تحليل البيانات، وأظهرت النتائج أن العوامل التالية (الفضول المدرك، التسويق الإلكتروني الشفهي، الكفاءة الذاتية، الخصوصية والأمان، والوعي) لها علاقة إيجابية تجاه تبني الذكاء الاصطناعي في قطاع التعليم اللبناني. تضيف هذه الدراسة إلى المعرفة النظرية القائمة حول حلول الذكاء الاصطناعي في قطاع التعليم، حيث يمكن لصانعي السياسات استخدام النتائج لتنظيم عملية التبني نحو الذكاء الاصطناعي في قطاع التعليم اللبناني. أخيرًا، سيتم تقديم الاستنتاجات والبحث المستقبلي في هذه الورقة.

**الكلمات المفتاحية:** الفضول المدرك، التسويق الإلكتروني الشفهي، الكفاءة الذاتية، الخصوصية والأمان، الوعي، التبني نحو الذكاء الاصطناعي.

## 1. Research Background

Artificial Intelligence (AI) has already become part of our everyday life (e.g. *intelligent household appliances, smartphones, Google, Siri, AI in computer games, . . .* ). Many of us know about the existence of services and devices based on AI. The term “Artificial Intelligence” was coined by Marvin Minsky and John McCarthy in 1956 (Haenlein & Kaplan, 2019). Tussyadiah (2020) defined AI as “thinks humanly acts humanly, thinks rationally, or acts rationally”. AI is a computing process that tries to emulate human learning, based on data, arriving at decisions similar to human cognition, which is especially useful in learning (Johnson et al., 2021). As a major source of innovation, AI has been increasingly adopted in the educational sector to provide the requisite impetus to the educational sector; hence, marketers should be aware of end-users’ perspectives (Samara et al., 2020). Reactions to these tools are the most extreme, a true reflection of general behavior towards innovation. More specifically, ChatGPT is responsible for the leap due to its capabilities to generate texts with high argumentative quality and ability to maintain a realistic conversation, all through a simple registration process (free of charge in the version released on November 30, 2022) available to the public (Roose, 2022).

The most catastrophic is to predict adverse effects for democracy or employment in the knowledge sector to mention a couple of examples. This divisive debate, especially skewed towards the harmful effects of the tool, has focused on the domains of Education and scientific production (García-Peñalvo, 2023). Among its advocates, one notable perspective is that of Marc Alier-Forment, who firmly believes that despite its infancy, ChatGPT has surpassed the deceptive level and has reached a disruptive level (García-Peñalvo, 2023). On the one hand, the use of ChatGPT in educational institutions is questioned (Marche, 2022; Stokel-Walker, 2022), and it has even been banned (Ropek, 2023) due to fear that students will use it automatically generate essays or class work. On the other hand, many people emphasize the errors (García-Peñalvo, 2023).

Understanding the perception and adoption of students toward AI is a challenging task for marketers and service providers (Pillai & Sivathanu, 2020). Even though, Yu and Ngan (2019) explored the impact of culture on service experiences delivered through artificial intelligence and suggested further exploration to understand the consumers’ perception toward usage of AI. Lately, based on the analytical hierarchy process, Jabeen et al. (2021) established that students' awareness and knowledge about technology are crucial factors for the implementation of AI in educational sector.

The objective of this paper is to investigate the following factors (perceived curiosity, electronic word-of -mouth, self-efficiency, privacy and security, and awareness) to adopt the adoption of artificial intelligence in the Lebanese education sector.

## 2. Theoretical Background

The theoretical background presents and defines the theory of social cognitive will be used.

### 2.1.Theory of Social Cognitive

Social Learning Theory was proposed in the (Bandura, 1977). SCT states that people learn in a social context through a dynamic interaction, behavior, and environment between them. Furthermore, it considers a person's past experiences contributing to behavioral action. The theory aims to explain how people regulate their behavior through control and reinforcement to achieve a specific behavior that is intended to be maintained over time (Stephan, 2015).

## 3. Literature Review and Hypotheses Development

The next paragraph will include various analysis relationships among variables and whether they have a positive or negative impact on the adoption of artificial intelligence in the educational sector, and it will aid in the construction of hypotheses to explore and obtain findings.

### 3.1.The Effect of Perceived curiosity on the adoption of artificial intelligence in the Lebanese education sector

Curiosity is described as an individual's ability and desired to get information that can be divided into trait and state levels. Trait curiosity is defined when the persons' overall tendency to demand for more information and experience whereas state curiosity proves persons' momentary desire for information. In this study, curiosity allows to capture students' information seeking desired toward adoption of artificial intelligence. Such motivational desire is predictive of future initiation of learning, engagement, and acceptance of the artificial intelligence (Chien et al., 2019). Moreover, perceived curiosity can be used to describe specific conduct as well as to explain the same action in a hypothetical way (Kerr, 2020). A study of the technology acceptance model found a significant association between perceived curiosity and adoption of artificial intelligence (Ceha et al., 2019; Chang, et al., 2013). In addition, according to Mustafa et al., (2022) revealed that curiosity is considered an important predictor toward adoption of AI. the following hypothesis has been framed:

**H1:** Perceived Curiosity is positively effect on the students' adoption toward artificial intelligence in Lebanese education sector.

