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MEASURING THE IMPACT OF DIGITAL TECHNOLOGY ON ENHANCING E-COMMERCE IN ALGERIA COMPARED TO A GROUP OF ARAB COUNTRIES (2010-2023)

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ABSTRACT

This study explores the influence of digital technology on the growth of e-commerce in Algeria compared to selected Arab countries – Tunisia, Egypt, Saudi Arabia, and the United Arab Emirates – over the period 2010 to 2023.

It examines the role of key technological advancements, including the Internet of Things (IoT), artificial intelligence (AI), machine learning, digital payment systems, and big data analytics, in shaping the expansion of business-to-consumer (B2C) e-commerce.

Using an econometric approach, the study employs panel models and analyzes the outputs generated by the EVIEWS 12 software. After conducting selection tests, the analysis determined that the fixed effects model is the most suitable for capturing the underlying relationships within the dataset.

The study concluded that a strong and positive correlation exists between the adoption of modern technologies and the evolution of e-commerce.

Among these technologies, artificial intelligence and machine learning emerged as pivotal drivers of growth in this sector. Following closely in significance, the Internet of Things (IoT) plays a crucial role in enhancing the operational efficiency of connected devices. Additionally, the study underscored the importance of e-wallet technology and big data analysis, albeit to a relatively lesser extent, in facilitating and optimizing electronic transactions.

These insights highlight the necessity of reinforcing digital infrastructure, advancing AI-powered solutions, and broadening the adoption of digital payment technologies to accelerate e-commerce development in Arab economies.

Keywords: Digital technology, E-commerce, Arab countries, Algeria, Artificial Intelligence, Internet of Things, Big Data Analytics, E-Wallet Technology, Panel Data Analysis

JEL Classification: O33, L81, O53, L86, 055, C55, G21, C23

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INTRODUCTION

E-commerce is among the most transformative advancements in the modern commercial landscape. The Arab market is particularly positioned for notable growth and development in this domain, with several Arab countries successfully establishing robust infrastructure and reasonably sound economic market foundations. The increasing speed and reliability of internet connectivity have further provided a strong impetus for the growth of international online trade and the rapid expansion of online sales.

However, many countries, including Algeria and other Arab nations, face considerable challenges in effectively leveraging and utilizing e-commerce. These challenges stem primarily from the underutilization of advanced technological tools and emerging technologies, which are essential enablers for fostering and optimizing this form of commerce.

This research investigates the effects of digital technology on the evolution of online business in Algeria compared to selected Arab countries, including Tunisia, Egypt, The Kingdom of Saudi Arabia, and the UAE, throughout the years 2010 to 2023. This paper utilizes econometric models based on panel data, to examine the influence of essential factors on B2C e-commerce. These variables include connected smart devices (IoT), intelligent automation (AI), digital payment systems, and big data analytics.

By integrating longitudinal and cross-sectional data, this study examines critical technological indicators, including mobile and fixed-line subscriptions, internet penetration rates, the use of credit and debit cards, as well as ICT trade flows, to understand their interplay with e-commerce growth. The model incorporates methodological rigour through panel data techniques to control for unobserved heterogeneity, enhance estimation precision, and identify trends within the economic structures of these countries.

The central issue of this study arises from the need to understand the role of digital technology in enabling e-commerce and overcoming the challenges associated with digital transformation in these countries.

In light of this, the research seeks to address the following key question:

How significantly does modern digital technology support the growth of e-commerce in Algeria compared to a group of Arab countries?

This primary question gives rise to a series of secondary questions:

1. Does Internet of Things (IoT) technology have a statistically significant impact on the volume of B2C e-commerce in Algeria, Tunisia, Egypt, the United Arab Emirates, and Saudi Arabia during the period 2010–2023?
2. Does artificial intelligence (AI) and machine learning technology have a statistically significant impact on the volume of B2C e-commerce in the sample countries during the period 2010–2023?
3. Does electronic wallet technology have a statistically significant impact on the volume of B2C e-commerce in the benchmark countries during the period 2010–2023?
4. Does big data analytics technology have a statistically significant impact on the volume of B2C e-commerce in the studied nations during the period 2010–2023?

To answer the previous questions, we put forward the following hypotheses:

First Hypothesis: There is a statistically significant relationship at a significance level of 0.05 between Internet of Things (IoT) technology and the volume of B2C e-commerce in Algeria, Tunisia, Egypt, the United Arab Emirates, and Saudi Arabia during the period 2010–2023. To test this hypothesis rigorously, it was subdivided into two sub-hypotheses as follows:

1. There is no significant impact of the number of ATMs per 100,000 people on B2C e-commerce sales.
2. There is no significant impact of fixed-line and mobile phone subscribers on B2C e-commerce sales.

Second Assumption: This study posits a statistically significant link at a 0.05 significance level between artificial intelligence (AI) and machine learning technologies and the volume of B2C e-commerce in the selected Arab countries during the period 2010–2023. For in-depth examination, this hypothesis was divided into two sub-hypotheses:

1. There is no significant impact of the percentage of internet users on B2C e-commerce sales.
2. There is no significant impact of high-tech exports on B2C e-commerce sales.

Third Supposition: A statistically significant connection is expected at a 0.05 significance level between e-wallet technology and the volume of B2C e-commerce in the focus countries during the period 2010–2023. To conduct a comprehensive test, this hypothesis was divided into two sub-hypotheses:

1. There is no significant impact on the proportion of people aged 15 and above with a debit card on B2C e-commerce sales.
2. There is no significant impact on the share of individuals who are 15 years or older with a credit card on B2C e-commerce sales.

Fourth Postulation: The hypothesis suggests a statistically significant impact at a 0.05 significance level between big data analytics and the volume of B2C e-commerce in the comparative group during the period 2010–2023. To systematically test this hypothesis, it was broken into two sub-hypotheses:

1. There is no significant impact of the inflow of digital and communication technology (ICT) products on digital commerce sales.
2. There is no significant impact of the outflow of digital and communication technology (ICT) products on online trade sales.

