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THE IMPACT OF SMARTPHONE TECHNOLOGY AND ARTIFICIAL INTELLIGENCE ON ACADEMIC PERFORMANCE IN LIBYAN SCHOOLS IN MALAYSIA

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Abstract

This study aims to investigate the impact of mobile technology and artificial intelligence on the academic performance of Libyan students in Malaysian schools. The problem highlighted the neglect of mobile technology usage in Libyan educational institutions and the limited use of artificial intelligence, which significantly contributed to the decline in academic performance in Libyan schools. Additionally, the lack of self-efficacy among students negatively affected the opportunity for utilizing artificial intelligence or mobile technology to enhance academic performance in Libyan schools in Malaysia. This study reveals the importance of using artificial intelligence in Libyan educational institutions and how to address traditional barriers that hinder the use of mobile technology and artificial intelligence in Libyan schools in Malaysia. Furthermore, the study sheds light on the prominent role played by students' self-efficacy in adapting the use of mobile technology and artificial intelligence to improve and develop academic performance, as well as enable the use of active learning methods and collaborative work among students with the assistance of teachers. The study adopts a quantitative approach to examine the impact of mobile technology and artificial intelligence on academic performance in Libyan schools in Malaysia. The study population consists of 550 students from the preparatory stage in Libyan schools in Malaysia, including the Libyan School in Ampang, the Libyan School in Damai, the Libyan School in Kajang, and the Libyan Future Steps School. The study sample comprised 226 students from Libyan schools in Malaysia. The study yielded several results, including a direct statistical relationship between the use of mobile technology and students' academic performance. Furthermore, there is an indirect statistical relationship between the use of mobile technology and artificial intelligence in relation to students' performance, with self-efficacy serving as a mediating variable. The study recommends the importance of expanding the application of artificial intelligence in various educational institutions in Libya and emphasizes the need to adopt multiple programs and applications that facilitate the use of artificial intelligence to enhance students' academic performance.

Keywords: Mobile Technology, Artificial Intelligence, Academic Performance, Libyan Schools, Malaysia

1. INTRODUCTION

Libyan educational institutions play a significant role in disseminating knowledge and education throughout Libya. Despite the development witnessed by Libyan educational institutions, they face numerous challenges, as indicated by a report issued by the Tripoli

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Western Studies Institution in 2019. The report highlighted the multiple failures of Libyan educational institutions, which negatively affected the educational performance of Libyan students, especially at the preparatory stage. The problem in Libyan educational institutions emerged from neglecting the use of artificial intelligence technology and smartphones, due in part to the lack of self-sufficiency among students. This negligence has greatly contributed to the decline in educational performance in Libyan schools in Malaysia.

The Libyan Audit Bureau's 2018 report confirmed that Libyan schools suffer from a lack of modern technological methods, despite increased expenditure on secondary aspects. This neglect of technology indicates a decline in educational performance. Additionally, the Administrative Control Authority's 2019 report indicated that Libyan schools adhere to traditional methods, which have had a negative impact on educational performance.

Mourgin (2016) pointed out that the Libyan government education system requires numerous terminologies, as Libyan schools continue to operate under outdated traditional systems. Changing these traditional systems is only allowed within limited boundaries, and there is a significant lack of spending on technology, leading to a deterioration in educational performance in Libyan schools.

The term "traditional education", also known as "back to basics," "conventional education," or "familiar education," refers to long-standing practices in schools that are considered suitable according to societal traditions. Some education reform movements support adopting advanced teaching methods and more inclusive curricula that focus on individual student needs and self-expression. Reformists argue that traditional teacher-centered methods that rely on memorization should be completely abandoned in favor of student-centered teaching methods and task-based approaches. However, many conservative parents and citizens are interested in maintaining objective educational standards, which reinforces traditional methods.

Mourgin (2016) confirmed that there is a clear decline in students' self-sufficiency, as Libyan students are not allowed to use smartphones to record lessons in Libyan schools. This has deprived a large sector of students of the opportunity to review lectures and lessons, leading to a decline in educational performance. El Falah (2018) pointed out that the problem of declining quality education outcomes in Libya is due to decision-makers' inability to develop the education system and rely on advanced technological levels in the educational process. This has negatively affected the utilization of artificial intelligence technology, wasting its benefits and hindering its application, especially in the education sector. El Falah also emphasized that many students try to use smartphones discreetly to evade teachers' refusal to explicitly allow their use in the educational process, which has negatively impacted active learning methods and wasted the opportunity for active learning. Similarly, Al-Mahjoubi (2018) stated that technology is not being used in education, and students are not given the opportunity to demonstrate their abilities, self-sufficiency, and verbal persuasion skills to improve academic achievement. This has contributed to a significant decline in educational performance in Libyan schools.