### 3.2.The Effect of EWOM on the adoption of artificial intelligence in the Lebanese education sector

One of the most powerful and widespread influences on customer behavior is described variably as "social communication," "word of mouth," "opinion leadership," or "buzz." In addition, electronic Word of Mouth are used to describe the effects that consumers have on one another when they communicate. Electronic word-of-mouth (E-WOM) is commonly used in business, is still regarded as the most effective type of advertising, thus marketers place a high value on it (Akdim, 2021). Electronic word-of-mouth (E-WOM) refers to any good or negative statement made about a product or firm by future, present, or past consumers that is made available to a large number of individuals and institutions over the Internet (Simay et al., 2023).

A meta-analysis examines the effect of E-WOM on the adoption of artificial intelligence toward the educational sector (Oday, 2021). Moreover, Verma et al., (2023) revealed that E-WOM had strong predictor in explaining consumers' adoption. Therefore, it can be hypothesized that:

**H2:** E-WOM is positively effect on students' adoption toward artificial intelligence in Lebanese education sector.

### 3.3.The Effect of self-efficiency on the adoption of artificial intelligence in the Lebanese education sector

Bandura (1977) discovered that an individual's self-efficiency has a significant impact on how he directs or tackles his goals, tasks, and obstacles. Self-efficiency is described as a person's confidence in executing a task successfully and without problems (Bandura, 1993). Self-efficiency is a person's belief in their capacity to finish a task or achieve a goal (Bandura, 2000). In addition, Self-efficiency refers to a person's confidence level in their ability to successfully perform a specific behavior **(**Rosen et al., 2009). People who have stronger self-efficiency are more hopeful about using new information technology, adopt it more easily, and have a greater sense of satisfaction (Awajan et al., 2021). Self-efficiency is defined as component of the self-system, which includes a person's attitudes, talents, and cognitive capabilities (Chen, 2022).

According to Cao et al., (2022), indicated that Self-efficacy directly influenced SVA adoption intention. in addition, Elnagar et al., (2021) found a positive relationship between self-efficacy and adoption of artificial intelligence.

Considering the above studies, the following hypothesis has been framed:

**H3**: Self-efficiency is positively effect on students' adoption toward artificial intelligence in Lebanese education sector.

### 3.4.The effect of privacy and security on the adoption of artificial intelligence in the Lebanese education sector

Security concern is known as one of the dimensions of the overarching privacy concerns. According to Belanger et al. (2002), privacy and security concerns should be understood as distinct. Security is the state of being free from danger or threat and privacy is the ability of an individual or group to seclude themselves or information about themselves (Garfinkel et al., 2018, January). According to Sahi et al., (2022) and Marikyan et al., (2022) revealed that there is a positive relationship between privacy and security and the adoption of artificial intelligence in the service industry. According to Cao et al., (2022), indicated that perceived privacy were the significant determinants to adopt the artificial intelligence in the service industry. Moreover, according to Flavián et al., (2022) indicated that customers' technological optimism increases, and insecurity decreases, their intention to use robo-advisors. Considering the above studies, the following hypothesis has been framed:

**H4:** Privacy and security are positively effect on students' adoption toward artificial intelligence in Lebanese education sector.

### 3.5.The Effect of awareness on the adoption of artificial intelligence in the Lebanese education sector

Awareness is the extent to which a target population is aware of the artificial intelligence and formed a general perception of what it entails. The concept of awareness appeared in innovation diffusion theory, which states that the decision-making process for adopting new technologies includes awareness, implementation and confirmation. It is further defined as an individual's active participation and increased interest in focal issues. The concept of awareness is central to human behavior in the social science, criminal justice, and medical behavioral science literature. Awareness is one of the most important components of consciousness raising because it fosters an understanding of the needs, events and processes and it is positively related to individuals' attitudes and cognitive development (Akther & Nur, 2022).

A study explained the role of AI that puts customers into a very passive role and reduces barriers to technology adoption. This analysis explained how consumers become aware of robo-advisors, and how this influences their acceptance by examining IoT awareness, users' and continued intention to use IoT to bring clarity to the growing yet fragmented literature on the path from IoT awareness to the continued use of IoT (Flavián et al., 2022). Moreover, the results indicated a positive relationship between awareness and intention to use artificial intelligence (Koohang et al., 2022).

Considering the above studies, the following hypothesis has been framed:

**H5**: Awareness is positively effect on the adoption of artificial intelligence in the Lebanese education sector.

### 3.6.Conceptual Framework

In this study, a conceptual model was built to explore the impact of five independent factors: perceived curiosity, electronic word-of-mouth, self -efficiency, privacy and security, awareness, on the dependent variable consumers adoptions of artificial intelligence.