LITERATURE REVIEW

The study "E-Commerce and Digital Transformation: Trends, Challenges, and Implications" highlights the transformative potential of integrating technologies like AI and blockchain in e-commerce, emphasizing both the operational benefits and societal challenges, such as the digital divide and environmental concerns (Rahul, Shramishtha, & Sanobar, 2023). Similarly, "Research on Digitizing and E-commerce in the Era of the Digital Economy" underscores the efficiency and profitability gains enabled by digitization, while addressing persistent issues like cybersecurity and accessibility, particularly for SMEs (Pan, et al., 2021). Complementing these findings, the study "E-Commerce and the Factors Affecting Its Development in the Age of Digital Economy" identifies digital infrastructure, regulatory harmonization, and socioeconomic factors as critical enablers of e-commerce growth, while emphasizing the importance of addressing regional disparities in digital access (Bădîrcea, et al., 2021).

The research centres on small and medium-sized enterprises (SMEs), and explores how business technologies contribute to the effectiveness of e-commerce strategies from their viewpoint: SMEs Perspective" reveals the strategic advantages of adopting CRM systems and analytics tools, though barriers like financial constraints and skill gaps persist (Almtiri & Miah, 2020). Expanding this lens globally, "The connection between digital finance and online commerce: based on data from 100 Countries" demonstrates how digital financial services amplify e-commerce growth, with the MENA region facing unique challenges in infrastructure and financial inclusion (Durani, 2023). Similarly, "E-Commerce and Digital Trade in Africa" highlights Africa's e-commerce potential driven by mobile adoption and regional trade initiatives, while advocating for investments in infrastructure and regulatory reforms to overcome barriers (Ofori-Sasu, N'guessan, & Nanziri , 2024).

On a more localized level, the ethnographic study on "Inbound Marketing by E-Commerce Platforms in Algeria" illustrates how platforms like "Jumia Algeria" and "Yassir" utilize tailored marketing strategies to drive customer engagement despite challenges in digital literacy and infrastructure (Meslem & Abbaci, 2023). Finally, the thesis "The Role of Digital Transformation in Developing E-commerce in Algeria during the Period 2016-2021" explores Algeria's digital transformation journey, noting progress during the COVID-19 pandemic but stressing the need for enhanced infrastructure and legal frameworks to sustain e-commerce growth. Together, these studies provide a comprehensive roadmap for leveraging digital innovation to advance e-commerce globally and regionally, with actionable insights for overcoming systemic challenges.

AIMS AND OBJECTIVES

1. Exploring the impact of Digital Technology on E-Commerce expansion:
   - The objective of this research is to explore the effect of digital technology on the growth of E-commerce for individual consumers (B2C) in Algeria and selected Arab countries, during the time span from 2010–2023. The analysis employs panel data models as a robust statistical methodology.
2. Conducting a Comparative Evaluation Among Countries:
   - The study seeks to perform a comparative analysis between Algeria and other Arab nations to identify the most influential factors in promoting e-commerce while accounting for geographical and economic disparities.
3. Highlighting the Role of Four Digital Technology Pillars:
   - Analyzing the impact of the Internet of Things (IoT): Examining variables such as the prevalence of fixed and mobile phone subscriptions.
   - Studying artificial intelligence (AI) and machine learning technologies: Focusing on internet usage rates and the export of advanced technologies.
4. Assessing the effect of electronic wallet technologies: Evaluating the adoption of credit and debit cards.
   - Measuring the influence of big data analytics: Using indicators like the imports and exports of ICT-related goods.

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5. Employing Advanced Statistical Tools for Data Analysis:
   - The study utilizes cutting-edge methodologies, including fixed and random effects models as well as robust regression techniques, to analyze the data. These approaches aim to provide precise insights into the challenges and opportunities within the e-commerce sector.

METHODS

The study adopted a quantitative methodology utilizing panel data, which integrates temporal and cross-sectional dimensions to offer an in-depth examination of the connection between digital technology and e-commerce across various countries. The panel data model was chosen for its capacity to account for unobserved, country-specific fixed effects and temporal variations, thereby ensuring the robustness and depth of the analysis. Furthermore, a comparative analysis was performed among five countries to identify and understand key differences in the impact of digital technology on e-commerce. By using:

Population and Sample. A sample comprising five Arab countries was selected: Algeria, the Tunisian Republic, Egypt, the Saudi Kingdom, and the UAE.

Variables and Dimensions:

The First Dimension: Internet of Things (IoT)

1. Number of ATMs per 100,000 people.
2. Number of fixed and mobile telephone subscribers.

The Second Dimension: Artificial Intelligence and Machine Learning

1. Percentage of internet users (%).
2. Exports of advanced technology as a proportion of total manufactured products exports).

The Third Dimension: Electronic Wallet Technology

1. Percentage of individuals aged 15 years and above with a debit card (%).
2. Percentage of individuals aged 15 years and above with a credit card (%).

The Fourth Dimension: Big Data Analytics

1. Imports of ICT goods (as a percentage of total goods imports).
2. Exports of ICT goods (as a percentage of total goods exports).

The Dependent Variable in the Model: E-Commerce (ECOM)

The dependent variable in the model is represented by B2C e-commerce sales, measured in USD billions. These sales encompass all types of electronic transactions, including the sale of goods and the provision of services conducted online, the data related to e-commerce were sourced from reliable and up-to-date references, for example, the W.B, the IMF, Statista, StatCounter, eMarketer, Mordor Intelligence, Euromonitor International, Internet World Stats, GlobalWebIndex, Think with Google, and other official platforms.

Independent Variables in the Model

- Netus: Percentage of internet users.
- Mobfix: Number of fixed and mobile telephone subscribers.
- Atms: Number of ATMs per 100,000 people.
- Credcard: Percentage of individuals aged 15 years and above with a credit card.
- Debcard: Percentage of individuals aged 15 years and above with a debit card.
- Exphitech: The proportion of high-tech product exports relative to total manufactured goods exports.
- Expict: The share of ICT-related exports within overall product exports.
- Impict: The percentage of ICT goods imported in relation to total imports of goods.

