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ESG IMPACT ON CORPORATE PERFORMANCE AND FIRM VALUE ACROSS EUROPEAN INDUSTRIES

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Abstract: *This paper investigates the impact of Environmental, Social and Governance (ESG) scores on both firm value and corporate performance across ten sectors, focusing on European companies listed on stock exchanges from 2014 to 2023. The findings reveal significant industry-specific variations in how the environmental, social, and governance pillars affect both performance and market valuation. Positive correlations are found only in the Basic Materials sector, where higher ESG scores are linked to improved performance and increased firm valuation. In contrast, sectors such as Industrials, Consumer Cyclical, Consumer Non-Cyclical, Financials, Technology, Utilities, and Real Estate show declines in financial performance and reduced market valuation with higher ESG scores, with the Real Estate and Utilities sectors experiencing the most negative effects. Larger firms benefit marginally from ESG practices, particularly in Financial and Utility sectors, while leverage negatively impacts both performance and valuation. Liquidity and financial health, as measured by the current ratio and interest coverage ratio (ICR), correlate positively with firm performance and valuation, especially in capital-intensive sectors. This study emphasizes the importance of tailored ESG strategies to enhance firm value and competitiveness in a sustainability-focused market.*

Key words: ESG scores, firm performance, corporate value, sector analysis

JEL Classification Codes: G32, M14, L25

1. Introduction
The impact of Environmental, Social, and Governance (ESG) scores on firm value and performance has become a subject of increasing importance across various sectors of the stock market. ESG ratings serve as a benchmark for assessing how well companies manage environmental risks, social responsibilities, and governance practices, and their influence on corporate financial performance varies significantly depending on the industry.

In the energy sector, ESG considerations are critical, with renewable energy companies being evaluated for their commitment to sustainable practices, while traditional oil and gas firms face mounting pressure to transition to lower-carbon alternatives. Likewise, the utilities sector, particularly those involved in electricity generation and water management, is closely monitored for how companies manage their energy sourcing, water usage, and environmental impact.

The basic materials sector, including mining and chemicals, faces intense scrutiny due to the environmental challenges associated with resource extraction, land use, and pollution. Companies in this sector must address biodiversity concerns and engage with local communities to maintain positive social and governance practices.

In the industrials sector, ESG factors center around operational efficiency, emissions reductions, and worker safety. Companies in manufacturing, construction, and transportation are evaluated based on how they manage environmental impact, including waste and emissions, as well as labor practices and innovation in sustainable technologies.

The consumer cyclical industry, including sectors such as automotive and retail, is increasingly judged on its ability to reduce carbon emissions, create sustainable supply chains, and embrace ethical labor practices. Companies that successfully transition to more environmentally and socially responsible practices can attract ESG-conscious investors and enhance their market value.

Similarly, in the consumer non-cyclical sector—comprising essential goods like food, beverages, and household products—firms are assessed on their labor standards, product safety, and efforts to minimize their environmental footprint. Sustainable sourcing and reduced packaging waste are key factors in driving ESG performance and long-term profitability.

The financial sector is evaluated based on responsible investment practices, governance structures, and risk management, with growing attention on ethical lending, green financing, and transparent reporting. ESG considerations are increasingly integrated into financial institutions' decision-making processes, affecting their reputation and firm value.

In the healthcare sector, companies are scrutinized for their social responsibility in areas such as patient care, access to medicines, and governance practices. Pharmaceutical firms are evaluated for their research ethics, pricing strategies, and supply chain transparency, all of which impact their ESG scores and corporate performance.

The technology sector focuses on social issues like data privacy, cybersecurity, diversity, and inclusion, while environmental factors such as energy consumption in data centers and e-waste management are becoming more significant. Tech companies that proactively address these issues can enhance their ESG profiles and strengthen their market position.

In the utilities sector, ESG evaluations focus on renewable energy adoption, carbon emissions, and governance. Companies leading in sustainability efforts and responsible governance tend to improve their ESG scores, enhancing market valuation and attracting investor interest.

The real estate industry is closely evaluated for its sustainable building practices, energy efficiency, and environmental impact, while social aspects such as tenant engagement and community development also contribute to ESG performance. Companies that excel in these areas are often rewarded with higher firm value and investor interest.

Given these sectoral variations, this paper aims to quantify the impact of ESG scores on firm value and corporate performance across these various industries. By analyzing the specific ESG scores within each sector, this study seeks to provide measurable insights into how firms can effectively leverage ESG strategies to enhance their financial performance and improve long-term market valuation.

2. Theoretical background

Prior empirical research provided mixed results regarding the impact of ESG on firm performance and market valuation.

Some studies point out that higher ESG scores can lead to improved financial performance, enhanced reputation, and greater investor interest, and that they may lead to increased firm value (Eccles et al., 2014; Flammer, 2015; Friede et al., 2015; Yoon et al., 2018; Zhao et al., 2018; Giese et al., 2019; Xie et al., 2019; Bhaskaran et al., 2020; De Lucia et al., 2020; Ahmad et al., 2021). According to these studies, ESG practices can drive increased firm performance and market valuation by enhancing long-term sustainability, reducing risks, improving stakeholder trust, and unlocking new opportunities for innovation and efficiency.

Other studies report either a negative or not significant impact of ESG practices on firm performance or market valuation due to several reasons (Lee et al., 2009; Fatemi et al., 2018; Capelle-Blancard and Petit, 2019; Garcia and Orsato, 2020; Duque-Grisales and Aguilera-Caracuel, 2021; Giannopoulos et al., 2022). First, ESG initiatives often require significant upfront investment, such as improving environmental efficiency or implementing social programs, which may lead to higher short-term costs. These expenses can reduce immediate profitability and cash flow, affecting market sentiment and stock prices. Additionally, ESG compliance can increase operational complexity, leading to inefficiencies or slower decision-making. In industries where ESG adoption is less aligned with core business models, firms may struggle to realize immediate financial benefits, reducing investor confidence. Furthermore, some investors may view ESG efforts as diverting focus from traditional financial objectives, which can result in undervaluation. Finally, inconsistent or unclear reporting standards may make it difficult for investors to accurately assess the financial value of ESG initiatives, adding uncertainty and driving down market valuations.

There are, however, some studies that provide mixed evidence of the connection between ESG and firm performance, respectively the market value. Some find a negative connection between ESG and firm performance, while they also find a positive connection between ESG and market value, possibly due to investors perceiving ESG initiatives as long-term value drivers despite their short-term costs or operational inefficiencies. Others find a positive connection between ESG and firm performance, while they found a negative or no connection at all between ESG and market valuation (Velte, 2015; Han et al., 2016; Lopez-de-Silanes et al., 2020; Gillan et al., 2021; Saygili et al., 2021; Aydoğmuş et al., 2022; Behl et al. (2022)).

Table 1 offers a comprehensive overview of the existing empirical literature, detailing key elements such as the sample size, the period of analysis, and the dependent and independent variables used in each study. Furthermore, the table will summarize the main findings of the studies, providing a clear comparison of results across different research efforts.

Table 1: Overview of main empirical background

Authors	Sample	Period of analysis	Dependent variables - measures for: a) firm performance b) market valuation	Control variables	Results
Lee et al. (2009)	Largest 2500 companies from Dow Jones Global	1998-2002	a) ROA, ROS and ROE b) -	Size, financial leverage, P/B ratio, liquidity ratio, total risk,	There is no evidence supporting a positive

	Index (DJGI), part of the Dow Jones Sustainability Index (DJSI)			market risk (beta), current ratio, marketable securities, free cash flow	association between social responsibility performance and corporate financial performance—this hypothesis is definitively rejected, regardless of the type of performance measure used.
Eccles et al. (2014)	180 companies (US)	1993-2010	a) ROA and ROE	Size, market value of equity over book value of equity (MTB), leverage	Companies with high sustainability practices consistently surpass their peers in the long run, demonstrating superior performance in both stock market returns and financial metrics. For firms with low sustainability practices, a positive impact is observed only on the Market-to-Book ratio (MTB), with no significant effect on Return on Assets (ROA).
Flammer (2015)	1500 companies (US, S&P 500)	1997-2012	a) abnormal returns, ROA, net profit margins, ROE	Institutional ownership. Inside ownership, labor productivity, capital expenditures, sales growth, leverage, cash	Value gains are greater for firms with lower pre-vote CSR levels, indicating diminishing returns to CSR. Additionally, companies in industries with stronger CSR norms see

					higher gains, as stakeholders in these sectors are more responsive to social initiatives.
Friede et al. (2015)	2200 empirical papers	1970-2015	-	-	There is a nonnegative ESG-corporate financial performance relationship.
Han et al. (2016)	94 companies (Korea)	2008-2014	a) ROE, MBR and stock return	Size, leverage, lagged dependent variables	No relationship for social score, positive relationship for governance score and negative for environment score
Velte (2017)	412 firms (Germany)	2010-2014	a) ROA b) Tobin's Q	R&D, beta, leverage, size, industry	ESG positively impacts firm profitability, but not firm value. Governance strongly impacts financial performance.
Fatemi (2018)	403 companies (US)	2006-2011	a) ROA b) Tobin's Q	Size, asset intensity, leverage, advertising intensity, advertising intensity, R&D intensity, R&D intensity missing, net to gross property, plant and equipment	ESG activities and reporting improve firm value. ESG concerns decrease firm value.
Yoon et al. (2018)	705 firms (Korea)	2010-2015	a) - b) market price	Book value per share, earning per share	CSR initiatives have a positive impact on market value.
Zhao et al. (2018)	20 large energy companies (China)	10 years	a) Return on capital employed (ROCE) b) -	Leverage, size	ESG and firm performance are positively related.

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Capelle-Blancard and Petit (2019)	100 world-wide large listed companies	2002-2010	a)	- Cumulative average abnormal returns	Size, P/E ratio, distance, characteristics of the targeted company (reputation, greenwashing, external pressures (sector's main concerns, trends), nature of the news	Standard ESG disclosures affect a firm's market value, typically in a negative way. The negative impact of ESG events is reduced when firms have disclosed more positive ESG information than peers or belong to sectors with strong ESG reputations. However, the loss worsens when the news is economically focused or emotionally connected to the firm.
Giese et al. (2019)	over 1600 stocks (MSCI World Index)	2007-2017	a) b)	Gross profitability Earnings-to-price ratio	Dividend yield, systematic volatility, residual CAPM volatility, historical beta, book-to-price	ESG factors influence company valuation and performance, primarily by altering their systematic risk profile, leading to reduced capital costs and enhanced valuations.
Xie et al. (2019)	6631 world-wide companies (74 countries and 11 sectors)	2015	a) b)	Tobin's Q, ROA, ROE -	R&D expenditure, firm size, leverage, industry type, country	The results reveal that a moderate level of ESG disclosure significantly boosts corporate efficiency, unlike high or low levels. The strongest positive relationship is seen with governance

					disclosure, followed by social and environmental disclosures. Conversely, low ESG disclosure levels are negatively associated with corporate efficiency, except for environmental disclosure, which shows a weak positive relationship.
Bhaskaran et al. (2020)	4887 global companies	2014-2018	a) Tobin's Q, ROA, ROE b) -	Price to earning, dividend yield, leverage, sales growth, R&D intensity, Capex intensity, advertisement intensity, firm size, systematic risk (five-year beta), management efficiency (% of independent board members)	Companies with a strong focus on environmental, governance, and social pillars are more likely to generate greater market value.
De Lucia et al. (2020)	1038 public companies (22 European countries)	2018-2019	a) ROA, ROE b) -	-	There is a positive association between various ESG measures and both ROA and ROE, except for environmental measures, which have a negative impact on both ROA and ROE.

Garcia and Orsato (2020)	2165 companies (emerging and developed countries)	2007-2014	a)	ROA and DCF (free cash flow)	Size, leverage, market capitalization, industry, dummy (company part of the sustainability index)	There is a positive correlation between ESG performance and corporate financial performance in developed countries, whereas in emerging countries, a negative relationship exists between ESG scores and financial performance.
			b)	-		
Lopez-de-Silanes et al. (2020)	large market capitalization companies (6 countries: United States, United Kingdom, France, Switzerland, Japan, Australia)	2015-2018	a)	Total annual returns	Size, leverage, intangible asset level, riskiness, industry	ESG scores have limited to no effect on risk-adjusted financial performance.
			b)	-		
Ahmad et al. (2021)	351 companies (UK)	2002-2018	a)	EPS	Size, Financial leverage	ESG has a positive impact on both firm value and financial performance. The impact of ESG on firm performance is influenced by company size. Moreover, firms in the top 20% of ESG scores outperform those in the bottom 20%.
			b)	Market value		
Duque-Grisales and Aguilera Caracuel (2021)	104 multinational firms (Latin America)	2011-2015	a)	ROA	Liquidity, geographic international diversification, firm size, leverage	Negative relationship between ESG scores (general and individual) and
			b)	-		

					financial performance.
Saygili et al. (2021)	Turkish companies from Borsa Istanbul Corporate Governance Index	2007-2017	a) ROA b) Tobin's Q	Free float percentage, size, foreign ownership, leverage, net profit margin, asset turnover, dividend yield	Negative relationship of environmental score on financial performance, positive relationship of governance with financial performance.
Aydoğmuş et al. (2022)	1720 large market capitalization companies from Bloomberg	2013-2021	a) ROA b) Tobin's Q	Size, leverage	The combined ESG score, along with the individual Environment, Social, and Governance scores, all show positive and significant correlations with firm profitability. However, only the Social and Governance scores have a positive impact on firm value.
Behl et al. (2022)	62 companies from the energy sector (India)	2016-2019	a) - b) Tobin's Q	-	ESG and its components negatively impact firm value in the short run, but have a positive long-term effect on the firm value.
Giannopoulos et al. (2022)	20 companies (Norway)	2010-2019	a) ROA b) Tobin's Q	Size, leverage	There is a negative relationship between ESG and firm performance, while ESG is positively related to Tobin's Q.

Source: Authors' own computation

Building on prior empirical studies that explore the relationship between ESG scores and various dimensions of corporate performance, our research aims to investigate the impact

of ESG scores on both firm financial performance and market valuation. In this regard, we propose and will empirically test the following hypotheses:

H1: There is a positive and significant relationship between a firm's ESG scores and its financial performance, suggesting that firms with higher ESG ratings are more likely to demonstrate superior financial outcomes, as proxied by return on assets.

H2: There is a positive and significant relationship between a firm's ESG scores and its market valuation, suggesting that firms with higher ESG ratings are perceived as lower-risk and more resilient by investors, leading to increased market capitalization relative to total assets, as proxied by Tobin's Q.

3. Data and methodology

3.1 Data

The data used in this study is sourced from Refinitiv. Our analysis focuses on European companies across various sectors, including energy, basic materials, industrials, consumer cyclical, consumer non-cyclical, financials, healthcare, technology, utilities, and real estate. By examining firms from these diverse sectors, we aim to capture a comprehensive view of how Environmental, Social, and Governance (ESG) scores influence both firm performance and valuation in different industry contexts. This broad sectoral representation allows for a more nuanced understanding of the ESG impact, accounting for the unique characteristics and challenges faced by companies in each industry.

This analysis includes a total of 1959 companies across various sectors, selected based on the availability of four continuous years of ESG score data from 2014 to 2023. The table below (Table 2) outlines the number of companies available and those ultimately chosen for each sector.

Table 2: Number of companies by sector

Sector	Available companies	Selected companies
Energy	410	78
Basic materials	792	145
Industrials	1934	381
Consumer cyclical	1548	286
Consumer non-cyclical	769	123
Financials	1741	328
Healthcare	732	169
Technology	1288	264
Utilities	373	65
Real estate	798	120
TOTAL	**10385**	**1959**

Source: Authors' own computation

3.2 Methodology

In this paper, we focus on two dependent variables—firm performance, proxied by return on assets (ROA), and firm value, proxied by Tobin's Q (QTOB)—to examine the impact of ESG scores on these metrics (Table 3). These two measures have been widely used in empirical research as standard proxies for firm performance and market valuation, as we could see in Table 1.

In our study, we choose to use pre-tax ROA, calculated as the ratio of pre-tax net income to total assets, providing insight into how effectively a company utilizes its assets to generate profit before the impact of taxes. Using pre-tax ROA as a performance metric allows for a

clear evaluation of operational efficiency, as it indicates the firm's ability to convert investments in assets into earnings without the distortion of tax effects. A higher pre-tax ROA signifies more efficient management and a greater ability to generate profit from the asset base, making it a relevant indicator for analyzing the impact of Environmental, Social, and Governance (ESG) scores on firm performance. Furthermore, pre-tax ROA is widely recognized in financial analysis for its ability to standardize performance across companies of different sizes, thus facilitating meaningful comparisons within the context of this study. By employing pre-tax ROA as the dependent variable, we can effectively gauge the relationship between ESG practices and operational effectiveness, contributing to a deeper understanding of how these factors influence overall firm value.

To evaluate firm value, this study employs Tobin's Q as a key proxy. Tobin's Q is calculated as the ratio of market capitalization to total assets, which provides a simplified yet effective measure of the market's valuation of a firm's assets relative to their recorded value. This metric serves as a useful proxy for firm value, as it reflects both investor perceptions and the intrinsic worth of the company's asset base.

The use of Tobin's Q is particularly suitable in assessing how effectively a firm's management utilizes its assets to create value. Specifically, Tobin's Q compares the market value (as represented by market capitalization) to the book value of total assets. A Q ratio greater than 1 indicates that the market values the firm's assets higher than their book value, suggesting strong growth potential and effective asset utilization, whereas a Q ratio less than 1 implies that the market believes the firm's assets are undervalued or not being utilized efficiently.

As a proxy for firm value, Tobin's Q offers several advantages. First, it captures market perception, which is a critical component of firm valuation, as it reflects investor expectations of future profitability and growth potential. A higher Tobin's Q suggests that investors anticipate greater returns from the company and view its assets as having a higher replacement cost. Second, it provides insight into management efficiency in deploying the company's assets for value creation. Firms with high Tobin's Q ratios are often seen as being well-managed, leveraging their resources effectively to generate substantial market value.

In this study, we focus on the impact of Environmental, Social, and Governance (ESG) scores on firm performance and valuation. We examine both the overall ESG score and the individual pillar scores: Environmental Pillar Score (EPS), Social Pillar Score (SPS), and Governance Pillar Score (GPS). The general ESG score reflects a firm's comprehensive sustainability practices, while the individual pillar scores provide nuanced insights into specific areas of performance. By analyzing these scores, we aim to determine how ESG practices influence operational efficiency, financial stability, and ultimately, firm value.

Table 3: Variable description and measurement

Type of variable	Variables	Description	Measurement
Dependent variables	Firm performance	Pre-tax return on assets **(ROA)**	Pre-tax income/Average total assets
	Firm value	Tobin's Q **(QTOB)**	Market capitalization/Total assets
Interest independent variables	ESG score	Environment, social and governance score **(ESG)**	The scores range from 0 to 100, a score of less than 50 is considered

	EPS score	Environmental pillar score **(EPS)**	relatively poor and more than 70 is considered relatively good
	SPS score	Social pillar score **(SPS)**	
	GPS score	Governance pillar score **(GPS)**	
Control variables	Size of company	Total assets **(SIZE)**	Log (Total assets)
	Risk	Debt to equity ratio **(LEV)**	$\text{Lev} = \dfrac{\text{Total debt}}{\text{Total equity}}$
	Liquidity	Current ratio **(CR)**	$\text{CR} = \dfrac{\text{Current assets}}{\text{Current liabilities}}$
	Financial health and solvency	EBITDA net interest coverage ratio **(ICR)**	$\text{ICR} = \dfrac{\text{EBITDA}}{\text{Net interest expense}}$

Source: Authors' own computation

In this study, we have considered the following control variables: size of the company (proxied by natural logarithm of total assets), risk (proxied by financial leverage), liquidity (proxied by the current ratio), and solvency (proxied by the EBITDA net interest coverage ratio). Size and leverage are two key control variables consistently considered in empirical studies examining the relationship between ESG scores and financial performance or market valuation. Additionally, liquidity is considered as an appropriate control variable in some of the empirical studies (Lee et al., 2009; Flammer, 2015; Duque-Grisales and Aguilera Caracuel, 2021). While other studies often rely on net profit margin and asset turnover as additional control variables (Saygili et al., 2021), we choose to use the EBITDA net interest coverage ratio because it provides a more comprehensive measure of a company's ability to cover its interest expenses with operational earnings, offering a clearer picture of financial stability and operational efficiency, especially in capital-intensive industries.

To investigate the impact of Environmental, Social, and Governance (ESG) scores on firm performance and valuation, we employ four regression analyses using panel data. The first regression examines the relationship between the overall ESG score and firm performance, specifically measured by pre-tax return on assets (ROA). The second regression analyzes the effect of the individual pillar scores on ROA. The third regression assesses the impact of the overall ESG score on firm valuation, measured by Tobin's Q (QTOB). Finally, the fourth regression focuses on how the individual pillar scores influence Tobin's Q. We apply fixed effects or random effects models, guided by the results of the Hausman test, to account for unobserved heterogeneity across firms, ensuring robust estimates of the relationships between ESG scores and the dependent variables.

$$ROA_{i,t} = \beta_0 + \beta_1 ESG_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 CR_{i,t} + \beta_5 ICR_{i,t} + \varepsilon_{i,t} \qquad (1)$$

$$ROA_{i,t} = \beta_0 + \beta_1 EPS_{i,t} + \beta_1 SPS_{i,t} + \beta_1 GPS_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 CR_{i,t} + \beta_5 ICR_{i,t} + \varepsilon_{i,t}$$
(2)

$$QTOB_{i,t} = \beta_0 + \beta_1 ESG_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 CR_{i,t} + \beta_5 ICR_{i,t} + \varepsilon_{i,t}$$
(3)

$$QTOB_{i,t} = \beta_0 + \beta_1 EPS_{i,t} + \beta_1 SPS_{i,t} + \beta_1 GPS_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 CR_{i,t} + \beta_5 ICR_{i,t} + \varepsilon_{i,t}$$
(4)

4. Results and interpretations

Furthermore, we will examine the results from the four regressions conducted. The R² values, which indicate the proportion of variance explained by the models, vary across industries. However, relative higher R² obtained for most models suggest that they explain a substantial portion of the variance in firm performance and market valuation for these sectors. The Durbin-Watson statistical values are close to 2 in most sectors, indicating that there is little to no evidence of autocorrelation in the residuals, meaning that the models are well-specified.

Table 4 illustrates the impact of ESG general score on firm performance. ESG scores show a negative effect in Consumer Non-Cyclical, Financials, Technology, and Real Estate sectors, with varying degrees of significance. The negative impact is strongest in Real Estate and Financials. This suggests that in these sectors, higher ESG scores might be associated with a decline in financial performance. This conclusion is in line with the results obtained by Capelle-Blancard and Petit (2019), Garcia and Orsato (2020), Duque-Grisales and Aguilera-Caracuel (2021) and Giannopoulos et al., (2022), among others, and might be explained by the increased costs of compliance with sustainability initiatives, a long-term focus that prioritizes future value over immediate profits, and the risk of higher investor expectations that could pressure the company to maintain high ESG standards at the expense of short-term returns.

The size of a firm has varied impacts on performance across different industries. In sectors such as Financials, Utilities, and Real Estate, firm size shows a positive and significant effect on performance, indicating that larger firms tend to perform better. This outcome is expected, as larger firms often benefit from economies of scale and have more resources to manage operations efficiently. However, in industries like Consumer Cyclical and Technology, size has a negative impact on performance. This negative relationship may reflect the challenges large firms face in fast-evolving industries, where agility and innovation are crucial for success.

Leverage generally has a negative effect on firm performance across most industries. This negative impact is especially significant in sectors such as Energy (-0.0007, significant at 5%), Basic Materials (-0.0007, significant at 1%), Consumer Non-cyclical (-0.0005, significant at 1*), Healthcare (-0.0301, significant at 1%), and Real Estate (-0.0014, significant at 1%). These results align with the expectation that higher debt levels increase financial risk, thereby negatively affecting performance. In contrast, leverage shows an insignificant or mixed effect in other sectors.

Table 4. Impact of ESG on firm performance

	Energy	Basic materials	Industrials	Consumer cyclical	Consumer non-cyclical	Financials	Healthcare	Technology	Utilities	Real estate
ESG	0.0012 (0.0008)	0.0010*** (0.0003)	-0.0002 (0.0001)	-0.0003 (0.0002)	-0.0004** (0.0002)	-0.0013** (0.0006)	-0.0009 (0.0006)	-0.0006** (0.0003)	-0.0005 (0.0003)	-0.0022*** (0.0003)
SIZE	0.0090 (0.0413)	0.0108 (0.0105)	0.0025 (0.0055)	-0.0450*** (0.008)	-0.0109 (0.0127)	0.0515*** (0.0132)	0.0480 (0.0320)	-0.0256*** (0.0080)	0.0689*** (0.0235)	0.0236** (0.0113)
LEV	-0.0007** (0.0004)	-0.0007*** (0.0002)	-0.0010 (0.0008)	-0.0003 (0.0005)	-0.0005*** (0.0002)	-0.0078 (0.0091)	-0.0301*** (0.0041)	-0.0003 (0.0002)	-0.0112* (0.0068)	-0.0014*** (0.0003)
CR	0.0250*** (0.0092)	0.0080* (0.0044)	0.0032* (0.0019)	0.0005 (0.0022)	-0.0016 (0.0012)	0.0009 (0.0006)	0.0066*** (0.0009)	-0.0186*** (0.0037)	0.0006 (0.0054)	$-1.35*10^{-5}$ (0.0021)
ICR	0.0001*** (0.0000)	$9.03*10^{-6}$* $(4.64*10^{-6})$	$1.95*10^{-5}$*** $(5.88*10^{-6})$	$4.15*10^{-5}$*** $(1.23*10^{-5})$	$1.40*10^{-6}$ $(9.33*10^{-7})$	$2.22*10^{-6}$*** $(8.33*10^{-7})$	$2.01*10^{-5}$** $(9.73**10^{-6})$	$8.53*10^{-7}$* $(5.28*10^{-7}))$	$1.55*10^{-5}$** $(7.58*10^{-6})$	$8.28*10^{-5}$ (0.000122)
R^2	0.3373	0.4975	0.5917	0.7127	0.6312	0.3720	0.8768	0.8609	0.5955	0.2951

*p < 0.1; **p < 0.05; ***p < 0.01.
Source: Authors' own computation

The current ratio has a significant positive impact on firm performance in most industries such as Energy, Basic Materials, Industrials, and Healthcare, indicating that firms with higher liquidity tend to perform better in these sectors. This is expected, as better liquidity allows companies to meet short-term obligations more effectively, contributing to greater operational stability. However, in the Technology sector, the current ratio has a negative impact on performance, with a coefficient of -0.0186, significant at 1%. This negative relationship may suggest that excessive liquidity in this industry could imply inefficient asset use, where capital might be better invested in innovation and growth rather than being held in current assets.

The EBITDA net interest coverage ratio, which measures a firm's ability to cover its interest expenses with earnings, has a positive and significant impact on performance across all sectors. This indicates that firms with a higher capacity to meet their interest obligations tend to perform better, likely due to reduced financial distress and improved overall financial health.

Table 5 presents the impact of individual ESG pillars (Environmental, Social, Governance) on firm performance across various industries, using multiple financial performance metrics.

When looking at EPS (Environmental pillar score), we observe a negative or statistically insignificant effect across most industries. Notably, in the financial sector, EPS is positively affecting firm performance, suggesting that ESG factors in this industry may improve earnings. In contrast, in the real estate sector, EPS has a significant negative effect on firm performance, implying that higher focus on this pillar may reduce earnings in this industry. This result seems in line with the one obtained by Han et al. (2016) or De Lucia et al. (2020), which find a negative connection between environment score and firm performance.

For SPS (Social pillar score), this shows a positive effect in the basic materials sector, while it has a negative impact in the utilities and real estate sectors. In real estate, this negative relationship is significant, which may suggest that SPS-related actions adversely affect firm performance in this industry.

When analyzing GPS (Governance pillar score), the effects of governance-related factors are negatively impacting the firm's performance across industries. In the financial sector especially, there is a significant negative effect, indicating that governance practices may restrict growth in this industry. Similarly, the real estate sector shows a negative impact, though to a lesser degree, highlighting the potential challenges posed by governance measures in this area.

The size of the company has a significant positive impact on industries such as financials, utilities and real estate. However, in the consumer cyclical sector, there is a significant negative effect, indicating that larger firms in this sector may experience diminishing returns from size when considering ESG factors. A similar connection is found in the case of companies from the technology sector.

Leverage generally shows a negative effect on firm performance across most industries. The healthcare sector exhibits the strongest negative impact, suggesting that higher debt levels reduce firm performance, possibly due to increased risk or financial constraints. Similar trends are seen in utilities and real estate sectors, where leverage negatively affects performance.

The current ratio, which measures liquidity, generally has a positive impact on firm performance. In the energy sector, a strong positive relationship is observed, indicating that firms with better liquidity perform better under ESG-related practices. This positive effect is also seen in the basic materials sector, where stronger liquidity appears to support better financial health in light of ESG considerations. The

technology sector is the only one where a negative relationship has been observed between the current ratio and firm performance. This suggests that, in this industry, higher liquidity may not necessarily lead to better financial outcomes. Unlike other sectors, where a strong liquidity position is typically linked to better performance, technology companies may prioritize rapid innovation, investment, and growth over maintaining high levels of current assets.

The interest coverage ratio (ICR), which measures a firm's ability to cover interest expenses from operating earnings, shows a highly significant positive effect across all industries. The financial sector, in particular, demonstrates a very strong influence of ICR in improving firm performance. The energy and technology sectors show especially a significant positive relationship between this variable and financial performance.

Overall, the table indicates that while the influence of individual ESG pillars on firm performance varies significantly across industries and financial metrics, the overall conclusion points to a negative correlation between them.

Table 5. Impact of each individual ESG Pillars (Environmental, Social, Governance) on firm performance

	Energy	Basic materials	Industrials	Consumer cyclical	Consumer non-cyclical	Financials	Healthcare	Technology	Utilities	Real estate
EPS	-0.0009 (0.0010)	0.0003 (0.0003)	$-2.24*_* 10^{-5}$ (0.0001)	0.0002 (0.0002)	$-9.53*10^{-5}$ (0.000186)	0.0013** (0.0006)	-0.0003 (0.0003)	-0.0002 (0.0002)	$5.31*10^{-5}$ (0.0003)	-0.0007*** (0.0002)
SPS	0.0007 (0.0007)	0.0010*** (0.0003)	$-2.08*10^{-5}$ (0.0001)	-0.0003 (0.0002)	-0.0002 (0.0002)	-0.0010 (0.0006)	0.0002 (0.0004)	-0.0001 (0.0003)	-0.0006* (0.0003)	-0.0008*** (0.0003)
GPS	0.0010 (0.0007)	-0.0002 (0.0003)	-0.0002* (0.0001)	-0.0002* (0.0001)	-0.0002 (0.0001)	-0.0012** (0.0005)	-0.0005* (0.0003)	-0.0004* (0.0002)	$-3.17*10^{-5}$ (0.000184)	-0.0008*** (0.0002)
SIZE	0.0102 (0.0400)	0.0122 (0.0109)	0.0025 (0.0055)	-0.0463*** (0.0080)	-0.0112 (0.0125)	0.0515*** (0.0131)	0.0409 (0.0333)	-0.0239*** (0.008)	0.0707*** (0.0244)	0.0243** (0.0114)
LEV	-0.0007** (0.0004)	-0.0006** (0.0003)	-0.0010 (0.0008)	-0.0004 (0.0005)	-0.0005*** (0.0002)	-0.0087 (0.0092)	-0.0298*** (0.0041)	-0.0003 (0.0002)	-0.0116* (0.0069)	-0.0014*** (0.0003)
CR	0.0249*** (0.0090)	0.0086* (0.0046)	0.0032* (0.0019)	0.0007 (0.0023)	-0.0016 (0.0013)	0.0010* (0.0006)	0.0066*** (0.0009)	-0.0186*** (0.0037)	0.0007 (0.0054)	$-8.22*_* 10^{-5}$ (0.0021)
ICR	$8.85*10^{-5} *** $ $(2.57*10^{-5})$	$7.94* 10^{-6}*$ $(4.75* 10^{-6})$	$1.95* 10^{-5}***$ $(5.86* 10^{-6})$	$4.21* 10^{-5}***$ $(1.22* 10^{-5})$	$1.39* 10^{-6}$ (9.447)	$2.21* 10^{-6}***$ $(8.31* 10^{-7})$	$1.98* 10^{-5}**$ $(9.51* 10^{-6})$	$8.42* 10^{-7}*$ $(5.28* 10^{-7})$	$1.72* 10^{-5}**$ $(7.63* 10^{-6})$	$8.13*_* 10^{-5}$ (0.0001)
R^2	0.3432	0.4955	0.5919	0.6681	0.6311	0.3784	0.8787	0.8613	0.5973	0.2947

*p < 0.1; **p < 0.05; ***p < 0.01.
Source: Authors' own computation

Table 6 presents the results of the analysis examining the impact of ESG (Environmental, Social, and Governance) general score on firm valuation, as measured by Tobin's Q, across several industries. The regression analysis includes control variables such as firm size (log of total assets), financial risk (total debt/total equity), liquidity (current ratio), and solvency (EBITDA net interest coverage ratio).

Starting with the impact of ESG scores on firm valuation, the energy sector shows a small but significant positive impact of ESG performance (0.0040*), indicating that better ESG performance tends to increase firm valuation. Similarly, in the basic materials and healthcare sectors, ESG performance has a positive and significant effect. However, in the consumer cyclical sector, as well as in the real estate sector the impact is significantly negative, suggesting that in these sectors, firms with better ESG performance may experience lower valuations. The positive relationship of the ESG score with the market valuation obtained in the case of some sectors is consistent with the results obtained by Bhaskaran et al. (2020), Ahmad et al. (2021) or Giannopoulos et al. (2022).

Firm size shows a consistently negative and significant impact on firm valuation across most industries. In basic materials (-0.5786***), industrials (-0.3294***), consumer cyclical (-0.5858***), consumer non-cyclical (-0.5612***), financials (-0.7990***), healthcare (-1.2569***), and technology (-0.7032***), larger firms are associated with lower firm valuations. This might suggest that as firms grow, they may face diminishing market valuations. The negative impact is particularly strong in healthcare, technology, and financials. In contrast, sectors like energy and utilities show insignificant impact, indicating that firm size may have a weaker relationship with valuation in these sectors.

The leverage ratio (LEV) has a negative impact on firm valuation. In basic materials (-0.0027*), consumer non-cyclical (-0.0046***), and real estate (-0.0029*), higher leverage is associated with lower valuations, implying that in these sectors, firms with higher debt levels tend to be valued less. However, the leverage effect is insignificant in other sectors like energy and financials, where the relationship between debt levels and valuation appears to be weaker.

The current ratio (CR), a measure of liquidity, shows a positive and significant effect on firm valuation in the energy and consumer cyclical sector, indicating that better liquidity leads to higher valuations in these industries. The technology sector also shows a significant positive relationship (0.1045*), suggesting that higher liquidity is beneficial for firm valuation in this sector as well. Conversely, in the basic materials sector (-0.0987***), better liquidity is associated with lower valuations, perhaps indicating inefficiencies in liquidity management or industry-specific factors that affect valuation.

Lastly, the interest coverage ratio (ICR), reflecting a firm's ability to meet its interest obligations, generally shows positive and significant impacts on firm valuation in the consumer cyclical and utilities sectors. This suggests that financial health, as measured by interest coverage, plays a significant role in firm valuation.

