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The Mediating Role of Marketing Effectiveness in the Relationship between Artificial Intelligence and Destination Competitiveness

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Keywords

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Abstract

Artificial Intelligence (AI) technologies have been classified into four categories since their inception: information presentation and knowledge-based systems, Machine Learning (ML), problem-solving, and distributed artificial intelligence. Nowadays, artificial intelligence (AI) has emerged as one of the most important technologies for assisting the tourism industry in increasing competitiveness and achieving excellence in a changing and volatile labor market; AI can also achieve a competitive advantage by transforming the traditional seller into a buyer's market. The prime objective of this research is to illustrate the mediating role of marketing effectiveness in the relationship between artificial intelligence and tourism destination competitiveness. Questionnaires were distributed electronically and hard copy to employees in tourism and hospitality institutions such as airports, airlines, governmental tourism authorities and private tourism authorities by the researcher. 944 questionnaires were found usable for analysis. The results indicated that artificial intelligence affects positively both marketing effectiveness and tourism destination competitiveness. As well, the results highlighted that Marketing effectiveness mediates the relationship between artificial intelligence and tourism destination competitiveness

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1. Introduction

In travel and tourism, artificial intelligence (AI) is utilized to make the entire travel experience more convenient and enriching. The travel industry is utilizing the benefits of artificial intelligence (AI) technology to predict travel preferences and create personalized travel solutions tailored to consumer demands. Increase client service and simplify in-trip and post-trip needs management the travel business relies on on-demand 24-hour support to deliver assistance in real-time. Travelers may be planning a vacation or experiencing problems while on the road and needing immediate and relevant assistance at any time of day or night. Using AI-powered chatbots and assistants for live assistance is an excellent approach to save time and money while increasing efficiency (Ivanov, and Webster.2020).
The study aims to A) explore the impact of artificial intelligence (AI) on marketing effectiveness, B) evaluate the effect of AI on destination competitiveness, C) assess the impact of marketing effectiveness on destination competitiveness and, D) investigate the role of marketing effectiveness in the relationship between artificial intelligence and tourism destination competitiveness).

Literature Review and hypothesis development:
The researcher will present AI tools such as forecasting, virtual reality, augmented reality, and chatbots which play an important role in traveler making decisions. AI can also help travelers make decisions as a driver that might potentially improve the tourism experience by offering more personalized products and services to fit each visitor's unique needs and preferences.

The relationship between artificial intelligence and marketing effectiveness:
Artificial intelligence marketing makes automated decisions based on data collecting, data analysis, and further observations of audience or economic trends that may affect marketing activities. AI is frequently utilized in marketing initiatives where speed is critical. Data and customer profiles are used by AI tools such as virtual reality, augmented reality, chatbots, and forecasting to learn how to best communicate with customers, then serve them tailored messages at the right time without intervention from marketing team members, ensuring maximum efficiency (Kandil, 2016; Samuely, 2016).
Many modern marketers employ AI to supplement marketing teams or to execute more tactical jobs that require fewer human nuances. a strategy that uses historical and contextual data to forecast the future based on current trends It is utilized in all industries and businesses to make judgments that require predicting what will happen (Yu and Schwartz, 2006). Forecasting can be used in the tourism industry to better understand tourist demand. (Buhalis and Amaranggana, 2014). To develop marketing strategies, for financial management and human resource allocation (Claveria et al. 2015), to detect restaurant frauds (Stalidis et al. 2015), and to assist facility management and maintenance needs (Buhalis and Leung 2018). However, the use of AI must be handled carefully, since the results of AI methods have been mixed. On the one hand, Yu and Schwartz (2006) discovered that complicated models do not

outperform basic, traditional models. Claveria and Torra (2014) reported more promising results, however, the degree of preprocessing drastically influenced the quality of the neural network predicting outputs. Several research, on the other hand, has demonstrated that AI approaches have higher prediction accuracy.