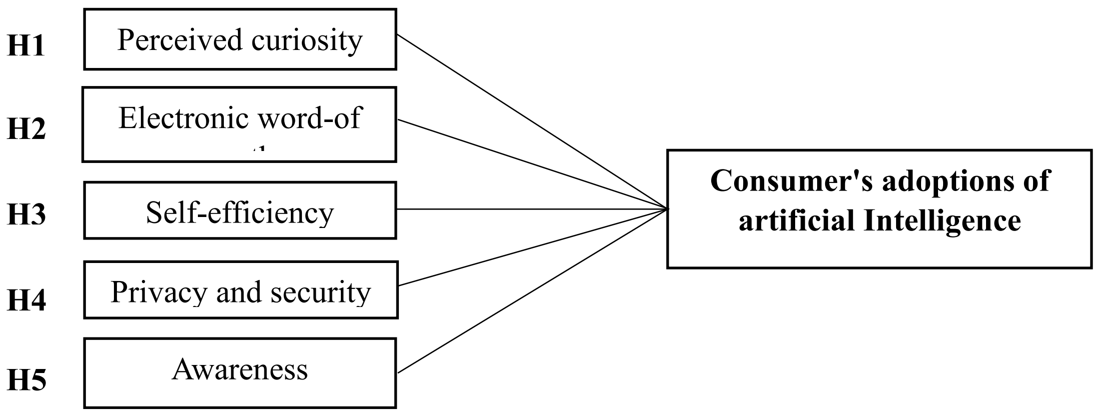


**Figure 1: Research Conceptual Framework.**

**Source: (Majdi.et al., 2021). Adjusted by the researcher.**

### 4.1.Variable’s Measurements

The conceptualization of the variables, as well as the measurement of the variables, are presented in the table below:

**Table 1: Variable’s measurement**

| Variables | Measurement |
|---|---|
| Perceived curiosity | 3 items on 5- point Likert scale according to (Aburbeian et al., 2022) |
| Electronic word of mouth | 4 items on 5- point Likert scale according to (Jiwon, 2019) |
| Self-efficiency | 3 items on 5- point Likert scale according to (Aburbeian et al., 2022). |
| Privacy and security | 3 items on 5- point Likert scale according to (Musaev and Yousoof (2015); Sharma et al. (2018)) |
| Awareness | 3 items on 5- point Likert scale According to (Bhatt & bhatt 2016; Amutha,2016; Hairhara & Pavithra2012; Mobarek 2007) |
| Adoption toward Artificial intelligence | 3 items on 5- point Likert (Bhatt & Bhatt, 2016; Waite and Harrison, 2002 and Swaid and wigard, 2007) |

### 4.2. Research Approach

The researcher will use a quantitative method in his research, employing questionnaire responses as main data and literature evaluations of preview studies as secondary data. Previous data and literature studies were gathered utilizing a quantitative technique in this study.

### 4.3.Population and Sample

All Lebanese students that had a previous experience toward adoption the artificial intelligence in the Lebanese private Universities. Withdrawing samples was chosen to be between the ages of 20 and above, and of both genders. The sample selected from the population, although it is randomly chosen.

In this research convenience sampling is used, it is a sort of non-probability sampling in which the sample is selected from a subset of the population that is nearby. The sample's results are used to build hypotheses regarding the entire population. In practice, the sample size is determined by a variety of factors and skills possessed by the researchers. In fact, the larger the samples, the more complicated and diversified the subject.

### 4.4. Data Collection

This study's data gathered using a self-administered online questionnaire between 30 May, 2023 and 30 August, 2023 in Lebanon. The questionnaire was distributed to 500 students from the target group using Google form with students have been heard about the artificial intelligence or have been adopt the artificial intelligence in the education level. 300 respondents were collected out of 500.

## 5. Descriptive Statistics

Descriptive statistics are a series of brief descriptive coefficients that summarize a set of data. This approach is used in this study to characterize the frequency for each gender, age, and other variables.

### 5.1. Sample Profiling

Demographics are the different features of a population that characterize it, such as age, race, ethnicity, education, economic level, and so on.

**Table 2: Descriptive Statistic for Gender**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Gender | male | 136 | 45.3 | 45.3 | 45.3 |
| | female | 164 | 54.7 | 54.7 | 100.0 |
| | Total | 300 | 100.0 | 100.0 | |
| Age | 20-30 | 163 | 54.3 | 54.3 | 54.3 |
| | 31-40 | 96 | 32.0 | 32.0 | 86.3 |
| | 41-50 | 27 | 9.0 | 9.0 | 95.3 |
| | 51-60 | 12 | 4.0 | 4.0 | 99.3 |
| | 61 and more | 2 | .7 | .7 | 100.0 |
| | Total | 300 | 99.7<br>100.0 | 100.0 | |

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Education level | high school | 13 | 4.3 | 4.3 | 4.3 |
| | graduate study | 88 | 29.4 | 29.4 | 33.7 |
| | Master degree | 172 | 57.3 | 57.3 | 91.0 |
| | PHD degree | 27 | 9.0 | 9.0 | 100.0 |
| | Total | 300 | 99.7 100.0 | 100.0 | |
| Income | $50-$200 | 178 | 59.3 | 59.3 | 59.3 |
| | $200-$800 | 80 | 26.7 | 26.7 | 86.0 |
| | $800-$2000 | 28 | 9.3 | 9.3 | 95.3 |
| | $2000-$5000 | 14 | 4.7 | 4.7 | 100.0 |
| | Total | 300 | 99.7 | 100.0 | |
| Marital status | Married | 79 | 26.3 | 26.3 | 26.3 |
| | Single | 208 | 69.3 | 69.3 | 95.7 |
| | Divorced | 6 | 2.0 | 2.0 | 97.7 |
| | Widowed | 7 | 2.4 | 2.4 | 100.0 |
| | Total | 300 | 99.7 100.0 | 100.0 | |

Table 2 represents the gender of the 300 respondents in Lebanon. The Female valid percent is (54.7 %) and male valid percent is (45.3 %). The results show that females are higher were more interested in adoption of technology than males.