Based on the aforementioned issues, this study aims to bridge the gap in literature resulting

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from the lack of studies discussing the role of smartphone technology and artificial intelligence in Libyan schools in Malaysia. No previous research has examined the impact of using these technologies on educational performance. Therefore, conducting this study will fill this gap by providing a quantitative study on these relationships. Furthermore, this study seeks to address another gap, which is the lack of studies on the mediating role of self-sufficiency in improving academic performance through the use of smartphone technology and artificial intelligence. Self-sufficiency plays a prominent role in the cognitive level, determining the purpose of using these technologies and thus enhancing educational performance. The objectives of this study are as follows:

1) Direct Impact Test of Smartphone and Artificial Intelligence Usage on Academic Performance
2) Indirect Impact Test of Smartphone and Artificial Intelligence Usage on Self-Efficacy and Academic Performance
3) Testing Self-Efficacy as a Mediating Variable between Smartphone and Artificial Intelligence Usage.

2. LITERATURE REVIEW

The study examined several relationships between variables, including the following:

2.1 The relationship between Smartphone Technology and Academic Performance

There are many studies that have indicated a relationship between smartphone technology and academic performance. Among these studies is the study conducted by Jamal (2020), which pointed out the relationship between smartphone technologies. The study used the same sub-variables as the independent variable, smartphone technology. Additionally, the study utilized the study conducted by Jamal (2020), which clearly highlighted academic performance. Based on the above, the following hypothesis can be formulated as follows:

Hypothesis 1: There is a direct statistical relationship between smartphone technology and academic performance among secondary school students in Libyan schools in Malaysia.

2.2 The relationship between artificial intelligence Technology and Academic Performance

There are many studies that have indicated a relationship between artificial intelligence technology and academic performance. Among these studies is the study conducted by Ahmad (2020), which pointed out the relationship between artificial intelligence technologies. The study used the same sub-variables as the independent variable, artificial intelligence technology. Additionally, the study utilized the study conducted by Aishawi (2021), which shed light on academic performance. Based on the above, the following hypothesis can be formulated as follows:

Hypothesis 2: There is a direct statistical relationship between artificial intelligence technology and academic performance among secondary school students in Libyan schools in Malaysia.

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2.3 The relationship between self-efficacy and Academic Performance

There are many studies that have indicated a relationship between self-efficacy and academic performance. The study conducted by Haddad (2016) revealed that self-efficacy consists of several variables. The current study used the same variables addressed by Haddad's study, including verbal persuasion, indirect experience, and prior experiences. Additionally, the study conducted by Hassanah (2020) addressed issues related to academic performance. Based on the above, the following hypotheses can be formulated:

Hypothesis 3: There is a direct statistical relationship between self-efficacy and academic performance among secondary school students in Libyan schools in Malaysia.

Hypothesis 4: There is a direct statistical relationship between smartphone technology and self-efficacy among secondary school students in Libyan schools in Malaysia.

Hypothesis 5: There is a direct statistical relationship between artificial intelligence technology and self-efficacy among secondary school students in Libyan schools in Malaysia.

2.4 The Relationship between Smartphone Technology, Artificial Intelligence, Academic Performance, and Self-Efficacy

There are several studies that have indicated a relationship between smartphone technology and academic performance. Among these studies is the study conducted by Hassan (2020), which highlighted the relationship between smartphone technologies. The study used the same sub-variables for the independent variable of smartphone technology. Additionally, the study shed light on academic performance. Haddad's study (2016) stated that self-efficacy consists of several variables, some of which were also examined in the current study, such as verbal persuasion, indirect experience, and prior experiences.

Hypothesis 3a: There is an indirect effect of self-efficacy on the relationship between smartphone technology and academic performance among secondary school students in Libyan schools in Malaysia.

Hypothesis 3b: There is an indirect effect of self-efficacy on the relationship between artificial intelligence and academic performance among secondary school students in Libyan schools in Malaysia.