Table 6. Impact of ESG on firm valuation

	Energy	Basic materials	Industrials	Consumer cyclical	Consumer non-cyclical	Financials	Healthcare	Technology	Utilities	Real estate
ESG	0.0040* (0.0022)	0.0042** (0.0021)	-0.0012 (0.0018)	-0.0069*** (0.0022)	-0.0017 (0.0021)	0.0006 (0.0039)	0.0095** (0.0049)	-0.0063 (0.0045)	-0.0003 (0.0025)	-0.0038*** (0.0006)
SIZE	-0.0484 (0.0791)	-0.5786*** (0.0684)	-0.3294*** (0.0791)	-0.5858*** (0.0836)	-0.5612*** (0.1345)	-0.7990*** (0.0785)	-1.2569*** (0.2941)	-0.7032*** (0.1283)	-0.0663 (0.1159)	-0.0465* (0.0261)
LEV	0.0003 (0.0005)	-0.0027* (0.0016)	0.0009 (0.0052)	-0.0063 (0.0046)	-0.0046*** (0.0011)	-0.0544 (0.0544)	-0.0445 (0.0307)	-0.0017 (0.0032)	-0.0122 (0.0179)	-0.0029* (0.0017)
CR	0.1869* (0.1039)	-0.0987*** (0.0285)	0.0268 (0.0236)	0.0602* (0.0326)	0.0120 (0.0162)	9.8410^{-7} (0.003599)	0.0025 (0.0124)	0.1045* (0.0598)	0.0752 (0.0720)	0.0044 (0.0034)
ICR	$7.25*10^{-5}$ (0.0001)	$4.31*10^{-5}$ $(3.02*10^{-5})$	$4.84*10^{-5}$ $(4.25*10^{-5})$	0.0005*** (0.0001)	$3.13**10^{-5}$ $(3.24**10^{-5})$	4.0410^{-6} $(4.96*10^{-6})$	0.0002 (0.0001)	$-4.32*10^{-6}$ $(8.64*10^{-6})$	$4.07*10^{-5**}$ $(1.75*10^{-5})$	0.0005 (0.0004)
R^2	0.6703	0.7906	0.8035	0.8692	0.8028	0.7494	0.8368	0.9198	0.8035	0.7102

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Source: Authors' own computation

Table 7 presents the impact of the individual ESG pillars — Environmental, Social, and Governance — on firm valuation, measured by Tobin's Q, across various industries.

Starting with the Environmental Pillar Score (EPS), we see a negative significant effect among industrials and real estate sectors. In the industrial sector, a significant negative relationship (-0.0046**) indicates that higher environmental performance tends to reduce firm valuation in this sector. Similarly, in real estate, the environmental pillar has a significant negative effect (-0.0013***), suggesting that greater focus on environmental issues could lower firm valuation. The results are in line with the ones obtained by Han et al. (2016) or the ones depicted by Aydoğmuş et al. (2022).

For the Social Pillar Score (SPS), the basic materials sector displays a significant positive impact (0.0052***), indicating that higher social performance is associated with higher firm valuation. This suggests that companies in this sector benefit from improved social practices. On the other hand, the real estate sector demonstrates a significant negative effect (-0.0011**), indicating that higher social scores in real estate reduce valuation.

The Governance Pillar Score (GPS) has a negative impact on firm valuation. In the consumer cyclical sector, a significant negative effect (-0.0043***) suggests that better governance practices might be perceived as a cost rather than a value driver. Similarly, real estate exhibits a significant negative relationship (-0.0014***), implying that strong governance measures might detract from firm value. Other industries show no significant relationship between governance scores and firm valuation. Our results contradict at least part of the previous empirical papers (Bhaskaran et al., 2020; Saygili et al. (2021); Aydoğmuş et al. (2022)).

Looking at the control variables, firm size has a largely negative and significant effect on firm valuation across most industries. This is especially evident in healthcare (-1.2818***), financials (-0.7948***), and technology (-0.6986***), suggesting that larger firms in these sectors may experience lower valuations, possibly due to diminishing returns or increased scrutiny under ESG criteria. The basic materials sector and consumer cyclical sector also show strong negative impacts of size on firm valuation.

Leverage (LEV) has a negative effect on firm valuation in several industries (consumer non-cyclical sector, and real estate sector). However, in the other sectors leverage appears to have a negligible impact on firm valuation, with insignificant coefficients.

The current ratio (CR), which measures a company's liquidity, has a positive and significant effect on firm valuation in certain industries. In the energy sector, liquidity is strongly positively associated with firm valuation (0.1873***), suggesting that firms with better liquidity are valued more highly when ESG factors are considered. In technology (0.1041*), a similar positive effect is observed. On the contrary, basic materials display a significant negative relationship (-0.1017***), indicating that greater liquidity may reduce firm valuation in this industry.

Lastly, the interest coverage ratio (ICR), reflecting a firm's ability to meet its interest obligations, generally has a positive and significant effect on firm valuation. The consumer cyclical sector shows a strong positive relationship, suggesting that firms with better interest coverage tend to have higher valuations. Other sectors like utilities also demonstrate significant positive effects, implying that better financial health, as measured by the interest coverage ratio, enhances firm valuation under ESG scrutiny.

Table 7. Impact of each individual ESG Pillars (Environmental, Social, Governance) on firm valuation

	Energy	Basic materials	Industrials	Consumer cyclical	Consumer non-cyclical	Financials	Healthcare	Technology	Utilities	Real estate
EPS	0.0034 (0.0030)	0.0001 (0.0019)	-0.0046** (0.0021)	-0.0012 (0.0019)	$-3.92*10^{-5}$ (0.002367)	0.0041 (0.0035)	0.0011 (0.0048)	-0.0009 (0.0040)	-0.0022 (0.0018)	-0.0013** (0.0005)
SPS	0.0004 (0.0028)	0.0052*** (0.0018)	0.0027 (0.0021)	-0.0005 (0.0023)	-0.0028 (0.0025)	0.0006 (0.0038)	0.0047 (0.0057)	-0.0011 (0.0045)	0.0021 (0.0019)	-0.0011** (0.0005)
GPS	0.0005 (0.0019)	-0.0010 (0.0016)	0.0002 (0.0011)	-0.0043*** (0.0015)	0.0014 (0.0014)	-0.0033 (0.0032)	0.0041 (0.0036)	-0.0042 (0.0032)	0.0001 (0.0010)	-0.0014*** (0.0005)
SIZE	-0.0521 (0.0753)	-0.6139*** (0.0709)	-0.3200*** (0.0797)	-0.5962*** (0.0860)	-0.5573*** (0.1326)	-0.7948*** (0.0783)	-1.2818*** (0.2987)	-0.6986*** (0.1292)	-0.0769 (0.1140)	-0.0465* (0.0261)
LEV	0.0003 (0.0009)	-0.0025 (0.0017)	0.0009 (0.0051)	-0.0065 (0.0046)	-0.0039*** (0.0011)	-0.0611 (0.0550)	-0.0439 (0.0305)	-0.0018 (0.0032)	-0.0092 (0.0184)	-0.0029* (0.0017)
CR	0.1873*** (0.0232)	-0.1017*** (0.0298)	0.0292 (0.0236)	0.0640* (0.0337)	0.0093 (0.0158)	0.0004 (0.0036)	0.0023 (0.0122)	0.1041* (0.0598)	0.0756 (0.0721)	0.0043 (0.0034)
ICR	$7.27*10^{-5}$ (0.000178)	$3.84*10^{-5}$ $(3.10*10^{-5})$	$5.00*10^{-5}$ (4.37E-05)	0.0005*** (0.0001)	$3.18*10^{-5}$ $(3.30*10^{-5})$	$4.07*10^{-6}$ $(4.96*10^{-6})$	0.0002 (0.0001)	$-4.46*10^{-6}$) $(8.65*10^{-6})$	$3.38*10^{-5}$* $(1.74*10^{-5})$	0.0005 (0.0004)
R^2	0.6706	0.7935	0.8040	0.8695	0.8035	0.7505	0.8370	0.9199	0.8040	0.7102

*p < 0.1; **p < 0.05; ***p < 0.01.
Source: Authors' own computation

5. Conclusions

Prior empirical research found mixed results regarding the impact of ESG on firm performance and market valuation. This study seeks to contribute to the understanding of how both the general ESG score and its constituent pillars affect firm performance and firm valuation metrics, thereby providing valuable insights for investors, corporate executives and strategic planners, and policymakers interested in the relationship between sustainability and corporate success.

Our study indicates that, in general, the impact of ESG scores on firm performance is negative across most industries. While the Basic Materials sector shows a positive correlation between higher ESG scores and improved performance—likely driven by reputational benefits and operational efficiencies—other sectors tell a different story. In Consumer Non-cyclical, Financials, Technology, and Real Estate, higher ESG scores are associated with declines in financial performance. This suggests that, in these sectors, the costs of implementing ESG initiatives or industry-specific constraints may outweigh any potential benefits. The negative impact is particularly pronounced in Real Estate, reflecting how certain industries may face greater challenges in aligning ESG strategies with financial success. Overall, the findings point to a generally unfavorable effect of ESG practices on firm performance, with variations depending on the sector.

The impact of individual ESG pillars on firm performance shows considerable variation across industries and financial metrics, with the majority of the effects being negative. Larger firms, particularly in the financial and utility sectors, show some benefit from ESG practices, but these are exceptions. Notably, the Governance pillar has the most negative impact, with negative coefficients observed in most sectors, suggesting that governance-related ESG practices may not align with improved financial performance. Additionally, higher leverage tends to adversely affect performance across most industries. While liquidity, as measured by the current ratio, and the ability to cover interest expenses (ICR), are positively correlated with better performance, this is especially true in capital-intensive sectors like energy, healthcare, and technology. However, the overall trend indicates that the benefits of ESG practices, particularly from the governance aspect, are limited or even detrimental to firm performance in many cases.

The impact of ESG performance on firm valuation varies significantly across industries. ESG performance tends to increase valuation in sectors like energy, basic materials, and healthcare, but may reduce valuation in consumer cyclical and real estate sectors. Firm size has a negative impact on valuation across almost all industries. Leverage is negatively correlated with market valuation, while liquidity and financial health generally contribute positively to firm valuation in most industries.

The impact of ESG pillars on firm valuation is highly industry-specific. The environmental and governance pillars tend to have negative effects on firm valuation in industries such as real estate, industrials and consumer cyclical sectors, while the social pillar has a positive impact in the basic materials sector. Larger firms generally face lower valuations in almost all industries, while liquidity and financial health are positively correlated with firm valuation across several sectors.

For the investment community, the paper underscores the financial materiality of ESG metrics, showing a positive correlation between ESG performance and market valuation in some sectors. This empowers investors to prioritize ESG factors in portfolio allocation, optimizing long-term growth. For corporate executives and strategic planners, the findings reveal a general negative impact of ESG initiatives on firm performance, highlighting the need for a balanced and selective approach. For corporate leaders, this emphasizes the importance of aligning ESG investments with core business objectives, focusing on

initiatives that drive measurable value and avoid overcommitting resources to areas with limited financial returns. This insight encourages a more strategic integration of ESG, ensuring efforts are both sustainable and supportive of long-term profitability. For policy makers to reassess how ESG frameworks are designed and implemented. Regulators can use this insight to refine policies, ensuring they provide clear guidance and incentives that support firms in achieving ESG goals without compromising financial viability.

Future research could explore the impact of ESG on firm performance by incorporating a broader range of regions, particularly outside of Europe, to capture diverse economic and regulatory environments. Additionally, applying advanced panel data modeling techniques, such as the Generalized Method of Moments (GMM), could improve the robustness of findings by addressing potential endogeneity issues.

References

Ahmad, N., Mobarek, A., Roni, N.N. and Tan A.W.K. 2021. Revisiting the impact of ESG on financial performance of FTSE250 UK firms: static and dynamic panel data analysis. *Cogent Business & Management*, 8(1), 1900500.

Aydoğmuş, M., Gülay, G. and Ergun G. 2022. Impact of ESG performance on firm value and profitability, *Borsa Istanbul Review*, 22(2), pp. S119-S127.

Behl, A., Kumari, P.S.R., Makhija, H. and Sharma, D. 2022. Exploring the relationship of ESG score and firm value using cross-lagged panel analyses: case of the Indian energy sector. *Annals of Operations Research*, 313, pp. 231-256.

Bhaskaran, R.K., Ting, I.W.K., Sukumaran, S.K. and Sumod, S.D. 2020. Environmental, social and governance initiatives and wealth creation for firms: an empirical examination. *Managerial and Decision Economics*, 41(5), 710-729.

Capelle-Blancard, G. and Petit, A., 2019. Every little helps? ESG news and stock market reaction. *Journal of Business Ethics*, 157(2), pp. 543-565.

De Lucia, C. Pazienza, P. and Bartlett, M. 2020. Does good ESG lead to better financial performance by firms? Machine learning and logistic regression models of public enterprises in Europe. *Sustainability*, 12(13), 5317.

Duque-Grisales, E. and Aguilera Caracuel, I. 2021. Environmental, social and governance (ESG) scores and financial performance of multilatinas: moderating effects of geographic international diversification and financial slack. *Journal of Business Ethics*, 168, pp. 315-334

Eccles, R.G., Ioannou, I. and Serafeim, G., 2014. The impact of corporate sustainability on organizational processes and performance. *Management Science*, 60(11), pp. 2835-2857.

Fatemi, A., Glaum, M., and Kaiser, S. 2018. ESG performance and firm value: the moderating role of disclosure. *Global Finance Journal*, 38, pp. 45-64.

Flammer, C., 2015. Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science*, 61(11), pp. 2549-2568.

Friede, G., Busch, T. and Bassen, A., 2015. ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, 5(4), pp. 210-233.

Garcia, A.S., and Orsato, R.J. 2020. Testing the institutional difference hypothesis: A study about environmental, social, governance, and financial performance. *Business Strategy and the Environment*, 29, pp. 3261–3272.

Giese, G., Lee, L.E., Melas, D., Nagy, Z. and Nishikawa, L. 2019. Foundations of ESG investing: how ESG affects equity valuation, risk, and performance, *Journal of Portfolio Management*, 45(5), pp. 69-83.

Giannopoulos, G., Kihle Fagernes, R.V., Elmarzouky, M. and Afzal Hossain, K.A.B.M. 2022. The ESG disclosure and the financial performance of Norwegian listed firms, *Journal of Risk and Financial Management*, 15(6), 237.

Gillan, S.L., Koch, A., Starks, L.T., 2021. Firms and social responsibility: A review of ESG and CSR research in corporate finance. *Journal of Corporate Finance*, 66, 101889.

Han, J.J., Kim, H.J. and Yu, J. 2016. Empirical study on relationship between corporate social responsibility and financial performance in Korea. *Asian Journal of Sustainability and Social Responsibility*, 1 pp. 61-76.

Lee, D. D., Faff, R.W. and Langfield-Smith, K. 2009. Revisiting the Vexing Question: Does Superior Corporate Social Performance Lead to Improved Financial Performance? *Australian Journal of Management*, 34, pp. 21–49.

Lopez-de-Silanes, F., McCahery, J.A. and Pudschedl, P.C. 2020. ESG performance and disclosure: a cross-country analysis. *Singapore Journal of Legal Studies*, pp. 217-241.

Saygili, E., Arslan, S. and Birkan, A.O. 2021. ESG practices and corporate financial performance: evidence from Borsa Istanbul. *Borsa Istanbul Review*, 22(3), pp. 525-533.

Velte, P. 2017. Does ESG performance have an impact on financial performance? Evidence from Germany. *Journal of Global Responsibility*, 8(2), pp. 169-178.

Xie, J., Nozawa, W., Yagi, M., Fuji, H. and Managi, S. 2019. Do environmental, social and governance activities improve corporate financial performance? *Business Strategy and the Environment*, 28(2), pp. 286-300.

Yoon, B., Hwan Lee, J. and Byun, R. 2018. Does ESG performance enhance firm value? Evidence from Korea. *Sustainability*, 10(10), 3635.

Zhao, C., Guo, Y., Yuan, J., Wu, M., Li, D., Zhou, Y. and Kang, J. 2018. ESG and Corporate Financial Performance: Empirical Evidence from China's Listed Power Generation Companies. *Sustainability*, 10(8), 2607.

Bio-note

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TAX REVENUE AND EDUCATION INFRASTRUCTURAL DEVELOPMENT IN NIGERIA

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Abstract: *The study examines the effect of tax revenues on education infrastructural development in Nigeria. Tax revenue may be the mainstay of Nigeria's economy as countries have continually drifted towards a cleaner and friendlier environment. Alternatives to fossil fuel power generation are being explored in countries to reduce the effect of global warming. Also, the continual instability in the price of crude oil in the world market predisposes that tax revenue may likely be a veritable source of funding government expenditure in the future in Nigeria. This study adopted the ex post facto research design to examine the link between tax revenue and education infrastructural development. The education infrastructural development was proxied by the annual allocation to education from 1994 to 2023. Tax revenues were proxied by internally generated revenue through personal income tax, company income tax, petroleum profit tax, tertiary education tax, value-added tax, and customs and excise duties. The error correction model was adopted as the estimation method in this study. These data were sourced from the Nigeria Bureau of Statistic Reports and the Central Bank of Nigeria Statistic Bulletin of the ensuing period. The study revealed a positive and statistically non-significant relationship between personal income tax and education infrastructural development; a negative and statistically non-significant relationship between company income tax, petroleum profit tax, value-added tax, and educational infrastructural development; and a positive and statistically significant relationship between tertiary education tax, customs and excise duty, and education infrastructural development, respectively. The study recommends that more funding from tax generation should be invested in education infrastructures to narrow the gap between the budgetary allocation to education and the 26% recommended by UNESCO. Furthermore, measures should be put in place to enable taxpayers to trace the quantum of tax revenues spent on various infrastructures provided by successive governments in Nigeria. This can go a long way to ensure that political officeholders remain accountable to the taxpayers on the custody of the public resources entrusted to them.*

Keywords: Educational Infrastructures, Taxation, Tertiary Education Trust Fund, Tertiary Education Tax

JEL Classification: M49, O23

1. Introduction
Education provides the required knowledge that supports individuals toward self-actualisation and is a path to the development of any society (Aina and Olorunsola, 2023; Omagu, 2016; Yizengaw, 2008). There has been a global push for education development. To ensure inclusive and equitable quality education for all, the United Nations Education, Scientific, and Cultural Organisation (UNESCO) recommends that the budgetary allocation

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to education should be at least 26% of the annual budget of any nation. This should be for the funding of educational infrastructural development through the supplies of educational facilities, capacity building, and other recurrent expenditures in the sector. Countries around the globe are working towards achieving this minimum standard of education development. The funding for public education in Nigeria rests mainly on the government. Thus, it is not surprising that education is poorly funded in Nigeria. The sector is one of the least funded by the government as the budgetary allocation to education has continually remained less than 9% in Nigeria. The budgetary allocation to education is funded from the pool of resources available to the government, ranging from the proceeds of crude oil to borrowings. Consequently, getting the government accountable for spending on education infrastructural development has remained elusive in Nigeria. This is because government spending is not solely financed by taxation (Borge, Parmer and Torvik, 2018; Moore, Prichard and Fieldstad, 2018; Sjursen, 2023). Funding infrastructural development through tax revenue can make the government accountable for its spending. This is because tax is a contract between governments and the citizens of a state (Besley, 2020) wherein the taxpayers are provided public facilities in return for the taxes they contributed to the government purse. Taxpayers may be committed to paying taxes when public facilities are funded using tax revenues.

The existing studies on the nexus between taxation and infrastructural development have been generic in approach, with very little based specifically on educational infrastructural development in Nigeria (Appah and Isele, 2024; Ajiteru, Aderanijo and Bakare, 2018; Anyaduba and Aronmwan, 2015; Ayeni and Afolabi, 2020, Daniel-Adebayo et al., 2022; Ejemai, Akintoye and Adegbie, 2020; Inyiama, Chinedu and Nnenna, 2017; Muojekwu and Udeh, 2023; Okoror, Mainoma and Uwaleke, 2019; Oladipupo and Ibadin, 2016; Olugbade and Adegbie, 2020; Osho, Olemija and Falade, 2019). The studies of Anaehobi and Agim, 2019, Nagbe and Micah, 2019, and Omobude et al., 2017 were specifically on educational infrastructural development but with tax revenue restricted to tertiary education tax in Nigeria. Etale and Bariweni (2023) extend the scope of tax revenue in their study by also investigating the effect of value-added tax on educational infrastructural development. However, the recurrent expenses were excluded from their proxy for measuring educational infrastructural development. The current study is different from these studies because the effect of other forms of taxation in addition to tertiary education tax on educational infrastructural development is investigated. Furthermore, the proxy of educational infrastructural development in the current study is budgetary allocation to education due to the seeming effect that annual tertiary education tax fund (TETFUND) sponsorship for conferences and further education of staff has on educational development in Nigeria.

2. Literature Review

2.1 Education Infrastructural Development
Infrastructure is the fundamental physical and administrative arrangements required to ensure effective societal control (Umar, Ogbu and Ereke, 2019). It comprises education, industries, buildings, roads, bridges, hospitals, and security to mention but a few (Egbunike, Emudainohwo and Gunardi, 2018; Olufemi et al., 2013). Education infrastructure is critical for an effective and equitable education system. Education infrastructure comprises structures, equipment, and people that enable a curriculum to be taught in a safe learning environment. It is a network of people, institutions, and legal framework in place to ensure education management and advancement of mankind Ibas and Uzoigwe (2020). Its development entails investment in educational facilities, technologies, and resources that support conducive learning.

In the 1970s, the quality of education in Nigeria was a thing of pride for the Black race and a standard for the rest of the African continent (Benjamin et al., 2012) because the

government as of then was investing heavily in educational facilities. Nigerian students were then the envy of several advanced and emerging countries. However, this glory was lost due to neglect, bad policies, corruption, diversion, and mismanagement of public funds.

Bennee, Okoye and Amahalu (2021) documented that educational infrastructural development is measured using federal government capital expenditure on educational infrastructures. Measuring educational infrastructural in this manner relegates staff training and development to the background. The development of the education system of any country cannot be completed without the training and development of staff. In line with this, the current study measured education infrastructural development by the annual allocation to the education sector in Nigeria.

2.2 Tax Revenue

Tax forms a contractual relationship between a taxpayer and the state (Besley, 2020; Bräutigam, Fjeldstad, and Moore, 2008; Levi, 1988; Moore, Prichard and Fjeldstad, 2018). In this contractual arrangement, the citizens of a country pay their taxes with the understanding that they will receive public services and withhold tax payments when the government is not acting up to their expectations. The government is punished when citizens withhold their taxes. Thus, financing infrastructural development through taxation can promote political accountability. There are various forms of tax in Nigeria such as personal income tax, company income tax, petroleum profit tax, tertiary education tax, value-added tax, and customs and excise duty, etc.

The personal income tax (PIT) is a tax levied on the income of persons (Anyaduba, 1999). Personal income tax is charged on salaries, wages, bonuses, rental incomes, and investment profits of individuals in a particular tax jurisdiction. Personal income tax is a form of progressive tax in Nigeria, as its calculation is based on gradual rates. The profit of a company is subjected to the company income tax (CIT) just like the income of an individual is subjected to PIT. The earnings of all companies in Nigeria except for those in the upstream sector of oil and gas activities are subjected to CIT. The current CIT rates in Nigeria are 30%, 20%, and 0%, respectively, for large, medium, and small companies. However, the incomes or profits of pioneer companies, companies in the extraction of solid minerals, and companies whose products form input used by manufacturing companies are exempted from CIT (Okoror, Mainoma and Uwaleke, 2019).

Conversely, the Petroleum Profit Tax (PPT) is a tax on the incomes arising from petroleum operations (Lateef et al., 2022). It is charged on the profit of upstream oil companies (Odusola, 2006). Upstream oil companies comprise companies in petroleum exploration, development, and production activities. PPT is one of the most important taxes in Nigeria due to its huge influence on government revenue and foreign exchange earnings (Lateef et al., 2022). The tax assessment rate has been changed from flat 85 % of the chargeable profit to graduated rates of 42.5% for onshore areas for Petroleum Mining Lease (PML), 37.5% for shallow water areas for PML, 22.5% for onshore areas for new license and leases granted post-PIA commencement and for marginal fields in shallow water areas, 5% from deep offshore areas for PML, and 10% for deep offshore areas for new licenses and leases granted post-PIA commencement (Olaniwun, 2021).

Unlike the PIT and CIT imposed specifically on companies in the upstream oil and gas sector and other companies, respectively, the tertiary education tax is charged to the assessable profit of all companies in Nigeria. The tertiary education tax is an initiative that has mandated companies to fund education infrastructures in public tertiary institutions in Nigeria. The Tertiary Education Trust Fund is responsible for imposing, handling, and distributing the tax revenue collected to government-owned tertiary institutions in Nigeria (Ogunode, Atobauka and Ayoko, 2023). The tertiary education tax rate is currently 3%.

Contrary to the earliest types of taxation described in this section, the value-added tax and customs and excise duty are examples of indirect tax in Nigeria. It is charged on the value

of goods and services consumed by individuals/economic agents or corporate entities (Ugwa and Embuka, 2012). VAT is chargeable at 7.5% in Nigeria (Finance Act, 2019; Lateef et al., 2022). The customs and excise duty is charged on imported and locally manufactured goods to generate revenue and protect domestic industries. The concept comprises "customs duty" and "excise duty". Customs duty is charged on imported goods. Its base is the value or quantity of imported goods. Excise duty, on the other hand, is levied on goods produced in Nigeria. Excise duty levied on a product can discourage the consumption of such products (Nwofia and Egege, 2021).

2.3 Empirical Review

This study is anchored on the benefit-received theory, which posits that a contractual relationship exists between taxpayers and the government wherein the taxpayers pay their taxes to enable the government to perform their statutory function (Bhartia, 2009; Anyafo, 1996). The inability of the taxpayers to pay their taxes as and when due can hinder the discharge of the responsibilities in terms of infrastructural development by the government (Lateef et al., 2022). Consequently, there are studies on the nexus between tax revenues and infrastructural development in Nigeria. Anaehobi and Agim (2019) examined the relationship between tertiary education trust fund intervention and the development of university libraries in South East, Nigeria, and they found a positive and significant association between TETFund intervention and the advancement of university libraries in South-East, Nigeria.
 Similarly, Omobude et al. (2017) found a positive and significant association between TETFUND research grants and infrastructural facilities at the University of Benin. This implies that redirecting tax revenue toward public goods would improve capital expenditure for economic development and encourage taxpayers to comply with their tax obligations (Osho, Olemija and Falade, 2019). Corroborating this is Inyiama, Chinedu and Nnenna (2017), Ajiteru, Aderanijo and Bakare (2018), Ayeni and Afolabi (2020), Ejemai, Akintoye and Adegbie (2020), Oladipupo and Ibadin (2016). However, there are other studies whose outcomes could not affirm that generating more through tax can lead to the provision of infrastructures (Anyaduba and Aronmwan, 2015; Daniel-Adebayo et al., 2022; Oladipupo and Ibadin, 2016).

3. Methodology

The ex post facto research design is adopted in this study. The data collected were used without any substantial modification. The data sets on tax revenues and budgetary allocation to education for 1994-2023 were used in this study. Tax revenue was proxy by personal income tax, company income tax, petroleum profit tax, tertiary education tax, value-added tax, and customs and excise tax. The proxy for educational infrastructural development was the budgetary allocation on education over the time frame of the study. This was so measured because the cost of maintaining and training educationists was taken as part of education infrastructural development in addition to physical and technical infrastructures. These data were sourced from the Central Bank statistical bulletin and the statistical reports of the Bureau of Statistics. The error correction regression was the method of data analysis because of the false correlation sometimes associated with time series data.
The econometrics model of Muojekwu and Udeh (2023), which explored the nexus between tax revenue and infrastructural development in Nigeria, was modified as stated below:

$$EDINF_t = \beta_o + \beta_1 PIT_t + \beta_2 CIT_t + \beta_3 PPT_t + \beta_4 TET_t + \beta_5 VAT_t + \beta_6 CED_t + \mu_t \ldots\ldots\ldots\ldots\ldots(i)$$

Where: EDINF = Education Infrastructural Development; PIT = Personal Income Tax; CIT = Company Income Tax; PPT = Petroleum Profit Tax; TETFUND = Tertiary Education Tax;

VAT = Value Added Tax; CED = Customs and Excise Duties; t = Period Covered; ų = the Stochastic Error Term;

4. DATA ANALYSES AND INTERPRETATIONS

4.1 Descriptive Statistics

This section presents the data summary on the variables of interest in the study. The data summary in terms of the mean, median, maximum, minimum, standard deviation, Jarque-bera statistics are detailed in table 4.1.

Table 4.1: Descriptive statistics

	EDINF	PIT	CIT	PPT	TET	VAT	CED
Mean	263.60	53.50	644.60	1329.90	113.00	582.10	454.60
Median	120.00	52.80	420.60	1290.00	68.40	401.70	281.30
Max.	876.00	107.70	2649.20	4209.00	328.70	2511.50	2240.90
Min.	0.10	15.90	12.30	24.60	31.80	7.30	18.10
Std. Dev.	267.10	25.90	670.90	1118.10	89.30	632.20	536.40
J-Bera	3.40	1.40	6.40	2.20	3.70	14.20	44.30
Prob.	0.20	0.50	0.00	0.30	0.20	0.00	0.00

Source: Researchers' compilation

Table 4.1 summarizes the data sets used in this study. The mean value of EDINF indicates that on average, about 263.6 billion naira was earmarked for education from 1994 to 2023. The standard deviation value of about 267.1 billion naira for EDINF indicates that the data sets on education infrastructural development are not closely clustered around the average value of education infrastructural development. The Jarque-Bera statistics of 3.4 and its associated probability of about 0.2 are indications that the data set on education infrastructural development met the normality requirements of a data set. The mean values on the data set for PIT, CIT, PPT, TET, VAT, and CED of about 53.5 billion naira, 644.6 billion naira, 1.3 trillion naira, 113 billion naira, 582.1 billion naira, and 454.6 billion naira, respectively, are indication that the petroleum profit income tax is the most generated in the period of the study.

4.2 Correlation Analysis

Table4.2:Correlation Analysis

Probability	EDINF	PIT	LCIT	PPT	LVAT	LTET	LCED
EDINF	1						

PIT	0.55***	1					
	0.0017	-----					
LCIT	0.80***	0.38**	1				
	0	0.0384	-----				

PPT	0.71***	0.30	0.83***	1			
	0	0.1066	0	-----			
LVAT	0.80***	0.38**	0.99***	0.82***	1		
	0	0.0397	0	0	-----		
LTET	0.89***	0.48***	0.93***	0.85***	0.91***	1	
	0	0.0076	0	0	0	-----	
LCED	0.85***	0.39**	0.95***	0.78***	0.97***	0.87***	1
	0.0000	0.0329	0.0000	0.0000	0.0000	0.0000	-----

Source: researchers' compilation
Note: *** significant at 1%, ** significant at 5%, *Significant at 10%

Table 4.2 presents the correlation analysis of the data set used in this study. The relationship between EDINF and PIT is positive and significant at 1% with a coefficient of 0.55. The {coefficient} and <probability values> in the relationships between EDINF and CIT {0.80} <0.0000>, EDINF and PPT {.71} <0.0000>, EDINF and VAT {0.80} < 0.0000 >, EDINF and TET {0.89} < 0.0000 >, and EDINF and CED {0.85} < 0.0000 > indicate that PIT, CIT, PPT, VAT, TET, CED significantly contributed to the funding of education within the review period in Nigeria.
The relationship between PIT and each of the following: CIT <0.0384>, VAT <0.0397>, TET <0.0076>, and CED <0.0329> is significant. However, the relationship between PIT and PPT was not statistically significant. CIT is statistically significant with PPT<0.0000>, VAT <0.0000>, TET <0.0000>, TET <0.0000>, and CED <0.0000>. PPT is significantly related to VAT <0.0000>, TET <0.0000>, CED <0.0000>. Similarly, VAT is significantly related to TET <0.0000> and CED <0.0000>, and TET is significantly related to CED <0.0000>.

4.3 Regression Analyses
This section presents the long-run and short-run (error correction model) regression conducted in the study. The section began with stationarity test which culminate into the long run regression analysis and end with the error correction model.

Table 4.3: Unit root test

| Variable | Level | | Ist Difference | |
	Augmented-Dickey Fuller T-statistics	Probability	Augmented-Dickey Fuller T-statistics	Probability
EDINF	-0.0225	0.9486	-5.3301	0.0002
PIT	-2.4708	0.1330	-7.2593	0.0000
LCIT	-1.9398	0.3102	-5.5842	0.0001
PPT	-0.8835	0.7784	-4.2786	0.0026
LVAT	-3.4543	0.0173	-7.3460	0.0000
LTET	-0.1132	0.9386	-5.3342	0.0002
LCED	-1.7172	0.4120	-6.2006	0.0000

Source: Researcher's Compilation

The augmented Dickey-Fuller statistics and their associated probability values at the data level are indications that the variables of the study are not stationary at the data level and suggest the need for a unit root test at first difference. Consequently, the probability values

associated with the ADF at first difference are indications that the variables of the study are stationary at first difference and that long run relationship may exist between education infrastructural development tax revenues. However, Engle-Granger cointegration test is conducted to further confirm the long-run relationship.

Table 4.4: Cointegration Analysis

Variable	Coefficient	Prob.	
PIT	0.8	0.0427	
LNCIT	-57.5	0.3454	
PPT	0.0	0.0171	
LNVAT	-192.7	0.0285	
LNTET	369.6	0.0000	
LNCED	317.1	0.0000	
C	-1725.6	0.0000	
		Value	Prob.*
Engle-Granger tau-statistic		-6.09	0.0266
Engle-Granger z-statistic		-32.28	0.0248
Source: Researcher's Compilation			

The probability values of less than 5% associated with the Engle-Granger tau-statistic and Engle-Granger z-statistic values confirmed that the variables of interest in this study are cointegrated in the long run.

Table 4.5: Long Run Regression Analysis

Variable	Coeff.	Prob.
PIT	0.84	0.2709
LCIT	-62.67	0.56
PPT	-0.02	0.3442
LVAT	-188.34	0.1765
LTET	355.9***	0.0001
LCED	318.3***	0.0004
C	-1682***	0.0000
R^2	0.92	
Adj. R^2	0.89	
F-statistic	42.46	
Prob(F-stat)	0.0000	
DW-stat		2.28

Source: Researcher's compilation
Note: *** significant at 1%, ** significant at 5%, *Significant at 10%

Table 4.5 presents the long-run regression analysis of the error correction model used in this study. The adjusted R^2 value of 0.89 indicates that about 89% of educational infrastructural development is explained by the tax revenues in the econometric model of the study. The F-statistics and its associated probability value of 42.46 and <0.0000> are

indications that the joint relationship between the explanatory and explained variables is significant at 1%. The coefficients and probability values of PIT {0.84} <0.2709>, TET {355.9} <0.0001>, and CED {318.3} <0.0004> indicate a positive relationship between education infrastructure development and personal income tax, tertiary education tax, and customs and excise duty, respectively. This implies that an increase in revenue generated by PIT, TET, and customs and excise duty, respectively, can lead to an 84%, 355%, and 318% increase in the funding of education infrastructural development and, by extension, tertiary education in Nigeria.