Virtual reality and Augmented reality

Related technologies have significant promise as promotional tools for encouraging in-person tourism trips (Fauzi and Gozali, 2015). VR is particularly appealing to the tourist industry as a means of communicating intangible travel experiences to a larger audience**.** The tourism industry has long relied on the use of visual imagery to interact with and influence consumers while advertising locations (Aziz and Zainol, 2011), However, as consumers become less receptive to traditional visual communication media such as brochures, TV ads, and even websites as key sources of information (Fransen et al., 2015). Advertisements that elicit positive attitudes are more likely to impact purchase intentions and are regarded as more effective overall. Although VR adoption is still in its early stages, it is thriving as an increasing number of businesses and organizations incorporate VR features into their marketing. Many travel promoters have already used virtual reality (VR) technologies to provide a preview of hotel buildings, cruise ships, and travel experiences. Samueley (2016). However, there is a significant lack of empirical research on the use of this technology for businesses, as well as destinations more broadly conducted a qualitative analysis of destinations operating in (Second Life) it is the largest user-created open platform virtual world, to provide users seeking travel information a uniquely personal experience (Mascho and Singh, 2014). The authors investigated the relationships between Second Life platform usage and real-world visitation. Although the Second Life platform creates a virtual world and has been demonstrated to correlate with real-world behavior, it does not provide a sensory immersion experience. VR has the potential to significantly alter passengers' expectations and perceptions of a destination by establishing connections and expectations prior to purchase and consumption. (Rizzo, 2016). Hence, the authors purpose the following hypothesis:

H1: Artificial intelligence affects positively marketing effectiveness.

AI and destination competitiveness:

AR and VR, which use artificial intelligence, are becoming the new advertising and marketing tools. They had been utilized by numerous brands to attract customers and increase client loyalty. The tourism industry has long relied on the use of visual images when promoting places in order to communicate with and influence consumers. (Aziz and Zainol, 2011), Users of smartphones and tablet computers can utilize (AR) to point their built-in cameras at whatever object they desire, which makes a 3D movie (Linaza et al, 2012). This object could be a print advertisement or even a coffee cup from a popular coffee shop. In other words, augmented reality enables businesses to merge the digital and physical worlds. This extraordinary feature is especially enticing to younger tech enthusiasts who are hesitant to use standard advertising strategies (Craig, 2013).

So, the authors purpose the following hypothesis:

H2: Artificial intelligence affects positively tourism destination competitiveness.

The relation between marketing effectiveness and destination competitiveness:

The requirement for destination branding is more important than ever because today's destinations provide excellent destination qualities like aodging and attractions, high-quality services and amenities, and nearly every place claims to have a distinct culture and legacy (Morgan and Pritchard, 2005). To remain competitive in today's tourism industry, destinations must invest in branding. As multiple writers have stressed, destinations must go through various technical phases, i.e. aspects of the destination branding process, in order to build a powerful destination brand. (Anholt, 2007 ETC/UNWTO, 2009; Kotler and Keller, 2012; Paliaga, 2007).

Identifying potential target groups is the first stage in the destination branding process. Destinations must identify the target audiences to whom they will communicate the defined brand. Destinations' relevant target groups are distinct visitor groupings. Knowing who their major target groups are, venues should develop a brand that will have the most impact on tourists' perceptions of the destination. The competition analysis is the second step in the branding process. The primary goal of a competition study should be to discover the strengths and drawbacks of other competing destinations (Kotler and Keller, 2012). The third step in the destination branding process is a SWOT analysis. It should identify and prioritize the main markets' strengths, weaknesses, opportunities, and risks for destinations (ETC/UNWTO, 2007). The next element of the strategic message is based on the points of differentiation presented above for the destination. The last and most important component is destination brand communication. The destination brand should be communicated to all target groups through various promotional initiatives (Kotler and Keller, 2012). The influence of a destination brand on the target audience is determined by innovative marketing execution. (ETC/UNWTO, 2007; Kotler and Keller, 2012). Therefore, the authors suggest the following hypotheses:

H3: Marketing effectiveness affects positively tourism destination competitiveness

H4: Marketing effectiveness mediates the relationship between artificial intelligence and tourism destination competitiveness.