3. RESEARCH METHODOLOGY

A quantitative research methodology was used in this study. A questionnaire was developed consisting of four sections, with each section containing 12 items. Thus, the total number of questionnaire items was 48. The questionnaire was distributed to 226 students from international students in the secondary stage, selected from the Libyan School in Ampang, Libyan School in Damai, Libyan School in Kajang, and Libyan Steps School of the Future.

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4. RESULTS AND ANALYSIS

The analysis of the study results can be divided into three sections: descriptive analysis of demographic data, measurement model analysis, and structural model analysis.

4.1 Descriptive Analysis

The study population consisted of secondary school students in Libyan schools in Malaysia, with a total of 550 male and female students. The research tool was applied to a purposive sample, specifically chosen. The sample included students from the first, second, and third year of secondary school. The sample size was determined as 226 students from the original population. Data was collected from both genders of respondents who completed the questionnaire. The response of both genders to demographic variables such as gender, age, and educational level is presented in Table 1.

Table 1: Respondent Profile (Frequencies)

Item	Choice	Frequency	Percent
Gender	Male	132	58.4%
	Female	94	41.6%
Age	Below 13	13	5.8%
	13	68	30.1%
	14	80	35.4%
	15	61	27.0%
	Above 15	4	1.8%
	Total	226	100.0%
Education	First grade	70	31.0%
	Second grade	84	37.2%
	Third grade	72	31.9%
	Total	226	100.0%

4.2 Measurement Model

The research model of this study was tested using SmartPLS 3.3. In addition, an examination was conducted in regard to the measurement model (validity and reliability of the measures) and the structural model (testing the hypothesized relationships).

Table **2** illustrate the convergent validity scores, all variables scored satisfactory values of Composite Reliability, and Cronbach's Alpha and above the cutoff point for 0.7 and 0.7 respectively as recommended by Hair et al. (2021). However, items ATI6, ATI7, PER7, PER8, SE9, SE10 and SE11 scored below 0.5 for factor loading, therefore, ATI6, ATI7, PER7, PER8, SE9, SE10 and SE11 were deleted as recommended by (Ramayah et al. (2018) (Ramayah, Cheah, Francis, et al., 2018). As a result, PER and SE scored low values of Average Variance Extracted (AVE) (0.432 and 0.426 respectively). This value is below the cut-off point for AVE (0.5), as recommended by Hair et al. (2017). Therefore, a form of modification was considered in the second run and, consequently, PER7, PER8, SE9, SE10 and SE11 were deleted in order to achieve satisfactory levels of AVE. Overall, all variables have achieved the cut-off point, as illustrated in

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Table **2**.

Table 2: Convergent Validity

Construct	Item	Factor Loading	Cronbach's Alpha	CR	AVE
Artificial Intelligence Technology (AIT)	AIT1	.788	.964	.969	.757
	AIT2	.850			
	AIT3	.871			
	AIT4	.851			
	AIT5	.902			
	AIT8	.883			
	AIT9	.893			
	AIT10	.867			
	AIT11	.865			
	AIT12	.925			
Performance (PER)	PER1	.644	.895	.914	.517
	PER2	.658			
	PER3	.726			
	PER4	.760			
	PER5	.721			
	PER6	.782			
	PER9	.668			
	PER10	.680			
	PER11	.805			
	PER12	.727			
Self-Efficacy (SE)	SE1	.737	.894	.916	.555
	SE2	.824			
	SE3	.833			
	SE4	.771			
	SE5	.788			
	SE6	.819			
	SE7	.704			
	SE8	.741			
	SE12	.438			
Smartphone Technology (ST)	ST1	.784	.938	.946	.596
	ST2	.752			
	ST3	.744			
	ST4	.821			
	ST5	.766			
	ST6	.757			
	ST7	.708			
	ST8	.811			
	ST9	.747			
	ST10	.699			
	ST11	.823			
	ST12	.833			