Concerning the age of the respondents in Lebanon. Analysis of the data collected showed that the valid percent were (54.3%) for 20- to 30 years old, (32%) for 31 - 40 years old, (9%) for 41 –50, (4%) for 51-60 years old, (0.7%) for 61 and more- to less than 60 years old. The results show that highest respondents were between 20 - 30 years in

Lebanon. The participants with age 20-30 were more interested in Artificial intelligence than other age demography.

In addition, the findings show the respondents' educational levels in Lebanon, with those with a high school representing (4.3%) of valid percent, those with a graduate study representing (29.4%) of valid percent, those with a master degree representing (57.3%) of valid percent, and those with a PHD degree representing (9%) of valid percent. The majority of respondents in Lebanon had a graduate degree, followed by a master degree. Additionally, the results show annual income level of respondents in Lebanon. Where the respondents who had between $50 to Less - $200 (9.3%) of valid percent, between $200 -$800 (26.7%) of valid percent, between $800 -$2,000 (20%) of valid percent, between $2,000 - $5,000 (4.7%) of valid percent. Thus, the majority of respondents in Lebanon who had an annual income between $50 to Less than $200 representing the highest valid percent (59.3%). Moreover, findings also show the marital status of the respondents in Lebanon, were married valid percent is (26.3%), single valid percent is (69.3%), divorced valid percent is (2%) and widowed valid percent is (2.4%). In Lebanon, the percentage of single respondents is the highest.

### 5.2. Reliability Analysis

The Cronbach alpha test was thought to be a test that evaluates the reliability and internal consistency of a questionnaire that contains several Likert scales and questions. Cronbach alpha is based on the replies provided for each variable (Qader & Albustanj, 2022).

The Cronbach alpha coefficient is a psychometric statistic used to assess the internal consistency or reliability (internal validity) of test questions, or how closely attached a group of items is. Alpha Cronbach's alpha is regarded as a reliability measuring scale.

**Table 3: Cronbach Alpha**

| Variables | Items | Cronbach's Alpha if Item Deleted |
|---|---|---|
| **Perceived curiosity** | **3** | **0.787** |
| **electronic word-of-mouth** | **3** | **0.785** |
| **self-efficiency** | **4** | **0.727** |
| **Privacy and security** | **3** | **0.763** |
| **Awareness** | **3** | **0.764** |

| | | |
|---|---|---|
| **Adoption of artificial Intelligence** | **3** | **0.781** |

The alpha coefficients for Perceived curiosity, electronic word-of-mouth, self-efficiency, Privacy and security, Awareness, adoption of artificial intelligence was (0.785), (0.787), (0.781), (0.727), (0.763), and (0.764), as shown in the table 3 above.

### 5.3.KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) Test assesses how well the given data is suited for factor analysis. KMO determines how sufficient each variable in the model is in respect to the overall model. This statistic examines the variation level that may be shared by the variables. The lower this level, the more suited the data is.

**Table 4: KMO and Bartlett's Test**

| Variables | KMO | Bartlett test | P |
|---|---|---|---|
| Perceived curiosity | 0.500 | 819.103 | 0.000 |
| electronic word-of-mouth | 0.497 | 929.055 | 0.000 |
| self-efficiency | 0.500 | 131.398 | 0.000 |
| Privacy and security | 0.522 | 0.392 | 0.000 |
| Awareness | 0.628 | 93.962 | 0.000 |
| Adoption of Artificial Intelligence | 0.501 | 22.455 | 0.000 |

The KMO test was used to assess the sampling appropriateness of each model element and to forecast if the questionnaire objects were likely to be factored based on the partial correlation and correlation. The KMO test has a range of 0 to 1.0, with an average result of 0.5 or above allowing factor analysis to proceed easily. All of the numbers above, as stated in table 10, are between 0.0 and 1.0 and more than 5. The second column shows the usage of the Bartlett measure, which tests for variance homogeneity and that variances are equal for all samples. It demonstrates that the assertion of equal variances is accurate until such statistical tests as the ANOVA are done.

**Table 5: ANOVA**

| Model | | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 17.925 | 5 | 3.586 | 226.334 | 0.000[b] |

| | | | | | | |
|---|---|---|---|---|---|---|
| Residual | 6.188 | 294 | 0.016 | | | |
| Total | 24.113 | 299 | | | | |

a. Dependent variable: adoption of Artificial Intelligence

b. Predictors: (constant): perceived curiosity, electronic word-of-mouth, self-efficiency, Privacy and security and Awareness.

The test statistic's F value is 226.334. The null hypothesis of equal population means is rejected since the test statistic is significantly greater than the significance level, and the researchers conclude that there is a (statistically significant) significant difference in population means. The test statistic has a p-value of 0.000, indicating that it is statistically significant at that level. The test statistic's F value is 226.334. The null hypothesis of equal population means is r rejected since the test statistic is significantly greater than the significance level, and the researchers conclude that there is a (statistically significant) significant difference in population means. The test statistic has a p-value of 0.000, indicating that it is statistically significant at that level.