Table 4.6: Short-Run Regression Analysis

Variable	Coefficient	t-Stat	Prob.
C	1.4613	0.0536	0.9578
D(PIT)	22.633	0.5946	0.5588
D(LCIT)	-35.723	-0.3564	0.7252
D(PPT)	-4.8614	-0.1641	0.8712
D(LTET)	163.03*	1.7319	0.0987
D(LVAT)	-89.546	-0.7685	0.4511
D(LCED)	232.51*	2.0323	0.0556
ECT(-1)	-0.8973***	-3.3107	0.0035
R^2	0.3862		
F-stat	1.7978		
Prob (F-stat)	0.1433		
DW stat	1.9999		

Source: Researcher's Compilation

Table 4.6 presents the short-run regression analysis of the variables in this study. The error correction of -0.89 and its probability value <0.0035> are indicators that the short-run model is appropriate. The coefficient of -0.89 indicates that about 89% of the discrepancy in the coefficient of the variables of the long-run and short-run models can be corrected within a year.
The positive coefficient between PIT and education infrastructural development both in the short run and long run indicates that more revenue generated from personal income tax can go a long way in boosting education infrastructural development in Nigeria. If more revenue was to be generated through the PIT in the reviewed period, funds allocated to education could have increased by about 2260%. This implies that the government could fund public education through the personal income tax, which is the viable means of revenue generation available to most state governments in Nigeria. This finding is in tandem with the studies of Osho, Olemija and Falade (2019), Daniel-Adebayo et al. (2022), and Inyiama, Chinedu and Nnenna (2017). The negative coefficients in the short-run and long-run relationship between company income tax and education infrastructural development are indications that revenues generated through company income tax are largely used to fund another area of economic development other than the education infrastructural. This is not surprising as company income tax is collected by the federal government, meanwhile, education is co-funded in Nigeria by the Federal and state governments. However, our findings in this regard contradicted the studies of Anyaduba and Aronmwan (2015) and Ayeni and Afolabi (2020). Also, the coefficients in the relationship between petroleum profit tax and education infrastructural development indicate that the petroleum profit tax is usually used to finance other aspects of infrastructural development in Nigeria. This study also deviated from the

studies of Anyaduba and Aronmwan (2015) and Oliver et al. (2017) and corroborates Inyiama, Chinedu and Nnenna (2017) and Ajiteru, Aderanijo and Bakare (2018). The positive coefficients and associated probability values in both the short- and long-run regression of tertiary education tax and education infrastructural development are pointers that 100% of the revenues generated through tertiary education tax is used to finance education infrastructural development in Nigeria. This is in tandem with Nagbe and Micah (2019), Anaehobi and Agim (2019), and Omobude et al. (2017). The negative relationship, both in the short and long run, between value-added tax and education infrastructural development is a pointer that education infrastructural development is not funded through the revenue generated from value-added tax. This is not surprising as most educative materials are VAT exempted in Nigeria. This is in tandem with Oladipupo and Ibadin (2016), but contrary to Anyaduba and Aronmwan (2015), Ayeni and Afolabi (2020), Oliver et al. (2017), and Okoror et al. (2019). Finally, the relationship between education infrastructural development and customs and excise duty in both the short and long run indicates education infrastructural development is funded by the customs and excise duty in Nigeria. This corroborated Ayeni and Afolabi (2020), Ejemai et al. (2020), and Inyiama, Chinedu and Nnenna (2017), but could not support the study of Oladipupo and Ibadin (2016), which provides contrary evidence.

5. Conclusion

Education is the bedrock of the development of any nation on the globe. Despite the relevance of education to the development of a country, a kid glove is always paid to education in Nigeria, where the allocation to education is currently a far cry from the 26% of the country's annual budget recommended by the United Nations Educational, Scientific, and Cultural Organisation. This has always brought most unions in the tertiary institutions and government to a loggerhead. Against this backdrop, this study investigated the impact of tax revenues on education infrastructural development in Nigeria. The study found that both tertiary education tax and customs and excise duty significantly influenced education infrastructural development in Nigeria. Other forms of taxation, such as personal income tax, company income tax, petroleum profit tax, and value-added tax, had statistically non-significant effects on education infrastructural development in Nigeria. The study recommends that measures can help taxpayers trace the quantum of tax revenues spent on educational infrastructures in Nigeria should be instituted. Furthermore, the quantum of allocation to education should be increased to narrow the gap between the allocation to education and the recommendation on education by UNESCO

References

Aina, A. C. and Olorunsola, E. O., 2023. Assessment of tertiary education trust fund (TETFund) interventions and academic staff job performance in public universities in Southwest, Nigeria. *American Journal of Education and Practice ISSN 2520-3991 (Online), 7*(2), 90 – 103.

Appah, E. and Isele, L. E., 2024. Taxes and health infrastructural development in Nigeria. *Journal of Advanced Research and Multidisciplinary Studies, 4(*3), PP 43-63

Ajiteru, W. O., Aderanijo, L. O. and Bakare, L. A., 2018. Tax revenue and infrastructural development in Osun State. *International Journal of Innovation Finance and Economic Research, 6(*2), PP. 50 – 61.

Anaehobi, S. A. and Agim, C. C., 2019. TETFund intervention and development of university libraries in South East, Nigeria. *Journal of Education and Practice, 10*(5), PP.116 - 125.

Ayanduba, J. O. and Aronmwan, E. J., 2015. Taxes and infrastructural development in Nigeria. *Nigerian Journal of Banking, Finance and Entrepreneurship Management,* 1, PP.14 – 28

Bennee, E., Okoye, P. V. C. and Amahalu, N. N., 2021. Infrastructural development and economic growth of Nigeria. *African Journal of Business and Economic Development,* (Online) Available at: <http:// www.ijaar.org>

Besley, T., 2020. State capacity, reciprocity, and the social contract. *Econometrica 88 (*4), PP.1307–1335.

Borge, L.E., Parmer, P. and Torvik, R., 2015. Local natural resource curse? *J. Public Econ. 131.* Available Through: ScienceDirect Website < http://www.sciencedirect.com/>

Bräutigam, D., Fjeldstad, O.H. and Moore, M., 2008. *Taxation and state-building in developing countries: Capacity and consent.* Cambridge University Press.

Daniel-Adebayo, O., Akintoye, I. R., Adegbie, F. F. and Ajayi-Owoeye, A. O., 2022. Tax revenue and infrastructure expectation gap in selected Sub-Saharan African countries. *International Journal of Accounting Research, 7(*1), PP.75-86.

Egbunike, F. C., Emudainohwo, O. B. and Gunardi, A., 2018. Tax revenue and economic growth: A study of Nigeria and Ghana. *Journal Ilmu Economic, 7*(20), PP. 213 – 220.

Ejemai, M. O., Akintoye, I. R. and Adegbie, F. F., 2020. Companies income, customs and excise duty tax gap and infrastructural development in Nigeria. *International Journal of Development Research, 10*(03), PP. 34891 - 34901.

Ibas, O. E. and Uzoigwe, M. C., 2020. Tertiary education trust fund intervention and quality assurance among public universities in Cross River State, Nigeria. *International Journal of Educational Benchmark, 17*(1), PP.1 – 10.

Inyiama, O. I., Chinedu, A. and Nnenna, C. V., 2017. Relevance of tax revenue resources to infrastructural development of Nigeria. *International Journal of Managerial Studies and Research, 5(*10), PP. 74–81.

Lateef, O. M., Lasisi, I. O., Adegboye, D., Ajepe, A. and Isife, B, N., 2022. Tax revenue collections and health care infrastructural development in Nigeria. *Journal of Finance and Accounting, 10*(1), PP. 19 - 24.

Levi, M., 1988. *Of rule and revenue.* {e-book} University of California Press. Available through: Jstor website <http://www.jstor.org/stable>.

Moore, M., Prichard, W. and Fjeldstad, O.H., 2018. *Taxing Africa: Coercion, reform and development.* Zed Books Ltd.

Muojekwe, H. O. and Udeh, F. N., 2023. Effect of tax revenue on infrastructural development in Nigeria. *Journal of Global Accounting, 9*(1), PP. 161-189.

Nagbe, O. I. and Micah, I. U., 2019. The relationship between tertiary education trust fund and development of tertiary institutions in Nigeria from 2009-2017. *Journal of Education and Practice, 6*(33), PP. 20 - 34.

Odusola, A., 2006. *Tax policy reforms in Nigeria, world institute for development economics and research.* Research Paper No. 2006/03. http://www.wider,unu.edu

Ogunode, N. J., Atobauka, I. S. and Ayoko, V. O., 2023. University education politicization in Nigeria: Implications and ways forward. *International Journal on Integrated Education, 6*(1), PP. 1 – 12.

Okoror, J. A., Mainoma, M. A. and Uwaleke, U. J., 2019. Companies income tax and infrastructural development in Nigeria. *Accounting & Taxation Review, 3(*3), PP. 24–43.

Oladipupo, A. O. and Ibadin, P. O., 2016. Indirect taxes and infrastructural development in Nigeria. *Igbinedion University Journal of Accounting, 2*, PP. 331-359.

Olaniwun, A. 2021. The petroleum industry act, 2021: Key highlights. [online] available at: www.olaniwunajayi.net

Olufemi, E. A., Olatunbosun, A. J., Olsode, O. S., and Adeniran, I. G., 2013. Infrastructure development and its effect on economic growth: The Nigerian perspective. *European Scientific Journal, 9*(31), PP. 431 - 452.

Olugbade J. A. and Adegbie F. F., 2020. Personal income tax and infrastructural development in Lagos State, Nigeria. *Journal of Finance and Accounting, 8(*6), PP. 276-287

Olutayo, A. O., 2010. Education infrastructure and unsustainable development in Africa. *Human Affairs, 20*, PP. 183 - 198.

Omagu, F. E., 2016. Infrastructural development in Nigeria: A panacea for transforming educational sector for sustainable national development. *International Journal of Capacity Building in Education and Management (IJCBEM), 3*(1), PP. 13 – 19.

Omobude, H., Ikhisemojie, M., Oyetunji, A. G. and Omorogbe, I. E., 2017. The influence of TETFUND research grants on sustainability of infrastructural facilities in the University of Benin. *The Nigerian Journal of Teachers Education and Teaching, 9*(1), PP. 48 - 55.

Osho, A. E., Olemija, T. L. and Falade, A. B., 2019. The influence of tax revenue on government capital expenditure and economic growth in Nigeria. *European Journal of Business and Management, 11(2*), PP. 39–49.

Sjursen, H. I., 2023. Accountability and taxation: Experimental evidence. *Journal of Economics Behaviour and Organisation, 216*, [online] available through: Science direct at: http://www.sciencedirect.com

Ugwa, M. and Embuka, A., 2012. Pay as you consume the value added tax. *Gauge: A quarterly publication of the Federal Inland Revenue Service, April June*.

Umar, K., Ogbu, C. and Ereke, E., 2019. The challenges of infrastructural development in Nigeria: An assessment of the pains and the gains. *International Journal of Political Science Development, 7*(4), PP. 101 – 108.

Yizengaw, T., 2008. *Challenges of higher education in Africa and lessons of experience for the Africa-US higher education collaboration initiative*. Being a Synthesis Report by National Association of State Universities and Land-Grant Colleges (NASULGC) Based on Consultations and Review of Literature Related to Higher Education and Development in Africa.

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GLOBAL TRADE IN A POST-PANDEMIC WORLD: SUPPLY CHAIN DISRUPTIONS, ECONOMIC IMPACT, AND THE PATH TO RESILIENCE

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Abstract: *The COVID-19 pandemic profoundly disrupted global trade, exposing vulnerabilities in highly interconnected supply chains and reshaping industries worldwide. This paper explores the pandemic's impact on key sectors, including energy, automotive, and food, and highlights the long-term shifts in global trade systems. By examining the sharp decline in trade volumes during 2020 and the uneven recovery in 2021-2022, the paper provides a statistical analysis of how different regions and industries fared through the crisis. Through a detailed case study of the automotive industry and the semiconductor shortage, the paper delves into the specific challenges faced by manufacturers and the economic consequences of supply chain disruptions. Furthermore, it discusses the broader trends toward regionalization, diversification, digital transformation, and the evolving role of trade policies in the post-pandemic era. The paper concludes by emphasizing the need for resilience, flexibility, and innovation in future global trade practices, arguing that the lessons learned from the pandemic will shape the trajectory of international commerce for years to come.*

1. Introduction

Prior to the COVID-19 pandemic, global trade flourished as a sophisticated network of supply chains designed to maximize efficiency and minimize costs. Fueled by decades of globalization, technological advancements, and reductions in trade barriers, this system enabled the rapid flow of goods across borders. A key component of this trade structure was the just-in-time (JIT) inventory model, which allowed businesses to reduce storage costs and synchronize deliveries with production schedules, ultimately optimizing resources.

Yet, this very system -reliant on the smooth, uninterrupted flow of goods- was revealed as fragile in the face of a global crisis. The COVID-19 pandemic triggered a massive disruption in global supply chains, exposing weaknesses that had been masked by the system's efficiency. Factories, particularly in Asia, which serve as key manufacturing hubs, were forced to shut down due to virus outbreaks, causing immediate shortages of goods across the globe. As national lockdowns and border closures compounded the disruptions, industries that depended on international suppliers found themselves struggling to meet demand or keep operations running.

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Shipping delays, workforce shortages, and reduced manufacturing capacity reverberated through industries such as automotive, pharmaceuticals, and food production, causing backlogs and price volatility. The semiconductor shortage, which halted car production, is just one example of how interdependence in global trade can turn into vulnerability under stress.

As a result, businesses and policymakers are reassessing global trade strategies, focusing less on pure efficiency and more on resilience. The global value chain framework emphasizes the importance of diversifying sourcing patterns to ensure supply chain resilience, as seen during the pandemic (Gereffi, 2020). This shift has led to increased interest in diversifying suppliers, stockpiling critical materials, and exploring regionalization. The long-term implications of these adjustments are reshaping global trade in profound ways.

The OECD (2020) suggests several policy measures for improving supply chain resilience, including incentives for reshoring critical industries and fostering public-private partnerships to enhance the robustness of global value chains.

This paper aims to explore how the pandemic has reconfigured global supply chains, particularly in industries like energy, automotive, and food. Additionally, it will assess the long-term effects of trade disruptions on the global economy, examine statistical trends in trade volume, and present case studies of industries most impacted by the pandemic.

The COVID-19 pandemic, described by Harvard Business Review (2020) as a 'wake-up call' for supply chain management, has pushed businesses to reexamine their reliance on cost-efficient but fragile supply chains and prompted a move towards more resilient structures.

This paper is organized into eight sections to systematically explore the impact of the COVID-19 pandemic on global trade and supply chains. Following this introduction, Section 2 outlines the methodological framework, detailing the combination of quantitative data analysis, qualitative case studies, and theoretical exploration of resilience frameworks. Section 3 presents a statistical analysis of global trade volume changes during the pandemic, highlighting the sharp contraction in 2020 and the uneven recovery observed in 2021–2022.

Section 4 provides a sector-specific analysis, focusing on two critical industries: energy and automotive. It examines the challenges faced by these sectors and the adaptive strategies employed to navigate disruptions. Section 5 delves deeper into the automotive sector with a case study on Volkswagen, analyzing the impact of semiconductor shortages on production and the company's response to this crisis.

In Section 6, the lessons learned from the pandemic are explored, with an emphasis on the Eurozone's efforts to bolster supply chain resilience and reduce reliance on external suppliers, particularly in the semiconductor industry. Section 7 discusses the broader implications of the pandemic on global trade, considering emerging trends such as regionalization, digital transformation, and resilience-oriented supply chain strategies.

Finally, Section 8 concludes the paper by summarizing the key findings, underscoring the shift from efficiency-driven to resilience-driven supply chains, and proposing future directions for research and policy-making in this area.

2. Methodology

To effectively analyze the disruptions caused by the COVID-19 pandemic to global trade and supply chains, this paper adopts a multi-pronged methodological approach, combining quantitative data analysis, qualitative case study, and theoretical exploration of resilience frameworks. This comprehensive methodology ensures a robust examination of both the macroeconomic implications and sector-specific dynamics of the pandemic's impact.

The analysis begins with the collection and interpretation of secondary data from reputable international organizations such as the World Trade Organization (WTO), the International

Monetary Fund (IMF), and the Organization for Economic Co-operation and Development (OECD).

The qualitative dimension of this research focuses on case studies, specifically examining the semiconductor shortage within the automotive industry. The case study method allows for a granular investigation of the systemic weaknesses exposed by the pandemic. Volkswagen (VW), a leader in the Eurozone automotive sector, serves as the focal point for this exploration. By analyzing VW's supply chain disruptions, production halts, and strategic responses, the case study illustrates the broader challenges and adaptive measures adopted by the industry.

This paper integrates the theoretical underpinnings of supply chain resilience into its analysis.

Finally, the methodology acknowledges its limitations. The reliance on secondary data, while comprehensive, may introduce biases related to data availability and granularity. Moreover, the case study approach, while insightful, may not fully capture the heterogeneity of responses across different industries or regions. To address these constraints, the paper suggests avenues for future research, including primary data collection through surveys or interviews with industry stakeholders.

3. Statistical analysis of trade volume changes

The COVID-19 pandemic triggered one of the sharpest contractions in global trade in modern history. As lockdowns, border closures, and restrictions on movement were implemented worldwide, supply chains ground to a halt, causing a significant decline in both imports and exports across most major economies. According to the World Trade Organization (WTO), global merchandise trade volumes fell by 9.2% in 2020, marking the steepest decline since the 2008 financial crisis. This sharp contraction highlighted the vulnerabilities in international trade and supply chains that had been optimized for efficiency at the expense of resilience (World Trade Organization, 2020).

Ivanov (2020) used simulation models to predict the impacts of epidemic outbreaks on supply chains, highlighting the cascading effects that a single disruption can have on interconnected networks. His findings indicate that proactive risk management and real-time monitoring can mitigate the severity of such disruptions.

3.1. Global Trade Decline in 2020

The pandemic's onset in early 2020 led to widespread factory closures and logistical bottlenecks. Key global trading regions such as the United States, Europe, and Asia saw sharp declines in exports and imports. In the United States, exports fell by 12%, as the country grappled with supply chain disruptions and a collapse in demand for non-essential goods. Europe saw an 8% decline in exports, with Germany, France, and Italy experiencing significant contractions due to prolonged lockdowns. Conversely, Asia fared relatively better, with trade volumes declining by only 5%. This was largely due to China's rapid recovery from the pandemic, where the economy reopened earlier than others, bolstering exports of electronics, medical supplies, and textiles. Globalization accelerated the integration of economies but also exposed them to vulnerabilities, as seen during the pandemic with failures in medical supply chains.

The decline in trade volumes had profound economic consequences. Countries that relied heavily on exports, such as Germany and Japan, saw their economies contract. The COVID-19 pandemic as such is serious, but not without historical precedent and not exceptionally severe in terms of mortality (van Bergeijk, 2021).

Developing countries that depend on imports of essential goods, like food and medical supplies, experienced shortages and price spikes. The pandemic also intensified pre-

existing global inequalities, as emerging markets struggled to access the resources needed to recover from the crisis. The global flow of goods is largely driven by innovations like the shipping container, which transformed logistics by significantly reducing transportation costs (Levinson, 2008).

3.2. Recovery and Growth in 2021–2022: Uneven Rebound

Global trade began to rebound in 2021, with trade volumes growing by 10.8%, according to WTO estimates. The recovery was driven by pent-up demand for goods and services as vaccination campaigns gained momentum and economies started to reopen. However, the recovery was uneven, with some regions and industries rebounding faster than others. East Asia, particularly China, led the recovery, with exports of electronics, textiles, and medical supplies surging to meet global demand. In contrast, regions like Latin America experienced a slower recovery due to the pandemic's prolonged impact on public health and economic conditions. The COVID-19 pandemic exposed over-reliance on key exporting economies like China for medical supplies and highlighted that many shortages were due to policy failures rather than market failures (Gereffi, 2020).

While demand for goods increased, supply chains remained constrained. Many industries continued to face bottlenecks, including shipping delays, labor shortages, and rising input costs. The automotive industry, which depends on global supply chains for components like semiconductors, saw continued production delays due to shortages. Meanwhile, the energy sector faced volatility as demand for oil rebounded sharply, causing price fluctuations.

The uneven nature of the recovery underscored the pandemic's lasting effects on global trade. While some industries and regions have regained pre-pandemic levels of activity, others, particularly in service sectors like travel and hospitality, continue to face significant challenges.

4. Sector-Specific Analysis: Energy and Automotive Trade

Energy Sector: The energy sector experienced dramatic fluctuations during the pandemic. The global value chain framework emphasizes the importance of diversifying sourcing patterns to ensure supply chain resilience as seen during the pandemic (Gereffi, 2020). In 2020, global oil trade volumes fell by 15% as demand for transportation fuel plummeted during lockdowns. This collapse in demand led to a historic decline in oil prices, with crude oil prices briefly turning negative in April 2020. As economies reopened in 2021, demand for energy rebounded, and oil exports began to recover. However, by the end of 2021, rising demand and geopolitical tensions led to an energy crisis in parts of the world, particularly in Europe, where natural gas shortages caused supply disruptions and price hikes.

A Capgemini report (2021) found that consumer products and retail companies are increasingly prioritizing supply chain resilience, with many firms investing in AI and automation to improve their ability to respond to future disruptions.

Automotive Sector: The global automotive sector was one of the most severely affected by pandemic-induced supply chain disruptions, especially due to the shortage of semiconductors. In 2020, global automotive exports declined by 16%, with production halting in many regions due to factory closures and component shortages. The shortage of semiconductors, crucial for modern vehicle production, delayed the production of millions of vehicles globally. The shortage of semiconductors, crucial for modern vehicle production, delayed the production of millions of vehicles globally. Despite a recovery in demand in 2021, automakers continued to struggle with semiconductor shortages, leading to long delays in vehicle delivery and rising prices in the new and used car markets.

A McKinsey report (2020) highlights the accelerated digital transformation across industries as companies strive to enhance risk management capabilities and balance their global supply chains. This trend has been particularly evident in sectors like automotive, where

companies are increasingly adopting predictive analytics and AI-driven tools for supply chain optimization.

According to the IBM Institute for Business Value (2020), the pandemic has significantly accelerated the adoption of digital technologies, which are now being leveraged to enhance supply chain visibility and predictive capabilities.

The challenges faced by the automotive industry highlighted the risks of relying on concentrated supply chains, particularly for critical components. The semiconductor shortage is a prime example of how a lack of diversification in suppliers can lead to severe production bottlenecks. Global value chains in specific sectors like medical devices and automotive industries were severely disrupted, exposing vulnerabilities in both producer-driven and supplier-driven chains (Gereffi, 2020).

Tukamuhabwa et al. (2015) provide a comprehensive framework for understanding supply chain resilience, emphasizing adaptive capability as a critical factor. The ongoing efforts to increase resilience through digital transformation and regional supply chains align with this theoretical foundation.

5. Case Study: Volkswagen (VW) and the Semiconductor Shortage in the Eurozone

The automotive industry in East Asia is experiencing unprecedented disruption due to significant ruptures in global supply chains. A notable example is the Korean car manufacturer Hyundai, which was compelled to shut down all its production plants in Korea because of a severe shortage of essential components sourced from China. Similarly, the Japanese automaker Nissan had to temporarily suspend operations at one of its factories in Japan, underscoring the widespread impact of these supply chain challenges. The ripple effects of this disruption have extended to Europe as well. Fiat-Chrysler issued a warning that it might soon have to halt production at one of its European facilities if the shortage persists. In a more dramatic move to mitigate the crisis, Jaguar Land Rover, a UK-based automaker, revealed that it might exhaust its inventory of critical parts by the end of February. To avert a complete shutdown, the company resorted to flying in emergency supplies from China using suitcases — a striking illustration of the lengths to which manufacturers must go to maintain operations. This crisis highlights the fragility of just-in-time manufacturing systems that many automotive companies have relied on for efficiency and cost reduction. As these companies scramble to adapt, the urgency of diversifying supply sources and increasing inventory buffers becomes ever more apparent (Baldwin & di Mauro 2020).

The proactive risk management approach adopted by Ericsson after a sub-supplier accident, as analyzed by Norrman and Jansson (2004), provides a relevant example of how companies can learn from disruptions to implement more robust strategies. Similarly, Volkswagen's shift to diversify semiconductor suppliers reflects a proactive stance to safeguard against future shortages.

The global automotive industry's reliance on semiconductors was starkly exposed during the COVID-19 pandemic, and the Eurozone, with its highly integrated automotive sector, was no exception. Volkswagen (VW), one of the largest automotive manufacturers in the world and a key player in the Eurozone economy, provides a telling example of how the semiconductor shortage disrupted production and led to significant economic and operational challenges. This section will explore how the semiconductor shortage impacted Volkswagen, how the company responded, and what lessons can be drawn from the crisis for the Eurozone automotive industry as a whole.

5.1. The Pre-Pandemic Context: VW's Supply Chain Vulnerabilities

Volkswagen operates one of the most extensive and complex supply chains in the automotive industry. Before the pandemic, the company was already experiencing the strain

of managing a global network of suppliers and manufacturing sites, where efficiency and cost savings were key priorities. This operational model included a reliance on just-in-time (JIT) inventory systems, which meant that parts were delivered to manufacturing facilities only when they were needed for production. This approach minimized storage costs but left VW vulnerable to any disruptions in the flow of components, especially semiconductors. The just-in-time (JIT) model, which focuses on efficiency, left many companies vulnerable during the pandemic. Shifting toward "just-in-case" strategies that prioritize resilience is key for future preparedness (Gereffi, 2020).

Christopher and Peck (2004) argue that resilience in supply chains can be significantly enhanced through strategies that incorporate flexibility, redundancy, and continuous monitoring of risks. This perspective underscores the shift from JIT to 'just-in-case' inventory models, which many companies, such as Volkswagen, adopted during the pandemic to buffer against unexpected disruptions.

Semiconductors are essential to the production of modern vehicles, particularly in VW's increasingly popular line of electric vehicles (EVs). These chips control various functions in vehicles, from engine management to infotainment systems and safety features. As the automotive industry moved toward greater digitization and automation, the demand for semiconductors increased significantly, with modern vehicles containing hundreds or even thousands of chips.

5.2. Impact of the Pandemic: Semiconductor Shortages in Europe

The electronics industry is revealing significant vulnerabilities due to its heavy reliance on just-in-time inventory practices and the scarcity of alternative sources for critical components. The practice of maintaining minimal inventory levels, intended to reduce costs and enhance efficiency, has instead exposed the industry to severe risks in the face of supply chain disruptions. For instance, manufacturers of semiconductors and specialized chips are struggling to meet production demands as key parts become scarce. The optics sector is similarly at risk, heavily dependent on precision components sourced from a limited number of suppliers. This dependence creates a bottleneck that threatens to halt production if even a single supplier experiences delay. Moreover, the increasing integration of optical technologies into consumer electronics, medical devices, and automotive systems amplifies the potential impact of these disruptions. The situation underscores a critical need for the electronics and optics industries to reconsider their supply chain strategies. Building more resilient networks, expanding supplier bases, and maintaining larger safety stocks could be vital steps toward mitigating such risks in the future.

When the pandemic struck in early 2020, Volkswagen, like other automakers, faced immediate challenges. Factory closures in Europe and around the world halted production. Initially, automakers -including VW- anticipated a prolonged downturn in demand for new vehicles and reduced their orders for semiconductors. This proved to be a miscalculation. By mid-2020, demand for vehicles, particularly electric vehicles (EVs) and hybrid models, rebounded more quickly than expected, as governments introduced stimulus measures to support the green energy transition and incentivized EV purchases.

However, during the early months of the pandemic, semiconductor manufacturers had redirected their production capacity to serve the booming consumer electronics market. As global demand for personal computers, smartphones, and gaming consoles surged due to the shift to remote work and online entertainment, semiconductor suppliers, many of which are based in Asia, prioritized orders from tech companies over automotive firms. As a result, when Volkswagen and other automakers sought to ramp up production in late 2020 and early 2021, they found themselves at the back of the queue for semiconductor supplies.

For Volkswagen, the timing could not have been worse. The company was in the midst of an ambitious plan to scale up production of its electric vehicle lineup, which was central to its strategy to lead the global EV market and meet stringent EU environmental targets. The

shortage of semiconductors, particularly chips used in advanced driver-assistance systems (ADAS) and battery management systems, severely hampered VW's ability to produce EVs and other high-tech models.

5.3. VW's Response: Production Halts and Strategic Shifts

The impact of the semiconductor shortage on Volkswagen was severe. In early 2021, the company announced significant production cuts across its global operations, including at its main factories in Wolfsburg, Germany, and other key plants in Europe. Volkswagen's flagship brand, alongside its Audi and Porsche subsidiaries, was forced to delay the release of new models, including several highly anticipated EVs. The shortage led to production halts at multiple plants, with VW temporarily suspending operations or reducing shifts to cope with the lack of components.

In total, VW's production cuts in 2021 were estimated to be in the hundreds of thousands of vehicles. The company reported that it lost the ability to produce approximately 800,000 vehicles during the year due to the semiconductor shortage, leading to a significant impact on its revenue and market position. The financial cost of these disruptions was immense, with VW estimating that the shortage reduced its operating profit by billions of euros. The company's CEO, Herbert Diess, described the semiconductor shortage as the "biggest supply chain disruption" in VW's history.

The shortage also had a ripple effect on the broader European economy. Volkswagen is one of the largest employers in the Eurozone and a critical part of the German economy. The production cuts led to layoffs and furloughs across the supply chain, from component suppliers to logistics companies, amplifying the economic impact of the crisis.

To mitigate these challenges, Volkswagen implemented several key strategies:

1. Diversification of Semiconductor Suppliers: Volkswagen, like many other automakers, sought to diversify its supplier base to reduce its reliance on a small number of semiconductor manufacturers. While much of the world's semiconductor production is concentrated in a few companies, primarily based in Asia, VW began negotiating with other suppliers to secure a more stable flow of chips. This included exploring partnerships with European semiconductor manufacturers to reduce reliance on imports from Asia.

2. Long-Term Supply Agreements: VW pursued long-term agreements with chip manufacturers to ensure a steady supply of semiconductors in the future. This included commitments to prioritize the automotive industry during periods of high demand for semiconductors. While these agreements were designed to address future shortages, they did little to alleviate the immediate crisis.

3. Increased Inventory Buffering: In response to the disruption, VW reconsidered its reliance on JIT models. The company began building up larger inventories of critical components, including semiconductors, to guard against future disruptions. This shift from JIT to "just-in-case" inventory management reflects a broader trend in the global automotive industry, where companies are willing to bear higher inventory costs in exchange for increased resilience.

4. Collaboration with Governments: Volkswagen, along with other major automakers in Europe, lobbied the European Union and national governments for greater support in securing semiconductor supplies. This included advocating for EU investments in semiconductor manufacturing capacity, as well as public-private partnerships to build more resilient supply chains within Europe.

6. Lessons learned and the Eurozone's Response

The semiconductor shortage highlighted the vulnerability of the Eurozone's automotive industry to global supply chain shocks. Volkswagen's experience illustrates how deeply integrated the automotive supply chain is with global manufacturing hubs, particularly in Asia, where the majority of semiconductors are produced. The crisis underscored the need for greater resilience and diversification within the Eurozone's supply chain, particularly as the automotive industry transitions toward electrification and autonomous driving technologies, both of which depend heavily on semiconductors.

The Eurozone has responded to the crisis with a combination of short-term measures and long-term strategies aimed at reducing dependence on foreign suppliers. The European Commission, under its Industrial Strategy, has prioritized increasing semiconductor production within Europe. The EU's Digital Compass strategy, announced in 2021, set an ambitious goal for Europe to double its share of global semiconductor production by 2030, from 10% to 20%.

To achieve this, the EU is investing in research and development, fostering innovation in semiconductor technologies, and providing incentives for semiconductor manufacturers to set up production facilities within the Eurozone. These efforts are aimed at reducing Europe's dependence on imports from Asia and ensuring that critical industries, like automotive, have a stable and secure supply of chips.

Volkswagen, along with other European automakers, is likely to benefit from these initiatives. However, building semiconductor manufacturing capacity in Europe will take years, and the automotive industry will need to navigate ongoing supply chain challenges in the meantime. VW has acknowledged that semiconductor shortages may continue into 2023, as global demand for chips remains high across multiple industries.

According to Sheffi (2005), companies that embed resilience into their operational strategies not only recover more quickly from disruptions but also gain a competitive advantage. The shift towards more diversified and localized supply chains post-pandemic echoes Sheffi's argument that resilience is not merely a defensive strategy but a pathway to sustainable growth.

7. Implications for the Future

The semiconductor shortage has fundamentally altered the way Volkswagen and the broader Eurozone automotive industry approach supply chain management. The reliance on a few key suppliers for critical components like semiconductors has been identified as a major risk, and efforts are now underway to build more resilient and diversified supply chains. Volkswagen's shift from JIT to more buffered inventories, along with its efforts to secure long-term supply agreements, reflects a broader recognition that the global automotive industry must be better prepared for future disruptions.

The Economist Intelligence Unit (2021) notes that governments are now playing a more active role in promoting supply chain resilience, with initiatives aimed at supporting local production capabilities and reducing dependency on critical imports.

For the Eurozone, the crisis has accelerated efforts to boost domestic semiconductor production and reduce reliance on imports from Asia. While these initiatives will take time to bear fruit, they represent a significant shift in the Eurozone's approach to industrial policy and supply chain management.

Volkswagen's experience during the pandemic serves as a cautionary tale for the automotive industry and highlights the need for a more resilient and adaptable supply chain in an increasingly uncertain global economy.

Kleindorfer and Saad (2005) outline a strategic framework for managing disruption risks, focusing on anticipation, mitigation, and recovery. This approach aligns with recent trends

towards 'just-in-case' supply chain strategies adopted by companies in response to pandemic-induced disruptions.

8. Conclusions, Limitations of the Research and Suggestions for Future Research

The COVID-19 pandemic exposed the vulnerabilities of global trade systems, forcing businesses and governments to reevaluate their reliance on efficient but fragile supply chains. The disruptions caused by the pandemic led to a shift toward building more resilient and diversified supply networks. Companies are moving away from just-in-time inventory models in favor of "just-in-case" strategies that prioritize stockpiling and supplier diversification to mitigate future risks. The COVID-19 pandemic revealed the fragility of global trade systems reliant on just-in-time inventory models. Volkswagen's semiconductor shortage serves as a case study (Gurnani, Mehrotra & Ray, 2011).

As the world adapts to the lessons of the pandemic, regionalization and technological advancements, such as blockchain and artificial intelligence, are likely to play a key role in shaping the future of global trade. While global trade volumes have rebounded, the post-pandemic world will not revert to pre-pandemic norms. Instead, the focus on resilience, regional supply chains, and digitalization will define the next era of international trade.

The automotive industry's struggles with semiconductor shortages serve as a case study in how global supply chains can collapse under pressure. As governments and companies invest in domestic production and secure long-term supply agreements, the future of supply chain management is likely to emphasize resilience over efficiency. The pandemic has indelibly altered the landscape of global trade, highlighting the need for flexibility and preparation in an increasingly uncertain world.

The theoretical usefulness of the this research contributes to the theoretical understanding of global trade disruptions and supply chain resilience in the context of large-scale systemic shocks. By integrating established frameworks such as Christopher and Peck's (2004) resilience model and Tukamuhabwa et al.'s (2015) adaptive capability framework, the study builds upon and contextualizes existing theories within the unprecedented scenario of the COVID-19 pandemic. The research provides an empirical basis for testing these frameworks under real-world conditions, highlighting both their strengths and limitations.

Moreover, the study advances the discourse on global supply chain management by emphasizing the shift from efficiency-driven strategies, like just-in-time (JIT) inventory models, to resilience-driven approaches, such as just-in-case (JIC) strategies.

The research's practical utility for businesses is to provides a roadmap for building more resilient supply chains. It highlights the importance of diversification, digital transformation, and long-term supplier relationships, offering concrete strategies to mitigate future disruptions. For example, the Volkswagen case study provides a practical example of how companies can adapt to supply chain shocks through proactive risk management, such as supplier diversification and rethinking inventory practices.

One of the most valuable aspects of this research is its ability to bridge the gap between theoretical exploration and practical application. By grounding its analysis in empirical data and real-world case study, the study ensures that its theoretical contributions are not only academically robust but also directly relevant to practitioners.

While this paper provides a comprehensive analysis of the impact of the COVID-19 pandemic on global trade and supply chains, certain limitations must be acknowledged to contextualize the findings and guide future research.

1. Data Availability and Reliability: The analysis primarily relies on secondary data sourced from international organizations, industry reports, and academic literature. While these sources are credible, they may suffer from limitations in scope, granularity, and timeliness.

2. Case Study Generalizability: The case study on Volkswagen and the semiconductor shortage provides a detailed exploration of supply chain disruptions in the automotive sector.

However, the findings from this case study may not fully capture the heterogeneity of experiences across other sectors, such as pharmaceuticals, electronics, or food production. The selection of one focal company, though illustrative, limits the generalizability of sector-specific insights to the broader landscape of global trade.