To analyze how digital technology influences e-commerce in Algeria, and the comparison countries, we selected eight explanatory variables representing digital technology. This approach enabled us to formulate the model as represented by the following equation:

$$ECOM = \beta_0 + \beta_1 netus + \beta_2 mobfix + \beta_3 atms + \beta_4 credcard + \beta_5 debcard + \beta_6 Exphitech + \beta_7 Expict + \beta_8 Impict + \varepsilon$$

Where: ECOM – The dependent variable representing the volume of e-commerce (B2C); β_0 – The intercept term; From β_1 to β_8 – These coefficients denote the regression values associated with the explanatory factors; ε – represents the stochastic error component.

RESULTS

1. Statistical Description of the Dependent Variable (E-Commerce)

Using the EViews 12 software, we obtained Figure 1, which presents the descriptive statistics for the e-commerce dataset (ECOM), covering the time period from 2010 to 2023.

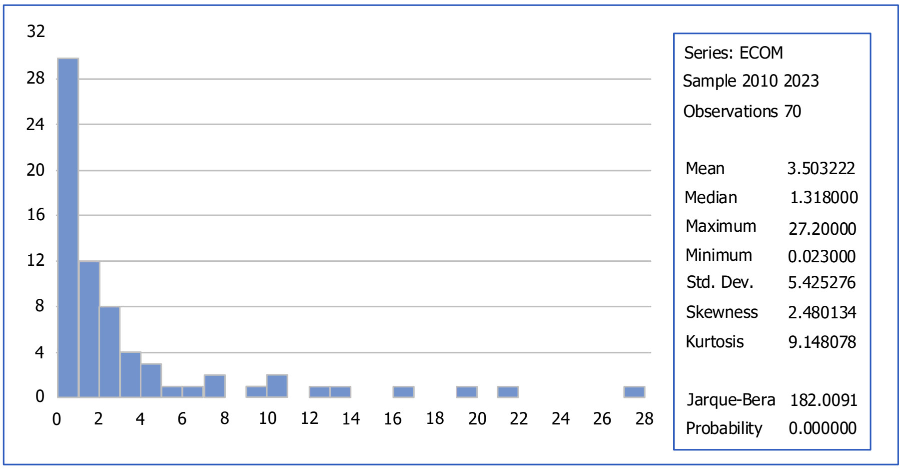

Figure 1. Descriptive Statistics of the E-Commerce Dataset for the Period 2010–2023. *(Source: compiled by the authors, utilizing EViews 12 program results)*

From Figure 1, certain observations can be derived (Gusti Ngurah, 2014, p. 11):

A Jarque-Bera test result of 182.0091, coupled with a p-value of 0.000000, supports a rejection of the null hypothesis, indicating non-normality in the dataset.

2. Statistical Description of the Independent Variables

By utilizing EViews 12, we conduct an analysis of Table 1, which illustrates the summary statistics for the dataset of the predictor variables, spanning the period from 2010 to 2023.

Table 1. Statistical Overview of the Determinant Factors covering the Years 2010–2023. *(Source: compiled by the researchers, utilizing EViews 12 program results)*

	ATMS	CREDCARD	DEBCARD	MOBFIX	NETUS	EXPHITECH	EXPICT	IMPICT
Mean	35.81771	14.91529	37.98771	47.05516	63.49857	3.009430	2.821351	6.506546
Median	30.10500	7.065000	24.33500	45.45000	65.70000	1.210283	2.272000	5.441500
Maximum	74.10000	50.40000	87.38000	115.6900	100.0000	10.16579	9.178000	17.18508
Minimum	5.92000	1.000000	5.000000	11.10100	13.60000	0.233281	0.000822	2.963291
Std. Dev.	23.62114	14.24361	27.03224	32.40606	25.89347	3.100995	2.067052	2.922411
Skewness	0.245192	0.910911	0.449736	0.804963	0.163460	0.883928	0.956403	1.626211
Kurtosis	1.487555	2.677528	1.596970	2.494179	1.925092	2.296608	2.052160	5.374243
Jarque-Bera	7.373231	9.983825	8.101166	8.308793	3.681796	10.81524	7.647091	47.28328
Probability	0.025057	0.006793	0.017412	0.015695	0.158675	0.004482	0.021850	0.000000

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According to Table 1, and based on the descriptive statistics and the Jarque-Bera test, it is observed that NETUS is the only variable that follows a normal distribution.

3. Quantitative Analysis in the Econometric Framework

To investigate how determinant factors influence B2C e-commerce, we begin by employing the "Panel Least Squares" regression model (Table 2):

Table 2. Results of the Regression Model Applying the Panel-Based Least Squares Approach. (*Source: developed by the researchers, using EViews 12 analytical outputs)*

Variable	Coefficient	t-statistic	Prob
C	-7.658125	-3.244199	0.0019
ATMS	-0.064628	-1.328209	0.1891
CREDCARD	0.068863	1.063075	0.2919
DEBCARD	0.066124	0.954372	0.3437
MOBFIX	0.047193	2.277107	0.0263
NETUS	0.085720	2.250887	0.0280
EXPHITECH	-0.075798	-0.239429	0.8116
EXPICT	0.099795	0.261401	0.7947
IMPICT	0.341187	0.997094	0.3227
Statistical Results			
f-stat	8.190333	F. statistical Probability	0.0000
Durbin-Watson	1.457819	R-squared	0.517873

From Table 2, the following conclusions can be drawn:

1. F-statistic: An observed value of 8,190333, accompanied by a probability value of 0.000000, demonstrates that the overall model exhibits statistical relevance. This highlights that the influencing variables, in combination, have a substantial effect on the outcome variable.
2. Determination Coefficient R^2: The result of 0.517873 suggests that the independent variables in the model explain approximately 51.79% of the variations in e-commerce, demonstrating a moderately adequate model fit.

4. Model Quality Assessment

The Standardized Residuals provide a powerful and effective tool for evaluating the quality of a regression model (Bourbonnais, 2015, p. 9).