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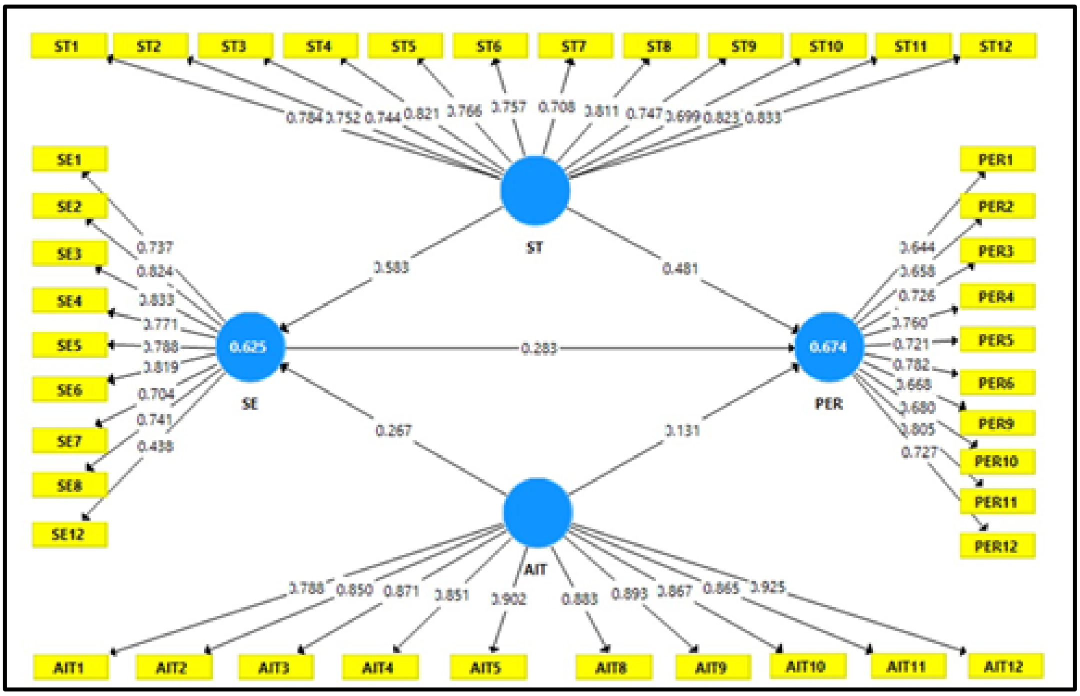

Figure 1: Model of PLS algorithm results (Measurement model)

4.3 Structural Model

The structural model represents the theoretical or conceptual element of the path model. Also referred to as the inner model in PLS-SEM, the structural model includes the latent variables and their path relationships (Hair et al., 2021). The next step after the evaluation of the measurement model is to assess the structural model. In sync with PLS-SEM, there are five steps required to assess the structural model (Hair et al., 2021) including the assessment of collinearity (step one), assessment of the path coefficients (step two), coefficient of determination (R^2 value) (step three), blindfolding and predictive relevance Q^2 (step four), effect size f^2 (step five), and assessment of the mediation analysis (step six). Furthermore, Table 3 summarizes the structural model results and PLS bootstrapping.

Table 3: Summary of Structural Model (PLS bootstrapping)

H	Path	Beta	Standard Deviation	T Statistics	P Values	2.50%	97.50%	VIF	f2	R2	Q2
H1	ST -> PER	.481	.045	10.655	.000	.388	.570	2.796	.254	.674	.341
H2	AIT -> PER	.131	.039	3.402	.001	.059	.208	2.080	.025		
H3	SE -> PER	.283	.045	6.262	.000	.199	.373	2.668	.092		
H4	AIT -> SE	.267	.048	5.590	.000	.161	.357	1.889	.101	.625	.341
H5	ST -> SE	.583	.043	13.435	.000	.504	.671	1.889	.480		

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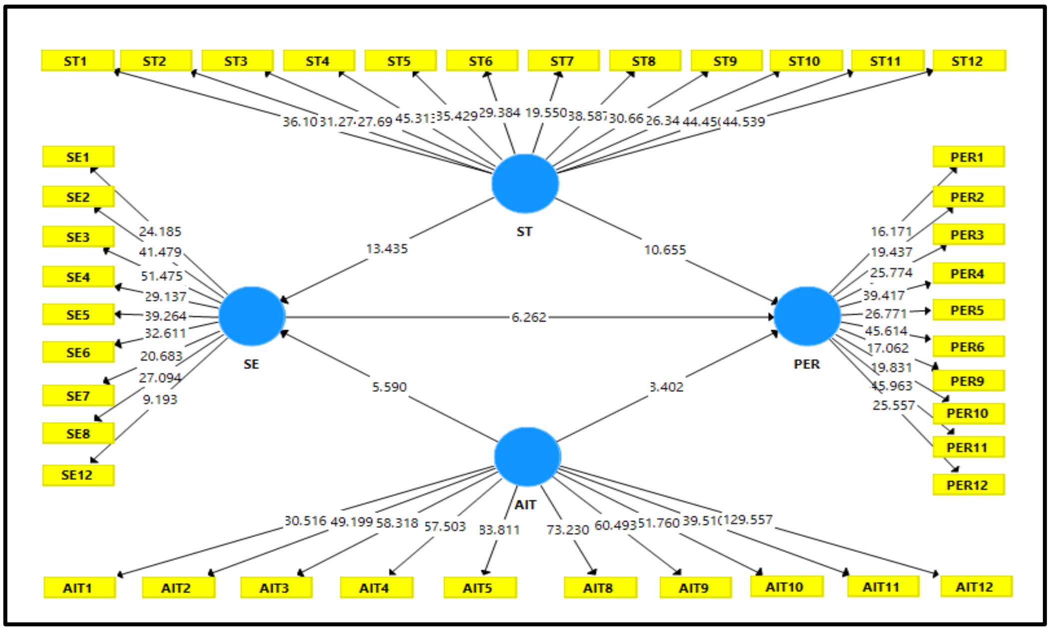