Research Methodology

Questionnaire design:

A questionnaire was created to collect statistical data about the respondents' attributes, artificial intelligence, marketing efficacy, and competitiveness. The questionnaire utilized in this study was divided into four sections. Part A of the questionnaire was concerned with the respondents' demographic and functional information. Four items were included in the questions: respondents' gender, age, degree of education, and workplace. Part B acquired information concerning artificial intelligence (AI) applications based on 20 items developed based on this section was split into four dimensions. The first dimension is forecasting (6 items) adopted from Claveria (2015). A sample item was " Forecasting can estimate arrivals tourist’s numbers". The second

dimension is Chatbots (CH) (7 items) which were developed by Gidumal (2020). A sample item was "Chatbots save customers time". While the third dimension is Virtual reality (VR) (5 items) which was prepared through Samuely (2016). A sample item was " VR is able to capture tourism destination in such a memorable and immersive way". The fourth dimension is Augmented reality (AR) (2 items) which was adopted from Linaza et al (2012). A sample item was “AR has the ability to place the user at the heart of the scene and makes it easier for them to imagine themselves at the location”
Part C gathered information concerning marketing effectiveness
(MK) based on eight items developed by Stalidisa et al (2015). A sample item was “AI applications can be used perfectly in the tourism industry”.
part D acquired information about Competitiveness (CM) based
on 13 items that developed from Stalidisa et al (2015). A sample item was “AI helps users to spend their vacation in a specific destination”

Sample size and data collection:
The sample size of the population was determined for a given population to become representative and ensure that results can be generalized to the whole population.
Questionnaires were distributed electronically and copied to employees in tourism and hospitality institutions such as airports, airlines, and governmental tourism authorities (Ministry of Tourism and Antiques and The Egyptian Tourism Authority). private tourism authorities (Beach Tours, Misr Travilco, Memphis Tours, and online traveling companies) by the researcher. Each questionnaire was attached to a covering letter indicating the purpose of the study and the importance of the participant’s involvement. The covering letter also confirmed the confidentiality and anonymity of data collection and that it is used for research purposes. To preserve anonymity, no name lists and ID numbers were required and no names or personal addresses were asked for. They were given clear instructions on how to answer the questionnaire and to confirm that all questions were answered within two months October and November (2021). After the agreed time period, the researcher collected questionnaires. There were online questionnaires were distributed, while 944 were collected.

Statistical tests:
To analyze the study data and test hypotheses, the researcher used statistical programs, namely SPSS V. 24 and AMOS V.24. The following statistical tests were used:

Exploratory factor analysis (EFA) and Confirmatory Factor Analysis (CFA): to test the reliability and validity.
Frequencies, percentages, means and standard deviation: to describe the characteristics of the sample, and to determine the responses of the sample members towards all the axes of the study tool.
Model fit indicators: to determine the extent to which the proposed study model matches the sample data.

Path analysis: to determine the direct effect of the independent variable on the dependent variable, and the indirect effect of the independent variable on the dependent variable through the mediating variable.

BOOTSTRAP method: to determine whether the mediating variable has a role in the relationship between the independent variable and the dependent variable.

There are conditions for conducting a path analysis using BOOTSTRAP to test the role of the mediating variable in the relationship between the independent variable and the dependent variable, and they are as follows (Al-Romeedy, 2019):

- If the indirect relationship between the independent variable and the dependent variable is significant, there is a mediating role for the mediator variable.
- If the indirect relationship between the independent variable and the dependent variable is insignificant, there is no mediating role for the mediator variable.
- If the direct relationship between the independent variable and the dependent variable is significant, there is a partial mediating role for the mediator variable.
- If the direct relationship between the independent variable and the dependent variable is insignificant, there is a full mediating role for the mediator variable.