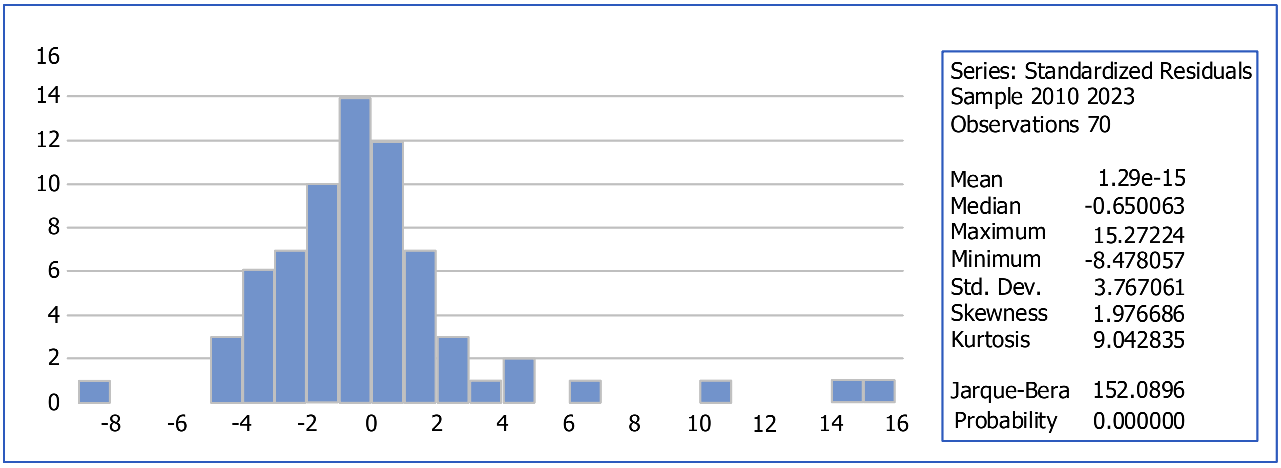

Figure 2. Distribution of Standardized Residuals for Regression Model Analysis. *(Source: created by the researchers, Using EViews 12 program results)*

As shown in Figure 2, the quality of the model can be examined by considering the following points: Jarque-Bera Test:152.0896, Prob=0.000000, This test measures the deviation of the distribution from normality. The probability value, which is approximately zero, strongly rejects the null hypothesis, implying that the residuals are not normally distributed.

5. Study Model Variable Stability Analysis

To assess the stability of the variables at different levels—whether at the first difference or second difference—the Dickey-Fuller and Phillips-Perron tests are employed (sennou & Elmouhib, 2025, pp. 3-4). These tests are applied to analyze the presence or absence of a constant and trend, as well as the effect of a trend without a constant or vice versa (Figure 3).

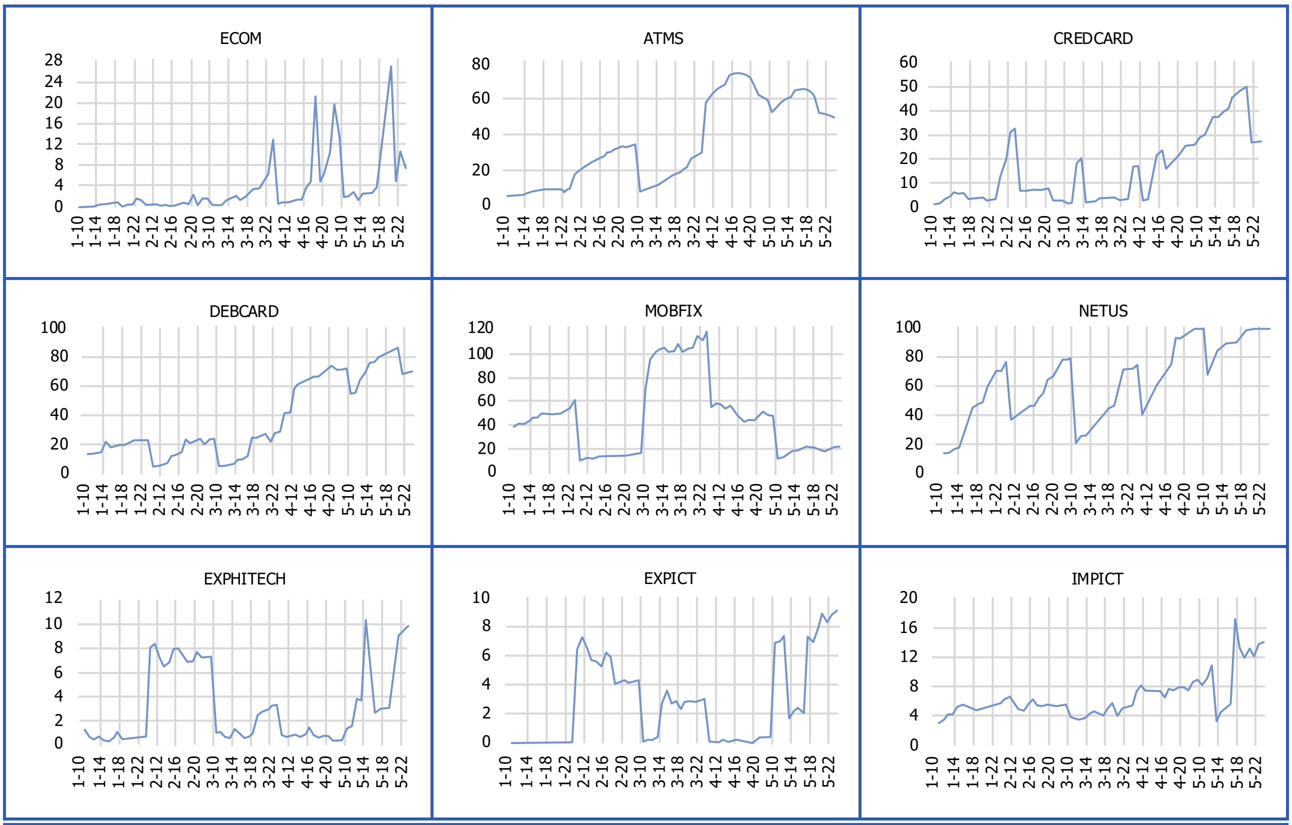

Figure 3. Stability of the Study Variables. *(Source: prepared by the researchers, based on EViews 12 software outputs)*

Based on the graphs presented in Figure 3, it is evident that most of the time series exhibit instability due to upward trends and significant fluctuations. To achieve stationarity, differentiation must be applied to transform the time series into a stable form (Baltagi, 2005, p. 18):

1. Levin, Lin & Chu t-Test: This test is employed to determine whether a unit root is present in the time series.
2. The ADF test, an extension of the Dickey-Fuller test, is utilized to determine the existence of a unit root and evaluate the stationarity of a time series.
3. PP - Fisher Chi-square Test: Another technique for examining the presence of a unit root is the Phillips-Perron test, which is used in the time series.