### 5.4.Correlation Coefficient

Pearson's Correlation Coefficient Correlation is a statistical measure of the relationship between two variables. There might be a positive (as one rises, the other falls) or negative (as one rises, the other falls) link. Correlation strength can range from poor to strong. Pearson Product Moment Correlation, sometimes known as Pearson Correlation, is one of the most widely used correlation statistics (Emerson, 2015). The correlation coefficient, r, denotes the degree and direction of a linear relationship between two variables, x and y. The linear model's dependability, on the other hand, is determined by the quantity of observed data points in the sample. The correlation coefficient r and sample size n must be considered simultaneously. The results are presented in a such that, as can be seen table 12, the correlations are replicated. The table presents the coefficient of correlation, the value of its significance and the size of the sample. What's important in this table is the value of Pearson' r – which varies between +1 and -1, where +1 is a perfect positive correlation, and -1 is a perfect negative correlation. 0 means there is no linear correlation at all and the correlation coefficient that can be sig if it is <0.05.

**Table 6: Correlations**

| | | Perceived curiosity | - electronic word-of-mouth | self-efficiency | Privacy and security | Awareness |
|---|---|---|---|---|---|---|
| Perceived curiosity | Pearson Correlation | 1 | .303* | .067 | .244 | .206 |
| | Sig. (2-tailed) | | .033 | .644 | .087 | .150 |
| | N | 300 | 300 | 300 | 300 | 300 |
| - electronic word-of - mouth | Pearson Correlation | .303* | 1 | .000 | .377** | .099 |
| | Sig. (2-tailed) | .033 | | 1.000 | .007 | .496 |
| | N | 300 | 300 | 300 | 300 | 300 |
| self-efficiency | Pearson Correlation | .067 | .000 | 1 | -.062- | -.074- |
| | Sig. (2-tailed) | .644 | 1.000 | | .669 | .611 |
| | N | 300 | 300 | 300 | 300 | 300 |
| Privacy and security | Pearson Correlation | .244 | .377** | -.062- | 1 | -.095- |
| | Sig. (2-tailed) | .087 | .007 | .669 | | .510 |
| | N | 300 | 300 | 300 | 300 | 300 |
| Awareness | Pearson Correlation | 209**<br>.000<br>300 | 271**<br>.000<br>300 | 386**<br>.000<br>300 | 268**<br>.000<br>300 | 1 |
| | Sig. (2-tailed) | | . | | . | 300 |
| Adoption of Artificial Intelligence | N | 300 | 300 | 300 | 300 | 300 |

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

The coefficient correlations range from +0.2 to +1. When the value of the coefficients increases, it suggests that the relation between the variables is becoming stronger. Table12 demonstrates that the variables are greater than zero, demonstrating a positive association between adoption of artificial intelligence and factors (perceived curiosity, awareness, privacy and security, self-efficiency and electronic word-of-mouth). This table demonstrates that the variables have a substantial linear connection. The regression line can be used to model the population's linear connection between variables.

**5.5.Multi Collinearity of Independent variables:**

Multi collinearity occurs when there is a correlation between independent variables in a regression model. This is contested since the study's independent variables should be independent. Tolerance and its inverse variance inflation factor, commonly known as VIF, are examples of collinearity statistics. VIF defined the variance of a model produced with only one term by the variance of a model constructed with multiple parameters in the model that encapsulates other components. In an ordinary test squares regression analysis, it evaluates the severity of multi-collinearity. Because to collinearity, the variance of a calculated regression coefficient is increased.

**Table 7: Collinearity Statistics**

| | | Collinearity Statistics | |
|---|---|---|---|
| Model | Dimension | Tolerance | VIF |
| 1 | Perceived curiosity | 0.697 | 1.437 |
| | electronic word-of-mouth | 0.443 | 2.258 |
| | self-efficiency | 0.415 | 2.414 |
| | Privacy and security | 0.194 | 5.158 |
| | Awareness | 0.192 | 5.235 |

a- Dependent variable: Adoption of Artificial Intelligence

To detect multicollinearity, the variance inflation factor and its inverse, tolerance, can be utilized (VIF). When the tolerance value is less than 0.2 or 0.1 and the VIF value is 10 or above, multicollinearity is a problem. As shown in table 13, the tolerance is more than 0.5, but the VIF quantities are all less than 10, suggesting that there is no multicollinearity.

**5.6.Hypotheses Testing Using Multiple Linear Regression Analysis**

Hypothesis testing is a statistical technique for evaluating a hypothesis about a population parameter by an analyst. Hypothesis testing is the process of evaluating the plausibility of a hypothesis using sample data. This data might come from a larger population or a data gathering system. Table 14 shows the R, R square, adjusted R square, and standard error of the estimate, which may be used to assess how well a regression model fits the data.

**Table 8: Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .0863[a] | 0.743 | 0.740- | 0.12531 |

a- Predictors: (constant), perceived curiosity, electronic word-of-mouth, self-efficiency, Privacy and security, Awareness.

The value of the multiple correlation coefficient's R is displayed in the R column. R may be seen of as one measure of the quality of the dependent variable's prediction; in this situation, R= 0.863 indicates a good degree of prediction. The value of R square, commonly known as the determination coefficient, is represented as "R square." In this case, the value of R square is 0.743, indicating that the independent variables (perceived curiosity, electronic word-of-mouth, self-efficiency, Privacy and security, Awareness) explain 74% of data variance is explained by the linear regression of the dependent variable adoption of artificial Intelligence.

### 5.7. Regression Analysis

MLR, also known as multiple linear regression, is a statistical approach that predicts the result of a response variable by integrating a large number of explanatory factors. MLR attempts to model the linear interaction between explanatory (independent) and response (dependent) factors.