Data Analysis and Findings

Demographic and other work-related information

Sample characteristics include four major items in this study. Table (1) indicates the results obtained after analyzing demographic variables. The frequency and percentage for each variable is listed according to the survey categories in the table.

Table (1) Demographic and work information

Demographic and work information		Freq.	%
Gender	Male	451	59.5%
	Female	307	40.5%
Age	Less than 20 years old	-	-
	20 – 39 years	385	50.8%
	40 – 59 years	332	43.8%
	60 years and above	41	5.4%
level of education	Less than bachelor	93	12.3%
	Bachelor	580	76.5%
	Master	34	4.5%
	PhD	23	3%
	Other	28	3.7%
Workplace	Travel agency	116	15.3%
	Hotel	252	33.2%
	Airport	84	11.1%
	Airlines	93	12.3%
	Governmental tourism authorities	95	12.5%
	Private tourism authorities	74	9.8%
	Other	44	5.8%

- **Regarding the gender of respondents**; More than half of the sample are male by 451 (59.5%), and there are 307 females by 40.5%.
- **When looking at the age of the respondents**; 385 (50.8%) of the respondents are (20 to 39 years), followed by who are (40 -59 years) by 332 (43.8%), and finally who are (60 years and above) by 41 (5.4%).
- **As for the level of education;** More than two thirds of the sample hold a bachelor's degree, with 580 respondents (76.5%), 93 respondents with a level of education less than a bachelor's degree (12.3%), then 34 respondents with a master's degree (4.5%), then 28 respondents with other educational qualifications (3.7%).), and finally, PhD holders with 23 respondents (3%).
- **Regarding the workplace of respondents;** 252 respondents are working in hotels (33.2%), followed by who are working in travel agencies by 116 respondents (15.3%), then who are working in governmental tourism authorities by 95 respondents (12.5%), then who are working in airlines by 93 respondents (12.3%), followed by who working in airports by 84 respondents (11.1%), then who are working in private tourism authorities by 74 respondents (9.8%), and finally who are working in other workplaces by 44 respondents (5.8%).

Exploratory factor analysis (EFA)

- The Kaiser-Meyer-Olkin KMO test and the Bartelett test for each variable. The exploratory factor analysis was carried out using Principal Components Analysis - PCA, and the orthogonal rotation of the dimensions was carried out using the Varimax Rotation method, assuming the independence of the extracted factors. The Kaiser-Meyer-Olkin KMO test and the Bartlett test were performed

to test the suitability and adequacy of the sample for exploratory factor analysis. The value of the KMO test should exceed 0.60, while the Bartlett test should be statistically significant less than 0.05 (Shrestha, 2021). The results in table (2) demonstrate that the percentage of KMO scale is 0.730, which is higher than 0.60. The Bartlett test has a significance level of 0.000, which is less than 0.05. This confirms that the sample is suitable for factor analysis.

Table (2) KMO test and the Bartelett test

KMO		.730
Bartelett test	APPROX. Chi Square	42887.925
	Df	1035
	Sig.	.000

Reliability Test

A high Cronbach's Alpha value reflects the reliability of scale and indicates cohesiveness among scale items. According to Ursachi et al. (2015), a high Cronbach's Alpha is an indirect indicator of convergent validity. However, on the contrary, the validity needed to be confirmed by CFA.

Table (3) highlights values of Cronbach's Alpha for all constructs. On the basis of the data presented in the table, there is sufficient evidence to suggest that the reliability of the constructs was acceptable given that the Cronbach's Alpha value is > .60.

Table (3) Reliability levels of instrument – Cronbach's Alpha

Variables	Cronbach's Alpha	No. of items
Forecasting (FC)	.735	6
Chatbots (CH)	.851	7
Virtual reality (VR)	.887	5
Augmented reality (AR)	.714	2
Artificial intelligence (AI)	.927	20
Marketing effectiveness (MK)	.766	8
Competitiveness (CM)	.807	13

Validity Test

The next step in the analysis was to test the validity, which is reported in detail in the following sections. Constructs validity, including both convergent and discriminant validity, was assessed by using average variance extracted (AVE). The following section discusses constructs validity.