3. Timeframe of Analysis: The research predominantly focuses on the pandemic's immediate impacts (2020–2022) and the subsequent recovery period. While this timeframe is critical for understanding the crisis, it may overlook longer-term shifts in trade patterns and supply chain strategies that could emerge over the next decade. Predicting these future trends requires a more dynamic approach, including longitudinal studies and scenario planning.

To address these limitations, future studies could:

- Collect primary data through surveys, interviews, or focus groups with key stakeholders across different industries and regions.
- Expand the scope of analysis to include underrepresented regions and sectors, offering a more holistic view of global trade dynamics.
- Investigate the role of qualitative factors, such as leadership decision-making and organizational adaptability, in shaping supply chain resilience.

By addressing these areas, future research can build on the foundations established in this paper and contribute to a deeper understanding of the complexities of global trade in an increasingly uncertain world.

References

Baldwin, R. E. & Weder di Mauro, B. (2020). *Economics in the Time of COVID-19*. London, UK: CEPR Press.

Choi, T. Y., Rogers, D., & Vakil, B. (2020). *Coronavirus Is a Wake-Up Call for Supply Chain Management. Harvard Business Review.* [online] *Available at:* https://hbr.org/2020/03/coronavirus-is-a-wake-up-call-for-supply-chain-management

Christopher, M., & Peck, H. (2004). *Building the Resilient Supply Chain. International Journal of Logistics Management*, 15(2), pp. 1-14.

Gereffi, G. (2020). *What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies. Journal of International Business Policy*, 3(3), pp. 287-301. https://doi.org/10.1057/s42214-020-00062-w

Gurnani, H., Mehrotra, A., & Ray, S. (2011). *Supply chain disruptions: Theory and practice of managing risk*. London: Springer.

Ivanov, D. (2020). *Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review*, Volume 136. https://doi.org/10.1016/j.tre.2020.101922

Kleindorfer, P.R., & Saad, G.H. (2009). *Managing Disruption Risks in Supply Chains. Production and Operations Management*, Volume 14(1), pp. 53-68. https://doi.org/10.1111/j.1937-5956.2005.tb00009.x

Levinson, M. (2008). *The box: How the Shipping Container Made the World Smaller and the World Economy Bigger*. Princeton, NJ: Princeton University Press.

Norrman, A., & Jansson, U. (2004). *Ericsson's proactive supply chain risk management approach after a serious sub-supplier accident. International Journal of Physical Distribution & Logistics Management*, Volume 34(5), pp. 434-456. https://doi.org/10.1108/09600030410545463,

Sheffi, Y. (2005). *The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage.* Cambridge, MA, USA: MIT Press.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2008). *Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies.* 3rd Edition, Boston: McGraw-Hill/Irwin Education.

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). *Supply chain resilience: definition, review and theoretical foundations for further study. International Journal of Production Research*, , Volume 53(18), pp. 5592-5623. https://doi.org/10.1080/00207543.2015.1037934

van Bergeijk, P. A. G. (2021). *Pandemic Economics*. Northampton, MA, USA: Edward Elgar Publishing.

Capgemini Research Institute. (2021). *The wake-up call: Building supply chain resilience in consumer products and retail for a post-COVID world*. [online] available at: https://www.capgemini.com/wp-content/uploads/2021/04/Supply-Chain-in-CPR_2021-03-10_Web-2.pdf

Trending Insight, IBM Institute for Business Value. (2020). *COVID-19 and future of business*. Armonk, NY 10504, USA.

McKinsey & Company. McKinsey Global Institute. (2020). *Risk, resilience, and rebalancing in global value chains.* by Lund, S., Manyika, J., Woetzel, L., Barribal, E., Krishnan, M., Alicke, K., Birshan, M., George, K., Smit, S., Swan, D., & Hutzler, K. [online] *available at:* https://www.mckinsey.com/capabilities/operations/our-insights/risk-resilience-and-rebalancing-in-global-value-chains

OECD. (2020). *COVID-19 and Global Value Chains: Policy Options to Build More Resilient Production Networks*.

The Economist Intelligence Unit. (2021). *Supply Chain Resilience for an Era of Turbulence*. Supported by Association for Supply Chain Management. London.

World Trade Organization, (2020). *Trade shows signs of rebound from COVID-19, recovery still uncertain*. Press/862 Press Release. [online] *available at:* https://www.wto.org/english/news_e/pres20_e/pr862_e.htm

Bio-note

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FACTORS INFLUENCING INFORMATION AND COMMUNICATION TECHNOLOGY ADOPTION IN SMALL AND MEDIUM ENTERPRISES IN JIJEL, ALGERIA

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Abstract: *The adoption of ICT can provide small and medium enterprises (SMEs) with a competitive advantage by enhancing quality, reducing costs, and increasing information flow. This study aims to identify the factors that influence the adoption of various information and communication technologies in Small and Medium Enterprises (SMEs) located in Jijel province in Algeria. A research model based on the Technological-Organizational-Environmental (TOE) framework extended to Individual context was proposed. Seven independent variables were selected (relative advantage, compatibility, top management support, competitive pressure, government support, owner/manager innovativeness and owner/manager ICT knowledge). The dependent variable, adoption of information and communication technology, was measured as the degree of adoption of six information and communication technologies by SMEs. Ordered logistic regression was utilized to analyze the collected data. The results showed that owner/manager ICT knowledge and government support are the primary factors that substantially influence most IC technologies. Relative advantage, compatibility and competitive pressure have all been found to affect one ICT. The remaining two factors, top management support and owner/manager innovativeness had no impact on any ICT. The study has significant consequences for scholars, practitioners and policymakers.*

Keywords: ICT, Adoption, SMEs, TOE framework, Ordered Logistic Regression, Algeria.

JEL classification: L25, M15, O33

1. Introduction

The introduction of information and communication technology (ICT) has completely changed how business is conducted (Jaganathan et al., 2018; Tan et al., 2009; Taylor, 2005). Research indicates that ICT has an impact on economic growth, productivity, employment, competitiveness and company performance (Kossaï et al., 2020; Tarutė and Gatautis, 2014; Al Busaidi et al., 2019; Giotopoulos et al., 2017). It has been demonstrated that ICT improves firm performance in terms of productivity, profitability, market value and

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market share, as well as intermediate performance measures like customer satisfaction, cost savings, organizational and process flexibility and process efficiency (Bayo-Moriones and Lera-Lopez, 2007). Moreover, ICT is a crucial tool for enhancing information generation and processing and effectively managing and transmitting information (Jere and Ngidi, 2020).

The adoption of ICT can give small and medium enterprises (SMEs) a competitive edge by improving quality, lowering operating costs and increasing information flow (Shahadat et al., 2023). However, SMEs adopt ICT more slowly than large companies (AlBar and Hoque, 2015; Consoli, 2012) because SMEs have fewer resources, competencies and technology (Consoli, 2012). SMEs still face several obstacles in implementing ICT, because of their small size, lack of supply chain support, inadequate infrastructure, lack of resources and training, lack of vision and ongoing weak security measures (Olatokun and Bankole, 2011). In Algeria, the adoption of ICT in SMEs remains modest. According to 2009 research conducted by the Centre for Applied Economic Research for Development (CREAD), 44.66% of SMEs incorporated ICT, with ICT product investments at 6.72%. Another study conducted in 2011 found that just 46.33% of surveyed entrepreneurs employed ICT, with only 53.1% aware of it. However, research of National Agency for SME Development (ANDPME) conducted in 2011 discovered that only 15% of Algerian SMEs adopted ICT (Djelti, 2016). Furthermore, according to Sidlo et al. (2020), the majority of Southern and Eastern Mediterranean (SEMED) countries have low adoption of digital applications for core business management functions, with fewer firms using ERP and CRM software.

Despite the abundance of research on factors influencing ICT adoption in SMEs, there have been few studies undertaken in Algeria (Atik and Ramdani, 2018; Diouani et al., 2023; Houache et al., 2020; Houari and Medjedel, 2009; Mezaour and Chadli, 2022; Sedkaoui and Khelfaoui, 2024). These studies did not account for individual aspects of SMEs' owner/manager such as owner/manager ICT knowledge and owner/manager innovativeness, which have been shown in previous research to be important in ICT adoption decisions in SMEs, particularly in developing countries (AlBar and Hoque, 2017; Alroussan et al., 2020; Elbaltagi et al., 2013; Thong and Yap, 1995). This study aims to address this highlighted gap by studying the factors of ICT adoption in SMEs in a province of Algeria based on the technology-organization-environment (TOE) framework by focusing on individual factors aspects such as owner/manager ICT knowledge and owner/manager innovativeness.

2. Literature review

Various theories and models have been employed to study the adoption and use of ICT in SMEs, including the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB) and Unified Theory of Acceptance and Use of Technology (UTAUT). At the firm level, the Diffusion of Innovation (DOI) theory and the Technological, Organisational and Environmental (TOE) framework are commonly used, with some research incorporating multiple theories.

Among these theories and models, the TOE framework offers a comprehensive theoretical framework for analyzing ICT adoption at the firm level. It has been extensively tested and validated in various studies (Albar and Hoque, 2019; Al-Qirim, 2007; Anjum, 2019; Hassan and Ogundipe, 2017; Huda and Lestari, 2018; Ifinedo, 2011; Jere and Ngidi, 2020; Kuan and Chau, 2001; Nawaz and Gunapalan, 2015; Premkumar and Roberts, 1999; Rahayu and Day, 2015; Ramdani and Kawalek, 2009; Shahadat et al., 2023; Skafi et al., 2020).

According to the literature, SMEs' adoption and usage of ICT are influenced by several factors. According to Juniarti and Omar's (2021) review of the literature on technology adoption in SMEs, which is based on the TOE framework, prior studies have divided the factors that influence technology adoption into four groups: individual, organizational, environmental, and technological contexts

• **Technological Context:** includes relative advantage, compatibility, complexity, trialability, and observability.
• **Environmental Context**: contains government/regulatory assistance, competitive pressure, external support, image, pollution, and industry.
• **Organisational Context**: involves top management support, financial resources, ICT knowledge, organizational scale, information, competitive advantage, organizational innovation culture.
• **Individual/Management Context**: covers owner/manager innovativeness, ICT expertise, attitude, innovation, age, gender, and education.

3. Framework and hypotheses development

This research will use the TOE framework to develop a model, which is shown in Figure 1, that can predict the determinants of the decision to adopt ICT in SMEs located in the province of Jijel in Algeria. The model is based on earlier research that used the TOE framework extended to individual factors (AlBar et al., 2017; Alroussan et al., 2020; Thong and Yap, 1995).
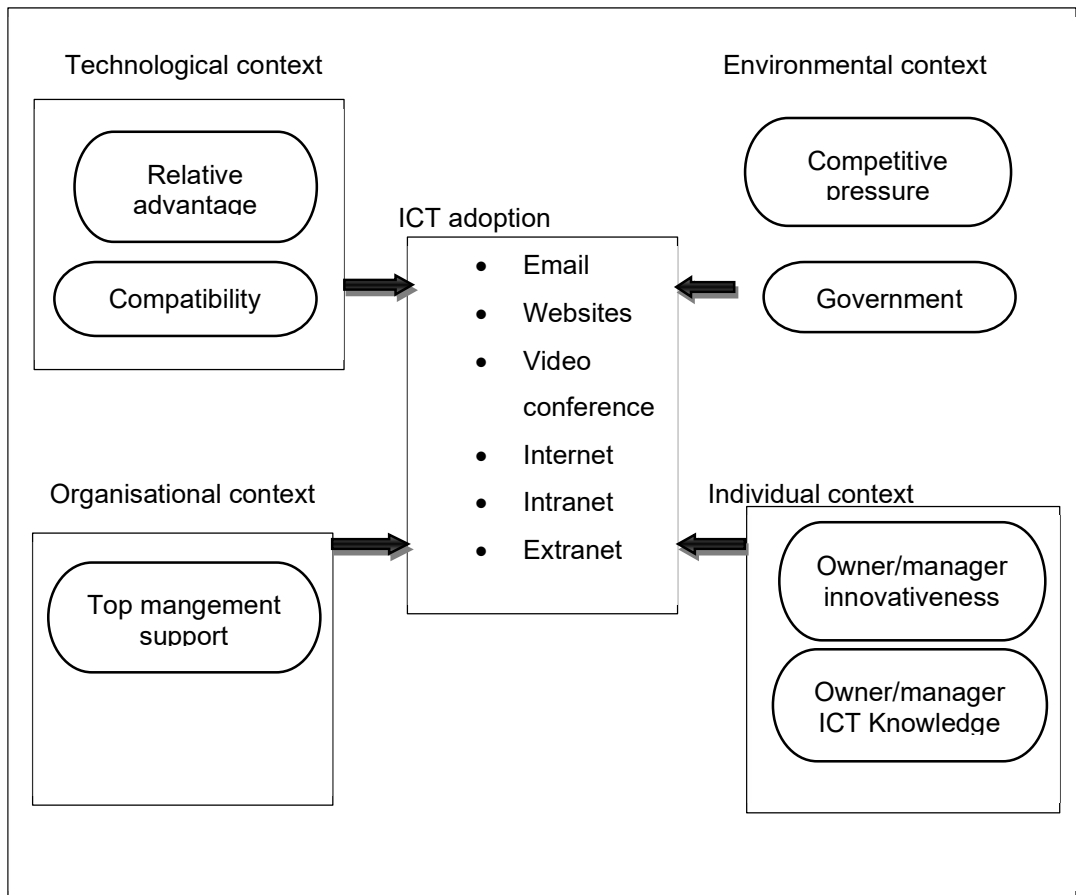

Figure 1: Research framework
Source: Authors' analysis /processing based on own data

Relative Advantage
Relative advantage, as defined by Roger (1983), refers to the perceived superiority of an innovation over its predecessor. It is a crucial factor in determining innovation uptake, distinguishing adopters from non-adopters (Shahadat et al., 2023). Studies have demonstrated that relative advantage significantly influences the adoption of ICT in SMEs (Albar and Hoque, 2019; Alroussan et al., 2020; Huda and Lestari, 2018; Ifinedo, 2011; Nawaz and Gunapalan, 2015; Premkumar and Robers, 1999; Ramdani and Kawalek, 2009; Shahadat et al., 2023; Tan et al, 2009). Therefore, this hypothesis is formulated :
H1: Relative advantage has a positive influence on ICT adoption in SMEs.

Compatibility
Compatibility refers to how well an invention aligns with potential users' values and needs (Roger, 1983). High compatibility reduces resistance to new technology adoption in firms (Nawaz and Gunapalan, 2015). Studies have shown that compatibility affects positively the adoption of ICT in SMEs (Nawaz and Gunapalan, 2015; Prekumar and Roberts, 1999; Tan et al., 2009). Hence, the following hypothesis is suggested :
H2: Compatibility has a positive influence on ICT adoption in SMEs.

Top management support
Top management support in SMEs is crucial for the adoption of ICT. It involves understanding the nature and functions of ICT and supporting its adoption through communication and reinforcement of ideas (Nawaz and Gunapalan, 2015). Top management plays a direct role in the ICT adoption process, making decisions for operations and investments (Ghobakhloo et al., 2011; Jere and Ngidi, 2020). Previous studies have shown that top management support influences ICT adoption in SMEs (AlBar and Hoque, 2017; Alroussan et al., 2020; Jere and Ngidi, 2020; Nawaz and Gunapalan, 2015; Premkumar and Roberts, 1999; Ramdani and Kawalak, 2009; Shahadat et al., 2023; Skafi et al., 2020). Thus, the following hypothesis is proposed:
H3: Top management support has a positive influence on ICT adoption in the SMEs.

Competitive pressure
The adoption of technology by a company can be influenced by its business partners and competitors (Kuan and Chau, 2001). Competitive pressure has been found a significant factor in determining ICT adoption in SMEs in various studies (Ifinedo, 2010; Kuan and Chau, 2001; Nawaz and Gunapalan, 2015; Premkumar and Roberts, 1999; Shahadat et al., 2023; Zhu et al., 2003). Therefore, the following hypothesis is suggested :
H4: competitive pressure has a positive influence on ICT adoption in the SMEs.

Government support
Government support is crucial in promoting the adoption of ICT in businesses, particularly for SMEs. Governments play a significant role in SMEs' growth, as they are often resource-constrained and require government assistance (Jere and Ngidi, 2020). Government-funded training programs can help SMEs adopt technology and establish the necessary technological infrastructure (Shaikh et al., 2021). Shahadat et al. (2023) indicate that government assistance for ICT adoption is vital for preparing the country for fundamental changes in facilities, including technical infrastructure, trained human resources, legal and policy support and financial infrastructure. Studies have shown that government support positively impacts the adoption of ICT in SMEs and this relationship is supported by various studies (Anjum, 2019; Ifinedo, 2010; Kuan and Chaud, 2001; Premkumar and Roberts, 1999; Shahadat, 2023). Hence, it is proposed the following hypothesis :
H5: Government support has a positive influence on ICT adoption in the SMEs.

Owner/Manager innovativeness
The innovativeness of owners and managers significantly influences ICT adoption decisions in SMEs, as they are more willing to accept innovations like technology (AlBar and Hoque, 2017; Jaganathan et al., 2018; Thong and Yap, 1995). This relationship has been confirmed by numerous studies, indicating that a more innovative owner or manager is more likely to adopt such innovations (AlBar and Hoque, 2017; Anjum, 2019; Elbeltagi et al., 2013; Rahayu and Day, 2015; Shahadat et al., 2023; Thong and Yap, 1995). Therefore, the hypothesis is the following :
H6: Owner/manager innovativeness has a positive influence on ICT adoption in the SMEs.

Owner/Manager ICT knowledge
SMEs often lack technical skills and specialised IT knowledge (Thong and Yap, 1995), but knowledgeable owners/managers are more likely to use ICT (Ghobakhloo et al., 2011, Jaganathan et al., 2018). The owner's current ICT usage abilities, knowledge, skills and experience positively impact ICT adoption (AlBar and Hoque, 2017). Previous research such as (AlBar, 2017; Alroussan, 2020; Elbeltagi et al., 2013; Rahayu and Day, 2015; Thong and Yap, 1995) has found a significant positive influence of owner/manager ICT knowledge on ICT adoption in SMEs. Thus, this hypothesis is proposed:
H7: Owner/manager ICT knowledge has a positive influence on ICT adoption in the SMEs.

4. Methodology

4.1 Instrument and Scale Development
A survey was performed to evaluate the study's presented hypotheses. An Arabic-language version of a self-administered questionnaire served as the research tool. There are three sections to the survey questionnaire. The information about the sample characteristics is covered in the first part. The second and third parts contain the items for the dependent and independents variables respectively.
The dependent variable (ICT adoption), considering the quantity and diversity of technologies concluded in ICT, was measured by the degree of adoption of each one of six information and communication technologies (email, websites, videoconference, Internet, Intranet and Extranet) (Al-Qirim, 2007; Bayo-Moriones and Lera-Lopez, 2007; Kurnia et al., 2015; Premkumar and Roberts, 1999; Osorio-Gallego et al., 2016) using a five-point Likert scale ranging from 1 (don't use) to 5 (always used). The independent variables were adopted from several studies, namely (Alrousan et al., 2020; Ifinedo, 2011; Moore and Benbasat, 1991; Premkumar and Roberts, 1999; Thong and Yap, 1995) and each item was measured on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

4.2 Sample and Data Collection
The population of this study consists of all private SMEs located in Jijel province, which is estimated at 7220 by the end of 2023. To collect the needed information, and given the absence of a framework for the targeted population, 84 questionnaires were distributed to a convenience sample through personal interviews, and 76 questionnaires were retrieved, of which 3 were excluded due to the missing data. The valid response rate is 86.9%.

5. Results

5.1 Sample characteristics
Table 1 shows the demographics of respondents and their firms. Most of the respondents were male (83.6%), over thirty years old (91.6%) and highly educated (72.6%). yet most of

the respondents were managers and owner/managers (46.6% and 37.0%, respectively), while only 16.4% were owners. Furthermore, the data indicate that the majority of SMEs were micro and small businesses (80.8%), operated in industry and services (82.2%) and served both local and national markets (82.2%).

Table 1: Descriptive statistics of sample characteristics

Respondent characteristics	Number of respondents (n=73)	Percentage (%)
Gender		
Male	61	83.6
Female	12	16.4
Age		
30 years and less	06	08.2
31-40	25	34.2
41-50	22	30.1
51 years and above	20	27.3
Education		
Secondary and less	08	11.0
Graduate	46	63.0
Postgraduate	7	09.6
Other	12	16.4
Occupation		
Owner	12	16.4
Manager	34	46.6
Owner/manager	27	37.0
No of Employees		
1-5	23	31.5
6-49	36	49.3
50-250	14	19.2
Activity sector		
Industry	36	49.3
Commerce	13	17.8
Services	24	32.9
Market scope		
Local	27	37.0
Regional	1	01.4
National	33	45.2
International	12	16.4

Source: Authors' analysis /processing based on own data

5.2 Validity and reliability
To assess the construct validity and reliability of the various factors, Cronbach's alpha and factor analysis were used.
Cronbach's alpha was used to evaluate the constructs' reliability. Table 2 shows that all constructs had appropriate alpha values (>0.6).

Table 2: Result of construct reliability

No of Item	Variable	No of items	Cronbach's alpha
1	Relative advantage	4	0.883
2	Compatibility	3	0.901

3	Top management support	3	0.944
4	Competitive pressure	3	0.857
5	Government support	3	0.864
6	Owner/manager innovativeness	4	0.833
7	Owner/manager Knowledge	3	0.920

Source: Authors' analysis /processing based on own data

Factor analysis was used to determine convergent and discriminant validity. Using principal components analysis and varimax criteria to rotate the result, seven factors were discovered as explaining the phenomena under examination in the current research (with eigenvalues greater than 1). The results are summarized in Table 3.

Table 3 shows that items load strongly (>0.5) on their linked factors and each item loads more strongly on its corresponding factor than any other factor, so convergent and discriminant validity were confirmed and validated (Kuan and Chau, 2001).

Table 3. Result of factor analysis

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
RA1		0.766					
RA2		0.889					
RA3		0.862					
RA4		0.861					
CM1				0.867			
CM2				0.928			
CM3				0.856			
TMS1			0.881				
TMS2			0.888				
TMS3			0.857				
CP1						0.847	
CP2						0.853	
CP3						0.855	
GS1					0.733		
GS2					0.904		
GS3					0.940		
OMI1							0.637
OMI2							0.933
OMI3							0.914
OMK1	0.849						
OMK2	0.878						
OMK3	0.851						
OMK4	0.811						

Source: Authors' analysis /processing based on own data

Pearson correlation matrix and Variance Inflation Factor (VIF) were calculated to assess the Multicollinearity problem.

Table 4 indicates that the maximum squared correlation among the independent variables was less than 0.8 (Al-Qirim, 2007).

Table 4. Correlation matrix of the research variables

Variable	RA	CM	TMS	CP	GS	OMI	OMK

RA	1					
CM	0.306	1				
TMS	0.353	0.390	1			
CP	0.188	0.199	0.328	1		
GS	0.050	-0.017	0.011	0.199	1	
OMI	0.104	0.123	0.256	0.127	0.089	1	
OMK	0.227	-0.048	0.369	0.337	0.357	0.331	1

Source: Authors' analysis /processing based on own data

Table 5 displays the findings from the VIF analysis. All the VIF values are below 5 (AlQirim, 2007). Consequently, no indication of a multi-collinearity issue is seen.

Table 5. Variance inflation factor (VIF) values

	RA	CM	TMS	CP	GS	OMI	OMK
RA		1.160	1.184	1.221	1.221	1.220	1.195
CM	1.284		1.194	1.329	1.384	1.338	1.235
TMS	1.528	1.392		1.534	1.533	1.559	1.419
CP	1.237	1.216	1.204		1.220	1.236	1.185
GS	1.191	1.188	1.159	1.175		1.191	1.056
OMI	1.161	1.151	1.150	1.161	1.162		1.080
OMK	1.610	1.504	1.482	1.576	1.458	1.530	

Source: Authors' analysis /processing based on own data

5.3 Hypotheses testing

The Ordered (ordinal) logistic regression was used to evaluate the hypotheses. This statistical method was used since the dependent variable was ordinal (Lal, 1999). The results are shown in Table 6.
The findings of Table 6 indicate statistical significance ($p<0.01$) across all six ordered logistic regressions. The results of Table 6 show also that owner/manager ICT knowledge and government support are the primary variables that substantially impact most IC technologies. Relative advantage, compatibility and competitive pressure have all been found to affect one ICT. The remaining two variables, top management support and owner/manager innovativeness had no impact on any ICT.

Table 6. Results of ordered logistic regression

Variable	Email	Websites	Videoconference	Internet	Intranet	Extranet
RA	1.115*	0.476	0.267	-0.628	-0.284	-0.891
CM	0.275	1.186*	0.013	0.508	0.301	0.395
TMS	-0.089	0.417	0.596	0.581	-0.166	0.605
CP	-0.457	0.167	0.458	0.897	0.731	1.189**
GS	1.359**	1.995**	0.713**	0.313	0.908**	0.798**
OMI	-0.116	-0.161	0.016	0127	0.294	0.091
OMK	1.417**	0.844	1.099*	1.963**	1.098*	1.117*
Log-likelihood	158.038	146.252	143.584	96.196	158.481	169.567
Chi-square	51.595**	64.434**	29.336**	36.958**	38.349**	45.830**

Note. * p<0.05; ** p<0.01
Source: Authors' analysis /processing based on own data

6. Discussion

The study explores the factors influencing ICT adoption in SMEs in Algeria's Jijel province, revealing that government support and owner/manager ICT knowledge are the primary influences.

The study found that owner/manager ICT knowledge significantly influences the adoption of ICT in SMEs, impacting all IC technologies except websites. This aligns with previous research, (AlBar and Hoque, 2017; Alroussan et al., 2020; Elbaltagi et al., 2013; Thong and Yap, 1995). This can be explained by the fact that the owners and managers are more likely to undertake ICT projects if they believe it will benefit their company financially and in other non-tangible ways (Thong and Yap, 1995). AlBar and Hoque (2017) argue that most decisions in SMEs, in Arabic states, particularly in Saudi Arabia, are made by the owner-manager, including whether to implement ICT in the firm.

The study found also that government support is a crucial factor in determining ICT adoption, affecting all IC technologies except the Internet. This aligns with previous research (AlBar and Hoque, 2017; Alroussan et al., 2020; Elbaltagi et al., 2013; Thong and Yap, 1995). The no significance of the Internet technology can explain by that the respondents may believe SMEs widely use certain EC technologies such as the Internet and hence do not require government support (Alam and Noor, 2009). This result may be due to the role played by the government's financial incentives and facilities in Algeria, such as the creation of specialized technical centers, national upgrading and PME II programs, in encouraging SMEs to adopt ICT(OECD/EU/ETF, 2014).

Unfortunately, the study reveals that competitive pressure, relative advantage and compatibility significantly influence the adoption of only one IC technology. Competitive pressure affects the Extranet. This result is consistent with Al-Qirim's (2007) findings, in which he argues that competition drives the adoption of Extranet in SMEs, as fast, secure access to remote databases is crucial for market competition. Relative advantage has a significant impact on email, which is consistent with previous research such as (Ghobakhloo, Arias-Aranda and Benitez-Amado, 2011; Prekumar and Roberts, 1999) findings. Compatibility affects significantly websites, which is similar to (Al-Qirim, 2007; Ghobakhloo, Arias-Aranda and Benitez-Amado, 2011; Teo et al., 1998) findings.

Surprisingly, the study found no significant impact of top management support and owner/manager innovativeness on ICT adoption in SMEs. This contradicts previous research but aligns with some ones such as (Anjum, 2019; Hassan, 2017) for top management and (Alroussan, 2020; Jaganathan et al., 2018; Shahadat et al., 2023) for owner/manager innovativeness. This result can be explained by the fact that top management engages only when technology incurs expenses (Hassan, 2017) and Managers may lack the innovative understanding necessary to effectively adopt ICT (Shahadat et al., 2023) or traditional innovation differs from technical innovation due to the need to change an SME's entire system and decision-maker's willingness to take risks when implementing new technology (Alroussan, 2020).

7. Conclusion

This study examined the factors influencing the ICT adoption in SMEs in Algeria's Jijel Province. The TOE framework was used to identify these factors. Based on the ordered logistic regression, the results of the study have identified two important determinant factors namely, owner/manager ICT knowledge and government support. However, compatibility,

top management, competitive pressure and owner/manager innovativeness were found to be not significant in influencing the adoption of most or all the IC technologies.

These findings contribute significantly to the literature on ICT adoption particularly in ICT adoption among SMEs in developing countries such as Algeria. On the other hand, the study's findings can help managers and policymakers to develop a plan for increasing ICT adoption among SMEs. The findings suggested that the role of the owner/manager's ICT knowledge and government support is essential in developing and promoting the adoption of ICT in Algerian SMEs.

However, this study suffers from some limitations. The study was conducted in only one province and adopted the convenience sampling technique which may hinder the generalization of the findings. Therefore, further studies with a larger representative of all regions, using probability sampling technique are suggested.

References

Alam, S.S. and Noor, M.K. M., 2009. ICT adoption in small and medium enterprises: an empirical evidence of service sectors in Malaysia. *International Journal of Business and Management*, 4(2), 112-125. https://doi.org/10.5539/ijbm.v4n2p112

AlBar, A. M., and Hoque, M. R., 2019. Factors affecting cloud ERP adoption in Saudi Arabia: An empirical study. *Information Development*, 35(1), 150–164. https://doi.org/10.1177/0266666917735677

Al Busaidi, N. S., Bhuiyan, A. B. and Zulkifli, N., 2019. The critical review on the adoption of ICTs in the Small and Medium Enterprises (SMEs) in the developing countries. *International Journal of Small and Medium Enterprises*, 2(2), 33-40. https://doi.org/10.46281/ijsmes.v2i2.437

Al-Qirim, N., 2007. The adoption of e-commerce communications and applications technologies in small businesses in New Zealand. *Electronic Com¬merce Research and Applications*, 6(4), 462–473. https://doi.org/10.1016/j.elerap.2007.02.012

Alrousan, M. K., Al-Adwan, A. S., Al-Madadha, A. and Al Khasawneh, M. H., 2020. Factors Affecting the Adoption of E-Marketing by Decision Makers in SMEs: Evidence from Jordan. *International Journal of E-Business Research*, 16(1), 1-27. https://doi.org/10.4018/IJEBR.2020010101

Anjum, A., 2019. Information and communication technology adoption and its influencing factors: A study of Indian SMEs. *Humanities and Social Sciences Reviews*, 7(5), 1238-1253. https://doi.org/10.18510/hssr.2019.75163

Atik, L., and Ramdani, B., 2018. SMEs Adoption of ICT: Evidence from Algeria. *Algerian Business Performance Review*, 13, 337-344.

Bayo-Moriones, A. and Lera-López, F., 2007. A firm-level analysis of determinants of ICT adoption in Spain. *Technovation*, 27, 352-366. https://doi.org/10.1016/j.technovation.2007.01.003

Chandavarkar, N. D. and Nethravathi, P. S., 2023. Analysis of Challenges faced during Adoption of ICT by Small and Medium Enterprises in India. *International Journal of Management, Technology, and Social Sciences (IJMTS)*, 8(2), 1-21. https://doi.org/10.47992/IJMTS.2581.6012.0267

Consoli, D., 2012. Literature analysis on determinant factors and the impact of ICT in SMEs. *Procedia – Social and Behavioral Sciences*, 62, 93-97. https://doi.org/10.1016/j.sbspro.2012.09.016

Diouani, H., Graa, A. Bechelaghem, K., 2023. Digital marketing adoption factors in Algerian small and medium enterprises: A TAM approach. *Management & Marketing*, 21(1), 134-150. https://www.mnmk.ro/documents/2023_1/8-9-1-23.pdf

Djelti, M., 2016. *Apport des TIC et d'Internet dans le developpement des entreprises algériennes : Etude de cas*. Ph. D. Université oran 2.

Elbeltagi, I., Al Sharji, Y., Hardaker, G. and Elsetouhi, A., 2013. The role of the owner-manager in SMEs' adoption of Information and Communication Technology in the United Arab Emirates. *Journal of Global Information Management (JGIM)*, 21(2), 23–50. https://doi.org/10.4018/jgim.2013040102

Ghobakhloo, Arias-Aranda, D. and Benitez-Amado, J., 2011. Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems*, 111(8), 1238-1269. https://doi.org/1108/02635571111170785

Ghobakhloo, M, Sabouri, M. S., Hong, T. S. and Zulkifli, N., 2011. Information technology adoption in small and medium-sized enterprises; An appraisal of two decades literature. Interdisciplinary *Journal of Research in Business*, 1(7), 53-80.

Giotopoulos, I., Kontolaimou, A., Korra, E. and Tsakanikasd, A., 2017. What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *Journal of Business Research*, 81, 60-90. https://doi.org/10.1016/j.jbusres.2017.08.007

Hassan, H., 2017. Organisational factors affecting cloud computing adoption in small and medium enterprises (SMEs) in service sector. *Procedia Computer Science*, 121, 976-981. https://doi.org/10.1016/j.procs.2017.11.126

Houache, H., Binti Abd Rahima, N. H., Mohamed Razi, M. J. and Shah, A., 2020. Factors Influencing the adoption of e-commerce by Small and Medium-Sized Enterprises (SMEs) in Algeria: a qualitative study. *International Journal on Perceptive and Cognitive Computing*, 6(2), 8-17. https://doi.org/10.31436/ijpcc.v6i2.147

Huda, n. N. and Lestar, Y. D., 2018. Determinants of information and communication technology (ICT) adoption: A study of Indonesian small and medium enterprises (SMEs). *International Research Journal of Engineering and Technology (IRJET)*, 5(7), 2674- 2678.

Houari, M. and Medjedel, A., 2009. The perception and attitudes of SMEs managers towards e-commerce in Southern Algeria: With special reference to the Ghardaia county. *Les cahiers du CREAD*, 25(90), 79-105.

Ifinedo, P., 2011. An empirical analysis of factors influencing Internet/e-business technologies adoption by SMEs in Canada. *International Journal of Information Technology & Decision Making*, 10(4), 731–766. https://doi.org/10.1142/S0219622011004543

Jaganathan, M., Ahmad, S., Ishak, K. A., Nafi, S. N. M. and Uthamaputhran, L., 2018. Determinants for ICT adoption and problems: Evidence from rural-based small and medium enterprises in Malaysia. *International Journal of Entrepreneurship*, 22(4), 1-13.

Jere, J. N. and Ngidi, N., 2020. A technology, organisation and environment framework analysis of information and communication technology adoption by small and medium enterprises in Pietermaritzburg. *South African Journal of Information Management*, 22(1), 1-9. https://doi.org/10.4102/sajim.v22i1.1166

Juniarti, R. P. and Omar, A., 2021. Technology Adoption in small and medium enterprises (SMEs) current issues and future research avenues. *Advances in Economics, Business and Management Research*, 193, 91-101. https://doi.org/10.2991/aebmr.k.211115.013

Kossai, M., Lapa de Souza, M. L., Ben Zaied, Y. and Nguyen, P., 2020. Determinants of the Adoption of Information and Communication Technologies (ICTs): the Case of Tunisian Electrical and Electronics Sector. *Journal of the Knowledge Economy*, 11, 845-864. https://doi.org/10.1007/s13132-018-0573-6

Kuan, K. K. Y. and Chau, P. Y. K., 2001. A perception-base model for EDI adoption in small businesses using a technology-organization-*environment framework. Information & Managemen*t, 38(8), 507-521. https://doi.org/10.1016/S0378-7206(01)00073-8

Kurnia, S., Choudrie, J., Mahbubur, R. M. and Alzougool, B., 2015. E-commerce technology adoption: A Malaysian grocery SME retail sector study. *Journal of Business Research*, 68(9), 1906-1918. https://doi.org/10.1016/j.jbusres.2014.12.010

Lal, K., 1999. Determinants of the adoption of information technology: A case study of electrical and electronic goods manufacturing firms in India. *Research Policy*, 28, 667–680. https://doi.org/10.1016/S0048-7333(99)00014-1

Looi, H. C., 2005. E-commerce adoption in Brunei Darussalam: Quantitative analysis of factors influencing its adoption. *Communications of the Association for Information Systems*, 15, 61-81. https://doi.org/10.17705/1CAIS.01503

Mezaour, A. and Chadli, C., 2022. Determinants of use of ICTechnologies by SMEs in the HassiMessaoud region by using the technology *acceptance model (TAM). Journal of business and finance economy*, 7(2), 821-830.