These tests are applied to ensure the reliability and validity of the data for further econometric modelling. Table 3 presents the results of these tests.

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Table 3. Assessment of Unit Root (Time Series Stationarity) for Independent Variables. *(Source: prepared by the researchers, based on EViews 12 software outputs)*

Variable	Test Type	Lag Period (Lag Length)	Unit Root Test Settings		p-value (Prob)	Test Statistic Value
ATMS	Levin, Lin & Chu t*	2	Second Difference	None	0.0000	-6.48552
	ADF – Fisher Chi-square	2			0.0000	38.6811
	PP – Fisher Chi-square	2			0.0000	92.2715
Credcard	**L**	1	Second Difference	None	0.0000	-7.92912
	A	1			0.0000	57.6395
	P	1			0.0000	89.2616
Debcard	**L**	1	Second Difference	None	0.0000	-8.78356
	A	1			0.0000	71.1846
	P	1			0.0000	108.663
Mobfix	**L**	1	Second Difference	None	0.0000	-9.18194
	A	1			0.0000	60.4150
	P	1			0.0000	84.7646
Netus	**L**	1	Second Difference	None	0.0000	-7.05974
	A	1			0.0000	52.0021
	P	1			0.0000	80.5321
Exphitech	**L**	1	First Difference	None	0.0000	-8.39445
	A	1			0.0000	61.3421
	P	1			0.0000	64.4832
Expict	**L**	5	First Difference	None	0.0000	-5.74923
	A	5			0.0000	39.2870
	P	5			0.0000	53.4406
Impict	**L**	5	First Difference	None	0.0000	-6.91584
	A	5			0.0000	54.9186
	P	5			0.0000	70.6901
Ecom	**L**	2	Second Difference	Individual Intercept & Trend	0.0000	-7.05808
	A	2			0.0000	42.6822
	P	2			0.0000	89.1250

The **L** test refers to the Levin, Lin & Chu t* test, The **A** test represents the ADF – Fisher Chi-square test, and the **P** test stands for the PP – Fisher Chi-square test.

Economic Interpretation: The ATMS, Credcard, Debcard, Mobfix, Netus, Exphitech, Expict, Impict, and Ecom time series all demonstrate stationarity, indicating the absence of a unit root.

6. Evaluation and Selection of Influential Variables in Regression Models

A precise and systematic approach was adopted to select the most impactful variables and eliminate the insignificant ones, in accordance with the following criteria: Statistical significance (p-value), Economic significance, and Interpretability of coefficients.

Table 4. Identification of Independent Variables Demonstrating High Statistical Significance and Economic Impact on E-Commerce. *(Source: prepared by the researchers based on Table 2)*

Variable	Statistical Description	Statistical Interpretation
(MOBFIX)	Coeffici:0.047193 t-statis:2.277107 (P): 0.0263	This variable demonstrates statistical significance, p < 0.05, suggesting a notable influence n e-commerce
(NETUS)	Coeffici: 0.085720 t-statis: 2.250887 (P): 0.0280	As the p-value is less than 0.05, these variable exhibits statistical significance, reflecting a substantial positive contribution to e-commerce
(CREDCARD)	Coeffici: 0.068863 t-statis: 1.063075 (P): 0.2919	This variable is not statistically significant (p > 0.05), but it shows a positive effect on e-commerce (+0.068863)
(IMPICT)	Coeffici: 0.341187 t-statis: 0.997094 (P): 0.3227	This variable is not statistically significant (p > 0.05), but it indicates a positive effect on e-commerce (+0.341187)

According to the information provided in Table 2, the variables: (CREDCARD) as well as (IMPICT)" were selected despite their lack of strong statistical significance for the following reasons: Theoretical Importance, Model Improvement, Potential Interactions, Temporal Dimension, and Regional Variations.

Table 5. Exclusion of Statistically Insignificant Variables from the Model. *(Source: prepared by the researchers based on Table 2)*

Variable	Statistical Description	Statistical Interpretation
(ATMS)	Coefficient: -0.064628 t-statistic: -1.328209 Probability (P): 0.1891	Since the probability value is higher than 0.05, it suggests that the effect lacks statistical significance.
(DEBCARD)	Coefficient: 0.066124 t-statistic: 0.954372 Probability (P): 0.3437	The p-value is greater than 0,05, which suggests that the effect does not reach statistical significance.
(EXPHITECH)	Coefficient: -0.075798 t-statistic: -0.239429 Probability (P): 0.8116	The probability value is considerably higher than 0.05, suggesting that there is no significant statistical effect.
(EXPICT)	Coefficient: 0.099795 t-statistic: 0.261401 Probability (P): 0.7947	The probability value is significantly greater than 0,05, indicating no statistical effect.