Test of Convergent validity

The first test is the composite reliability of each measure. This was assessed using Nunnally's (1978) guideline for assessing reliability coefficients. Followed, the second test is average variance extracted (AVE) by each construct, which indicates the amount of variance in the item explained by the item explained by the construct relative to the amount attributed to measurement error (Shaffer & DeGeest, 2016). The Fornell and Larcker criterion, which confirmed that the AVE should be > .50, was used to assess the AVE for all constructs.

Some of the measures used for convergent validity include the reliability if each items, AVE, and composite reliability. The following tables reveal that all the indicators were statistically significant for the proposed constructs, thereby providing strong evidence for convergent validity (Hair et al., 2021).

For more details, the composite reliability values for artificial intelligence (.901), marketing effectiveness (.878), and competitiveness (.844). These values of composite reliability exceeded the desired threshold of .70 in accordance with Fornell and Larcker's (1981) proposal.

Also the following tables clarify that AVE values for artificial intelligence (.754), marketing effectiveness (.703), and competitiveness (.689), which exceeded the suggested value (0.50). So, the model seems to possess adequate convergent validity.

In details, table (4) clarifies that composite reliability for all items exceeded the desired threshold of .70. additionally, this table shows that AVE for artificial intelligence instrument exceeded the suggested value (0.50). As well, this table indicates that the factor loading for all items of artificial intelligence instruments are greater than (.50).

Table (4) Construct validity of artificial intelligence instrument

Constructs	Factor loading	Composite reliability	AVE
FC1	.856	.901	.754
FC2	.810		
FC3	.897		
FC4	.792		
FC5	.866		
FC6	.907		
CH1	.852		
CH2	.871		
CH3	.861		
CH4	.830		
CH5	.799		
CH6	.756		
CH7	.913		
VR1	.831		
VR2	.751		
VR3	.745		
VR4	.793		
VR5	.856		
AR1	.810		
AR2	.777		

Table (5) indicates that composite reliability for all items exceeded the desired threshold of .70. Further, this table shows that AVE for marketing effectiveness instrument exceeded the suggested value (0.50). Also, this table concludes that the factor loading for all items of marketing effectiveness instrument are greater than (.50).

Table (5) results summary for construct validity of marketing effectiveness instrument

Constructs	Factor loading	Composite reliability	AVE
MK1	.902	.878	.703
MK2	.841		
MK3	.834		
MK4	.900		
MK5	.853		
MK6	.792		
MK7	.771		
MK8	.835		

Table (6) indicates that composite reliability for all items exceeded the desired threshold of .70. Moreover, this table depicts that AVE for competitiveness of Egyptian tourism destination instrument exceeded the suggested value (0.50). Too, this table highlights that the factor loading for all items of competitiveness of Egyptian tourism destination instrument are greater than (.50).

Table (6) results summary for construct validity of competitiveness of Egyptian tourism destination instrument

Constructs	Factor loading	Composite reliability	AVE
CM1	.742	.844	.689
CM2	.792		
CM3	.897		
CM4	.788		
CM5	.752		
CM6	.910		
CM7	.739		
CM8	.745		
CM9	.853		
CM10	.897		
CM11	.804		
CM12	.867		
CV13	.872		

Discriminant validity

Hair *et al.* (2016) and Al-Romeedy (2019) have clarified that the square sroots of AVE should surpass the highest squared correlation with any other construct. On the basis of table (7), it can be noted that the square root of AVE for a given construct is greater than the absolute value of the standardization correlation of the given construct with any other construct in the analysis (AVE > correlations^2).