Moore, G. C. and Benbasat, I., 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research* 2(3), 192-222. https://doi.org/10.1287/isre.2.3.192

Nawaz, S. and Gunapalan, S., 2015. Evaluating the adoption of enterprise applications by small and medium enterprises in Sri Lanka. *European Journal of Business and Management*, 7(4), 324-334.

Olatokun, W. and Bankole, B., 2011. Factors Influencing Electronic Business Technologies Adoption and Use by Small and Medium Scale Enterprises (SMEs) in a Nigerian Municipality. *Journal of Internet Banking and Commerce*, 16(3), 1-26.

Oliveira, T. and Martins, M. F., 2011. Literature review of information technology adoption models at firm level. *The Electronic Journal of Information Systems Evaluation*, 14(1), 110-121.

Osorio-Gallego, C. A., Londoño-Metaute, J. H. and López-Zapata, E., 2016. Analysis of factors that influence the ICT adoption by SMEs in Colombia. Intangible Capital, 12(2), 666-732. https://doi.org/10.3926/ic.726

Premkumar, G. and Roberts, M., 1999. Adoption of new information technologies in rural small businesses. *Omega*, 27(4), 467–484. https://doi.org/10.1016/S0305-0483(98)00071-1

Rahayu, R. and Day, J., 2015. Determinant factors of e-commerce adoption by SMEs in developing country: Evidence from Indonesia. *Procedia: Social and Behavioral Sciences*, 195, 142–150. https://doi.org/10.1016/j.sbspro.2015.06.423

Ramdani, B., Kawalek, P. and Lorenzo, O., 2009. Predicting SMEs' adoption of enterprise systems. *Journal of Enterprise Information Management*, 22(1), 10–24. https://doi.org/10.1108/17410390910922796

Rogers, E. M., 1983. *Diffusion of innovations*. 3rd ed. New York: Free Press.

Sedkaoui, S. and Khelfaoui, M., 2024. Challenges for marketing analytics application in Algerian enterprises: An empirical analysis. *Review of socio-economic perspectives*, 9(1), 99-108. https://doi.org/10.19275/RSEP178

Shahadat, M. M. H., Nekmahmud, M., Ebrahimi, P. and Fekete-Farkas, M., 2023. Digital technology adoption in SMEs: What technological, environmental and organizational factors influence in emerging countries?. *Global Business Review*, 1-27. https://doi.org/10.1177/09721509221137199

Shaikh, A. A., Kumar, A., Syed, A. A. and Shaikh, M. Z., 2021. A two-decades literature on challenges faced by SMEs in technology adoption. *Academy of Marketing Studies Journal*, 25(3), 1-13.

Sidlo, K. W., Karunska, K, Salmeri, C., Bieliei, S. and Albinyana, R., 2020. *Digitalisation of small and medium enterprises (SMEs) in the Mediterranean*, European Committee of the Regions. https://data.europa.eu/doi/10.2863/206606

Skafi, M., Yunis, M. M. and Zekri, A. A., 2020. Factors influencing SMEs' adoption of cloud computing services in Lebanon: An empirical analysis using TOE and contextual theory. *IEEE Access*, 20, 79169-79181.

Tan, K. S., Chong, S.C., Lin, B. and Eze, U. C., 2009. Internet-based ICT adoption: evidence from Malaysian SMEs. *Industrial Management & Data Systems*, 109(2), 2009. https://doi.org/10.1017/CBO9780511761942

Tarutė, A. and Gatautis, R., 2014. ICT impact on SMEs performance. *Procedia-Social and Behavioral Sciences*, 110, 1218-1225. https://doi.org/10.1016/j.sbspro.2013.12.968

Taylor, P., 2015. The importance of information and communication technologies (ICTs): An integration of the extant literature on ICT adoption in small and medium enterprises. *International Journal of Economics and Management*, 3(5), 274-29.

Teo, T. S. H., Tan, M. and Buk, W. K., 1997. A contingency model of Internet adoption. *International Journal of Electronic Commerce*, 2(2), 95-118. https://doi.org/10.1080/10864415.1997.11518310

Thong, J. Y. and Yap, C. S., 1995. CEO characteristics, organizational characteristics and information technology adoption in small businesses. *Omega*, 23(4), 429–442. https://doi.org/10.1016/0305-0483(95)00017-I

Tornatzky, L. G., and Fleischer, M., 1990. *The processes of technological innovation*. Lexington: Lexington Books.

Zhu, K., Kraemer, K. L. and Xu, S., 2003. Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems*, 12, 251-268. https://doi.org/10.1057/palgrave.ejis.3000475

OECD/The European Commission/ETF, 2014. SME Policy Index: The Mediterranean Middle East and North Africa 2014: Implementation of the Small Business Act for Europe, OECD Publishing. http://dx.doi.org/10.1787/9789264218413-en

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HEURISTICS AND EMOTIONS IN TOURIST DESTINATION SELECTION: A REVIEW AND RESEARCH DIRECTIONS

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Abstract: *The rational choice assumption dominates most research on the decision-making process in the tourism field. As human beings, tourists have limited cognitive abilities, limited time, and a large amount of information, resulting in irrational decisions and cognitive biases. Tourism research in tourist decision-making concerning cognitive biases is still in its initial phase. This study aims to investigate state-of-the-art research regarding the role of heuristics in tourist destination selection to explore its research opportunities, focusing on destination image and emotions. Destination image is an alternative heuristic indication for selecting a destination, which can be based on emotions as specific feelings. This study applied a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to select the reviewed literature. The review involved seventeen documents, covering journal articles and a conference paper from the Scopus and Web of Science databases. Investigation using a structured review framework of theory, context, and methods in this study revealed that most researchers use several relevant theories related to behavioural economics and psychology discipline to conduct empirical research in the context of a general destination. Furthermore, this study discusses the advantages and dark side of exploiting emotions in selecting a destination and provides future research directions.*

Keywords: cognitive bias; destination image; mindless emotion; tourist decision.

JEL classification: D91, M31, Z32

1. Introduction

As consumers act to satisfy their needs and wants, tourists also behave in ways that optimise their satisfaction and encourage others to visit. However, tourism is a different sector to consumer products. To enjoy and experience the service directly, tourists must visit tourist destinations. Accordingly, because of limited resources, tourists must be able to make correct decisions in the pre-, during, and post-visitation phases. Decision-making is also critical in consumer or tourist behaviour, predominantly supported by rational decision-making assumptions (Cohen, Prayag and Moital, 2014).

The assumption that tourist decision-making is a cognitive process, with a complete decision-making process occurring before the ultimate purchase, has been widely established in the study of tourist decision-making for many years (McCabe, Li and Chen, 2016). However, as human beings, tourists have limited cognitive ability, time constraints,

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and an information overload, which leads to an irrational and biassed decision, recognised as a cognitive bias (Mayer, Santos and Marques, 2020; Cong, 2021; Wang, Feng and Wang, 2022). In their study, Wattanacharoensil and La-ornual (2019) identified the type of cognitive biases that occur in the pre-, during, and post-tourism visit phases, as illustrated in Figure 1. The authors posit that the pre-visit decision-making process is rife with cognitive biases, influencing the selection of a destination, the evaluation of tourism products, and the choice of a product. They considered heuristics to be one of the four most prevalent biases. The others are social bias and stereotypes, framing effect, and cognitive dissonance.

Moreover, research in the tourism field and tourists' decision-making processes concerning cognitive biases is still in its preliminary stages (Li et al., 2022). Accordingly, this study aims to investigate the state-of-the-art research concerning the role of heuristics and emotions in tourist destination selection. Seven questions serve as the research's guiding principles.

RQ 1. Does selecting a destination by applying mindless emotion to its image receive greater attention from researchers today?

RQ 2. What are the general characteristics of the existing articles?

RQ 3. What theories are often used to learn about the role of heuristics and emotions in destination selection?

RQ 4. In what context has the relevant research been conducted, and what methodology has been employed?

RQ 5. What are the advantages and disadvantages of considering heuristics and emotions in tourism research, particularly in destination marketing and branding research, and why do we need to pay more attention to this area of enquiry?

RQ 6. To what extent do affective factors outweigh cognitive and conative considerations when selecting a destination?

RQ 7. In what ways might this review contribute to the development of the research field and guide future studies?
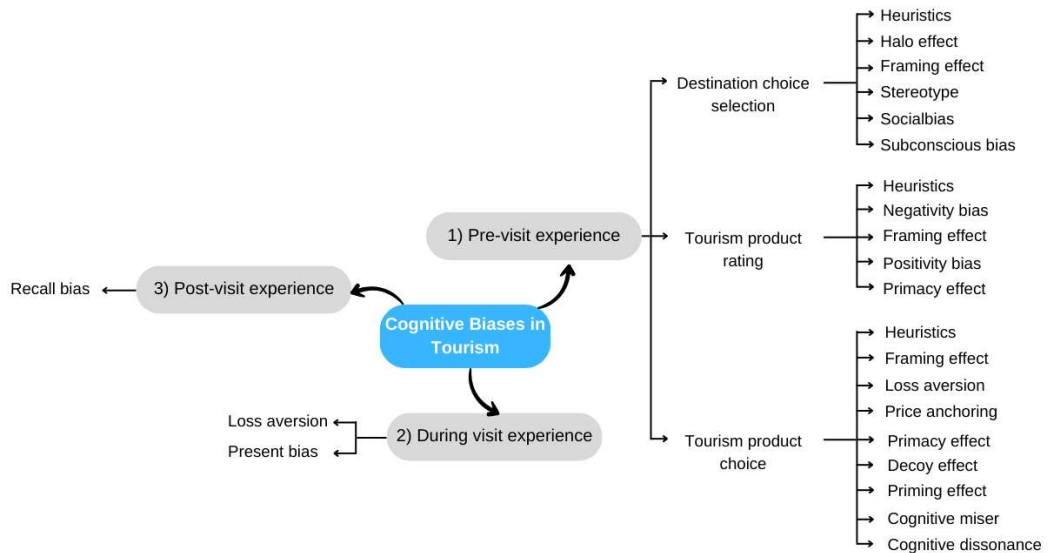
Figure 1: Type of cognitive bias found in pre-, during, and post-visit experience
Source: Modified from Wattanacharoensil and La-ornual (2019)

Based on the above explanation, the structure of this study will consist of five parts. The first part is the introduction, which provides the study's background and contribution. The second part presents the theoretical background, which discusses several related concepts, e.g., feelings and emotions, heuristics, and destination image. Next, the third section will be the

research method. After that, section four will discuss the findings and answer the research questions (RQ 1-7). Last, section five will provide conclusions.

2. Theoretical background

This study develops a framework of thinking to understand the role of heuristics sourced from emotions in selecting a destination, as portrayed in Figure 2. In the figure, emotions are a proxy of feelings or affect. In the tourism context, destination image can be used as a proxy of heuristics (Castelltort and Mäder, 2010). The next part will further explain the related concept.
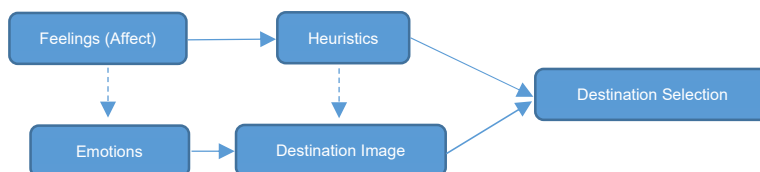
Figure 2: Framework of thinking
Source: Own elaboration

2.1 Feelings as a source of information

Feelings and their variety, such as moods, emotions, and affect, are eminent sources of information for tourist decision-making (King and Slovic, 2014). In their study, King and Slovic (2014) discussed the concept of moods as blurred feelings, emotions as specific feelings (Mothersbaugh, Hawkins and Kleiser, 2020) and affect as a subjective state of feelings (like and dislike). Affect can also refer to a certain quality of goodness or badness (Slovic et al., 2007). Related to tourism and destination marketing/branding research, this study focuses more on emotions.

Emotions are critical in studying tourism consumer behaviour to understand the decision process (Cohen, Prayag and Moital, 2014; Gomez-Diaz, 2019). Positive emotions play a significant role in tourism decision-making (Gnoth, 1997; Goossens, 2000). Gnoth (1997) suggested a motivation and expectation development model in which emotional and cognitive characteristics are essential when assessing tourism reasons for choosing a destination. According to Goossens (2000), emotions are critical in vacation decision behaviour because they are positive feelings related to the expected leisure experience. Both studies empirically indicate the importance of studying emotions to understand individual motives for selecting tourism destinations.

2.2 Heuristic

Heuristics is a "mental shortcut" often used to simplify decisions (Tversky and Kahneman, 1974: Mothersbaugh, Hawkins and Kleiser, 2020). This concept is valuable and applicable, especially when people lack the resources or time to make better decisions. Based on the concept of affect heuristics, feelings are used for generating judgments and decisions because feelings are instant and automatic; people tend to base their decisions and judgments on their feelings and emotions instead of using reasoned analysis (Slovic et al., 2007).

The application of affect heuristics in tourism research is still very limited. The search in the Scopus database using the keyword of *tourism AND "affect heuristics"* only found two articles, entitled: *Why pay more for sustainable services? The case of ecotourism* (Kazeminia, Hultman and Mostaghel, 2016) and *Understanding local policy elites' perceptions on the benefits and risks associated with high-voltage power line installations in the State of Arkansas* (Moyer and Song, 2016). The former discussed affect heuristics in the

context of ecotourism interest, while the latter discussed affect heuristics as a perception of benefits and risks of high-voltage power line installations to the tourism-based local economy in influenced regions. Accordingly, this study focuses on reviewing tourism research that discussed selecting a destination through emotions-based heuristics as a cognitive bias in decision-making. In tourism, the primary variable frequently considered as a heuristic signal before tourists make a final selection is destination image (Wattanacharoensil and La-ornual, 2019).

2.3 Destination image

Destination image has been widely researched in tourism concerning its critical concept for the decision-making process, which was introduced in the early 1970s. Various disciplines including psychology (Fridgen, 1987), marketing (Assael, 1995), and consumer behaviour (Herzog, 1963) highlight the complex and multidimensional nature of destination image. Scholars generally agree that destination image comprises cognitive and affective components (Baloglu and Brinberg, 1997; Baloglu and McCleary, 1999). The cognitive dimension encompasses knowledge, perceptions, and beliefs about a destination (Gensch, 1978), forming the basis for comparison and evaluation (Blackwell, Engel, and Miniard, 2006). The affective dimension involves emotional responses, such as favourability or excitement, which are influenced by cognition (Baloglu and McCleary, 1999). Some researchers argue for their separation in order to better understand tourists' evaluations (Russel and Snodgrass, 1987). Empirical evidence confirms that affective image exerts a more significant influence on overall destination image than cognitive image (Kim, 2003). Furthermore, Zhang's (2014) meta-analysis reveals that affective image significantly enhances tourist loyalty. The destination image is also linked to behavioural intentions, or the conative component, which reflects the likelihood of visiting a destination (Gartner, 1994; Pike and Ryan, 2004). Echtner and Ritchie (1991, 1993) propose a holistic approach, integrating functional and psychological traits.

Further, Gartner (1994) explained the cognitive component of image as the entire set of an object's beliefs and attitudes, the affective component of image as motives for selecting a destination, which affects an assessment, and the conative as the action component. Additionally, Agapito, Oom do Valle and da Costa Mendes (2013) empirically tested Gartner's image formation process and found that the mediated role of the affective component has made the influence of cognitive on the conative component higher. Typically, destination image influences tourist choice, implying that destinations with very positive images are more likely to be selected (Mikalauskas, Strunz and Afifi, 2014). Therefore, the destination image is critical in destination selection through its heuristics part. While modern studies increasingly emphasise the behavioural aspects of destination image, incorporating theories of consumer behaviour and emotions, research on the affective component (emotions) remains limited (Mikalauskas, Strunz and Afifi, 2014; Gomez-Diaz, 2019)

3. Research method

This study carried out a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to select the reviewed literature, as depicted in Figure 3.

The PRISMA protocol has been widely applied in business and management research, i.e. by Hollebeek et al. (2023). Based on the PRISMA protocol, this study selected relevant articles in three steps as follows:

1. First was the identification step. This study searched articles in Scopus and Web of Science (WoS) databases which were published between 1960 and 2022, by applying the keywords of *"destination image" AND emotion AND decision*. In this case, the

destination image was the proxy of heuristics, and emotion was the proxy of feelings and affect. The process was conducted in March 2023. The document search found eleven and 23 relevant documents collected from Scopus (title-abstract-keywords) and WoS (topic), respectively. In the identification step, this study also removed documents considered duplicates, non-English articles, and review articles. This process obtained twenty documents.

2. Second was the screening step. This study manually screened those twenty documents consisting of journal articles and conference papers based on their title, abstracts, and keywords. This process excluded two unrelated content documents.

3. Third was the screening steps. This step provided eighteen documents to be retrieved. Unfortunately, one document was not accessible. Therefore, only seventeen documents were included in step three and ready to be reviewed.

After that, this study answered research questions using a structured theory, context, and method (TCM) framework to answer several questions as implemented in Rosado-Serrano, Paul and Dikova (2018).
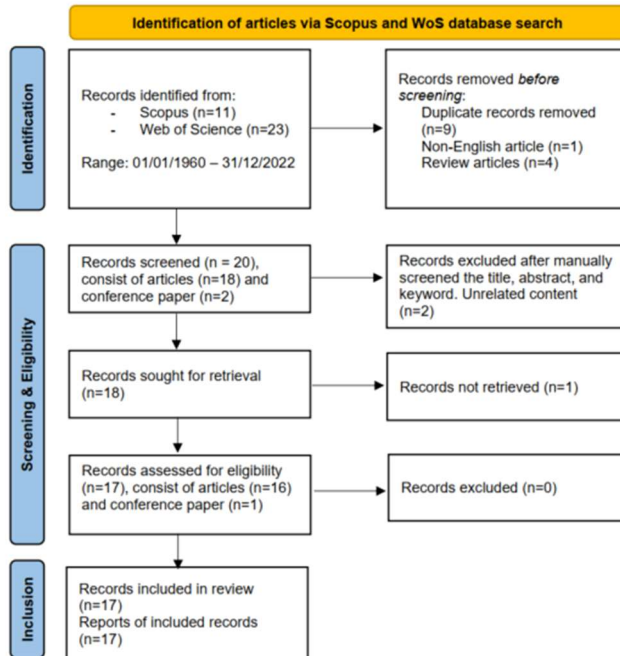
Figure 3: Selection procedure based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)
Source: Own elaboration, adapted from Hollebeek et al. (2023)

4. Results and discussion

4.1 Research interest and general characteristics of existing relevant articles

This section answers the first and second research questions. Regarding the first question, whether selecting a destination by applying mindless emotion to its image receives greater attention from researchers today. Figure 4 depicts the rise and fall of the seventeen documents on "using emotion in selecting a destination" from 2014 to 2023. Nevertheless, the figure shows an increasing trend of interest, although the total number of relevant publications was still limited. Of the seventeen relevant documents, the highest number of publications was published in 2022, with four documents.

Additionally, Figure 5 provides a word cloud generator. It shows the interest of researchers in exploring the relevant keywords. The size of each keyword revealed its frequency. The high-frequency keywords were destination, image, emotions, tourism, customer, tourist, risk, behaviour, marketing, perceived, decision-making, and affective. Interestingly, researchers used the keyword of emotions more often than affective.
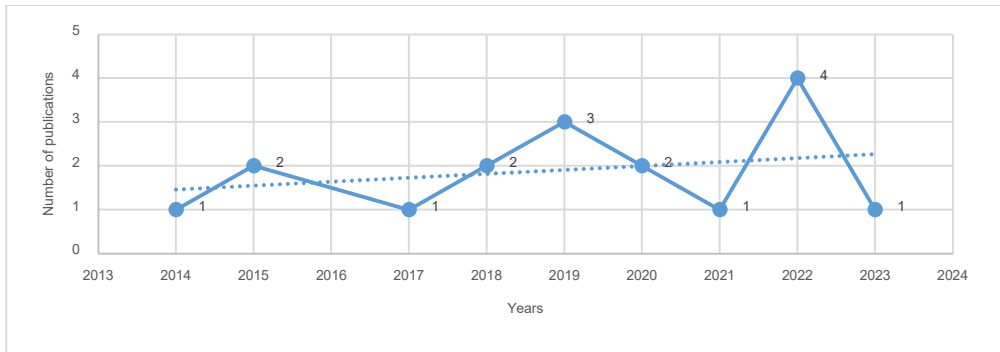
Figure 4: Number of publications
Source: Own elaboration

Figure 5: Word cloud of author keywords
Source: Own elaboration

Meanwhile, regarding the second research question, Table 1 provides the general characteristics of the existing articles. It details the author and year, Google Scholar (GS) citations, title of documents, source title, Scopus rank, aims of the research, and country of study. The order of the documents in the table is based on the GS citations, with the highest citation value of 84 citations and the lowest of 0. Additionally, most documents in Table 1 were published in the Q1 Scopus rank journal.

Further, Table 1 presents the aims of the relevant documents. Several documents aim to investigate one variable/construct's impact on the other (Articles No. 2 and 15). Moreover, some articles aim to clarify or gain an understanding of specific issues (Articles No. 3, 4, 5, and 6). There are also articles which aim to make comparisons (Articles No. 7 and 11). Furthermore, Table 1 portrays the country of study of each article. Most articles studied China, three studied Spain, and one studied Belgium and Japan. Besides, the two articles did not specify the country of study because they were conceptual works.

Table 1: General characteristics of the existing articles

No	Authors, year, & GS citations	Titles	Source title & Scopus rank	Aims	Country of study
1	Rodríguez-Molina, Frías-Jamilena, and Castañeda-García; 2015; 84	The contribution of website design to the generation of tourist destination image: The moderating effect of involvement	Tourism Management (Q1)	to explore how a tourist's view of a destination is shaped by the website's design and how they digest information	Spain
2	Bastiaansen et al.; 2018; 59	My destination in your brain: A novel neuromarketing approach for evaluating the effectiveness of destination marketing	Journal of Destination Marketing and Management (Q1)	to examine how a popular destination marketing film affects tourist destination photo emotions	Belgium and Japan
3	Torres, Milman and Park; 2018; 22	Delighted or outraged? Uncovering key drivers of exceedingly positive and negative theme park guest experiences	Journal of Hospitality and Tourism Insights (Q3)	- to determine what makes customers happy or unhappy - to analyse causes of positive and negative experiences - to develop models for delight and disappointment	North America
4	Jin et al.; 2020; 19	Effects of place attachment and image on revisit intention in an ecotourism destination: Using an extended model of goal-directed behaviour	Sustainability (Q1/Q2)	to discover how tourists choose sustainability	China
5	Zheng et al.; 2017; 18	Exploring sub-dimensions of intrapersonal constraints to visiting dark tourism sites: a comparison of participants and non-participants	Asia Pacific Journal of Tourism Research (Q1)	to examine intrapersonal limits on visiting cemeteries and compare participants to non-participants	China
6	Pelegrín-Borondo et al.; 2015; 14	Dimensions and basic emotions: A complementary approach to the	Journal of Vacation Marketing (Q1)	to examine the basic and dimensional approach of emotions in the tourism industry	Spain

		emotions produced to tourists by the hotel			
7	Iordanova and Stainton; 2019; 9	Cognition, emotion and trust: A comparative analysis of Cambodia's perceived and projected online image	Tourist Studies (Q1)	to compare projected images from destination management organisations and perceived images from UGC (such as travel blogs), consider cognitive and affective aspects and trust in destination image building	Cambodia
8	Quan, Al-Ansi and Han; 2021; 9	Spatial and human crowdedness, time pressure, and Chinese traveller word-of-mouth behaviours for Korean restaurants	International Journal of Hospitality Management (Q1)	to investigate the links between the perceptions of crowdedness (Human, Spatial), emotions, customer satisfaction, and word-of-mouth (WOM) intentions when visiting a bustling eatery in Korea.	Korea
9	Stojanovic, Andreu and Curras-Perez; 2022; 5	Social media communication and destination brand equity	Journal of Hospitality and Tourism Technology (Q1)	to examine the impact of social media communications on each destination's brand equity components, as produced by both users (UGC) and tourist destinations (DGC).	Spain
10	Zhang, Cai and Qiu; 2019; 3	The Chinese Cohort 60s and Japan: A journey of emotions	Tourist Studies (Q1)	to find out how the country's collective memory has impacted the Chinese Cohort 60's feelings and perceptions of Japan and how this has affected their travel choices regarding Japan.	China
11	Sönmez and Tasci; 2020; 3	Characteristics and behaviours of anti-gun and pro-gun travellers	Tourism Review (Q1)	to compare anti- and pro-gun opinions with Florida's permissive gun laws and high tourism	Florida, USA

12	Javed, Tučková and Jibril; 2022; 3	Towards understanding tourist revisit of zoo attraction: Evidence from the Czech Republic	Cogent Social Sciences (Q2)	to determine what factors influence tourists' desire to return to the famous zoo	Czech Republic
13	Campo and Alvarez; 2022; 3	Animosity based on traditional enmity versus other causes	Asia Pacific Journal of Marketing and Logistics (Q2)	to see if traditional and other enmity affect tourism destination product perception and decisions differently	China
14	Mikalauskas, Strunz and Afifi; 2014; 2	Relationship between sport events and destination image: Some theoretical approaches	Transformations in Business and Economics (Q2/Q3)	to identify the main theories linking sports and tourism	Not specified
15	Gomez-Diaz; 2019; 0	The influence of emotions and country stereotypes on destination image and word of mouth	Proceedings of the International Conference on Tourism Research	to determine how basic emotions and country stereotypes affect destination image	Not specified
16	Zhang; 2022; 0	Model Construction of the Influence of Tourist Destination Image on Tourists' Word-of-Mouth Communication Based on Cognitive and Emotional Environment	Journal of Environmental and Public Health (Q2)	to develop a model of tourism awareness and word-of-mouth communication based on cognition and emotion to study how tourist destination image affects such communication	China
17	Luo et al.; 2023; 0	Exploring destination image through online reviews: an augmented mining model using latent Dirichlet allocation combined with probabilistic hesitant fuzzy algorithm	Kybernetes (Q2)	- to understand travellers and how they view scenic sites to provide recommendations based on their needs - to help scenic area managers make decisions to improve their sites through optimisation. - to dynamically understand scenic area management and operating difficulties	China

* GS stands for Google Scholar
Source: Own elaboration

4.1 Theoretical underpinnings

Based on Table 2, this section answers the third question by identifying theoretical underpinnings to further study the role of heuristics and emotions in selecting a destination. This study discovered that each research used various theoretical frameworks. The earliest research used the Theory of Destination Involvement. In contrast, the latest research used the Theory of Sentiment Tendency Analysis. However, the three documents (in Table 1) did not mention any theoretical framework. They only used their interpretations of the terms and ideas in other theories, i.e., Articles No. 2, 12, and 13.

Table 2: Theories used

Theories	Article number and authors
Destination involvement	14 (Mikalauskas, Strunz and Afifi, 2014)
The componential theory of emotion	6 (Pelegrín-Borondo et al., 2015)
Social judgment theory	1 (Rodríguez-Molina, Frías-Jamilena, and Castañeda-García, 2015)
Leisure constraints theory	5 (Zheng et al., 2017)
Cognitive Appraisal Theory (CAT)	3 (Torres, Milman and Park, 2018)
Grounded theory	10 (Zhang, Cai and Qiu, 2019)
Sociolinguistic theoretical perspectives of the tourism language	7 (Iordanova and Stainton, 2019)
Stereotype content model & Appraisal Tendency Framework (ATF)	15 (Gomez-Diaz, 2019)
Model of goal-directed behaviour	4 (Jin et al., 2020)
The cultural theory of risk	11 (Sönmez and Tasci, 2020)
Attribution theory	8 (Quan, Al-Ansi and Han, 2021)
Cognitive theory of emotion	16 (Zhang, 2022)
Schema theory from cognitive psychology	9 (Stojanovic, Andreu and Curras-Perez, 2022)
Theory of sentiment tendency analysis	17 (Luo et al., 2023)

Source: Own elaboration

4.2 Contexts and methods used

Regarding research question No.4 on the context and methods of the relevant research, this section presents the context in which the relevant research has been done, as depicted in Table 3. Most articles (18 percent or three) conducted research in the context of general destination. Additionally, two articles focused on the context of scenic spot research. Moreover, some articles focused on tourism marketing concepts, i.e., destination marketing, destination websites, social media, and generational cohorts. Meanwhile, the rest of the documents researched other specific destinations.

Table 3: Contexts

Contexts	Article count	%	Article number and authors
Destination	3	18	2 (Bastiaansen et al., 2018); 13 (Campo and Alvarez, 2022); 15 (Gomez-Diaz, 2019)
Scenic spot	2	12	16 (S. Zhang, 2022); 17 (Luo et al., 2023)
Destination marketing	1	6	7 (Iordanova and Stainton, 2019)
Destination website	1	6	1 (Rodríguez-Molina, Frías-Jamilena, and Castañeda-García, 2015)
Social media and tourist destination	1	6	9 (Stojanovic, Andreu and Curras-Perez, 2022)

Generational cohort	1	6	10 (Zhang, Cai and Qiu, 2019)
Dark tourism sites	1	6	5 (Zheng et al., 2017)
Ecotourism destination	1	6	4 (Jin et al., 2020)
Hotel	1	6	6 (Pelegrín-Borondo et al., 2015)
Restaurant	1	6	8 (Quan, Al-Ansi and Han, 2021)
State destination	1	6	11 (Sönmez and Tasci, 2020)
Sports tourism/Events	1	6	14 (Mikalauskas, Strunz and Afifi, 2014)
Theme Park	1	6	3 (Torres, Milman and Park, 2018)
Zoological garden	1	6	12 (Javed, Tučková and Jibril, 2022)
Total	**17**	**100**	

Source: Own elaboration

Meanwhile, this section identifies the methods used in research, which consider the use of mindless emotion in selecting a destination, as depicted in Table 4. Of the seventeen articles in Table 4, around 41 percent or seven articles used empirical methods in their research. This status implies that the empirical method was still popular in relevant research. However, relatively rare or new methods were also used in the context of tourism, such as experimental design, neuromarketing experiments, and sentiment analysis. A neuromarketing experiment is a research method for observing people's reactions to travel images after viewing marketing materials (Bastiaansen et al., 2018), while sentiment analysis can help the researcher obtain emotional information through the mining and analysis of the emotional content expressed in the text, sentence, or word level (Luo et al., 2023).

Table 4: Used methods

Methods	Article count	%	Article number and authors
Empirical	7	41	13 (Campo and Alvarez, 2022); 12 (Javed, Tučková and Jibril, 2022); 4 (Jin et al., 2020); 6 (Pelegrín-Borondo et al., 2015); 8 (Quan, Al-Ansi and Han, 2021); 11 (Sönmez and Tasci, 2020); 9 (Stojanovic, Andreu and Curras-Perez, 2022)
Content analysis	2	12	7 (Iordanova and Stainton, 2019); 3 (Torres, Milman and Park, 2018)
Experimental design	2	12	1 (Rodríguez-Molina, Frías-Jamilena, and Castañeda-García, 2015); 16 (Zhang, 2022)
A neuromarketing experiment	1	6	2 (Bastiaansen et al., 2018)
Exploratory analysis	1	6	5 (Zheng et al., 2017)
Interview	1	6	10 (Zhang, Cai and Qiu, 2019)
Literature review	1	6	15 (Gomez-Diaz, 2019)
Sentiment analysis	1	6	17 (Luo et al., 2023)
Theoretical analysis	1	6	14 (Mikalauskas, Strunz and Afifi, 2014)
Total	17	100	

Source: Own elaboration

4.3 The advantages and dark side of emotions and heuristics
This section discusses research questions No.5 and 6: Why do academicians and researchers need to pay more attention to heuristics and emotions in tourism research, particularly in destination marketing/branding research, based on their advantages and

drawbacks? Is the affective component more important than the cognitive and conative part in selecting a destination?

The review of research findings of relevant documents revealed that emotions and heuristics play significant roles in selecting destinations, which implies their advantages. First, emotion is a strong predictor of tourist behaviour. In their study, Stojanovic, Andreu and Curras-Perez (2018) found that both user-generated content (UGC) and destination-generated content (DGC) influence tourist behaviour positively. Therefore, researchers can suggest that to boost destination brand equity and future behaviour, Destination Management Organizations must create extremely relatable material that elicits emotion and inspires travellers to share their experiences.

Second, the affective destination image contributed to a more decisive influence than the traditional one (cognitive destination image). For example, affective destination image in the form of amateur travel blogs created more influence on consumer decision-making than the material presented by tourist websites because travel bloggers usually share their experiences and position as the same audience as travellers (Iordanova and Stainton, 2019). Therefore, researchers can suggest that destination marketers cooperate with travel bloggers.

Third, emotions could be used to establish tourist segments. For example, three types of emotional stimuli can affect purchasers, as Pelegrín-Borondo et al. (2015) revealed: emotions caused by the purchased product, emotions caused by various components of the assessment process, and emotions caused by variables unconnected to buying itself. These different types of emotions can help hospitality managers design appropriate strategies for different tourist segments defined by their emotions.

On the contrary, some research implies the drawback of applying heuristics that are based on emotion in tourist decision-making. First, emotions are dynamic and complex. The findings of Zhang, Cai and Qiu (2019) revealed that emotional reactions appeared at different degrees based on diverging reasons, influenced by memory, and changed over time. Therefore, to consider tourist emotions as a critical factor for tourist decision-making, marketing research should be conducted regularly to define an appropriate strategy because tourist decision-making based on emotion will occasionally differ. Nevertheless, emotional branding and marketing, which identifies consumers' unique emotional demands, applies companies' emotional marketing strategies, and weaves the main line of "emotion" throughout the marketing process, might be one solution (Zhang et al., 2022). Second, decision-making based on feelings (affect, mood, and emotions), such as heuristics, can lead to cognitive biases. Additionally, affect can be manipulated, particularly in business (Slovic et al., 2007). Therefore, to protect consumers and ensure efficient resource usage by producers, public and non-profit organisations might adopt policies based on common biases, as exemplified in the case of food safety (James, Segovia and Giwa-Daramola, 2023).

Meanwhile, whether the affective component is more important than the cognitive and conative part in selecting a destination can be discussed from the perspective of dual system theory (Kahneman, 2013). Due to bias, emotions may not accurately reflect genuine decision-making. Again, people have two distinct systems: System 1 (relatively unconscious thinking process) and System 2 (analytical thinking process). System 1 operates with the assistance of System 2. Thus, there must be a balance between the two. Moreover, businesses should conduct ethics in exploiting customers' emotions, and people might consider the concept of smart economic decision-making introduced by Altman (2017).

Further, the findings of this study can inform the development of marketing strategies and business decisions within the tourism industry, assisting businesses in comprehending and capitalising on cognitive biases and emotional responses in their marketing activities.

4.4 Future research directions

Despite the limited sources of the relevant keywords, this review might fill in the gaps in the research field and serve as a direction for further study, which answers the last research question. This study gathers research progress and knowledge to better understand the tourist decision-making process. Several future research directions can be derived from the reviewed article. For example, some research could be expanded by cross-cultural analyses that allow for comparing the perceptions of tourists from different nations, giving the model more validity (Stojanovic, Andreu and Curras-Perez, 2022). The current research on destination image could also be expanded and related to research on destination brands. The branding extension approach could be a feasible strategy to strengthen the image (Mikalauskas, Strunz and Afifi, 2014), for example, by investigating the ability of a brand to evoke positive feelings.