**Table 9: Table of Coefficients**

| Model | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| 1 (Constant) | 0.101 | 0.179 | | 0.566 | 0.000 |
| Perceived curiosity | 0.223 | 0.029 | 0.232 | 7.569 | 0.000 |

| | | | | | |
|---|---|---|---|---|---|
| electronic word-of-mouth | 0.355 | 0.031 | 0.440 | 9.675 | 0.000 |
| self-efficiency | 0.437 | 0.045 | 0.383 | 11.468 | 0.000 |
| Privacy and security | 0.075 | 0.032 | 0.135 | 2.324 | 0.20 |
| Awareness | 0.068 | 0.031 | 0.132 | 2.232 | 0.028 |

a. Dependent Variable: Adoption of Artificial Intelligence

Table 9 shows the coefficient values for each variable, allowing you to assess their significance. All factors in the table are significant predictors since their p-value is less than 0.05. self-efficiency has the most effect (beta=0.045), while Perceived curiosity has the lowest (beta=0.029). By comparing linear approach. Every variable has a significant positive impact on adoption of artificial Intelligence.

The hypotheses utilized in this study will be examined depending on their P value, as shown in the table 9. This helps us to determine whether or not these hypotheses are supported. If the relevant P value is 0.05, the hypothesis is considered supported. In table 16 hypotheses are tested as follows:

**H1**: *Perceived curiosity has a positive effect on consumer toward adoption of Artificial Intelligence*

Regression result: Based on table 9 results consumer’s perceived curiosity P value (p=0.000) which is lower than the significance level of 0.05. Therefore, since P value is lower than 0.05. H1 is supported.

**H2**: *electronic word-of-mouth has a positive effect on consumers toward adoption of Artificial Intelligence*

Regression result: Based on table 9 results electronic word-of-mouth P value (p=0.000) which is lower than the significance level of 0.05. Therefore, since P value is lower than 0.05. H2 is supported. In this scenario, customers' adoption of *Artificial Intelligence* is positively influenced by the electronic word-of-mouth.

**H3**: *self-efficiency has a positive effect on consumers adoption of Artificial Intelligence.*

Regression result: Based on table 9 results consumer's outcome expectation P value (p=0.000) which is lower than the significance level of 0.05. Therefore, since P value is lower than 0.05. H3 is supported. In this instance, it has a beneficial impact on customers' adoption of *Artificial Intelligence*.

**H4:** *Privacy and security in protecting them, it has a positive effect on consumers*

*Adoption of Artificial Intelligence.*

Regression result: Based on table 15results privacy and security P value (p=0.020) which is lower than the significance level of 0.05. Therefore, since P value is lower than 0.05. H4 is supported. In this scenario, customers' adoption of *Artificial Intelligence* is positively influenced by their privacy and security.

**H5**: *Awareness has a positive impact on consumers adoption of Artificial Intelligence.*

Regression result: The P value for consumer cues to action (p=0.028) is lower than the significance level of 0.05, based on table 9 findings. As a result, because the P value is less than 0.05, H5 is accepted. In this scenario, awareness had a favorable impact on customers' adoption of *Artificial Intelligence*.

**Table 16:**

| Number of Hypothesis | Hypothesis statement | Results |
|---|---|---|
| H1 | ***Perceived curiosity has a positive effect on consumer toward adoption of artificial intelligence in the educational sector*** | Supported |
| H2 | ***Electronic word-of-mouth has a positive effect on consumers toward adoption of artificial intelligence in the educational sector*** | Supported |
| H3 | ***self-efficiency has a positive effect on consumers adoption of artificial intelligence in the educational sector*** | Supported |

| Number of Hypothesis | Hypothesis statement | Results |
|---|---|---|
| **H4** | ***Privacy and security in protecting them, it has a positive effect on consumers toward adoption of artificial intelligence in the educational sector*** | **Supported** |
| **H5** | ***Awareness has a positive impact on consumers toward adoption of artificial intelligence in the educational sector*** | **Supported** |

## 6. Discussions

The results of the study indicated that the Perceived curiosity, E-WOM, self-efficiency, privacy and security and awareness are positively influence on adoption toward the artificial intelligence.

Concerning the H1, the findings indicated a positive relationship between perceived curiosity and adoption toward artificial intelligence. It means that the student has the pleasure and curiosity to know and explore more about the artificial intelligence, that will help the adoption of artificial intelligence in the educational sector. The results are aligning with the previous studies (Chien et al., 2019; Kerr, 2020; Ceha et al., 2019; Chang, et al., 2013; Mustafa et al., 2022).

Regarding the H2, the results of the study indicated that there is a positive relationship between E-WOM and adoption toward the artificial intelligence. This means that the higher that the students have heard positive comments and feedback about the artificial intelligence, the higher that the student use the artificial intelligence. Additionally, the learner become more interested in emanating the power of E-WOM in building and developing an image toward artificial intelligence. The findings of this study confirmed with the literature review (Simay et al., 2023; Oday, 2021; Verma et al., 2023).

Refer to the H3, the findings indicated that there is a positive relationship between self- efficacy and the adoption toward artificial intelligence in the education sector. These results are consistent with the recent studies (Awajan et al., 2021; Chen, 2022; Cao et al., 2022; Elnagar et al., 2021). This explained that students who have stronger self-efficiency employ a more proactive risk-preparation strategy in order to adopt new technology. These kinds of students are more likely to take risk on the adoption of artificial intelligence.