Table (7) Discriminate Validity for all variables

	FC	CH	VR	AR	AI	MK	CM
FC	***.868***						
CH	.721	***.829***					
VR	.497	.421	***.851***				
AR	.588	.732	.569	***.810***			
AI	.669	.552	.585	.637	***.829***		
MK	.459	.597	.432	.556	.705	***.838***	
CM	.663	.710	.397	.697	.700	.696	***.830***

Bold and italic values indicate the square roots of AV

Confirmatory Factor Analysis

Confirmatory factor analysis was used for the three variables using the maximum likelihood method (Maximum Likelihood - ML). The results resulted in a good fit for the five variables. The following table shows the value of the matching indicators for the five variables. It is noted from the following table that the value of the good match indicators exceeds (0.95), which indicates an acceptable good match.

Table (8) Confirmatory Factor Analysis

	CFI	GFI	AGFI	NFI	NNFI	IFI	TLI	RMSEA
FC	.985	.977	.973	.983	.980	.974	.966	.015
CH	.963	.958	.982	.966	.975	.958	.983	.028
VR	.974	.983	.981	.964	.959	.988	.970	.018
AR	.955	.977	.976	.978	.971	.959	.983	.009
AI	.956	.968	.968	.958	.976	.954	.960	.034
MK	.971	.958	.982	.963	.970	.956	.967	.041
CM	.964	.968	.974	.959	.974	.983	.955	.019

Descriptive statistics

Table (9) Mean value and standard deviation (SD)

Artificial intelligence's applications	Mean	SD	T	Sig.	Rank
FC	**3.7212**	**.78810**	**26.593**	**.000**	**3**
CH	**3.4868**	**.78358**	**17.104**	**.000**	**4**
VR	**3.9034**	**.74936**	**33.192**	**.000**	**2**
AR	**3.9063**	**.89091**	**28.008**	**.000**	**1**
AI applications in tourism industry	**3.7644**	**.67351**	**31.249**	**.000**	
Marketing effectiveness	**3.8786**	**.73509**	**32.908**	**.000**	
Competitiveness of the Egyptian tourism destination	**3.8909**	**.51948**	**47.217**	**.000**	

The results of table No. (9) refer to the study sample's responses to the artificial intelligence's applications in tourism industry statements. In general, it appears from the results of the table that the total mean of the responses of the respondents to artificial intelligence's applications in tourism industry amounted to (3.7644) with a standard deviation of (.67351), and based on the standard used In this study and the responses of the sample, this mean indicates that the evaluation of artificial intelligence's applications in tourism industry was high.

As well as, the table depict to the study sample's responses to the marketing effectiveness variable statements. In general, it appears from the results of the table that the total mean of the responses of the respondents to marketing effectiveness amounted to (3.8786) with a standard deviation of (.73509), and based on the standard used In this study and the responses of the sample, this mean indicates that the evaluation of marketing effectiveness was high.

The results also indicate to the study sample's responses to the competitiveness of the Egyptian tourism destination variable statements. In general, it appears from the results of the table that the total mean of the responses of the respondents to competitiveness of the Egyptian tourism destination amounted to (3.8909) with a standard deviation of (.51948), and based on the standard used In this study and the responses of the sample, this mean shows that the evaluation of competitiveness of the Egyptian tourism destination was high.

The table also shows the low dispersion in the responses of the study sample about the three variables and its statements, which reflects the convergence of the sample members' views on the importance of the three variables. The table also indicates the convergence in the values of the mean, where it is noted from the statistical significance values associated with the calculated (t) values that there are no differences in the opinions of the study sample members about the statements of this variable, as the statistical significance of all levels was lower than the level of the significance (0.05).

Test of hypotheses

H1: Artificial intelligence affects positively marketing effectiveness

Table (10) reveals the outputs of multiple regression test of the effect of artificial intelligence on marketing effectiveness.