From Table 5, it can be concluded that the four excluded variables (ATMS, EXPHITECH, EXPICT, and DEBCARD) were not statistically significant based on their p-values and t-statistic values. This can be further clarified through the correlation table presented as follows:

Table 6. Interrelationships of Model Factors. *(Source: Compiled by the researchers, using data from EViews 12 results)*

	ECOM	ATMS	CREDCARD	DEBCARD	MOBFIX	NETUS	EXPHITECH	EXPICT	IMPICT
ECOM	1.000000								
ATMS	0.461274	1.000000							
CREDCARD	0.486258	0.656591	1.000000						
DEBCARD	0.599697	0.900752	0.743044	1.000000					
MOBFIX	-0.003755	-0.325344	-0.467138	-0.299273	1.000000				
NETUS	0.616727	0.741664	0.593449	0.821468	-0.303516	1.000000			
EXPHITECH	-0.003190	0.081139	0.233388	-9.75E-05	-0.570539	0.245897	1.000000		
EXPICT	0.217155	0.156787	0.464934	0.159903	-0.468319	0.317387	0.747299	1.000000	
IMPICT	0.541805	0.611169	0.652869	0.710060	-0.378002	0.644479	0.217735	0.566596	1.000000

7. Estimation of the Three Panel Models

After excluding the four variables that were not significant at the 5% significance level in explaining the dependent variable, and after entering the data using EViews 12 software, the model was constructed and estimated using three methods (Sul, 2019, p. 60):

Table 7. Model Estimation Results. *(Source: generated by the authors, using EViews 12 outputs)*

Variables	Pooled Regression		Fixed Effects		Random Effects	
	Probability	**Coefficient**	**Probab**	**Coeffic**	**Prob**	**Coeff**
C	0.0000	-8.881509	0.1117	-6.178908	0.0000	-8.881509
CREDCARD	0.0008	0.088722	0.0000	0.126620	0.0004	0.088722
MOBFIX	0.0018	0.054013	0.1656	-0.117099	0.0011	0.054013
NETUS	0.0782	0.086625	0.0040	0.190370	0.0641	0.086625
IMPICT	0.0630	0.448373	0.0076	0.662814	0.0507	0.448373
R-squared	0.501863		0.577928		0.501863	
F-statistic	16.37152		10.44062		16.37152	
Probabi (F.statistic)	0.000000		0.00000		0.0000	
Durbin Watson Statistic	1.492165		1.777579		1.492165	

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8. Comparison Between Models

We conduct a comparison between the panel models based on the following tests: (the restricted Fisher test, the homogeneity test, the Lagrange Multiplier test, and the Hausman test):

Restricted Fisher Test

Null Hypothesis (H0): The Pooled Regression Model is suitable.

Alternative Hypothesis (H1): The Fixed Effects Model is suitable.

Table 8. Redundant Fixed Effects Tests. *(Source: prepared by the researchers, based on EViews 12 software outputs)*

	Statistical Measure	Probability
Cross-Sectional F Statistic	2.748322	0.0361
Chi-square Statistic for Cross-section	11.598931	0.0206

Based on Table 8, the Redundant Fixed Effects Tests indicate the following:

The p-value for both the "F test", and the "Chi-square test" is below 0.05, suggesting that the fixed effects are statistically significant. This implies that the fixed-effects approach is the best choice (Alshdaifat, et al., 2024, pp. 6-7).

Hsiao's Homogeneity Test Outcomes (1986)

This test is used to determine the degree of homogeneity in terms of intercepts and slopes (Hsiao, 2014, p. 36).

Table 9. Results of the Hsiao Homogeneity Test. *(Source: compiled by the researchers, using EViews 12 software outputs)*

Test	Test Statistic	p-value
Total Homogeneity Test (F1)	4.97	6.19e-06
Slope Homogeneity Test (F2)	2.50	0.011881
Intercept Homogeneity Test (F3)	9.59	5.447e-06

From Table 9, the following can be observed the rejection of the null hypothesis that assumes homogeneity of intercepts.

LM test for Lagrange Multiplier

A Breusch Lagrange Multiplier (LM) test is employed to compare the pooled regression framework with the random effects model, and it is based on testing certain hypotheses (Godfrey, 1989, p. 94):

H0: The combined regression model is the most suitable.

H1: The model with random effects is the most suitable.

Table 10. Lagrange Multiplier Test. *(Source: developed by the research team, drawing upon EViews 12 software-generated outputs)*

Test	Test Statistic	p-value
Lagrange Multiplier (LM) Test Breusch-Pagan	156.8848	(0.0000)

Based on Table 10, we observe that the model with random influences is the most appropriate.

Hausman Test

Hausman's statistical test is employed to assess the differences between the fixed and the random effects model based on the evaluation of two specific hypotheses (Hausman, 1976, p. 5):

H0: The model incorporating random influences is deemed more suitable.

H1: The model with fixed effects is considered the better choice.

Table 11. Hausman's Method. (Reference: compiled by the authors, using results derived from EViews 12 software)

Test	Statistic Value	p-value
Hausman Test	10.993287	0.0266

According to the findings shown in Table 11, the fixed effects model appears to be the more appropriate model (Gharios, Awad, Khalaf, & Seissian, 2024, pp. 8-9).

9. Model Quality Evaluation

The model quality evaluation phase is based on the implementation of two tests: the first test (Wooldridge) to detect the issue of autocorrelation in the errors, and the second test (LR Heteroskedasticity Test) to detect the issue of heteroscedasticity in the errors (Vijayagopa, Jain, & Viswanathan, 2024, pp. 5-6).

Wooldridge Test for Autocorrelation. (Wooldridge, 2002, p. 25)*:*

H0: There is no autocorrelation. H1: There is autocorrelation.

Table 12. Wooldridge Test. *(Source: developed by the authors, using EViews 12 software outputs)*

Test	Statistic Value	p-value
Breusch-Pagan LM	9.185483	0.5146
The Pesaran Scaled Lagrange Multiplier (LM) test	-0.182132	0.8555
Pesaran's CD test for cross-sectional dependence	-0,709600	0,4780

Since all p-values exceed the conventional 0,05 significance threshold, this suggests that the fixed effects model used in the analysis does not suffer from cross-sectional dependence.

Test for Heteroskedasticity

This test is used to verify that the variance of the errors (residuals) is not constant and varies across observations (Williams, 2020, p. 74).

H0: There is no heteroskedasticity between the cross-sections.

H1: There is heteroskedasticity between the cross-sections.

Table 13. Panel Cross-section Heteroskedasticity LR Test. *(Source: generated by the researchers, utilizing EViews 12 program results)*

Test	Statistic Value	p-value
Heteroskedasticity Test	82.98993	0.0000

From Table 13, it is evident that the p-value is 0.0000, providing strong justification for null hypothesis rejection, considering uniform variance across the cross-sections. Therefore, it is necessary to address this issue to ensure the reliability of the estimates (Tripathi, 2023).