Concerning the H4, findings indicated that privacy and security significantly influences customers adoption toward artificial intelligence, which means that privacy and security will be an essential predicator to push students to adopt the new tools of technology related to the education. These findings are in line with the previous studies (Sahi et al., 2022; Marikyan et al., 2022; Cao et al., 2022; Flavián et al., 2022).

Finally, the findings demonstrate a positive relationship between Awareness and consumers adoption toward artificial intelligence. Thus, H5 is accepted. This means that the more the students are aware of the artificial intelligence, they will adopt these kinds of technology. The results are in line with (Akther & Nur, 2022; Flavián et al., 2022; Koohang et al., 2022).

### 6.1. Theoretical Implications

The study revalidates the Social Cognitive model theory and proposed a theoretical model of the relationship between the factors (perceived curiosity, EWOM, privacy and security, awareness, and self- efficiency) affecting adoption toward artificial intelligence in the educational sector in Lebanon. In addition, the findings of this study aids in greater understanding, analyzing, then explaining consumer behavior toward new technology. The study also provided essential criteria for adoption of artificial intelligence and determining personal and societal characteristics. This study supplied academics with a thorough knowledge of the prime motivating elements of adoption of artificial intelligence in the Lebanese educational sector. As a result, the research serves as the foundation for further research into the variables influencing students' adoptions toward artificial intelligence.

### 6.2. Research Recommendations

The researcher suggests numerous approaches for policymakers to cope with the findings of the study. As a result, the study suggests to policymakers and managers of education institutions to arrange several training and skills development for their instructors to improve the Lebanese educational level.

Moreover, the study suggests for marketers to leverage positive E-WOM to spread the word about successful AI implementations in Lebanese education sector. Additionally, the study suggests that fast tracking immersive literacy in policy makers, regulators and politicians, they must be aware of these immersive technologies and the activity that occurs on these immersive platforms. Accordingly, the researcher suggested that Lebanese policymakers take note of the fact that self-efficacy has a beneficial effect on artificial intelligence in the education sector, and that it is a good attribute to use. Thus, the decision maker should develop training programs and resources to boost educators' and students' self-efficacy in using AI tools. In addition, the researcher suggested that information distribution is one of the most powerful tools that can be used today to raise awareness and emphasizing the importance of increasing awareness about AI benefits and applications in education among stakeholders.

### 6.3.Limitations and Ideas for Future Research

There are major limitations to this study report that should be considered:

First, the research is being conducted in Lebanon, which has a low population density. Furthermore, Lebanon has one of the highest levels of uncertainty avoidance. As a result, the findings may change for various nations with varying degrees of uncertainty avoidance.

The second limitation in this research is that it only offered the Social Cognitive belief model theory to investigate and limited factors that affect adoption of artificial intelligence. An expansion of this research might go towards developing new ideas or researching of new variables such as expected regret, panic buying and perceived pandemic, instead of the five variables (perceived curiosity, E-WOM, privacy and security, awareness, and self-efficiency that could affect the adoption of artificial intelligence. The third constraint is related to the data gathering period and size. For future research, the researcher suggests enlarging the size of sample and enlarge the period to have a large number of respondents.

## References

Akdim, K. (2021). The influence of eWOM. Analyzing its characteristics and consequences, and future research lines. *Spanish Journal of Marketing-ESIC*, *25*(2), 239-259.

Akther, T., & Nur, T. (2022). A model of factors influencing COVID-19 vaccine acceptance: A synthesis of the theory of reasoned action, conspiracy theory belief, awareness, perceived usefulness, and perceived ease of use. *PLoS One*, *17*(1), e0261869.

Awajan, I., Mohamad, M., & Al-Quran, A. (2021). Sentiment analysis technique and neutrosophic set theory for mining and ranking big data from online reviews. *IEEE Access*, *9*, 47338-47353.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational psychologist*, *28*(2), 117-148.

Bandura, A. (2000). Self-efficacy: The foundation of agency. *Control of human behavior, mental processes, and consciousness: Essays in honor of the 60th birthday of August Flammer*, *16*.

Bandura, A., & Walters, R. H. (1977). *Social learning theory* (Vol. 1). Prentice Hall: Englewood cliffs.

Belanger, F., Hiller, J. S., & Smith, W. J. (2002). Trustworthiness in electronic commerce: the role of privacy, security, and site attributes. *The journal of strategic Information Systems*, *11*(3-4), 245-270.

Cao, D., Sun, Y., Goh, E., Wang, R., & Kuiavska, K. (2022). Adoption of smart voice assistants technology among Airbnb guests: A revised self-efficacy-based value adoption model (SVAM). *International Journal of Hospitality Management*, *101*, 103124.

Ceha, J., Chhibber, N., Goh, J., McDonald, C., Oudeyer, P. Y., Kulić, D., & Law, E. (2019, May). Expression of curiosity in social robots: Design, perception, and effects on behaviour. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-12).

Chang, C. C., Tseng, K. H., Liang, C., & Yan, C. F. (2013). The influence of perceived convenience and curiosity on continuance intention in mobile English learning for high school students using PDAs. *Technology, Pedagogy and Education*, *22*(3), 373-386.

Chen, 2022. Effects of consumer motives on search behavior using Internet advertising. Cyber Psychology and Behavior,7 (4), 430-442.