Figure 2: Structural Model (PLS bootstrapping)

First: Assessment of the Structural Model for Collinearity Issues

The first step in the structural model is to assess collinearity issues. It is vital to safeguard against collinearity issues between the constructs before performing a latent variable analysis in the structural model. As such, the collinearity has been measured by measuring the VIF value. The threshold value for the assessment is 3.3, following the recommendation of Diamantopoulos and Siguaw (2006) (Diamantopoulos & Siguaw, 2006). In this study, as illustrated in Table 3, all inner VIF values for the constructs are within the range of 1.889 to 2.796. All are less than 3.3, thus indicating that collinearity is not a concern in this study.

Second: Assessing the Significance of the Structural Model Relationships

The relevance of the route coefficients was determined by evaluating the structural paths included inside the model's structural representation. Examining the path coefficients as well as the t-values allowed for a determination of the relevance of the structural paths. In order to verify the validity of the hypothesis, both the PLS algorithm and bootstrapping were executed. The PLS technique was used to acquire the t-values, while bootstrapping was used to obtain the path coefficients and R2 values. As recommended by Hair at el. (2017), if the p-value is equal or less than .05, the accepted level of t-value is at least 1.645. As per the Table 3, all of the t-value scores have met the accepted level recommended by Hair at el. (2017), and therefore, all hypotheses will be supported.

Third: The Coefficient of Determination (R^2)

The next stage is to evaluate the model's predictive accuracy through the derived value of the coefficient of determination (R^2). The value of R^2 is linked to the model's predictive power and ranges from zero to one, with a higher value indicating a higher level of predictive accuracy

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(Hair et al., 2017). Using the SmartPLS algorithm, the value of R^2 has been calculated as shown in Table 4.

Furthermore, Hair et al. (2017) detailed 3 different levels of R^2 scores. If R^2 is above .75 it will be considered as substantial, if R^2 is above .50 it will be considered as moderate, and if R^2 is above .25 it will be considered as weak, while if R^2 below .25 it will be considered as unacceptable. As per Table 4, the score of R^2 for PP is considered as in Moderate level as recommended by Hair et al. (2017).

Table 4: Path Coefficient (R^2)

Construct	R^2
ATI	.674
SE	.625

Fourth: Assessment of the effect size (f^2)

In this stage, the effect sizes (f^2) have been evaluated. The value of f^2 is connected to the relative impact of a predictor construct on endogenous constructs. According to Sullivan and Feinn (2012), aside from reporting the p-value, both the substantive significance (effect size) and statistical significance (p-value) are crucial to be reported (Sullivan & Feinn, 2012). Furthermore, in order to measure the effect size, a guideline set by Cohen (1988) has been followed. Based on the study of Cohen (1988), the values of 0.02, 0.15, and 0.35 represent small, medium, and large effects respectively (J. Cohen, 1988). As it can be viewed in Table 3, H2, H3 and H4 have f^2 values above 0.02 and less than 0.15 which indicated weak size of effect. H1 has f^2 value above 0.15 and less than 0.35 which indicated medium size of effect. While, H5 has f^2 values more than 0.35 which indicated substantial size of effect.

Fifth: Assessment of the Predictive Relevance (Q^2)

The Q^2 value (along with the R^2 value) of each of the endogenous constructs is shown in Table 5. Because the value of Q^2 was greater than zero, it provided support for the predictive significance of the model with respect to the endogenous latent variables. This was in accordance with the recommendations made by Stone (1974), Geisser (1974), and Hair et al (2017). In conclusion, the use of a single indicator construct as a predictor construct in this research did not present any issues of its own (Geisser, 1974; J. F. Hair et al., 2017; Stone, 1974).