Model Correction

After identifying that the model suffers from heteroskedasticity, the model was corrected using the robust regression method (Bourbonnais, 2015, p. 61), which takes these issues into account.

The adjusted estimation results are displayed in the next Table:

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Table 14. Outcomes of Robust Regression. *(Source: created by the researchers, using EViews 12 software-generated results)*

Variable	Coefficient	Prob
C	-1.588565	0.0000
CREDCARD	0.029835	0.0013
MOBFIX	0.012682	0.0001
NETUS	0.021801	0.0000
IMPICT	0.079767	0.0798
R-squared	0.385590	
Rn^2 metric	111.9160	
Probability of Rn^2 statistic	0.00000	

1. R-squared = 0.385590 indicates that approximately 38.6% of the outcome variable's variability is attributable to the independent factors.
2. With an Rn^2 statistic of 111.9160 and a Probability of 0.000000, the results confirm the statistical significance of the entire model.

DISCUSSION

1. Testing the First Hypothesis

The validation of the first hypothesis depends on verifying the accuracy of the following two sub-hypotheses:

1.1. Testing the First Partial Hypothesis

Since the statistical results indicate insufficient significance (P = 0.1891 > 0.05), a minimal effect size (coefficient = -0.064628), and low statistical power (t = -1.328209), the null hypothesis cannot be rejected. This implies that the number of ATMs per 100,000 people does not have a significant effect on B2C e-commerce sales. Consequently, we reject the alternative hypothesis.

1.2. Testing the Second Partial Hypothesis

Given the statistically significant results indicating the effect of fixed and mobile phone penetration on B2C e-commerce sales—with a highly significant p-value (P = 0.0001 < 0.05) and a substantial positive effect coefficient (0.012682)— the null hypothesis (H0) is rejected in favour of the alternative hypothesis. This confirms a strong and positive significant impact of the number of fixed and mobile phone subscribers on B2C e-commerce sales.

Based on the results of the two partial hypotheses tests, we accept the validity of the first hypothesis, albeit with relative qualification.

2. Testing the Second Hypothesis

The validation of the third hypothesis is based on verifying the accuracy of the following two sub-hypotheses:

2.1. Testing the First Partial Hypothesis

In light of the statistical results showing the effect of the internet user percentage on B2C e-commerce sales, which revealed extremely high statistical significance (P = 0.0000) coupled with a strong positive effect coefficient (0.021801). A conclusive rejection of the null hypothesis (H0) supports the acceptance of the alternative hypothesis, confirming a strong and positive significant effect of the internet user percentage on B2C e-commerce sales.

2.2. Testing the Second Partial Hypothesis

Since the statistical analysis of the effect of advanced technology exports on B2C e-commerce sales revealed statistically insignificant results (P = 0.8116 > 0.05), with a minimal and negative effect coefficient (-0.075798) and an extremely low t-value (-0.239429). As the null hypothesis (H0) is not rejected, it suggests that advanced technology exports have no substantial impact on B2C e-commerce sales, leading to the rejection of the alternative hypothesis.

Drawing from the outcomes of sub-hypothesis testing and statistical evaluation, the second hypothesis is considered valid, though in a relative sense.

3. Testing the Third Hypothesis

The validation of the third hypothesis depends on verifying the accuracy of the following two sub-hypotheses:

3.1. Testing the First Partial Hypothesis

Since the statistical analysis of the relationship between the percentage of individuals over the age of 15 who possess a debit card and B2C e-commerce sales yielded statistically insignificant results ($P = 0.3437 > 0.05$). Given the small effect size (0.066124) and the relatively low t-value (0.954372), the null hypothesis (H0) is upheld, suggesting that this variable has no significant effect on B2C e-commerce sales, leading to the rejection of the alternative hypothesis.

3.2. Testing the Second Partial Hypothesis

In light of the precise statistical analysis of the impact of credit card penetration on B2C e-commerce sales, which demonstrated a highly significant result ($P = 0.0013 < 0.05$), coupled with a noticeable positive effect size (0.029835). The null hypothesis (H0) is decisively rejected in favour of the alternative hypothesis, confirming the existence of a significant and positive effect on the percentage of individuals over the age of 15 who own credit cards on B2C e-commerce sales.

Consequently, we accept the validity of the third hypothesis, albeit in a relative manner.

4. Testing the Fourth Hypothesis

The testing of the fourth hypothesis is based on the verification of the validity of the following two partial hypotheses:

4.1. Testing the First Partial Hypothesis

In light of the statistical results regarding the impact of ICT goods imports on B2C e-commerce sales, which showed limited statistical significance ($P = 0.0798$) coupled with a notable positive effect size (0.079767), we lean towards rejecting the null hypothesis (H0) while supporting the alternative hypothesis suggests recognizing a positive effect of ICT goods imports on B2C e-commerce sales, although less pronounced statistically compared to other variables.

4.2. Testing the Second Partial Hypothesis

Since the statistical analysis results for the impact of ICT goods exports on B2C e-commerce sales showed no statistical significance ($P = 0.7947 > 0.05$), with a minimal effect size (0.099795) and a very low t-value (0.261401), we accept the null hypothesis (H0), indicating that ICT goods exports do not have a significant on B2C e-commerce sales.

Thus, we accept the validity of the fourth hypothesis, albeit in a relative manner.

CONCLUSIONS

To analyze the impact of digital technology on e-commerce across the benchmark countries from 2010 to 2023, we employed a panel data model and selected eight explanatory variables representing digital technology. These variables were classified into four main categories: the IoT, AI & machine learning, e-wallet technology, and big data analytics.

The preliminary results indicated an R^2 coefficient of 0,517873, suggesting that the determining factors account for approximately 51.79% of the variability of the response variable.

The empirical study involved evaluating 03 approaches: pooled regression, fixed effects, and random effects models. After performing framework comparison tests (Redundant Fixed Effects, Hsiao, LM, and Hausman), the fixed-effects model was determined to be the best fit. However, the Panel Cross-section Heteroskedasticity LR test revealed variance heterogeneity across countries, necessitating model correction using the Robust Least Squares regression method.