Moreover, understanding cognitive and emotional biases can help design better tourism management and marketing strategies. Tourists often rely on heuristics to simplify complex decisions, leading to bounded rationality. Future research could delve deeper into specific biases like anchoring, mental accounting, and projection bias and their effects on tourism decisions (Mayer, Santos and Marques, 2020; Li et al., 2022). Social media-induced tourism behaviours and the associated cognitive biases, such as the bandwagon effect, also require further exploration (Siegel, Tussyadiah and Scarles, 2023; Oan-Oon and Choibamroong, 2025). Further, while cognitive biases stem from mental shortcuts and can lead to irrational choices, emotional biases are driven by feelings and can also significantly shape tourists' preferences and behaviours in pre-, during-, and post-visit experiences. For instance, 1) emotions in social media communication significantly impact travellers' intentions to visit and their word-of-mouth behaviour (Schoner-Schatz, Hofmann and Stokburger-Sauer, 2021); 2) emotions elicited by negative events during travel, such as flight delays, can lead to different emotional responses and subsequent actions, impacting tourists' behavioural intentions (Jiang, Huang and Scott, 2020); and 3) post-visit exposure to positive or negative stimuli can significantly influence destination loyalty (Godovykh and Tasci, 2021). Future research is needed to understand the complex and dynamic nature of emotions in tourism, including the integration of technology, social media and sustainability issues.

Additionally, this study proposes future research directions concerning context, methods, and empirical research ideas. Concerning the context, future research might be conducted in other specific contexts such as heritage destinations, smart destinations, sustainable tourism, or mountainous destinations. Moreover, regarding the methods, research using a multi-method approach has not appeared in relevant research, whereas this method can provide a more rigorous result. Further, due to minimal research on the affect heuristics in tourism, interesting empirical research can be designed for future research, such as the judgement of risk and benefit in visiting a destination in the post-pandemic era.

5. Conclusions

This study compiles research findings and information in the field of tourism research to better comprehend the tourist decision-making process in selecting a destination by applying heuristics using emotion. The increasing trend of reviewed documents also shows the growing interest in the discussed topic, which is supported by the visualisation of keywords on the word cloud generator. The framework of the review reveals underpinning theories, context, and methods. Various theories are used, such as the theory of sentiment tendency analysis and the theory of destination involvement related to marketing and psychology. Moreover, most research is conducted in the context of general destinations. Furthermore, the empirical research method has become popular in the reviewed articles. Despite the limitation of the chosen database, this study also provides recommendations for future research.

References

Agapito, D., Oom do Valle, P. and da Costa Mendes, J., 2013. The Cognitive-Affective-Conative Model of Destination Image: A Confirmatory Analysis. *Journal of Travel and Tourism Marketing*, 30(5), pp.471–481. https://doi.org/10.1080/10548408.2013.803393

Altman, M., 2017. Introduction to smart decision-making. In Altman, M. Ed. *Handbook of Behavioural Economics and Smart Decision-Making: Rational Decision-Making within the Bounds of Reason.* Cheltenham; Northampton, MA: Edward Elgar, pp.1-8.

Assael, H., 1995. *Consumer Behaviour and Marketing Action.* United States: South-Western College Publishing.

Baloglu, S., and Brinberg, D., 1997. Affective images of tourism destinations. *Journal of Travel Research*, 35(4), pp. 11–15. https://doi.org/10.1177/004728759703500402

Baloglu, S., and McCleary, K. W., 1999. A model of destination image formation. *Annals of Tourism Research*, 26(4), pp.868–897. https://doi.org/10.1016/S0160-7383(99)00030-4

Bastiaansen, M., Straatman, S., Driessen, E., Mitas, O., Stekelenburg, J. and Wang, L., 2018. My destination in your brain: A novel neuromarketing approach for evaluating the effectiveness of destination marketing. *Journal of Destination Marketing and Management*, 7, pp.76–88. https://doi.org/10.1016/j.jdmm.2016.09.003

Blackwell, R. D., Engel, J. F., and Miniard, P. W., 2006. *Consumer Behaviour*. India: South-Western.

Campo, S. and Alvarez, M. D., 2022. Animosity based on Traditional enmity versus other causes. *Asia Pacific Journal of Marketing and Logistics*, 34(3), pp.524–542. https://doi.org/10.1108/APJML-10-2020-0708

Castelltort, M. and Mäder, G., 2010. Press media coverage effects on destinations - A Monetary Public Value (MPV) analysis. *Tourism Management*, 31(6), pp.724–738. https://doi.org/10.1016/j.tourman.2009.06.007

Cohen, S. A., Prayag, G. and Moital, M., 2014. Consumer behaviour in tourism: Concepts, influences and opportunities. *Current Issues in Tourism*, 17(10), pp.872–909. https://doi.org/10.1080/13683500.2013.850064

Cong, X., 2021. Research on the tourism decision-making mechanism: A case study of American outbound tourism. *Informing Science: The International Journal of an Emerging Transdiscipline*, 24, pp.129-147. https://doi.org/10.28945/4878

Echtner, C. M., and Ritchie, J. R. B., 1991. The meaning and measurement of destination image. *The Journal of Tourism Studies*, 2(2), pp.2–12. Echtner, C. M., and Ritchie, J. R. B. 1993. The measurement of destination image: An empirical assessment. *Journal of Travel Research*, 31(4), pp.3–13. https://doi.org/10.1177/004728759303100402

Fridgen, J. D., 1987. Use of cognitive maps to determine perceived tourism region. *Leisure Sciences*, 9, pp.101–117. https://doi.org/10.1080/01490408709512150

Gartner, W. C., 1994. Image Formation Process. *Journal of Travel & Tourism Marketing*, 2(2–3), pp.191–216. https://doi.org/10.1300/J073v02n02_12

Gensch, D. H., 1978. Image-measurement segmentation. *Journal of Marketing Research*, 15(3), pp.384–394. https://doi.org/10.1177/00222437780150030

Gnoth, J., 1997. Tourism motivation and expectation formation. *Annals of Tourism Research*, 24(2), pp.283–304. https://doi.org/10.23912/9781911396437-3632

Godovykh, M., and Tasci, A. D., 2021. The influence of post-visit emotions on destination loyalty. *Tourism Review*, 76(1), pp. 277-288. https://doi.org/10.1108/TR-01-2020-0025

Gomez-Diaz, L., 2019. The influence of emotions and country stereotypes on destination image and word of mouth. *Proceedings of the International Conference on Tourism Research*, pp.120–127.

Goossens, C., 2000. Tourism information and pleasure motivation. *Annals of Tourism Research*, 27(2), pp.301–321. https://doi.org/10.1016/S0160-7383(99)00067-5

Herzog, H., 1963. Behavioural science concepts for analysing the consumer. in P. Bliss Ed. *Marketing and the behavioural sciences* Boston, MA: Allyn & Bacon, pp. 76–86.

Hollebeek, L. D., Sarstedt, M., Menidjel, C., Sprott, D. E. and Urbonavicius, S., 2023. Hallmarks and potential pitfalls of customer- and consumer engagement scales: A systematic review. *Psychology Marketing*, pp.1–15. https://doi.org/10.1002/mar.21797

Iordanova, E. and Stainton, H., 2019. Cognition, emotion and trust: A comparative analysis of Cambodia's perceived and projected online image. *Tourist Studies*, 19(4), pp.496–519. https://doi.org/10.1177/1468797619837970

James, H., Segovia, M. and Giwa-Daramola, D., 2023. Food safety and cognitive biases: what we know, what we need to know, and why. British Food Journal, 125(10), pp.3717-3733. https://doi.org/10.1108/bfj-09-2022-0824

Javed, M., Tučková, Z. and Jibril, A. B., 2022. Towards understanding tourist revisit of zoo attraction: Evidence from the Czech Republic. *Cogent Social Sciences*, 8(1), pp.1-15. https://doi.org/10.1080/23311886.2021.2024673

Jiang, Y., Li, S., Huang, J., and Scott, N., 2020. Worry and anger from flight delay: Antecedents and consequences. *International Journal of Tourism Research*, 22(3), 289-302.https://doi.org/10.1002/jtr.2334

Jin, M. L., Choi, Y., Lee, C. K. and Ahmad, M. S., 2020. Effects of place attachment and image on revisit intention in an ecotourism destination: Using an extended model of goal-directed behavior. *Sustainability (Switzerland)*, 12(18): 7831. https://doi.org/10.3390/SU12187831

Kahneman, D., 2013. *Thinking, fast and slow*. Farrar, Straus and Giroux.

Kazeminia, A., Hultman, M. and Mostaghel, R., 2016. Why pay more for sustainable services? The case of ecotourism. *Journal of Business Research*, 69(11), pp.4992–4997. https://doi.org/10.1016/j.jbusres.2016.04.069

Kim, S., and Yoon, Y., 2003. The hierarchical effects of affective and cognitive components on tourism destination image. *Journal of Travel & Tourism Marketing*, 14(2), pp.1-22. https://doi.org/10.1300/J073v14n02_01

King, J. and Slovic, P., 2014. The affect heuristic in early judgements of product innovations. *Journal of Consumer Behavior*, 13, pp.411–428. https://doi.org/10.1002/cb

Li, S., Liu, Y., Dai, S. and Chen, M., 2022. A review of tourism and hospitality studies on behavioral economics. *Tourism Economics*, 28(3), pp.843-859. https://doi.org/10.1177/13548166211060889

Luo, Y., Tong, T., Zhang, X., Yang, Z. and Li, L., 2023. Exploring destination image through online reviews: An augmented mining model using latent Dirichlet allocation combined with probabilistic hesitant fuzzy algorithm. *Kybernetes*, 52(3), pp.874–897. https://doi.org/10.1108/K-07-2021-0584

Mayer, V., Santos, G. and Marques, O., 2020. Option framing for upselling tourism services: does cognitive availability prevent irrational choices? *Tourism Economics*, 28(2), pp.476-494. https://doi.org/10.1177/1354816620949722

McCabe, S., Li, C. and Chen, Z., 2016. Time for a radical reappraisal of tourist decision making? Toward a new conceptual model. *Journal of Travel Research*, 55(1), pp.3–15. https://doi.org/10.1177/0047287515592973

Mikalauskas, R., Strunz, H. and Afifi, G. M. H., 2014. Relationship between sport events and destination image: Some theoretical approaches. *Transformations in Business and Economics*, 13(2A), pp.297–310.

Mothersbaugh, D. L., Hawkins, D. I. and Kleiser, S. B., 2020. Consumer behavior: Building marketing strategy. In *McGraw-Hill Education* (14th ed.). McGraw-Hill Education.

Moyer, R. M. and Song, G., 2016. Understanding Local Policy Elites' Perceptions on the Benefits and Risks Associated with High-Voltage Power Line Installations in the State of Arkansas. *Risk Analysis*, 36(10), pp.1983–1999. https://doi.org/10.1111/risa.12548

Oan-Oon, R., and Choibamroong, T., 2025. Multidimensional bandwagon effect and dual-process decision making: An integrated model of the theory of planned behaviour from the perspective of American millennials' travel intention. *Heliyon*, 11(1). https://doi.org/10.1016/j.heliyon.2024.e41375

Pelegrín-Borondo, J., Juaneda-Ayensa, E., González-Menorca, L. and González-Menorca, C., 2015. Dimensions and basic emotions: A complementary approach to the emotions produced to tourists by the hotel. *Journal of Vacation Marketing*, 21(4), pp.351–365. https://doi.org/10.1177/1356766715580869

Pike, S., and Ryan, C., 2004. Destination positioning analysis through a comparison of cognitive, affective, and conative perceptions. *Journal of travel research*, 42(4), pp.333-342. https://doi.org/10.1177/0047287504263029

Quan, W., Al-Ansi, A. and Han, H., 2021. Spatial and human crowdedness, time pressure, and Chinese traveller word-of-mouth behaviours for Korean restaurants. *International Journal of Hospitality Management*, 94. https://doi.org/10.1016/j.ijhm.2020.102851

Rodríguez-Molina, M. A., Frías-Jamilena, D. M. and Castañeda-García, J. A., 2015. The contribution of website design to the generation of tourist destination image: The moderating effect of involvement. *Tourism Management*, 47, pp.303–317. https://doi.org/10.1016/j.tourman.2014.10.001

Rosado-Serrano, A., Paul, J. and Dikova, D., 2018. International franchising: A literature review and research agenda. *Journal of Business Research*, 85, pp.238–257. https://doi.org/10.1016/j.jbusres.2017.12.049

Russell, J. A., and Snodgrass, J., 1987. Emotion and environment. In D. Stockols and I. Altman Eds. *Handbook of environmental psychology*. New York: John Wiley, pp. 245–280.

Schoner-Schatz, L., Hofmann, V., and Stokburger-Sauer, N. E., 2021. Destination's social media communication and emotions: An investigation of visit intentions, word-of-mouth and travellers' facially expressed emotions. *Journal of Destination Marketing & Management*, 22, 100661. https://doi.org/10.1016/j.jdmm.2021.100661

Siegel, L. A., Tussyadiah, I., and Scarles, C., 2023. Exploring behaviors of social media-induced tourists and the use of behavioural interventions as salient destination response strategy. *Journal of destination marketing & management*, 27, 100765. https://doi.org/10.1016/j.jdmm.2023.100765

Slovic, P., Finucane, M. L., Peters, E. and MacGregor, D. G., 2007. The affect heuristic. *European Journal of Operational Research*, 177(3), pp.1333–1352. https://doi.org/10.1016/j.ejor.2005.04.006

Sönmez, S. and Tasci, A. D. A., 2020. Characteristics and behaviours of anti-gun and pro-gun travelers. *Tourism Review*, 75(2), pp.347–368. https://doi.org/10.1108/TR-01-2019-0002

Stepchenkova, S. and Mills, J. E., 2010. Destination image: A meta-analysis of 2000-2007 research. *Journal of Hospitality Marketing and Management*, 19(6), pp.575–609. https://doi.org/10.1080/19368623.2010.493071

Stojanovic, I., Andreu, L. and Curras-Perez, R., 2018. Effects of the intensity of use of social media on brand equity: An empirical study in a tourist destination. *European Journal of Management and Business Economics*, 27(1), pp.83–100. https://doi.org/10.1108/EJMBE-11-2017-0049

Stojanovic, I., Andreu, L. and Curras-Perez, R., 2022. Social media communication and destination brand equity. *Journal of Hospitality and Tourism Technology*, 13(4), pp.650–666. https://doi.org/10.1108/JHTT-11-2020-0302

Torres, E. N., Milman, A. and Park, S., 2018. Delighted or outraged? Uncovering key drivers of exceedingly positive and negative theme park guest experiences. *Journal of Hospitality and Tourism Insights*, 1(1), pp.65–85. https://doi.org/10.1108/JHTI-10-2017-0011

Tversky, A. and Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, 185(4157), pp.1124-1131. http://www.jstor.org/stable/1738360

Wang, F., Feng, Y. and Wang, Z., 2022. Inspiring desirability or ensuring feasibility: destination image and psychological distance. *International Journal of Tourism Research*, 24(5), pp.667-676. https://doi.org/10.1002/jtr.2529

Wattanacharoensil, W. and La-ornual, D., 2019. A systematic review of cognitive biases in tourist decisions. *Tourism Management*, 75, pp.353–369. https://doi.org/10.1016/j.tourman.2019.06.006

Zhang, S., 2022. Model construction of the influence of tourist destination image on tourists' word-of-mouth communication based on cognitive and emotional environment. *Journal of Environmental and Public Health*, 2022. https://doi.org/10.1155/2022/3343946

Zhang, Y., Tu, Z., Zhao, W. and He, L., 2022. Design of emotional branding communication model based on system dynamics in social media environment and its influence on new product sales. *Frontiers in Psychology*, 13. https://doi.org/10.3389/fpsyg.2022.959986

Zhang, Y., Cai, L. and Qiu, S., 2019. The Chinese Cohort 60s and Japan: A journey of emotions. *Tourist Studies*, 19(1), pp.62–88. https://doi.org/10.1177/1468797618791127

Zheng, C., Zhang, J., Zhang, H. and Qian, L., 2017. Exploring sub-dimensions of intrapersonal constraints to visiting "dark tourism" sites: a comparison of participants and non-participants. *Asia Pacific Journal of Tourism Research*, 22(1), pp.21–33. https://doi.org/10.1080/10941665.2016.1175489

Bio-note

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UNFOLDING FACTORS INFLUENCING PINEAPPLE PRODUCTION: EMPIRICAL EVIDENCE FROM BAGAMOYO IN TANZANIA

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Abstract: *This paper examined factors that influence pineapple production in Bagamoyo using cross-sectional data collected during the harvesting season of 2023/2024. A sample of 150 smallholder pineapple farmers was randomly selected using a systematic random sampling procedure. We used the Ordinary Least Squares with a Cobb- Douglas function to estimate the parameters after log- linearize the Cobb- Douglas function. The coefficient of determination $R^2 = 0.81$ showed that the explanatory variables were fit for the model as 81% of the variation in the production of pineapples is explained by the selected seven factors. Further results revealed that out of the seven predictors, labour, age and farming experience were statistically significant (p-values: 0.000, 0.003 and 0.000) respectively, all of which the p-value was less than a 5 per cent level of significance. The other variables namely education level, soil quality, technology use and farm size were insignificantly explaining pineapple production. We conclude that labour (family and hired), age and farming experience are positively correlated to the quantity of pineapple production. We recommend that the policy on agriculture should insist on the provision of extension services to be offered timely to ensure quality yield for both local consumption as well as exports. Encouraging exports through promotion to address the challenge of untapped potential for exports of the pineapple which in turn encourages production and lastly, investment in agricultural research would steer up the need for further research into pineapple seed breeding, pest control and post-harvest technology. Such initiatives would promote crop production and thereby improve the livelihood of the smallholder farmers.*

1. Introduction

Ananas Comosus is among the cultivated crops in the Sub- Saharan Africa and Tanzania is ranked 18th in the list of top 20 pineapple-producing countries (Worldatlas, 2025). It is a tropical and economic fruit with encouraging market potential in the global market (Shelindina et al. 2023; Jaji, Man and Nawi, 2018; Hemalatha & Anbusehi, 2013). According to Akrong et al. (2022), pineapple is an important horticultural export as well as a cash crop which creates employment opportunities among the rural population. Further, pineapple is one of the most beloved tropical fruits in the world offers significant health benefits and is rich in vitamin C, B vitamins, fibre, and minerals (Firatoiu et al. 2021). In Tanzania, the *ananas comosus* is an important fruit crop (Makaranga et al. 2018) and its production is expanding rapidly with an increasing tendency toward commercial cultivation through the expansion of existing farms and the opening of new farms. This trend has been caused by

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increased demand for pineapple in local and internal markets particularly in the Middle East. The origin of pineapple has been traced back to Brazil and Paraguay in the Amazon basin where the fruit was first domesticated (Collins, 1949). There is evidence that pineapple cultivation provides sustainable livelihood to many smallholder farmers in developing countries (Campıta, Tokuda and Sales, 2022) and has gained global popularity as both a delectable fruit and a versatile ingredient in culinary delights with its vibrant taste and rich nutritional content make it a sought-after delight among consumers worldwide (Shelindina et al., 2023). Commercial production of pineapples in Tanzania is limited due to many challenges such as difficulty in obtaining high-yielding, uniform and disease-free planting materials in large quantities and lack of reliable markets. The low yield is partly due to the slow rate of pineapple multiplication by conventional methods and the lack of high-quality seeds. Pineapple production in the Bagamoyo district still uses traditional farming and no evidence that farmers apply fertilizers or agro-inputs. Consequently, the production volume has not been stable. Even though Tanzania is gifted with enough productive arable land, varied climatic zones and a bounty of water sources all across the country, the production of pineapple and its contribution to the country's economy is still petty. There are several factors for the unstable pineapple production mostly farm size, number of farm labour, seed, fertilizer, and experience in the farming system (Ariani and Tanjung, 2024; Ojeyele, 2021; Ria, Wiludjeng and Mulyatno, 2021; Akhilomen et al. 2014). Also, access to markets, cost of inputs and transportation and cost of labour, influenced the pineapple production (Haji and Babune, 2023).

Despite its economic importance, the production of pineapple in the study area has been low and as such, influences the ability of smallholder farmers to maximize the potential opportunities and enjoyable socio-economic benefits of pineapple farming in the area. Also, existing studies on pineapple production in Tanzania (Magasha, Alex & Mlage, 2025; Haji & Babune, 2023; Makaranga et al. 2018; Bakewell- stone, Lieblein & Francis, 2008) focus on a narrow set of regions, leaving out important pineapple-producing areas like Bagamoyo. As a result, a broader understanding of the regional differences in pineapple cultivation and challenges might be lacking given the significance and the potential of Bagamoyo in the pineapple production. This paper is set to examine the factors influencing pineapple production in Tanzania, using Bagamoyo as a case study. Bagamoyo is chosen due to its predominance in pineapple production as a result of a combination of favourable climatic conditions, market accessibility and agricultural tradition. Thus, the findings will be used to generalize to other areas in the country and subsequently to all other areas with similar characteristics regarding weather, soils, and other climatic conditions. The paper is organized as follows; section 2 is on materials and methods while section 3 is on results and discussion. Section 4 concludes and section 5 gives the policy implications.

2. Materials and Methods

2.1 Data, Sampling and Sample Size

The study used primary data that were collected from 150 pineapple smallholder farmers in Bagamoyo. Precisely, data were collected from the most pineapple-producing area in the district, namely Kiwangwa, having a population of 25,997 according to population and housing census of 2022 (NBS, 2022). The data collected were for the 2024/2025 production season. The pineapple farmers were selected using a systematic random sampling procedure after a list of smallholder pineapple farmers was made available. Farmers were listed in some order to make it possible to randomly select the desired sample size. The area of study is shown in Figure 1 underneath.
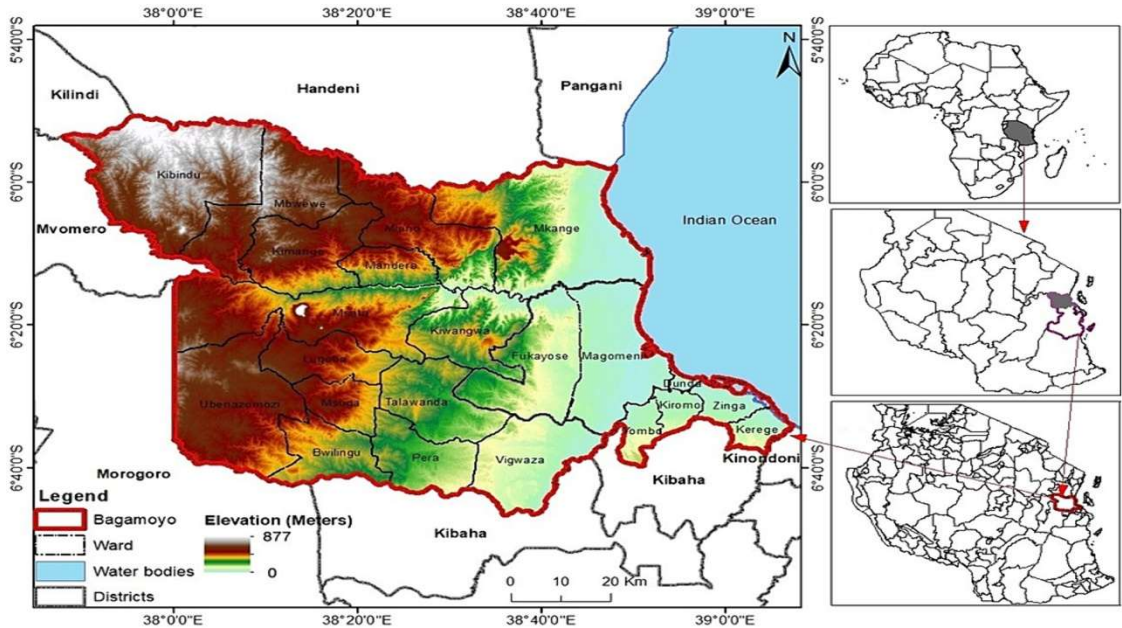
Figure 1: Bagamoyo district map
Souce: Adapted from Mugabe et al. (2024)

Figure 1 shows the Bagamoyo district and its location. It is one of eight administrative districts of the Coastal Region in Tanzania. The district covers an area of 945 km^2. The district is surrounded by the Chalinze District to the north and west, the Zanzibar Channel to the east, the Kibaha District to the south, and the Kinondoni District to the southeast in the Dar es Salaam Region. The district is comparable in size to the land area of Turks and Caicos Islands. As of 2022, the population of Bagamoyo district is 205,478. The area has potential for pineapple production. The area is characterized by a warm and humid tropical climate, which is ideal for growing pineapples. The fruit thrives in regions with temperatures between 20°C and 30°C (68°F - 86°F), which is characteristic of many coastal areas in Tanzania, including Bagamoyo. Also, having well-drained soils provides a conducive environment for pineapple cultivation. The region's soils are generally rich in nutrients and can support the growth of pineapples without significant irrigation.

2.2 Production Theory

Production is the process of transforming inputs into outputs (Jehle and Reny, 2011). The fundamental reality that must be contended with in this process is technological feasibility. The state of technology determines and restricts what is possible in combining inputs to produce output, and there are several ways this constraint can be represented. According to Jehle and Reny (2011), the most general way is to think of the production unit as having a production possibility set, where each vector is a production plan whose component indicates the amounts of the various inputs and outputs. The advantage of the production possibility set is by far the most general way to characterize any production unit's technology because it allows for multiple inputs and multiple outputs. In our case, we consider a farm producing only a single output from many inputs. For this reason, we describe the farm's technology in our case in terms of a production function.

Let a production technology utilize a vector of inputs denoted by $X = (X_1,..., X_n) \in \mathfrak{R}_+^n$ to produce a non-negative vector of outputs denoted by $y = (y_1,..., y_m) \in \mathfrak{R}_+^m$. The production possibility set of a given production unit is a subset of Z of the space $\mathfrak{R}_+^{m+n}$. A production unit may select any input-output configuration $(x, y) \in Z$ as its production plan. The production possibility set is the collection of all feasible input and output vectors and it is represented as $Z = \{(y, x) : x \ can \ produce \ y\} \subset \mathfrak{R}_+^{m+n}$ 　　　　　Eq1

Furthermore, according to Fare et al (1994) production possibility set can be represented by an input requirement set $F(y)$ or output producible set $G(x)$. The input requirement set represents the collection of all input vectors $x = (x_1, x_2,..., x_n) \in \mathfrak{R}_+^n$ that yield at least output vectors $y = (y_1, y_2,..., y_m) \in \mathfrak{R}_+^m$ which can be represented as;

$$F(y) = \{x : (x, y) \ is \ feasible\} \qquad \text{Eq. 2}$$

The output producible set is the collection of all output vectors $y = (y_1, y_2,..., y_m) \in \mathfrak{R}_+^m$ that are produced from the given input vector $x = (x_1, x_2,..., x_n) \in \mathfrak{R}_+^n$, which can also be represented as; $G(x) = \{y : (x, y) \ is \ feasible\}$ 　　　　　Eq. 3

2.3 The model

This study used the Ordinary Least Squares with a Cobb- Douglas function to estimate the parameters after log- linearize the Cobb- Douglas function. The mathematical form of the Cobb-Douglas production function is given by $Q = AL^\alpha K^\beta$, whereby Q is the output, A is the technology used in the production of the output, L is the labour input and K is the capital input. The parameters α and β are elasticities. There are several functional forms for estimating the physical relationship between inputs and outputs. However, if there are three or more explanatory variables in the model, the Cobb- Douglas functional form is still preferred (Hanley and Spash, 1993). In his paper while arguing a case for Cobb-Douglas production function, Murthy (2002) found that apart from its capability to handle multiple inputs in its generalized form, the function does not even introduce distortions of its own in the face of imperfections in the market. The production function of any farmer is determined by the resource availability of a farmer. A basic form of a production function is given by $Q = f(L_d, K, L)$, where Q is the production output, which is a function of land (L_d), the capital, K and labour force (L), used for the production of the same output. In our case, the output is pineapple production while the inputs becomes labour, farm size, farming experience, farming technology, age, soil quality and education, the factors which are hypothesized to influence pineapple production. Other merit of the Cobb- Douglas function is its capability in handling various econometric estimation problems such as serial correlation, heteroscedasticity and multicollinearity in an easy and adequate manner. It is further argued that the Cobb-Douglas function facilitates computations and has the properties of explicit representability, uniformity and flexibility. Also, the elasticities of individual inputs can be easily obtained, read and interpreted. Thus, to determine the factors that influence the production of pineapple, the following functional relationship was specified and empirically, the linearized Cobb – Douglas model of unknown parameters is presented as follows:

$$In\ Y \ = \ In\beta_0 + In\beta_1 x_1 + In\beta_2 x_2 + In\beta_3 x_3 + In\beta_4 x_4 + In\beta_5 x_5 + In\beta_6 x_6 + In\beta_7 x_7 + \ \varepsilon_i$$

Where:
Y = Pineapple output in kgs
x_1 = labour; x_2 = farm size (ha); x_3 = farming experience; x_4 = farming technology

x_5 = Age; x_6 = soil quality; x_7 = education; ε_i = Error term
ln = natural logarithm
$\beta_1 \, to \, \beta_7$ are Coefficient parameters to be estimated

Table 1: Variables in the model and their description

Variable	Description	Expected sign
Pineapple output (kgs)	The amount of pineapple harvested in the 2017/2018 season	
Labour (family and hired)	The number of family members and hired workers who are involved in all of the pineapple farming activities.	+
Farm size	The size in acres of the pineapple farm	+
Farming experience	The number of years (s) in the pineapple production	+
Technology used	Dummy variable for the type of technology used by a farmer (1= if modern technology; 0= if otherwise)	+
Age	The age (in years) of the pineapple farmer	+
Soil quality	Dummy variable on the influence of soil quality on pineapple production (1=if yes; 0=if otherwise)	+
Education level	Dummy variable for education level of pineapple farmer (1= no formal education, 2= primary education, 3= secondary education and 4= tertiary education)	+

Source: Created by author (s)

3. Results and discussion

3.1 Pineapple Production in Tanzania

December is the season for pineapple harvest in Tanzania. The pineapple took a total of 18 months from planting to harvest and between this season, there is a weeding eight times. One acre that is well-kept yields an average of 20,000 pineapples equivalent to 50 tons. Over the ten years (2014- 2023), pineapple production has not been stable to establish a significant change. However, in general, the production has been insignificantly increased throughout the years as shown in Figure 2. For example from 2014 to 2018, there was no significant change in the production until 2019 when it started to increase towards 2022. In 2023 there was a declining production though not significant.
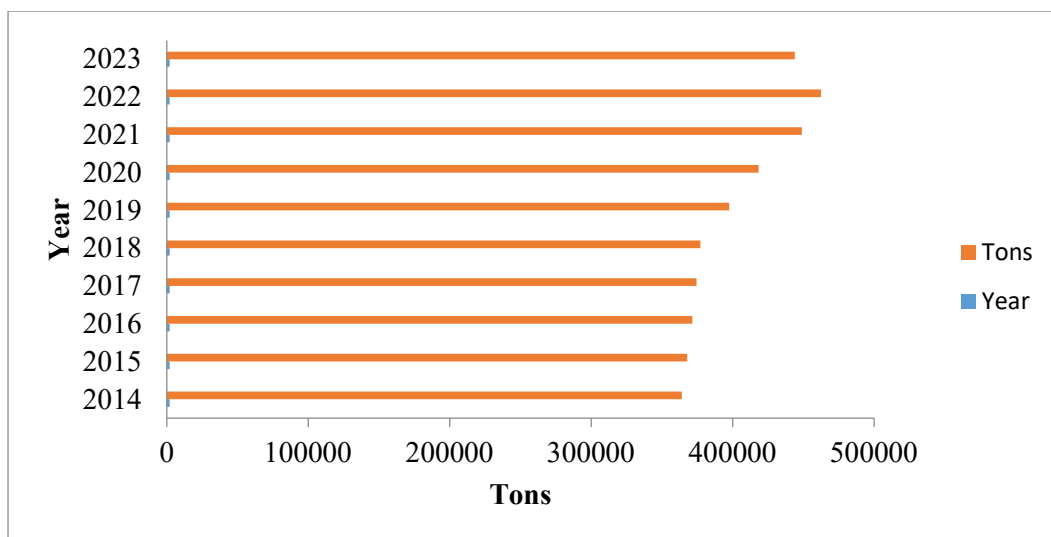
Figure 2: Trend of pineapple production (2014- 2023)
Source: Extracted from FAOSTAT (2025)

Further, both the production, area harvested and yield (kg/ha) show an increasing trend but at a slow pace and suggest that there is hope for sustainable growth in crop production in the future years, if measures are taken to address the production challenge. Table 2 shows the annual changes in production, area harvested and yields.

Table 2: Production, harvested areas and average yield in Tanzania

Year	Production	Area harvested(ha)	Yield (kg/ha)
2014	364178.88	15500	23495.4
2015	367927.39	14845	24784.3
2016	371483.7	15242	24372.8
2017	374543.39	15619	23979.4
2018	377257.3	15939	23668.2
2019	397658.04	17014	23372.2
2020	418498.21	17212	24313.7
2021	448885	18476	24295.8
2022	462512.51	18969	24383
2023	443910.5	18136	24477.2

Source: Extracted from FAOSTAT, 2025

It is evident from Table 2 that the production, though increasing over the years, the pace is too slow than expected, given the available production opportunities in the area. It is for that reason this study is set to examine the factors influencing the pineapple production in the area.
We begin the analysis by providing the technical considerations that paved the leeway to perform the econometric model analysis. In all the families of regression models, it is inappropriate to enter into the same regression model predictors which are highly correlated with each other. It also makes modest sense to include independent variables in the model that are highly correlated, as they would not be making an exceptional contribution to the regression model. This is because of the danger that they will mask each other's effects. If the variables are highly correlated among themselves, the predictive power of the predictors will obscure the predictive power of the response variable. While we recognize that there is

a possibility of having very high multicollinearity (sometimes perfect multicollinearity) even if the coefficients of correlation between all pairs of variables are not very high, it was important to check for the presence of multicollinearity before embarking on modelling so that to have a prior determination of the behavior of explanatory variables to be included in the model. The dependent variable used was the quantity (in kgs) of the pineapples produced in the 2023/2024 harvest season, while the independent variables were age, education, farm size, soil quality, farming experience, technology use and labor. Table 3 shows the results of the diagnosis checks of the multicollinearity using a correlation matrix.

Table 3: Correlation analysis for multicollinearity test

Variables	Pearson correlation coefficient	Sign.
Labor		
(a) Farm size	0.843**	0.000
(b) Experience	0.129	0.114
(c) Technology used	0.104	0.205
(d) Quantity of fertilizer used	0.858**	0.000
(e) Age	0.373**	0.000
(f) Soil quality	0.009	0.914
(g) Educational level	0.027	0.739
Farm size		
(a) Experience	0.283**	0.000
(b) Technology used	0.103	0.212
(c) Quantity of fertilizer used	0.965**	0.000
(d) Age	0.538**	0.000
(e) Soil quality	-0.002	0.980
(f) Educational level	-0.091	0.266
Experience		
(a) Technology used	-0.057	0.489
(b) Quantity of fertilizer used	0.318**	0.000
(c) Age	0.367**	0.000
(d) Soil quality	-0.005	0.949
(e) Educational level	0.153	0.062
Technology used		
(a) Quantity of fertilizer used	0.107	0.192
(b) Age	0.036	0.660
(c) Soil quality	0.010	0.908
(d) Educational level	0.018	0.824
Quantity of fertilizer used		
(a) Age	0.521**	0.000
(b) Soil quality	-0.004	0.958
(c) Educational level	-0.038	0.642
Age		
(a) Soil quality	-0.013	0.871
(b) Educational level	-0.298**	0.000
Soil quality		
(a) Educational level	0.068	0.409

** means the correlation is significant at 0.01 level (2-tailed)
Source: Created by author (s)

It was imperative to check whether the independent variables used in the model were highly correlated among themselves so that they would not create an endogeneity problem. According to Foster et al. (2006), multicollinearity is shown by low tolerance; a tolerance of 1 indicates that a variable is not correlated with others, and a tolerance value of 0 shows a perfect correlation. Also, another index that can be used is the Variance Inflation Factor (VIF) a value of 2 for VIF shows a close correlation, and a value of 1 shows little correlation. Both the tolerance and VIF should be in the region of 1. The multicollinearity test suggested that two variables (farm size and quantity of fertilizer used) should be dropped from the analysis as shown in Table 4 since they have the VIF beyond the accepted range.