Table (10) the effect of artificial intelligence on marketing effectiveness

Model	Coefficients (B)	T	Sig.	R	R^2	F	Sig.
(Constant)	.802	8.456	.000	.786	.617	303.597	.000
FC	.119	3.934	.000				
CH	.151	3.726	.000				
VR	.711	17.765	.000				
AR	.208	5.257	.000				

The results in table (10) depict that the sig. value is less than (.05) which mean there is a statistical significant correlation between artificial intelligence and marketing effectiveness. Table also shows that the correlation between artificial intelligence and marketing effectiveness was positive, where correlation coefficient value is (.786). This means; the higher the level of artificial intelligence, the higher the level of marking effectiveness. It also indicates the reliability of model used in testing the effect of artificial intelligence on marketing effectiveness. F value is (303.597) with sig. level (0.001). This model indicates the percent of change on marketing effectiveness in which explained through artificial intelligence. It also indicates that R Square is (0.617) which means that the independent variable (artificial intelligence) explain (61.7%) of change in the dependant variable (marketing effectiveness). This result is in line with Gidumal (.2020) study which indicated that AI has a positive impact on marketing effectiveness. Hence, H1 is supported.

H2: Artificial intelligence affects positively tourism destination competitiveness

Table (11) reveals the outputs of multiple regression test of the effect of artificial intelligence on competitiveness.

Table (11) The effect of artificial intelligence on competitiveness

Model	Coefficients (B)	T	Sig.	R	R^2	F	Sig.
(Constant)	2.155	27.446	.000	.689	.475	170.070	.000
FC	.087	3.477	.001				
CH	.049	2.000	.046				
VR	.612	18.449	.000				
AR	.207	8.449	.000				

The results in table (11) show that the sig. value is less than (.05) which means there is a statistically significant correlation between artificial intelligence and competitiveness. Table also indicates that the correlation between artificial intelligence and competitiveness was positive, where the correlation coefficient value is (.689). This means, The higher the level of artificial intelligence, the higher the level of competitiveness. The table also indicates the reliability of the model used in testing the effect of artificial intelligence on competitiveness. F value is (170.070) with sig. level (0.001).

This model depicts the percent of change in competitiveness which is explained through artificial intelligence. It also shows that R Square is (0.475) which means that the independent variable (artificial intelligence) explains (47.5 %) of the change in the dependent variable (competitiveness). This result is in line with Fauzi and Gozali (2015) study which supported that AI affects positively tourism destination competitiveness. So, H2 is supported.

H3: Marketing effectiveness affects positively tourism destination competitiveness

Table (12) shows the outputs of a simple linear regression test of the effect of marketing effectiveness on competitiveness.

Table (12) the effect of marketing effectiveness on competitiveness

Model	Coefficients (B)	T	Sig.	R	R^2	F	Sig.
(Constant)	1.869	27.283	.000	.738	.544	301.947	.000
marketing effectiveness	.521	30.032	.000				

The results in table (12) display that the sig. value is less than (.05) which means there is a statistically significant correlation between marketing effectiveness and competitiveness. Table highlights that the correlation between marketing effectiveness and competitiveness was positive, where the correlation coefficient value is (.738). This means the higher the level of marketing effectiveness, the higher the level of competitiveness. Additionally, this table indicates the reliability of the model used in testing the effect of marketing effectiveness on competitiveness. F value is (301.947) with sig. level (0.001). This model indicates the percent of change on competitiveness which is explained through marketing effectiveness. As well, it displays that R Square is (0.544) which means that the independent variable (marketing effectiveness) explains (54.4%) of the change in the dependant variable (competitiveness). This result is in line with Anholt (2007) study which supported that marketing effect on competitiveness. So, H3 is supported.

H4: Marketing effectiveness mediates the relationship between artificial intelligence and tourism destination competitiveness.