Using the fixed effects model, we formulated a separate equation for each country as follows:

$$ECOM_{Algeria} = 1.340373 + 0.029835*CREDCARD + 0.012682*MOBFIX + 0.021801*NETUS + 0.079767*IMPICT$$

$$ECOM_{Tunisia} = -6.138050+ 0.029835*CREDCARD + 0.012682*MOBFIX + 0.021801*NETUS + 0.079767*IMPICT$$

$$ECOM_{Egypt} = 9.933265 + 0.029835*CREDCARD + 0.012682*MOBFIX + 0.021801*NETUS + 0.079767*IMPICT$$

$$ECOM_{Saudia} = -1.324960 + 0.029835*CREDCARD + 0.012682*MOBFIX + 0.021801*NETUS + 0.079767*IMPICT\ U$$

$$ECOM_{UAE} = -11.753455 + 0.029835*CREDCARD + 0.012682*MOBFIX + 0.021801*NETUS + 0.079767*IMPICT$$

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Pratical Implications:

Dimension 1: IOT Technology

The IoT is a crucial variable, ranking second after Artificial Intelligence (AI) and Machine Learning. It has a positive impact on the dependent variable, with a strong statistical significance. An increase of one million subscribers in both fixed and mobile phone subscribers lead to a rise in B2C e-commerce sales by approximately USD 12.682 million.

Dimension 2: Artificial Intelligence and Machine Learning

The variable NETUS, demonstrates a clear positive impact on the dependent variable, with an extremely strong statistical significance. Consequently, it is considered one of the most important variables. A 1% increase in the percentage of internet users boosts B2C e-commerce sales by USD 21.801 million.

Dimension 3: E-wallet Technology

A 1% increase in the percentage of individuals possessing credit cards results in an increase of USD 29.835 million in B2C e-commerce sales. This effect is statistically significant (Prob = 0.0013). This variable exerts a stronger favourable impact on the target variable in terms of the coefficient compared to MOBFIX, but it is less significant in terms of statistical relevance. It ranks third in importance.

Dimension 4: Big Data Analytics

A 1% increase in imports of ICT goods (as a proportion of overall imports) raises B2C e-commerce sales by USD 79.767 million, with a probability value of 0.0798, indicating near statistical significance. Despite having the largest coefficient among the variables, it remains statistically insignificant at the 0.05 level, reducing its relative importance.

For Countries:

Algeria (1.340373) and Egypt (9.933265) exhibit positive coefficients, suggesting a favourable baseline for e-commerce sales driven by population size. This indicates that a larger consumer market contributes to increased e-commerce sales.

The presence of negative coefficients for the UAE (-11.753455), Tunisia (-6.138050), and Saudi Arabia (-1.324960) in the context of e-commerce sales can be reasonably attributed to their relatively lower population sizes compared to Algeria and Egypt.

Prospects for Future Research

Building upon the insights derived from this study, several promising avenues for future research emerge, particularly in exploring the evolving role of digital technologies in shaping e-commerce trends in Algeria and the wider Arab region. The following key areas warrant further investigation:

1. Strengthening Digital Infrastructure.
2. Human Capital Development in Digital Transformation.
3. Exploring the Role of National Artificial Intelligence Programs.
4. Advancing Financial Inclusion and Digital Payment Ecosystems.
5. Assessing Cross-Border E-Commerce Potential.
6. The Role of Emerging Technologies in E-Commerce Growth.
7. Sustainability and Green E-Commerce.
8. Cybersecurity and Data Privacy in E-Commerce.

Study Proposals

Based on the findings derived from this study, we present a series of relevant recommendations and suggestions, which can be summarized as follows: strengthening digital infrastructure, developing human capacities in the field of technology, launching national programs for artificial intelligence, expanding financial inclusion and digital payments.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ВИМІРЮВАННЯ ВПЛИВУ ЦИФРОВИХ ТЕХНОЛОГІЙ НА РОЗВИТОК ЕЛЕКТРОННОЇ КОМЕРЦІЇ В АЛЖИРІ ПОРІВНЯНО З ГРУПОЮ АРАБСЬКИХ КРАЇН (2010-2023)

У цьому дослідженні вивчається вплив цифрових технологій на зростання електронної комерції в Алжирі порівняно з вибраними арабськими країнами – Тунісом, Єгиптом, Саудівською Аравією та Об'єднаними Арабськими Еміратами – за період із 2010 по 2023 рік.

Розглянута роль ключових технологічних досягнень, у тому числі Інтернету речей (IoT), штучного інтелекту (AI), машинного навчання, цифрових платіжних систем і аналітики великих даних, у формуванні розширення електронної комерції від бізнесу до споживача (B2C).

Використовуючи економетричний підхід, дослідження звертається до панельних моделей та аналізує результати, створені програмним забезпеченням EVIEWS 12. Після проведення тестів відбору аналіз визначив, що модель фіксованих ефектів є найбільш придатною для охоплення базових зв'язків у наборі даних.

Дослідження дійшло висновку, що між упровадженням сучасних технологій і еволюцією електронної комерції існує тісний і позитивний зв'язок.

Серед цих технологій штучний інтелект і машинне навчання стали ключовими рушійними силами зростання в цьому секторі. Услід за значенням вирішальну роль у підвищенні ефективності роботи підключених пристроїв відіграє Інтернет речей (IoT). Крім того, дослідження підкреслило важливість технології електронного гаманця та аналізу великих даних, хоча й відносно меншою мірою, для сприяння електронним транзакціям та їх оптимізації.

Ці висновки підкреслюють необхідність зміцнення цифрової інфраструктури, удосконалення рішень на основі штучного інтелекту та розширення впровадження цифрових платіжних технологій для прискорення розвитку електронної комерції в арабських країнах.

Ключові слова: цифрові технології, електронна комерція, арабські країни, Алжир, штучний інтелект, Інтернет речей, аналіз великих даних, технологія електронного гаманця, аналіз панельних даних

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