Table 4: Collinearity statistics (Tolerance and VIF)

Independent Variable	Tolerance	VIF
Age	0.571	1.752
Education level	0.780	1.282
Soil quality	0.994	1.006
Experience	0.701	1.426
Technology type	0.977	1.023
Labour (family and hired)	0.230	1.355
Farm size	0.063	15.798

Variance Inflation Factor (VIF) was high and more than 10 for the variables farm size and quantity of fertilizer causing multicollinearity between the two. In the presence of multicollinearity, the variables concerned may not reveal their significant influence as they mask the effect of each other, hence leading to imprecise estimates that affect the predictive power of the model. According to Gujarati (2014), the solution to the problem is to drop them, even though when the multicollinearity is moderate it can be tolerated. The decision applied to solving the multicollinearity problem is to look at the value of VIF if exceeding 10 and at the same time, the Tolerance value is closer to zero. (Gujarati, 2014: pp.362-363, 372).

3.2 The model estimations
Overall, the goodness-of-fit test revealed that the model fits the data (F- value =101.364, p-value= 0.000) at a 5% level of significance, implying that the explanatory variables are determinants of the response variable and can thus be used to explain the influence of the predictors to the response variable. Also, the coefficient of determination was 0.810 (81%) indicating that 81 per cent of the variation in the production of pineapple, is explained by the selected factors. It can be concluded that the explanatory power of the multiple linear regression model is satisfactory and thus the model can be used to explain the factors that affect pineapple production. The variables that were included in the model are; age, labor, farming experience, education level, soil quality, and technology used. The estimated coefficients are presented in Table 5.

Table 5: Estimated Coefficients for Multiple Regression Model

Variables	Unstandardized Coefficients β	Std Error	Standardized Coefficient Beta	t	Sig.
Constant	-589.504	8470.818		-0.070	0.945
Age	451.793	105.900	0.197	4.266	0.000*
Education level	-2062.473	1249.202	-0.067	-1.651	0.101
Soil quality	-2564.562	6995.978	-0.013	-0.367	0.714

Farming experience	352.982	118.516	0.123	2.978	0.003*
Technology used	1929.346	4996.041	0.014	0.386	0.700
Labour	2671.912	139.107	0.769	19.208	0.000*

Note: (*) Indicates Significant at 5% level.
R = 0.900 R^2 = 0.810   Adjusted R^2 = 0.802   F = 101.364 statistically significant at p<0.05
Source: Created by author (s)

Table 5 shows that the coefficients for variables age, farming experience and labour were all positive and significant. The positive sign implies the positive relationship between each of these variables with the pineapple production., any unit increase of either of the variables will result in an increased pineapple production by some amount. Being significantly influencing the production of the pineapple means there is a close causal-effect relationship with the dependent variable which is pineapple production. The significance is shown by the p- values 0.000, 0.000 and 0.003 for age, farming experience and labour respectively all of which are less than the 5% level of significance. The coefficients for the other variables, namely education level and soil quality were negatively related to pineapple production meaning that when each of these increases, pineapple production decreases and vice versa though were all insignificant. Similarly, the technology used was insignificant even if having a positive sign. The insignificance of the other variables might have been attributed to a lack of variation in the data collected. For example, if education levels are uniformly high or low in the study area, the variability needed to establish a relationship with pineapple production may not be present. Similarly, if all the soil in the region is of similar quality, the variable soil quality would not show significant variation to explain production differences. The insignificance of soil quality is contrary to Verhulst et.al (2010) who contended that high soil quality equates to the ability of the soil to maintain high productivity. Similarly, regarding education, the literature suggests that education is important and significantly increases production (Ninh, 2021; Eric, Prince & Elfreda, 2014), helps manage the farms and combine inputs in a better way. Unfortunately, this is contrary to the findings in this study. Further, age is positively influencing pineapple production indicating that a year increase in age of a pineapple farmer would increase production by 452kgs times, ceteris paribus. The finding is consistent with Mamuye (2016) who concluded that younger farmers are less productive than older farmers. This result is also consistent with the findings by Anigbogu et. al. (2015) in that age is among the socioeconomic factors influencing agricultural production among cooperative farmers in Nigeria.

Labour is one of the most important factors of production. The study revealed that the amount of labour used in pineapple production had a statistically significant influence on pineapple production. The positive coefficient means when all other factors are held constant, an increase in the number of labourers hired or family labour would increase pineapple production by 2671.912 Kgs which is consistent with Ojeleye (2021) and Akhilomen et al. (2014) in their studies on profitability assessment of pineapple production and economic efficiency analysis in pineapple production respectively.

The experience that the farmer has in farming activities is a determinant of increased agricultural output. In this study, we found that farming experience has a significant influence on pineapple production. The positive sign coefficient means that, under *ceteris paribus*, an additional year in the farming experience increases the amount of pineapple production by 352.982 Kg. This result is consistent with Ria, Wiludjeng & Mulyatno (2021); and Abdulai et al. (2013) who found that the experience that the farmer has, positively determines crop production. Further, Abdulai et. al. (2013) stressed that farmers with many years of experience were more technically efficient than those with few years of experience.

4. Conclusion

This study examined factors influencing pineapple production in Tanzania using estimated results from the Cobb- Douglas function. The results show that out of seven predictor variables used, three were statistically significantly influencing pineapple production and are namely, age, labour and farming experience while four variables namely farm size, soil quality, farming technology and education level of the farmer were statistically insignificant. Despite available literature on factors affecting horticulture crop production, little has been documented specifically in the pineapple production of which this study tried to fill this gap. This opens up another investigation avenue to further include variables other than the ones used in this study in examining factors influencing pineapple production in other areas not covered by the present study.

5. Policy Implications

There are various policy interventions given the state of the art of pineapple production in the study area and that can be generalized to other production places. It is also evident from the statistics that the production of pineapple, even though shows a non-decreasing trend, but the increase over time is too slow. To stimulate production, the agricultural policy may provide incentive packages to smallholder farmers in the area to better access inputs such as seeds, fertilizer, as well as extension services to improve their production, productivity and profitability. The policy could also insist on the provision of extension services to be offered timely to ensure quality yield for both local consumption as well as exports. Encouraging exports through promotion to address the challenge of untapped potential for exports of the pineapple which in turn encourages production. Lastly, investment in agricultural research would steer up the need for further research into pineapple seed breeding, pest control and post-harvest technology. Such initiatives would promote crop production and thereby improve the livelihood of the smallholder farmers.

References

Abdulai, S., Donkoh, A.S., and Nkegbe, P., 2013. Technical efficiency of maize production in Northern Ghana. *African Journal of Agricultural Research*. Vol. 8(43), pp.5251-5259.

Akhilomen, L.O., Bivan, G.M., Rahman, S.A. and Sanni, S.A., 2014. Economic efficiency analysis of pineapple production in Edo State, Nigeria: a stochastic frontier production approach.

Anigbogu, U.T., Okoli, M.I., and Agbasi, E.O., 2015. Socioeconomic Factors Influencing Agricultural Production among Cooperative Farmers in Anambra State, Nigeria. *International Journal of Academic Research in Economics and Management Sciences.Vol.4: pp 43-58*

Ariani, R. and Tanjung, A.F., 2024. Economic Efficiency of Pineapple Farming Using the Stochastic Frontier Approach. *Jurnal AGRISEP: Kajian Masalah Sosial Ekonomi Pertanian dan Agribisnis*, pp.667-684.

Bakewell-Stone, P., Lieblein, G. and Francis, C., 2008. Potentials for organic agriculture to sustain livelihoods in Tanzania. *International Journal of Agricultural Sustainability*, *6*(1), pp.22-36.

Campıta, M.C.F., Tokuda, H. and Sales, H.M., 2022. The Factors of Marketing Channel Selection of Queen Pineapple Farmers in Camarines Norte. *Journal of Management Marketing and Logistics*, *9*(2), pp.49-62.

Collins, J.L., 1949. History, taxonomy and culture of the pineapple. *Economic Botany*, 3(4):335

Eric, O.O., Prince, A.A. and Elfreda, A.N.A., 2014. Effects of education on the agricultural productivity of farmers in the Offinso Municipality. *International Journal of Development Research*, *4*(9),   pp.1951-60.

Firatoiu, A.R., Chiurciu, I.A., Marcuta, L., Chereji, A.I., Soare, E., Voicu, V. and Marcuta, A., 2021. Study on the production and marketing of Pineapples Worldwide. *Proceedings of the 37th International Business Information Management Association (IBIMA), Cordoba, Spain*, pp.1-2.

Food and Agriculture Organization of the United Nations Statistics, FAOSTAT (2025)

Foster, J.J., Barkus, E., and Yavorsky, C., 2006. Understanding and Using Advanced Statistics. SAGE Publications Ltd. London. Pp.38

Gujarati, D.N., 2014). *Basic econometrics,* (4th ed). The McGraw-Hill Companies. New York.

Haji, S. and Babune, G.J., 2023. Opportunities and Challenges of Pineapple Smallholder Farmers in Improving Rural Livelihoods: A Case Study of Donge Village in Zanzibar. *Management*, *11*(2), pp.10-15.

Hanley, N., and Spash, C., 1993. Farm management research for small farmer development. *Food   and Agriculture Organization of the United Nations*, Rome.

Hemalatha R & Anbuselvi, S., 2013. Physicochemical constituents of pineapple pulp and waste. J.Chem. Pharmaceuticals Res, 5(2), pp 240-42.

Jaji, K., Man, N. and Nawi, N.M., 2018. Factors affecting pineapple market supply in Johor, Malaysia. *International Food Research Journal*, *25*(1).

Jehle, G.A., and Reny, P.J., 2011. Advanced Microeconomic Theory. 3rd Ed. England. Prentice Hall.

Joosten, F., et al., 2015. *How does the Fruit and Vegetable Sector contribute to Food and Nutrition Security?* Wageningen, LEI Wageningen UR (University & Research centre),LEI Nota 2015-076. 58 pp.; 4 fig.; 7 tab.; 52 ref.

Magasha, O., Alex, S. and Mlage, F.V., 2025. The Impact of Collective Action on Enhancing Crop Productivity: A Multimethod Analysis of Farmers' Groups in Morogoro District, Tanzania. *African Quarterly Social Science Review*, *2*(1), pp.109-122.

Makaranga, A., Seth, M.S., Ndee, A., Mneney, E.E., Mbwambo, G., Lema, K., Godfrey, A., Mrema, L., Kachiwile, A., Mrema, E. and Msogoya, T.J., 2018. Diversity and genetic identity of pineapple [Ananas comosus (L.) Merr.] in Tanzania based on microsatellite markers. *African Journal of Biotechnology*, *17*(26), pp.811-817.

Mugabe, P., Kipkulei, H., Sieber, S., Mhache, E. and Löhr, K., 2024. Examining climate trends and patterns and their implications for agricultural productivity in Bagamoyo District, Tanzania. *Frontiers in Climate*, *6*, p.1346677.

Mamuye, N., 2016. *Statistical analysis of factors affecting banana production in Gamo Gofa District, Southern Ethiopia.* Engineering and Applied Sciences. Vol. 1, No. 1.

Murthy, K.V.B., 2002. "Arguing a Case for Cobb- Douglas Production Function". Review of Commerce   Studies.   Vol.   20-21,   No.1.   [online]   available   at: http://ssrn.com/abstract=598082

National Bureau of Statistics, 2022*. Population and Housing Census Report,* Tanzania.

Ninh, L.K., 2021. The economic role of education in agriculture: evidence from rural Vietnam. *Journal of   Economics and Development*, *23*(1), pp.47-58.

Ojeleye, A.E., 2021. Profitability assessment of pineapple production in Ejigbo local government area of   Osun state, Nigeria. *Sustainable Development*, *7*(2), pp.1-10.

Ria, B.N., Wiludjeng, R. and Mulyatno, S.B., 2021. Factors affecting agribusiness competitiveness of pineapple (Ananas comosus L. Merr) in Pemalang Regency, Indonesia. *Russian Journal of Agricultural and Socio-Economic Sciences*, *119*(11), pp.160-173.

Shelindina, S., Bahari, B., Rosmawaty, R. and Saediman, H., 2023. Strategy for developing pineapple farming in South Konawe District of Southeast Sulawesi. *International Journal of Research in Engineering, Science and Management*, 6(8), pp.83-88.

Verhulst, N., Govaerts, B., Verachtert, E., Castellanos-Navarrete, A., Mezzalama, M., Wall, P., Deckers, J. and Sayre, K.D., 2010. Conservation agriculture, improving soil quality for sustainable production systems. *Advances in soil science: food security and soil quality*, *1799267585*, pp.137-208.

World Atlas. Top Pineapple Producing Countries. https//www.worldatlas.com. Online Publisher.2025.

Bio-note

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THE ROLES OF ORGANIZATIONAL LEARNING AND EXPLICIT KNOWLEDGE SHARING IN THE RELATIONSHIP BETWEEN TACIT KNOWLEDGE SHARING AND ORGANIZATIONAL INNOVATION CAPABILITY FROM A PUBLIC SECTOR PERSPECTIVE

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Abstract: *Knowledge is a valuable resource with innovation potentials, yet studies have not fully presented how the tacit knowledge sharing affects the innovation capability of an organization, public organizations in particular. Due to this limited understanding, the study aimed to examine how tacit knowledge sharing affects organizational innovation capability, focusing on organizational learning and explicit knowledge sharing as mediators. The study collected cross-sectional data from 178 employees of public hospitals in Asaba, Delta State, Nigeria, using a structured questionnaire. The partial least squares technique was used to analyze the data. The study found that tacit knowledge significant and positive effect on innovation capability was fully and sequentially mediated by organizational learning and explicit knowledge sharing. The study concluded that tacit knowledge sharing is important for innovation, but organizations, especially public service organizations, will yield better outcomes when they cultivate an environment that supports continuous learning to acquire practical insights. The creative tension between different knowledge bases enhances explicit knowledge as well as its sharing, which potentially contributes to improving the capacity to create something new and of public benefit. Practical implications were also discussed to improve the connections among the constructs.*

1. Introduction
The knowledge-driven era calls for the productive use of knowledge to improve and maintain an organization's competitive position with limited resources through innovation. Research on innovation acknowledges the significance of knowledge in creating and delivering value in highly competitive business environments. This knowledge often resides explicitly or tacitly within an organization. Explicit knowledge comprises actionable information expressed in numbers or words, codified in paper and electronic formats, and readily shared without the need for discussion. Tacit knowledge is defined as the subjective understanding and interpretation of information obtained from practical experiences and interactions at

work (Santos and Lopes, 2014; Ondari-Okenwa and Smith, 2009). Public organizations today face numerous, evolving problems that they cannot fully comprehend due to limited explicit information. This necessitates that they extend their focus beyond their explicitly held knowledge to the context-specific knowledge embedded in the minds of employees. Studies (e.g., Polanyi, 2009; Souto, 2013; Chen and Mohamed, 2010) suggest that tacit knowledge can generate unprecedented value or transformative changes that could never be attained by combining explicit knowledge. This makes the sharing of this knowledge crucial for improving organizational capability to innovate.

Innovations happen when people with different knowledge bases interact with each other, especially when the problem context is not clearly defined. Employees possess a repertoire of hidden knowledge, and this knowledge constitutes an underutilized innovation resource in a bureaucratized setting. Public bureaucracy follows strict and complex procedures that prioritize the sharing of explicit knowledge above tacit knowledge (Yeboah, 2023). The high level of hierarchical coordination and formalization could make employees less motivated and impede their participation in some knowledge-based activities. Therefore, the benefits of tacit knowledge in knowledge work may not be fully realized because its share is highly limited and directed (Seidler-de Alwis, Hartmann and Germunden, 2004). Possibly, organizations grounded in public bureaucracy may want their operations to be more predictable, stable, and under control. But with the constantly evolving societal challenges and pressures, they need to leverage knowledge that transcends explicit knowledge to find context-specific knowledge for effective problem-solving. Therefore, the study contends that improving tacit knowledge sharing can improve the innovation capabilities of public organizations.

In knowledge management, organizational learning provides the means for the improvement of shared knowledge via knowledge creation and application. It enables the transformation of individual knowledge into organizational knowledge (Basten and Haamann, 2018). The development of organizational knowledge fosters a better understanding of a problem context for the purpose of maintaining superior performance. Public organizations must quickly learn and adapt, or they simply will not be responsive to the changing public expectations and demands. This shows that organizational learning makes strategic renewal possible. Therefore, organizational learning may require knowledge sharing and its management to impact performance. Reinforcing this statement, research shows that organizational learning mediates the relationship between knowledge sharing and other desirable firm-level outcomes, such as organizational effectiveness (Yang, 2007), organizational innovation (Rao, Yang and Yang, 2018), and employee performance (Meher and Mishra, 2022). Public organizations place more emphasis on using explicit knowledge to guide and support organizational activities.

The study argues that tacit knowledge sharing could improve innovation capabilities by encouraging organizational learning and explicit knowledge sharing sequentially. This is because organizational learning facilitates the development and organization of unstructured knowledge around evolving organizational activities. By ensuring the well-articulated use of relevant knowledge, it instills a learning perspective in knowledge sharing, thereby enhancing the scope for change. The structuring of tacit knowledge improves the quality of explicit knowledge via its transfer and integration. The improvement in specific aspects of explicit knowledge to convey new understanding fosters its sharing for problem-solving. Explicit knowledge sharing may impact organizational effectiveness regarding their capacity for innovation (Zhimin and Choon, 2018; Meher et al., 2021).

Given the above, the mediational value of organizational learning has been tested in private organizations, but there is no single study that has confirmed its relevance to the public sector, particularly within an African country setting. There is also no existing research that connects tacit knowledge sharing, organizational learning, explicit knowledge sharing, and innovation abilities in public organizations in a single framework. Elliott (2022) asserts that it

is important for research to consider whether knowledge sharing and organizational learning influence change in public organizations for the following reasons. First, tacit knowledge forms a significant part of organizational knowledge, but it often goes unnoticed, even though it can advance innovation activities considerably. Usually, tacit knowledge maintains knowledge-based advantages because it possesses context-specific qualities and benefits that are not yet explicit (Ononye, 2023). Furthermore, public organizations face mounting pressures, stemming from the changing societal needs and expectations, to become more effective and efficient in value creation and delivery. This drives the need to learn via reflection and inquiry to develop a better understanding of the way forward. It also reinforces the need for innovation to effectively meet the changing externalities. Therefore, the study aimed to examine how tacit knowledge sharing affects organizational innovation capability, focusing on organizational learning and explicit knowledge sharing as mediators.

2. Literature Review

2.1. Tacit Knowledge Sharing and Innovation Capability
The tacit knowledge-sharing process can be depicted in a saying: "If you have knowledge, let others light their candles in it"—Margaret Fuller. It is the process of engaging in collaborative interactions to exchange context-specific knowledge, skills, and experience among employees. As such, employees are transferring their knowledge to others (i.e., knowledge donating) or consulting others for their know-how (i.e., knowledge collecting) (Yesil et al., 2013). The aim of knowledge sharing is to create a nexus between where knowledge is located and where it can be optimally utilized to attain value (Najla et al., 2017). This guarantees the effective utilization of tacit knowledge. Oneway organizations can leverage their knowledge resources is by improving their innovation capabilities. Innovation capability is the creative ability to transform knowledge into practical solutions that benefit both the organization and the public. By sharing tacit insights with one another, the capacity to define and solve problems is improved, thereby creating an organization prepared to effectively and efficiently meet changing public demands. Several studies (Asbari et al., 2019; Ononye and Igwe, 2019; Kucharska and Erickson, 2023) have provided evidence of the positive and significant effect of tacit knowledge sharing on innovation capability. Therefore, the first hypothesis was proposed:
H_1: Tacit knowledge sharing is significantly and positively related to innovation capability.

2.2. Organizational Learning and Innovation Capability
Organizational learning is a dynamic ability that fosters the coordinated use of knowledge through the process of sharing, creating, and integrating knowledge related to a given problem context for better organizational action and performance. The aim is to increase the value of organizational knowledge by facilitating the effective development and management of knowledge. The change in organizational knowledge develops an organizational ability to adapt to change. Furthermore, it offers insights that innovation processes can utilize to produce outcomes that are valuable and in line with evolving environmental conditions. Organizational learning and innovation capability are inextricably linked to cultivating new ways of managing change based on knowledge acquired from practical experiences and interactions. The creation of new knowledge through learning increases the capacity to understand and apply this knowledge for value creation. Empirical studies (Abdi et al., 2018; Rao et al., 2018; Asbari et al., 2019) show that organizational learning enhances innovation capability. Therefore, the study formulated the second hypothesis.
H_2: Organizational learning is significantly and positively related to innovation capability.

2.3. Tacit Knowledge Sharing and Organizational learning

Knowledge sharing among employees enables organizations to learn something new and make sense of a given situation via its application. It is important to keep in mind that learning emerges from collaborative and constructive interactions among employees (Ononye, 2022). Ample research (Yang, 2007; Liao & Wu, 2010; Abdi et al., 2018; Rao et al., 2018; Meher and Mishra, 2020) shows that knowledge sharing increases organizational learning. Therefore, the third hypothesis was suggested.

H_3: Tacit knowledge sharing is significantly and positively related to organizational learning.

2.4. Tacit Knowledge Sharing, Organizational Learning, and Innovation Capability

The contextual utility of organizational learning is important in redefining or extending the practicality of tacit knowledge to support value creation in dynamic environments. Learning occurs through the dynamic interplay of shared knowledge, perceptions, and experiences. The insights gained from critical reflection and inquiry have the potential to be integrated and applied to accelerate innovative work. Studies (Liao and Wu, 2010; Abdi et al., 2018; Rao et al., 2018; Asbari et al., 2019) show that knowledge sharing enhances organizational learning to improve innovation. Although their focus was on general knowledge sharing within the knowledge management framework, this study examined the sharing of tacit knowledge. Consequently, the fourth hypothesis was put forward.

H_4: The significant and positive relationship between tacit knowledge sharing and innovation capability is mediated by organizational learning.

2.5. The Mediation of Organizational Learning and Explicit Knowledge Sharing

The objective of organizational learning based on the dynamic view of knowledge is to convert tacit knowledge into explicit knowledge and to retain this converted knowledge in organizational memory for access and use by others. Empirical research (e.g., Rao et al., 2018; Meher and Mishra, 2020) has shown that knowledge sharing enhances organizational learning. It has also revealed that organizational learning promotes knowledge sharing to influence firm-level capabilities (Meher et al., 2021). Asbari et al. (2019) found that both tacit and explicit knowledge sharing influence organizational learning to improve employees' innovation potentials. This study did not show how the knowledge-sharing mechanisms interact to influence innovation capabilities at the individual level. Nonaka and Takeuchi (1995) propose that the sharing of tacit knowledge triggers its codification. More so, organizational learning helps in this codification process, as it seeks to synthesize tacit knowledge explicitly for knowledge retention and use. This means that tacit knowledge sharing may directly or indirectly affect explicit knowledge sharing through organizational learning. Nevertheless, there is limited empirical information on the specific knowledge-sharing mechanism that influences and is influenced by organizational learning.

The study pointed out that organizational learning's ability to continuously improve organizational knowledge through the interplay of individual knowledge bases enhances innovation capabilities. This is especially true when the articulated individual knowledge is associated with creativity and discovery. According to the knowledge-based theory, knowledge is a valuable strategic asset that provides an edge to organizations operating in environments marked by high uncertainty and complexity. Organizations often encourage the sharing of this knowledge in both tacit and explicit forms, necessitating its complementary use to maintain superior performance. However, an organizational system that limits the use of any knowledge dimension may impede effective performance, as they have the roles that they play in enhancing it. For this reason, tacit knowledge sharing should occur within a formal learning process to ensure that it becomes embedded in an organizational knowledge system. The stimulation of organizational learning allows for the careful articulation of knowledge and the effectuation of change to existing knowledge. We anticipate that refining and sharing explicit knowledge will significantly enhance innovation

capability. This relational sequence ensures tacit knowledge is utilized and explicit knowledge is enriched for innovation activities. The sequential mediation argument is presented as follows.

H_5: Explicit knowledge sharing is significantly and positively related to innovation capability.

H_6: Organizational learning is significantly and positively related to explicit knowledge sharing.

H_7: The significant and positive relationship between tacit knowledge sharing and innovation capability is sequentially mediated by organizational learning and explicit knowledge sharing.
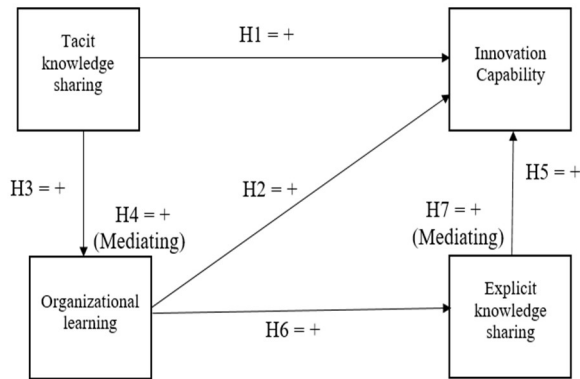
Figure 1: Research Framework
Source: Author's Own (2024)

3. Methodology

3.1. Sample and Data Collection Procedure

This study conducted a cross-sectional survey by obtaining data from employees in the public hospitals in Asaba, Delta State, Nigeria. When selecting the sample frame for research of this nature, it is apt to choose organizations that are close to and have ongoing interactions with customers because they are likely sites for innovations. Additionally, it is necessary to include participants from knowledge-intensive organizations because they leverage knowledge to manage different and evolving health challenges. Therefore, knowledge-based activities, such as knowledge sharing, learning, and innovation, may be observable in this setting. A questionnaire based on related studies provided the data for analysis. Given the busy work schedule and limited manpower in the target organizations, the convenient sampling was adopted to select participants who had time to participate in the survey.

The researcher requested the respondents go through the cover letter and read their rights as participants, which included anonymity of response, freedom to exit the survey at any time, and the right to see the results upon request. Before fully administering the questionnaire, the researcher sought consent for voluntary participation. The questionnaire was self-administered and retrieved from November 2024. We received 181 returned questionnaires, with 3 deemed unusable due to missing values. The demographic characteristics of the respondents showed that 112 were males and 66 were females with a mean age and tenure of 39.5 and 15.5 years, respectively. The respondents had at least a graduate degree qualification. The professional background of the respondents revealed

that 63 were medical doctors, 77 were nurses, 4 were medical laboratory scientists, 2 were pharmacists, and 32 were in allied health fields.

3.2. Measures

The measurement items were taken from the validated scales of previous investigations and were assessed using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The eight questions for tacit knowledge sharing (4 items) and explicit knowledge sharing (4 items) were taken from Wang and Wang (2012). A sample item for tacit knowledge sharing is, "I interact with people in my organization to create a shared or common understanding of a problem." A sample question for explicit knowledge sharing is, "People in my organization often share existing reports and official documents with members of my organization." Thomas et al. (2017) provided the four measures for organizational learning. A sample item is, "There is free, open, and constructive communication in my organization." Grawe, Chen and Daugherty (2009) provided the four measures for innovation capability. One of the sample measures is, "My organization often evaluates and uses ideas that arise from stakeholders' interactions to develop itself."

The questionnaire was pre-tested before its full application to ascertain the ability of scales to capture consistent and desired information. Two management professors and three directors from the target organization ensured the face validity of the questionnaire. Fifteen participants were approached using convenient sampling to complete the questionnaire for the purpose of ascertaining the construct reliability. The results of the Cronbach's alpha test, analyzed using SPSS 20.0 software, showed the following scores: tacit knowledge sharing was 0.897, explicit knowledge sharing was 0.721, organizational learning was 0.836, and innovation quality was 0.880. These scores suggest that the internal consistency among the constructs was acceptable.

3.3. Data Analysis

This study selected the partial least square (PLS) path modeling as the analytical method for hypothesis testing. This approach to structural equation modeling aims to elucidate variance and predict relationships among constructs, especially when there are mediators. It also does not impose any stringent data assumptions and makes use of small sample sizes to achieve stable estimations. This study adhered to the two-step estimation procedure to explain the psychometric properties of the measurement model and simultaneously assess the parameters of the structural model for causal relationships (Yesil et al., 2013). This procedure ensured the constructs' reliability and validity prior to establishing the linkages among the constructs. The analysis was performed using SmartPLS 4 software. The PLS guidelines suggested in Hair et al. (2022) were applied for data interpretation.

4. Results

Following the procedure previously described in the methodology, the data analysis began with the evaluation of the measurement model. A confirmatory factor analysis was done to find out how tacit knowledge sharing, explicit knowledge sharing, organizational learning, and innovation capability are related to each other and to their specific indicators. This study conducted a preliminary test using SPSS 20 software to assess the data's suitability for factor analysis. This test included the Kaiser-Meyer-Olkin Measure (KMO) and Bartlett's test for sphericity (BTS). Tacit knowledge sharing, explicit knowledge sharing, organizational learning, and innovation capability had KMO scores of 0.663, 0.638, 0.760, and 0.705, respectively. These scores exceeded the permissible limit of 0.60, suggesting the adequacy of the sample for factor analysis. Furthermore, their BTS scores were all statistically significant at $p < 0.05$, suggesting that the distribution of the multivariate data is normal and

acceptable for factor analysis. Given the KMO and BTS results, the data was considered factorable, allowing for confirmatory factor analysis.

Table 1: Measurement Model Estimations

Latent Constructs		FL	T-Stat	CR	AVE	VIF
Tacit Knowledge Sharing				0.836	0.651	1.089
1	People in my organization often share their experience, skills, or insights with me when I ask them to.	0.884	75.103			
2	I share my experience, skills, or insights with people in my organization when they ask for it.	0.884	68.116			
3	People in my organization will share lessons from past failures when they feel necessary.	0.917	90.415			
4	I interact with people in my organization to create a shared or common understanding of a problem.	0.862	53.883			
Explicit Knowledge Sharing				0.823	0.685	1.301
6	People in my organization often share existing reports and official documents with members of my organization.	0.861	55.546			
7	People in my organization often share reports and official documents that they prepare by themselves with members of my organization.	0.848	54.291			
8	People in my organization often collect reports and official documents from others in their work.	0.871	61.969			
9	People in my organization are facilitated by IT systems invested for knowledge sharing.	0.887	68.864			

Note: FL = Factor loading, CR = Composite reliability, AVE = Average variance extracted, VIF = Variance inflation factor, $p < 0.05$

Source: Researcher's PLS Computation output (2024).

Table 2: Measurement Model Estimations Cont'd.

Latent Constructs		FL	T-Stat	CR	AVE	VIF
Organizational Learning				0.796	0.624	1.272
10	My organization encourages and supports creativity and innovation.	0.845	61.113			
11	People in my organization are known for taking risks in the development of new practices, processes, and/or products.	0.837	51.972			

12	We interact with our external environment to collect, disseminate, and use crucial information.	0.813	40.115			
13	There is free, open, and constructive communication in my organization.	0.770	22.250			
Innovation Capability				0.879	0.708	
14	We constantly seek new ways to develop organizational practices, processes, and products	0.747	19.161			
15	Our organization is able to change current practices, processes, and services to adapt to changes in the external environment.	0.717	18.594			
16	Our organization is quick to develop and integrate new ideas into practices, processes, and services.	0.781	25.688			
17	My organization often evaluates and uses ideas that arise from stakeholders' interactions to develop itself.	0.761	23.981			

Note: FL = Factor loading, CR = Composite reliability, AVE = Average variance extracted, VIF = Variance inflation factor, $p < 0.05$

Source: Researcher's PLS Computation output (2024).

Table 1 and 2 presents the results of the measurement model. The factor loadings of the indicators vary from 0.717 to 0.917, which is above the acceptable level of 0.707 for adequate item reliability. Therefore, the indicators related well with the respective latent constructs. Furthermore, the t-values of the indicators revealed that all of them were statistically significant to their respective constructs, as they (t-statistics) exceeded 1.96 (t-table) at a confidence level of 95%. Therefore, the indicators had practical importance to their underlying constructs. The composite reliability scores were above the recommended limit of 0.70 for attaining adequate construct reliability. Satisfactory convergent validity was attained, as the average variance extracted values were above 0.50. This indicates that the constructs' own indicators can explain at least 50% of their variability. The variance inflation factor is a test for multicollinearity. The results show that the values were not above 5.0, which suggests the absence of a significant multicollinearity problem due to highly correlated constructs.

Table 3: Fornell-Larcker criterion

Latent Constructs	Discriminant Validity			
	1	2	3	4
1. Explicit knowledge sharing	**0.772**			
2. Innovation capability	0.136	**0.783**		
3. Organizational learning	0.293	0.285	**0.745**	
4. Tacit knowledge sharing	0.170	0.226	0.301	**0.756**

Source: Researcher's PLS Computation output (2024).

Table 3 presents the discriminant validity results using the Fornell-Larcker criterion. The results show that the correlations of each construct (the diagonal scores) were greater than their inter-construct correlations (the off-diagonal scores). Thus, the constructs were unrelated to each other. The results from the measurement model in Tables 1 and 2 showed acceptable scores, meeting the quality criteria for validity and reliability. Therefore, the statistical inferences made can be considered reliable and valid.

Table 4: Structural Model Results

Paths	β (*p*-value) Model 1	β (*p*-value) Model 2	β (*p*-value) Model 3	Remark
1. TKS→IC	0.107 (0.048)	0.105 (0.067)	0.105 (0.067)	Accept
2. OL →IC	0.434 (0.000)	0.434 (0.000)	0.434 (0.000)	Accept
3. TKS→OL		0.283 (0.000)	0.283 (0.000)	Accept
4. TKS→ OL →IC		0.103 (0.014)	0.102 (0.039)	Accept
5. EKS →IC			0.227 (0.000)	Accept
6. OL →EKS			0.250 (0.000)	Accept
7. TKS→ OL →EKS →IC			0.097 (0.038)	Accept
R^2	0.432	0.494	0.506	Moderate
SRMR	0.075	0.073	0.070	Good fit

Note. TKS = Tacit knowledge sharing; OL = Organizational learnng; IC = Innovation capability; EKS = Explicit knowledge sharing; *p < 0.05*
Source: Researcher's PLS Computation output (2024).

Table 4 shows the structural model results based on the path coefficients and p-values. The study applied the bootstrapping technique using 5000 subsamples to determine the significance of the path coefficients. The PLS results showed that both tacit knowledge sharing (β = 0.107, $p < 0.05$) and organizational learning (β = 0.434, $p < 0.05$) were significantly and positively related to innovation capability, which supports H_1 and H_2. Furthermore, tacit knowledge sharing was found to be positively and significantly related to organizational learning (β = 0.283, $p < 0.05$), lending support to H_3. The role of organizational learning as a mediator was examined, and the results showed that it significantly and positively mediated the relationship between tacit knowledge sharing and innovation capability (β = 0.103, $p < 0.05$), which validates H_4. The mediation type was deemed to be full because the relationship between tacit knowledge sharing and innovation capability became insignificant (β = 0.105, $p > 0.05$). The model incorporated explicit knowledge sharing to determine the causal sequence by which tacit knowledge sharing affects innovation capability through multiple intervening factors. In this sequential mediation framework, organizational learning acts as a precursor of explicit knowledge sharing. The results indicated that explicit knowledge sharing had a significant and positive relationship with organizational learning (β = 0.250, $p < 0.05$) and innovation capability (β = 0.227, $p < 0.05$), validating the acceptance of H_5 and H_6. The sequential mediation estimates (β = 0.097, $p < 0.05$) demonstrated support for H_7, which states that the significant and positive relationship between tacit knowledge sharing and innovation capability is sequentially mediated by organizational learning and explicit knowledge sharing.
The predictive quality of the model was assessed based on the R^2 and standardized root mean squared residual (SRMR). The R^2 result showed that the link between tacit knowledge sharing, organizational learning, and explicit knowledge sharing accounted for 50.6% of the changes in innovation capability, suggesting a moderate explanatory power (Chin, Peterson and Brown, 2008). The introduction of a mediating pathways improved the predictive power

of tacit knowledge sharing on innovation by 0.062 points in model 2. This was improved further by 0.012 points in model 3. The SRMR assesses the model fitness, with values below 0.08 denoting a good fit. An SRMR value of 0.065 indicates that the model fit is satisfactory.