Table (13) indicates Model fit for path analysis from artificial intelligence to competitiveness of destination through marketing effectiveness as a mediator

Table (13) Model fit for path analysis from artificial intelligence to competitiveness of destination through marketing effectiveness as a mediator

Indicators	Value
χ^2/df	2.015
Comparative Fit Index – CFI	.968
The Goodness of Fit Index – GFI	.971
Normative Fit Index – NFI	.954
Incremental Fit Index – IFI	.958
Tuker – Lewis Index – TLI	.960
Root Mean Square Error of Approximation – RMSEA	.021

Table (13) shows the values of model fit indicators of the path analysis model for the impact of artificial intelligence on competitiveness of destination through marketing effectiveness as a mediator. Through the table, it is clear that the value of chi-square is less than 5, reaching (2.015). The results show that the value of the (CFI) is (0.968). Moreover, the results in the table indicate that the value of the (GFI) is (0.971). Table also indicates that the value of the (NFI) is (0.954). as well, it is clear that the value of the (IFI) is (0.958). The (TLI) value is (0.960). Finally, the results in the table show that the (RMSEA) value is (0.021). Through all the mentioned indicators, it becomes clear that the proposed model fitted the sample data. Table (15) reveals the direct and indirect effect of artificial intelligence on competitiveness of destination through marketing effectiveness as a mediator.

Table (14) the direct and indirect effect of artificial intelligence on competitiveness of destination through marketing effectiveness as a mediator

Path		Direct effect		Indirect effect	
		Value	Sig.	Value	Sig.
Effect of artificial intelligence on competitiveness of destination through marketing effectiveness as a mediator	artificial intelligence ---> marketing effectiveness	.731	.000	.522	.000
	marketing effectiveness ---> competitiveness	.553	.000		
	Artificial intelligence ---> competitiveness	.430	.000		

Table (14) shows the results of the BOOTSTRAP path analysis using Amos software. Based on the conditions for using this method, it is clear from the table that marketing effectiveness plays a partial mediating role in the relationship between artificial intelligence and competitiveness, due to the following:

- The indirect relationship between the independent variable (artificial intelligence) and the dependent variable (competitiveness) is significant, and this means that there is a mediating factor for the mediating variable (marketing effectiveness).
- The direct relationship between the independent variable (artificial intelligence) and the dependent variable (competitiveness) is significant,

and this means that there is a partial mediation of the mediating variable (marketing effectiveness).

The table also indicates the values of the direct effect between the independent, mediate and dependent variables, as the value of the direct effect of the artificial intelligence on the marketing effectiveness of is (0.731). The value of the direct impact of marketing effectiveness on competitiveness is (0.553). In addition, the value of the direct impact of the artificial intelligence on the competitiveness is (0.430).

The indirect effect of the artificial intelligence on the competitiveness in the presence of the marketing effectiveness as a mediating variable is (0.522), which confirms the role that the marketing effectiveness plays a mediating role (partial) in enhancing the effect of the artificial intelligence on the competitiveness. Therefore, H4 is supported.

Results and Recommendations:

The study aims to discover the mediating role of marketing effectiveness in the relationship between artificial intelligence and competitiveness. The study reached a number of results related to the level of adoption by the travel and tourism industry of artificial intelligence applications, the level of marketing effectiveness and the extent of the competitiveness of the destination. The results indicated that the tourism and travel industry apply some applications of artificial intelligence in its various operations such as chatbots, virtual reality, augmented reality and forecasting. The marketing policies of the travel and tourism industry are suitably effective. The Egyptian tourist destination is characterized by high competitive capabilities. Artificial intelligence affects positively both marketing effectiveness and tourism destination competitiveness. Marketing effectiveness affects positively tourism destination competitiveness. Finally, Marketing effectiveness mediates the relationship between artificial intelligence and tourism destination competitiveness.

To enrich the advantages of using the artificial intelligence applications in the tourism and travel industry and its role in enhancing both marketing effectiveness and the competitiveness of the destination the researchers provide some recommendations; specialists should draw the attention of the government to enable the artificial intelligence applications which referred to in this research, in addition to providing the opportunity for other applications such as robots, holograms and metaverse technology. Ministry of Tourism and Antiques should strengthen using artificial intelligence tools which offer digital experience. moreover, general authority for tourism promotion should use augmented reality and virtual reality instead of old ways of promotion and providing technical and financial support for the Egyptian tourism market to be ready to use artificial intelligence technology. Additionally develop and improve marketing policies for the travel and tourism industry in the Egyptian tourist destination.

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