Table 5: Path Coefficient (Q^2)

Construct	Q^2
ATI	.341
SE	.324

Sixth: Assessment of mediating variable Analysis

In general, the purpose of the present investigation, which was to evaluate the mediating influence of self-efficacy (SE) (Namely: H3a and H3b), The research is going to use PLS bootstrapping in order to determine both the direct and indirect effects that come from self-

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efficacy. According to the recommendations made by other academics, the researcher will use the bias-correlated and accelerated (BCa) approach for determining confidence intervals (Ramayah, Cheah, Chuah, Ting, & Memon, 2018). The findings of the PLS bootstrapping analysis for both the direct and indirect effects are shown in Table 6

Table 6: The results of PLS bootstrapping for the indirect effect

H	Relationship	Path P1 Beta	Path P2 Beta	Path P3 Beta	Indirect P1*P2	Std Error	t value	Confidence Interval		P value	Decision
								Lower	Upper		
H3a	ST -> SE -> PER	0.267	0.283	0.481	0.165	0.028	5.931	0.117	0.224	0	Supported
H4a	AIT -> SE -> PER	0.583	0.283	0.131	0.076	0.021	3.692	0.039	0.121	0	Supported

As shown in Table 6, the current study presented 2 hypotheses were constructed in order to assess the mediating effect of Self-Efficacy (SE). In the current study, the mediating effect analysis carried out using Smart PLS found the following:

In H3a: Self-Efficacy (SE) plays a significant mediating role on the relationship between Smartphone Technology (ST) and Performance (PER).

In H3a: Self-Efficacy (SE) plays a significant mediating role on the relationship between Artificial Intelligence Technology (AIT) and Performance (PER).

5. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Based on the previous results obtained from the study, the researcher recommends the necessity of finding ways to employ and enhance the use of artificial intelligence technology in Libyan schools in Malaysia. This can be achieved by developing suitable plans and courses that align with the educational environment, enabling easier utilization and maximizing the benefits of artificial intelligence technology in schools. Additionally, individual differences among students resulting from the lack of training, guidance, and counseling in optimizing the use of artificial intelligence technology should be taken into consideration. This can be addressed by designing educational plans to enhance students' academic and cognitive levels.

The researcher also recommends adopting artificial intelligence and its educational applications as part of the curriculum in teacher preparation programs at educational institutions. Furthermore, training courses should be organized for teachers to introduce them to the concept of artificial intelligence and its applications in the field of education. It is essential to develop methods for assessing computer skills and utilize alternative assessment methods, such as observation cards for practical aspects of these skills, particularly those related to artificial intelligence languages. Special educational evaluation systems should be designed as alternatives to traditional assessment methods to leverage artificial intelligence techniques in assessing all aspects of learning, extending beyond academic achievement and student progress to include practical performance and the learner's personality, such as their perseverance and motivation towards learning.

There is a need to monitor students by conducting modern scientific programs and tests regarding the methods of using artificial intelligence and smartphone applications. Academic

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and technical guidance should be provided to solve any problems or dilemmas encountered during the implementation of these technologies. It is important to expand the use of artificial intelligence and smartphone technology in education based on the acceptance of both teachers and learners. Developing educational information infrastructure and providing necessary resources for employing artificial intelligence applications and communications in education is crucial.

Efforts should be made to enhance students' knowledge and awareness of artificial intelligence applications, how intelligent and expert systems work in solving various problems, and to develop an integrated plan for the application of artificial intelligence technology in the educational field. Leveraging smartphone technology to attract students and improve the quality of its applications is also recommended. Work on all aspects that promote the use of smartphone technology and its applications in accessing information. Students should be educated on distinguishing between accurate and inaccurate information and appropriate behavior towards it. Faculty members should be trained on the educational uses of smartphone applications, and they should keep up with updates and advancements in this field.

Increasing students' awareness of the importance of evaluating information disseminated through smartphone applications, understanding the accuracy and usefulness of information, and refraining from spreading it until the sources are verified is essential. Conducting comprehensive studies on ways to activate the use of smartphone technology in accessing information and utilizing the potential of relevant entities involved in information production and management, as well as smartphone applications, in delivering information, is also recommended.

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