Chien, S. E., Chu, L., Lee, H. H., Yang, C. C., Lin, F. H., Yang, P. L., ... & Yeh, S. L. (2019). Age difference in perceived ease of use, curiosity, and implicit negative attitude toward robots. *ACM Transactions on Human-Robot Interaction (THRI)*, *8*(2), 1-19.

Elnagar, A., Afyouni, I., Shahin, I., Nassif, A. B., & Salloum, S. A. (2021). The empirical study of e-learning post-acceptance after the spread of COVID-19: A multi-analytical approach-based hybrid SEM-ANN. *arXiv preprint arXiv:2112.01293*.

Emerson, R. W. (2015). Causation and Pearson's correlation coefficient. Journal of visual impairment andblindness, 109(3), p. 242-244.

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293-320.

García-Peñalvo, F. J. (2023). The perception of Artificial Intelligence in educational contexts after the launch of ChatGPT: Disruption or Panic?.

García-Peñalvo, F. J. (2023). The perception of Artificial Intelligence in educational contexts after the launch of ChatGPT: Disruption or Panic?.

Garfinkel, S. L., Abowd, J. M., & Powazek, S. (2018, January). Issues encountered deploying differential privacy. In *Proceedings of the 2018 Workshop on Privacy in the Electronic Society* (pp. 133-137).

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California management review*, *61*(4), 5-14.

Jabeen, G., Ahmad, M., & Zhang, Q. (2021). Factors influencing consumers' willingness to buy green energy technologies in a green perceived value framework. *Energy Sources, Part B: Economics, Planning, and Policy*, *16*(7), 669-685.

Johnson, M., Jain, R., Brennan-Tonetta, P., Swartz, E., Silver, D., Paolini, J., ... & Hill, C. (2021). Impact of big data and artificial intelligence on industry: developing a workforce roadmap for a data driven economy. *Global Journal of Flexible Systems Management*, *22*(3), 197-217.

Kerr, 2020 T. T. T. Doan, "The Effect of Perceived Risk and Technology Self-Efficiency on Online Learning Intention: An Empirical Study in Vietnam," Finance. Econ. Bus., vol. 8, no. 10, pp. 385– 393.

Koohang, A., Sargent, C. S., Nord, J. H., & Paliszkiewicz, J. (2022). Internet of Things (IoT): From awareness to continued use. *International Journal of Information Management*, *62*, 102442.

Marche, S. (2022). The college essay is dead. *The Atlantic*, *6*, 2022.

Marikyan, D., Papagiannidis, S., Rana, O. F., & Ranjan, R. (2022). Blockchain adoption: A study of cognitive factors underpinning decision making. *Computers in Human Behavior*, *131*, 107207.

Mustafa, S., Zhang, W., Anwar, S., Jamil, K., & Rana, S. (2022). An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. *Scientific Reports*, *12*(1), 20056.

Oday, A., Ozturen, A., Ilkan, M., & Abubakar, A. M. (2021). Do eReferral, eWOM, familiarity and cultural distance predict enrollment intention? An application of an artificial intelligence technique. *Journal of Hospitality and Tourism Technology*, *12*(3), 471-488.

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199-3226.

Qader, M., & Albustanj, K. (2022). The relationship between knowledge-based systems and supply chain management in competitive advantage. *Uncertain Supply Chain Management*, *10*(4), 1339-1344.

Roose, K. (2022). The brilliance and weirdness of ChatGPT. *The New York Times*.

Ropek, L. (2023). New York City Schools Ban ChatGPT to Head Off a Cheating Epidemic. Gizmodo.

Rosen, L., Zucker, D., Brody, D., Engelhard, D., & Manor, O. (2009). The effect of a handwashing intervention on preschool educator beliefs, attitudes, knowledge and self-efficacy. *Health education research*, *24*(4), 686-698.

Sahi, A. M., Khalid, H., Abbas, A. F., Zedan, K., Khatib, S. F., & Al Amosh, H. (2022, April). The research trend of security and privacy in digital payment. In *informatics* (Vol. 9, No. 2, p. 32). MDPI.

Samara, D., Magnisalis, I., & Peristeras, V. (2020). Artificial intelligence and big data in tourism: a systematic literature review. *Journal of Hospitality and Tourism Technology*, *11*(2), 343-367.

Simay, A. E., Wei, Y., Gyulavári, T., Syahrivar, J., Gaczek, P., & Hofmeister-Tóth, Á. (2023). The e-WOM intention of artificial intelligence (AI) color cosmetics among Chinese social media influencers. *Asia Pacific Journal of Marketing and Logistics*, *35*(7), 1569-1598.

Stephan, 2015. Study on Metaverse Hype for Sustainable Growth. Int. J. Adv. Smart Converg. 2021, 10, 72–80.

Stokel-Walker, C. (2022). What do we know about covid vaccines and preventing transmission?. *bmj*, *376*.

Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research*, *81*, 102883.

Verma, D., Dewani, P. P., Behl, A., & Dwivedi, Y. K. (2023). Understanding the impact of eWOM communication through the lens of information adoption model: a meta-analytic structural equation modeling perspective. *Computers in Human Behavior*, *143*, 107710.

Yu, C. E., & Ngan, H. F. B. (2019). The power of head tilts: gender and cultural differences of perceived human vs human-like robot smile in service. *Tourism Review*, *74*(3), 428-442.