4. Discussion

The study found tacit knowledge sharing enhances the innovation capability of these public organizations. This finding agrees with earlier research that reported a positive and significant association between both concepts. Because the problem context facing these organizations could be evolving in an unpredictable manner, personal experiences, observations, and insights as one interacts in the workplace may prove useful in generating practical solutions. It is important that organizations incorporate tacit knowledge to improve their capabilities for solving problems that are not yet comprehensively understood or explicitly defined. Some public organizations do provide opportunities for the sharing of tacit insight for collective and effective action. This often occurs through certain socialization processes, such as meetings, face-to-face discussions, public forums, training, seminars, conferences, and workshops (Ononye, 2022). However, for shared tacit knowledge to generate more value, organizations should set up learning mechanisms to acquire, integrate, and retain this knowledge in organizational memory for use by others in the future. This is important for organizations that prioritize the use of explicit knowledge to facilitate innovative work. By making unknown (or hidden) knowledge known, they can achieve some form of stability, predictability, and control. The study found that the innovation benefit or potential of tacit knowledge sharing is fully activated when organizational learning is taking place. This finding aligns with previous research (Liao and Wu, 2010; Abdi et al., 2018; Rao et al., 2018; Asbari et al., 2019) that found knowledge sharing enhances organizational learning to improve innovation. It equally extends this research by focusing on the share of a specific dimension of knowledge—tacit knowledge.

The research also found that explicit knowledge sharing and organizational learning mediated the link between tacit knowledge sharing and innovation capability. Previous research (e.g., Rao et al., 2018; Asbari et al., 2019; Meher & Mishra, 2022; Meher et al., 2022) has shown that there is a significant and positive relationship among the constructs, but no study has demonstrated the relational sequence in a sequential mediation framework. This represents an original contribution to existing knowledge. These organizations significantly benefit from tacit knowledge sharing when they articulate and codify relevant and useful tacit particulars through learning. Tacit knowledge sharing should be situated within a formal learning context to foster its retention, transfer, and application. By codifying the tacit insights that come with discovery and creativity, these organizations are better able to come up with new ways to meet changing needs and expectations of the public. In this organizational setting, tacit knowledge sharing enriches the explicit knowledge shared among employees for problem-solving. Based on the arguments in the knowledge-based theory, this makes sure that knowledge is used in the best way possible to gain innovation and performance advantages in environments that are always changing and becoming more complex.

5. Conclusion, Recommendations, and Areas for Further Research

This study examined tacit knowledge sharing's direct and indirect relationships with innovation capability, focusing on organizational learning and explicit knowledge sharing as mediating factors in a sequential framework. The study collected cross-sectional data from 178 employees of public hospitals in Asaba, Delta State, Nigeria, using a structured questionnaire. The partial least squares technique was used to analyze the data. The study found that tacit knowledge sharing is significantly and positively related to innovation capability. However, organizational learning and explicit knowledge sharing fully and sequentially mediate this relationship. In conclusion, tacit knowledge sharing is important for

innovation, but organizations, especially those rooted in public bureaucracy, will benefit more when they create an environment that encourages continuous learning. The acquisition of practical insights from the creative tension of individual knowledge bases enhances explicit knowledge. The sharing of this explicit knowledge conveys a new understanding, which improves organizational capacity to come up with something new and of public value.

The study recommends that public organizations can enhance innovation capability by leveraging the tacit knowledge of employees via its sharing. However, to optimize the use of this valuable knowledge resource, they need to activate organizational learning processes to facilitate the codification, transfer, retention, and application of tacit knowledge. This integration can improve explicit knowledge sharing, as explicit knowledge evolves to support new and expansive thinking patterns for effective action. The centrality of organizational learning and explicit knowledge sharing is crucial because this organization utilizes structured knowledge to get things done. Thus, their development can help in the structuring of tacit knowledge for use across the organization.

Future research may extend the applicability of this study to other public service organizations, as the study concentrated on public hospitals. Studies should also expand the geographic regions to improve the generality of the results. Although the use of convenient sampling may be justified due to the tight work schedule of employees in public hospitals, it is important to extend this research for more reliable and representative insights. The study observed that the framework comprising tacit knowledge sharing, organizational learning, and explicit knowledge sharing moderately explained the variations in innovation capability. This means that there are other factors not included in this study that could improve its predictive power. It would be worthwhile for future research to identify and evaluate these factors. In this context, we should take into account the concept of knowledge management and its related activities. The study made use of cross-sectional data, which can be flawed with the issue of common method bias; future studies can examine the causality better when they make use of longitudinal data.

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References

Abdi, K., Mardani, A., Senin, A. A., Tupenaite, L., Naimaviciene, J., Kanapeckiene, L., and Kutut, V., 2018. The effect of knowledge management, organizational culture and organizational learning on innovation in automotive industry. *Journal of Business Economics and Management*, 19(1), pp. 1–19.

Asbari, M., Wijayanti, L. M., Hyun, C. C., Purwanto, A., and Santoso, P. B., 2019. Effect of tacit and explicit knowledge sharing on teacher innovation capability. *Dinamika Pendidikan*, 14(2), pp. 47–59.

Basten, D., and Haamann, T., 2018. Approaches for Organizational Learning: A Literature Review. *Sage Open*, 8(3). https://doi.org/10.1177/2158244018794224

Chen, L., and Mohamed, S., 2010. The strategic importance of tacit knowledge management activities in construction. *Construction Innovation,* 10(2), pp. 138–163.

Chin, W. W., Peterson, R. A., and Brown, S. P., 2008. Structural equation modeling in marketing: Some practical reminders. *Journal of Marketing Theory and Practice*, 16, 287-298.

Elliot, I. C., 2020. Organizational learning and change in a public sector context. *Teaching Public Administration*, 38(3), pp. 270–283.

Grawe, J. S., Chen, H., and Daugherty, J. P., 2009. The relationship between strategic orientation, service innovation, and performance. *International Journal of Physical Distribution & Logistics Management*, 39(4), pp. 282–300.

Hair, J. F., Hult, M. T. G., Ringle, M. C., Sarstedt, M., Danks, P. N., and Ray, S., 2021. *Partial least squares structural equation modeling (PLS-SEM) using R*. Springer.

Kucharska, W., and Erickson, G. S., 2023. Tacit knowledge acquisition and sharing, and its influence on innovations: A Polish/US cross-country study. *International Journal of Information Management*, 71, 102647. https://doi.org/10.1016/j.ijinfomgt.2023.102647

Liao, S-H., and Wu, C-c., 2010. System perspective of knowledge management, organizational learning, and organizational innovation. *Expert Systems with Applications*, 37(2), pp. 1096–1103.

Meher, J. R., and Mishra, R. K., 2022. Examining the role of knowledge sharing on employee performance with a mediating effect of organizational learning. *VINE Journal of Information and Knowledge Management Systems*, 52(2), pp. 205–223.

Meher, J. R., Nayak, L., Mishra, K. R., and Patel, G., 2021. Impact of organizational learning culture on organizational effectiveness: A serial mediation analysis with knowledge sharing and employee competencies. *Vine Journal of Information and Knowledge Management Systems*, 54(2), pp. 324-338.

Najla, P., Filipovic, D., and Kovac, M., 2017. Knowledge sharing and firm innovation capability in Croatian ICT companies. *International Journal of Manpower*, *38*(4), pp. 632–644.

Nonaka, I., and Takeuchi, K., 1995. *The Knowledge Creating Company*. New York: Oxford University Press.

Ondari-Okenwa, E., and Smith, G. J., 2009. The role of knowledge management in enhancing government service-delivery in Kenya. *South African Journal of Libraries and Information Science*, 75(1), pp. 28–39.

Ononye, U., 2023. Perceived organizational support and organizational trust link to innovative work behavior by the mediation of tacit knowledge sharing. *International Journal of Business and Society*, 24(3), pp. 952–966.

Ononye, U., 2022. Linking tacit knowledge sharing to employee innovation with job thriving as a mediational factor: A public sector perspective. *International Journal of Public Policy and Administration*, 9(2), pp. 22–32.

Ononye, U. H., and Igwe, A., 2019. Knowledge sharing process and innovation success: Evidence from public organizations in Southern Nigeria. *Interdisciplinary Journal of Information, Knowledge, Management*, 14, pp. 183–198.

Podsakoff, P. M., MacKenzie, S. B., and Podsakoff, N. P., 2012. Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63(1), pp. 539–569.

Polanyi, M., 2009. *The tacit dimension.* Chicago: University of Chicago Press.

Rao, Y., Yang, M., and Yang, Y., 2018. Knowledge Sharing, organizational learning and service innovation in Tourism. *Journal of Service Science and Management*, 11, pp. 510–526.

Santos, D. F., and Lopes, T. I., 2014. The linkage between tacit knowledge and models of innovation. In Galbraith, B. (Ed.), *Innovation and Entrepreneurship* (pp. 556–564). Reading: Academic Conferences and Publishing International Limited.

Seidler-de Alwis, R., Hartmann, E., and Gemunden, G. H., 2004. The role of tacit knowledge in innovation management. Paper presented at the *20th Annual IMP Conference,* 2-4 September, Copenhagen. [online] Available at www.impgroup.org/uploads/papers/4585.pdf [accessed on 15.08.2024]

Souto, P. C. N., 2013. Using the tacit dimension of knowledge in creating knowledge for innovation: Implications for tacit knowledge communication. *Int. J. Technological Learning, Innovation and Development,* 6(4), pp. 303–354.

Thomas, A., Dorrington, P., Costa, F., Loudon, G., Francis, M., and Fisher, R., 2017. Organisational learning capability in SMEs: An empirical development of innovation in the supply chain. *Cogent Business & Management*, 4(1), 1364057. https://doi.org/10.1080/23311975.2017.1364057

Wang, Z., and Wang, N., 2012. Knowledge sharing, innovation and firm performance. *Expert Systems with Applications*, 39, pp.8899–8908.

Yang, J., 2007. The impact of knowledge sharing on organizational learning and effectiveness. *Journal of Knowledge Management,* 11(2), pp. 83–90.

Yeboah, A., 2023. Knowledge sharing in organization: A systematic review. *Cogent Business & Management*, 10(1). 2195027. https://doi.org/10.1080/23311975.2023.2195027

Yesil, S., Koska, A., and Buyukbese, T., 2013. Knowledge sharing process, innovation capability and innovation performance: An empirical study. *Procedia Social and Behavioural Sciences*, 75, pp. 217–225.

Zhimin, W., and Choon, L. K., 2018. The Mediation Role of Knowledge Sharing Between Organizational Learning and Technological Innovation Practice. *International Journal of Knowledge Management*, 14(3), pp. 48–68.

Bio-note

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CHALLENGES OF ARTIFICIAL INTELLIGENCE FOR KNOWLEDGE MANAGEMENT SYSTEMS: A BIBLIOMETRIC ANALYSIS PERSPECTIVE

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Abstract: *This paper explores the opportunities and challenges associated with integrating artificial intelligence (AI) into knowledge management systems (KMS), by using a bibliometric analysis. The rapid advancement of AI technologies, particularly generative models, has opened new avenues for enhancing KMS theories and practices. The study examines publication trends, key contributors, predominant research themes, and the practical applications of AI in KMS, with a specific focus on how these technologies can transform knowledge creation, sharing, and dissemination. The study draws on data from the Scopus database, revealing the significant impact of AI on KMS practices, particularly its capacity to enhance knowledge transfer, support decision-making processes, and foster organizational learning. However, the study also identifies several challenges, including ethical concerns, the interpretability of AI-driven tools, and the scalability of AI methods. The analysis underscores the need for further research in addressing these challenges and exploring the full potential of AI to fill knowledge gaps and create new knowledge artefacts. This paper provides valuable insights for scholars, practitioners, and organizations looking to harness AI for improving KMS theories and practices, offering a systematic analysis for future research on the evolving intersection of AI and KMS.*

Keywords: knowledge management systems, artificial intelligence, deep learning, large language models, bibliometric analysis.

JEL classification:
D83, O32, O33, C88, L86, M15, J24

1. Introduction

The rapid evolution of Artificial Intelligence (AI) has brought transformative changes across various organizational domains, particularly in Knowledge Management (KM). Traditionally, KM has centered on systematically identifying, creating, capturing, organizing, storing, sharing, and effectively utilizing knowledge and information within an organization or community. However, the advent of generative AI technologies, encompassing machine learning, natural language processing (NLP), and advanced data mining, is opening new possibilities for automating knowledge-intensive tasks, enhancing analytical capabilities, and optimizing decision-making processes (Taherdoost and Madanchian, 2023). These advancements are not only reshaping conventional KM practices but are also driving

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broader innovation across sectors such as education, where AI is unlocking unprecedented opportunities (Rahman et al., 2024; Farrokhnia et al., 2023; Górriz et al., 2020).

The integration of generative AI into KM practices has the potential to revolutionize the management of both explicit and tacit knowledge within organizations. Explicit knowledge, easily codified and shared, aligns well with traditional knowledge management systems (KMS). However, tacit knowledge—rooted in personal experience and inherently challenging to articulate—has long posed a significant hurdle. Generative AI's capability to process vast amounts of unstructured data provides promising avenues for addressing this challenge, rendering tacit knowledge more accessible and actionable (Papagiannidis et al., 2023). This shift underscores the transformative potential of AI-driven systems in enhancing KM processes, facilitating improved knowledge sharing and organizational learning (Bratianu et al., 2011), and fostering innovation across organizational contexts (Harfouche et al., 2023).

Despite these advancements, several significant gaps remain, particularly in the integration of AI across all facets of KM. One critical gap is the development of comprehensive frameworks that fully incorporate generative AI (GenAI) into KMS. While existing research has focused on the application of AI to specific KM tasks, there is a lack of studies examining the integration of AI in KMS from a bibliometric analysis perspective. This gap highlights the need for a more systematic investigation into how AI technologies interact with and enhance different aspects of KMS. Additionally, the ethical considerations surrounding AI's integration into KMS are underexplored. As AI technologies continue to advance, there is an urgent need for research addressing the ethical challenges they pose, ensuring that the benefits of AI are maximized while mitigating potential risks, such as biases, privacy concerns, and unintended consequences (Harfouche et al., 2023). This points to a need for frameworks that not only optimize AI integration but also incorporate ethical considerations to maintain organizational integrity and trust. For the present research, we formulate the following research question (RQ):

RQ: What are the key challenges and emerging trends in the integration of Artificial Intelligence (AI) into Knowledge Management Systems (KMS) based on the scholarly research landscape over the past decade?

2. Literature review

The rapid evolution of artificial intelligence (AI) technologies, particularly generative models (GenAI), graph neural networks, and deep learning, has significantly influenced the knowledge management (KM) domain. The integration of AI into KM marks a transformative step in how organizations handle knowledge. While AI brings notable advantages in automating and improving KM processes, further research is required to address challenges such as managing tacit knowledge, artificial knowledge (Nakash & Bolisani, 2024), and navigating ethical concerns. As organizations increasingly implement AI-powered KM systems, it becomes essential to balance AI's technical capabilities with the human-centric aspects of KM to fully harness these technologies' potential.

The relationship between AI and KM is becoming more synergistic, with AI providing robust tools to enhance KM practices across multiple sectors. KM, which traditionally focuses on capturing, organizing, and sharing knowledge to foster better decision-making, innovation, and efficiency, is being transformed by AI integration. These technologies not only automate KM processes but also elevate their sophistication, enabling advanced knowledge discovery, personalization, and decision-support capabilities.

2.1. Definitions and key concepts

Knowledge Management (KM) is a structured approach to capturing, sharing, and utilizing knowledge within organizations to enhance learning, innovation, and decision-making

(Dalkir, 2023). It involves managing both explicit knowledge, which is formalized and easily shared, and tacit knowledge, which is deeply rooted in individual experiences and challenging to articulate (Harfouche et al., 2023). Effective management of both knowledge types is essential for organizations to remain agile, adapt to environmental changes, and sustain a competitive advantage. According to Bratianu (2022), KM is a process that encompasses the creation, acquisition, sharing, transfer, and utilization of knowledge within organizations. Expanding on this, Bratianu and Bejinaru (2020, 2023) emphasize the nonlinear and multidimensional nature of knowledge, considering its rational, emotional, and spiritual dimensions, as well as its transformative potential. They introduce the concept of knowledge fields, inspired by thermodynamics, to explain how knowledge flows and influences organizational processes, underscoring its role in driving innovation and achieving strategic goals.

A Knowledge Management System (KMS) is the framework that supports this process by integrating technology, people, processes, and organizational context. It enables the efficient creation, sharing, and application of knowledge through technological tools such as knowledge repositories, collaboration platforms, and expert catalogues. The system is dependent on the human resources involved, who carry out KM activities and contribute to organizational learning. The organizational context, including culture, structure, and management style, further influences how the system is designed and functions. As organizations rely on KMS for sustained innovation and competitiveness, aligning it with the organization's knowledge management strategy and adapting it to both internal and external environments is crucial for ensuring its effectiveness (Ben Chouikha Zouari & Dakhli, 2018).

Artificial Intelligence (AI) represents a generic concept for a large variety of software programs that imitate the cognitive functions of human intelligence. They range from learning and decision-making to playing chess or go (Baker, 2025; Russell & Norvig, 2022). AI is based on sophisticated algorithms using deterministic thinking like in the first stage of its development, or probabilistic thinking like in the new deep learning programs. A subfield of AI that has exploded in the last few years is represented by Generative AI (GenAI). GenAI is a specialized branch of artificial intelligence that leverages advanced natural language processing (NLP), neural networks, and machine learning (ML) models to create original, human-like content. It falls under the category of Large Language Models (LLMs), which process vast datasets across multiple domains, including human languages, programming code, mathematical expressions, and images (Baker, 2025, p. 8). One of the most known products of GenAI is ChatGPT, in a spectrum of applications.

Deep learning refers to the process of learning from an initial huge data set using many layers of neural networks. Deep learning is the most used technology for complex applications like visual objects recognition, machine translation, speech synthesis, and image synthesis (Russell & Norvig, 2022). It is important to underline that GenAI and LLMs are not capable of human thought; instead, they function by making predictions. While the prediction process is highly complex, it remains fundamentally a form of prediction (Baker, 2025, p. 8).

2.2. AI techniques and emerging themes in KMS

The integration of AI into KMS represents a paradigm shift in how organizations manage and leverage knowledge. By automating complex processes, AI techniques can enhance knowledge discovery, personalization, and collaboration within knowledge networks. However, alongside these advancements, challenges emerge related to scalability, adaptability, and transparency, making it essential to align AI solutions with organizational needs and human-centric KM practices. Exploring these techniques and addressing their limitations is crucial to ensure sustainable and ethical AI-driven KMS development (Baker, 2025; Floridi, 2023).

Wu et al. (2021) highlight the role of Graph Neural Networks (GNNs) in mapping knowledge networks, enabling organizations to visualize and optimize knowledge-sharing pathways. However, a key challenge in AI-KMS integration is the effective management of relational knowledge structures, especially in large, dynamic organizations where knowledge networks frequently evolve. GNNs require extensive data preparation and network maintenance, which poses scalability challenges when applied to rapidly changing knowledge environments.

The concept of Explainable AI (XAI), explored by Barredo Arrieta et al. (2020) and Adadi and Berrada (2018), emphasizes the importance of transparency and interpretability in AI-driven KMS. While AI can significantly automate KM processes, many AI models operate as black boxes (Adadi & Berrada, 2018), making it difficult for organizations to trust the insights generated. This lack of transparency can hinder the adoption of AI-based KM tools, particularly in industries where accountability and ethical concerns are paramount (Floridi, 2023). Thus, one of the primary challenges is developing AI systems that deliver understandable, actionable insights while maintaining high performance.

Transfer learning, discussed by Weiss et al. (2016), addresses the challenge of cross-domain knowledge transfer, a critical component of KMS. AI-driven KMS must adapt knowledge to new organizational contexts, but this requires models to efficiently reuse and adapt existing knowledge without retraining from scratch. The challenge lies in applying transfer learning techniques to heterogeneous datasets in a way that preserves knowledge accuracy while reducing the costs and time associated with model retraining. KMS should be able to integrate human knowledge and artificial knowledge into complex organizational learning processes and decision-making.

Alzubaidi et al. (2021) and Khan et al. (2020) discuss deep learning architectures and processes that handle unstructured data such as text, audio, and video. While these technologies are essential for managing the growing volume of unstructured organizational knowledge, they also pose challenges in terms of data processing and categorization. AI-based KMS must be able to automatically classify, sort, and retrieve relevant knowledge from large repositories. The difficulty in ensuring that AI tools can accurately interpret and categorize diverse forms of knowledge presents a significant challenge.

Sentiment analysis, as described by Taboada et al. (2011), introduces the theme of feedback-driven KM strategies, allowing organizations to extract valuable insights from employee and customer feedback. However, the challenge lies in ensuring that sentiment analysis tools account for context and nuance in textual data, which can vary across cultures and languages. Although sentiment analysis uses rational knowledge, it suggests how emotional and spiritual knowledge influence decision-making and consumer behaviour (Bratianu & Bejinaru, 2020; Hill, 2008). Similarly, text summarization and semantic analysis techniques, discussed by Erkan and Radev (2004) and Turney and Pantel (2010), improve knowledge accessibility by summarizing extensive data repositories. The challenge here is developing AI tools that can accurately summarize knowledge while retaining essential contextual information.

Link prediction methods, proposed by Liben-Nowell and Kleinberg (2007), focus on identifying potential collaborations within knowledge networks. In KMS, these methods can help organizations foster innovation by connecting individuals with complementary expertise. However, the challenge lies in ensuring that link prediction techniques remain relevant in dynamic organizational contexts where relationships and knowledge flows are constantly changing.

Finally, generative AI models hold significant potential for creating artificial knowledge and filling knowledge gaps within KMS. These models can simulate decision-making scenarios and generate insights based on integrating human knowledge with artificial knowledge. However, the ethical challenges surrounding generative AI—including data privacy, algorithmic bias, and transparency—remain underexplored in the KM context. Additionally,

ensuring that generative models produce reliable and accurate knowledge outputs is a significant challenge.

The following table (Table 1) illustrates how different AI techniques contribute to KMS enhancement, while also presenting unique challenges.

Table 1: Key AI techniques and challenges in AI-KMS integration

AI Technique	Focus Area	Application in KMS	Key Challenge Identified
Graph Neural Networks (Wu et al., 2021)	Relational data analysis	Mapping and optimizing knowledge networks	Scalability and network maintenance
Explainable AI (Barredo Arrieta et al., 2020; Adadi & Berrada, 2018)	Transparency and interpretability	Building trust in AI-driven KMS tools	Ensuring interpretability without sacrificing performance
Transfer Learning (Weiss et al., 2016)	Cross-domain knowledge transfer	Reusing knowledge across contexts	Efficient adaptation to heterogeneous datasets
Deep Learning (Alzubaidi et al., 2021; Khan et al., 2020)	Unstructured data processing	Automating classification of text, audio, video	Accurate categorization of diverse knowledge types
Sentiment Analysis (Taboada et al., 2011)	Feedback analysis	Extracting insights from textual feedback	Accounting for context and cultural differences
Text Summarization (Erkan & Radev, 2004)	Knowledge accessibility	Summarizing large knowledge repositories	Retaining essential context in summaries
Link Prediction (Liben-Nowell & Kleinberg, 2007)	Social network analysis	Predicting collaborations and knowledge flows	Relevance in dynamic organizational contexts
Generative Models	New knowledge creation	Creating knowledge artefacts and decision-making scenarios	Ethical concerns and reliability of outputs

Source: Author's processing

This table serves as a foundation for understanding the diverse roles of AI in KMS serving as a basis for the bibliometric analysis conducted in this study that will not only validate the challenges identified in the existing literature but may also uncover new ones.

3. Methodology
To explore the paradigm of AI integration in KMS, we have employed a bibliometric analysis using data from the Scopus database. Building on insights from prior literature regarding the transformative potential of AI technologies in KMS, this analysis aims to identify both opportunities and challenges in the field. The initial search query returned 17,000 documents, which were rigorously filtered based on predefined criteria, resulting in a refined dataset of 8,510 documents, including 3,832 open-access publications. This methodological approach enables a comprehensive exploration of key trends, challenges, and research gaps, providing valuable insights into the current state of AI-driven advancements in KMS.

Data collection involved searching Scopus using a detailed string of keywords, related to the concepts of Knowledge Management System, and Artificial Intelligence, targeting titles, abstracts, and keywords.

To ensure data relevance, several filters were applied. The study included only peer-reviewed journal articles published in English, thereby maintaining high-quality and consistent content. Conference papers, book chapters, and other formats were excluded. The dataset was further refined by focusing on keywords that emphasized the integration of AI and KMS, ultimately resulting in 3,832 relevant open-access journal articles.

The bibliometric analysis was conducted using Biblioshiny (Ghorbani, 2024) within the R-based Bibliometrix package, focusing on the combined dataset of articles related to both Artificial Intelligence (AI) and Knowledge Management Systems (KMS). Conducting the analysis on the sum of articles ensures a holistic understanding of how AI is shaping KMS, aligning with the paper's focus on addressing the challenges posed by integrating AI into KMS processes across various domains and disciplines. This approach was chosen to provide a broader, more insightful perspective on the complex and interdisciplinary challenges that organizations face when adopting AI-driven knowledge management solutions.

4. Results

The bibliometric analysis of 3,832 documents reveals several key statistics that highlight both the opportunities and challenges posed by AI in KMS. These challenges primarily revolve around rapid technological evolution, interdisciplinary collaboration, ethical concerns, and practical integration into KM processes.

The rapid annual growth of AI-related literature (16.58%) reflects technological advancements but poses difficulties for organizations in keeping KMS updated and avoiding information overload. The high level of international collaboration indicates a globally connected research field, yet it brings challenges in standardizing knowledge across regions and managing regulatory, cultural, and ethical differences. A moderate citation rate (37.06 citations per document) suggests the field's importance but reveals fragmentation, with many studies lacking comprehensive frameworks that address both explicit and tacit knowledge management. Additionally, the young average document age (1.89 years) indicates a focus on cutting-edge innovations but highlights a scarcity of long-term studies on practical and ethical implications, creating challenges in adopting new AI technologies while mitigating risks like data privacy, algorithmic bias, and transparency concerns.

Insights drawn from the average citation analysis (Figure 1) further emphasize the challenges in AI integration within KMS. High citation rates in the early years (1984-2001) suggest that seminal works in both KMS and AI played a foundational role in shaping the academic discourse, establishing the basis for future research. However, as the field expanded and more studies emerged between 2005 and 2014, citation rates began to moderate, reflecting the maturation of the field. The recent decline in average citations per year (2015-2024), despite the surge in publications, presents a critical challenge. This decline may be attributed to a variety of factors, including citation lag, where newer publications struggle to gain visibility and recognition in an increasingly saturated research environment. With more publications competing for attention, AI-driven KMS studies face difficulty standing out among the vast number of articles published annually. This highlights the need for more targeted and impactful research that not only contributes novel insights but also addresses the practical integration of AI within KMS in a way that resonates with both academia and industry practitioners.
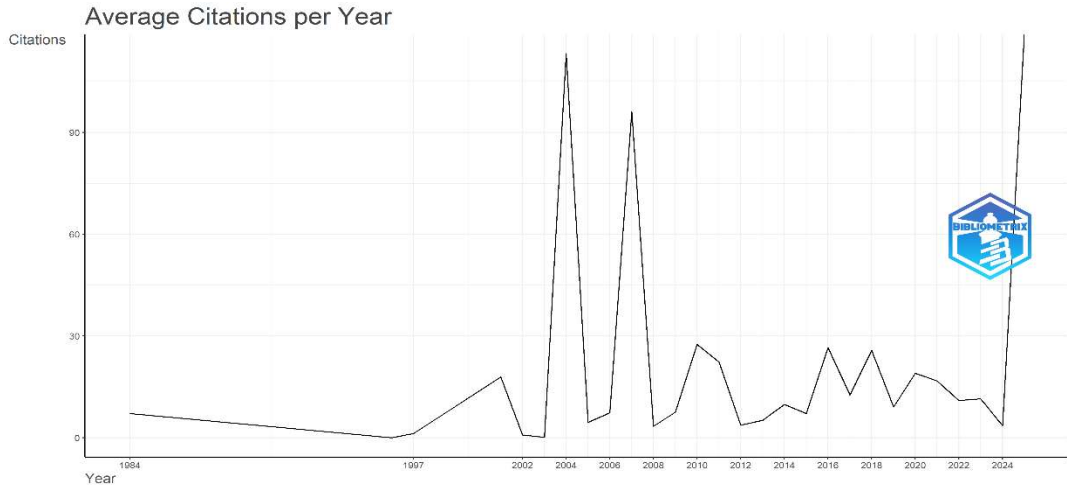
Figure 1: The average citations per year of articles on AI and KMS
Source: Author's analysis /processing based on own data

Moreover, the decline in citations could suggest that the novelty of the initial AI-KMS integration studies is wearing off, leading to less frequent citations as researchers explore more niche or specific topics within the broader framework. This could indicate a shift in focus from foundational to more specialized research areas, which may not yet have had enough time to accumulate significant citations. For organizations looking to implement AI-enhanced KMS, this trend emphasizes the challenge of keeping up with the evolving nature of both AI technology and KMS design while ensuring that new research continues to contribute to solving integration challenges in a meaningful and widely recognized way.

The next conducted analysis focuses on identifying trends in research topics using authors' keywords. The parameters for this analysis were set with a minimum frequency of 10 occurrences per keyword and a selection of up to 5 keywords per year. This analysis sheds light on the most prominent AI-related technologies and their evolving relevance within KMS. The data reveals a substantial rise in the frequency (Figure 2) of terms related to advanced AI technologies, with deep learning (466), machine learning (367), and artificial intelligence (346) emerging as the most frequently published topics, particularly between 2021 and 2024. These terms signify a dominant shift toward AI-driven approaches in KMS, highlighting their growing role in automating processes, improving knowledge discovery, and enhancing decision-making. However, integrating such technologies into KMS presents several challenges, as organizations must navigate the complexity of aligning new AI tools with existing organizational structures and knowledge processes.
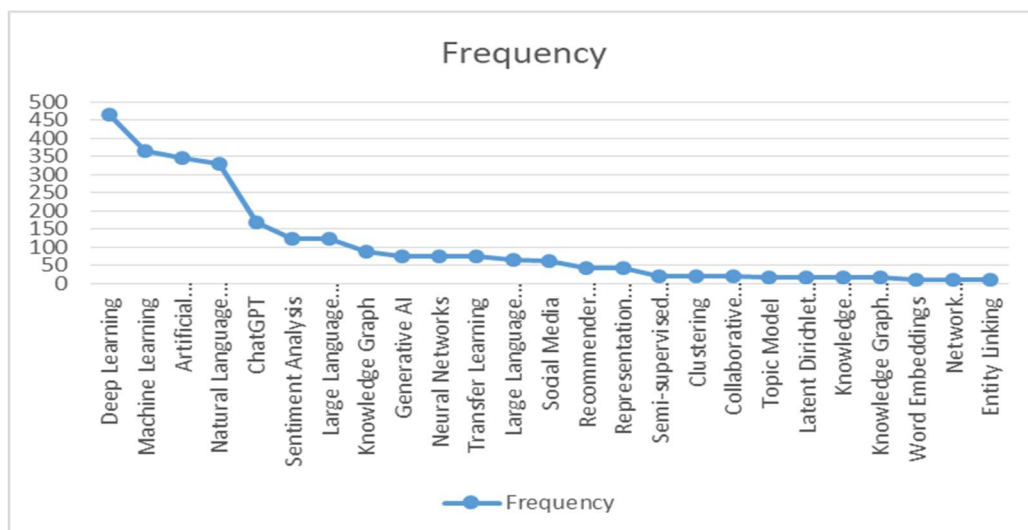
Figure 2: Keyword frequency trend chart
Source: Author's analysis /processing based on own data

A key challenge identified from the data is the rapid advancement and diversification of AI technologies. The popularity of natural language processing (330) and ChatGPT (168) reflects the increasing demand for better human-machine interaction and more efficient knowledge retrieval within KMS. While these technologies offer significant potential, their integration requires overcoming technical challenges such as ensuring that AI models can understand and process domain-specific knowledge. The growing focus on large language models (125) and generative AI (75) further complicates this integration, as organizations must invest in specialized infrastructure and continually update these models to keep pace with AI advancements.

Additionally, more specialized AI technologies such as knowledge graphs (88) and semi-supervised learning (22) are gaining traction. These focus on improving knowledge representation and enabling the use of partially labelled data, which are crucial for enhancing KMS functionality. However, their integration into KMS requires expertise in both AI and domain-specific knowledge, as well as considerable effort to adapt these technologies to the specific needs of organizations. The rise of knowledge representation (16) and topic modelling (18) reflects the increasing sophistication of KMS, where the focus is on improving how organizational knowledge is structured and interpreted. This shift highlights the need for organizations to develop not only the technological infrastructure but also the human expertise required to leverage these advanced AI tools effectively.

While innovations like deep learning, natural language processing, and generative AI promise to revolutionize knowledge management, their successful integration presents challenges that require a careful alignment of technological, human, and organizational factors. The diversity of AI technologies and the pace of their development call for continuous adaptation and expertise to ensure that KMS can harness AI's full potential while addressing the complexities inherent in such integration.

To further explore the challenges of AI integration in KMS, a thematic network cluster map (Figure 3) was generated using a clustering algorithm Walktrap to analyse authors' keywords with parameters of a minimum word frequency of 10 and a minimum cluster frequency of 5. This analysis identified two prominent clusters: deep learning and artificial intelligence. These clusters reflect key trends in AI technologies, which are closely tied to KMS, particularly in their ability to enhance technological tools within KMS.

Figure 3. Thematic network cluster map.
Source: Author's analysis /processing based on own data

However, several challenges in the integration of these technologies into KMS emerged from this analysis.

Firstly, deep learning emerged as the dominant cluster, reflecting its widespread application in areas such as neural networks, transfer learning, and reinforcement learning. While these technologies can significantly enhance KMS capabilities—enabling more efficient data processing, automated knowledge extraction, and improved decision-making—integrating them into existing KMS infrastructure presents challenges. These challenges include the need for substantial computational resources and specialized expertise in managing and maintaining deep learning models. Additionally, aligning these advanced AI technologies with organizational processes, structures, and cultures presents a considerable hurdle. The complexity and technical nature of deep learning may also limit its accessibility for non-experts within the organization, leading to potential barriers in adoption and use.

Secondly, the artificial intelligence cluster, which includes generative AI, large language models (LLMs), and ChatGPT, reveals the increasing focus on AI's ability to generate, process, and adapt knowledge within KMS. While these technologies offer the promise of more dynamic, responsive, and user-friendly systems, their integration raises several challenges. One key challenge is the need for continuous updates and retraining of LLMs to ensure they remain relevant and accurate. As new models emerge, KMS must be agile enough to integrate these advancements without disrupting existing systems. Furthermore, the ethical implications of using generative AI in knowledge management—such as the potential for bias, misinformation, or over-reliance on AI-generated content—present additional challenges that organizations must address. There is also the issue of ensuring that AI-generated knowledge aligns with the strategic goals of the organization and does not conflict with human expertise or organizational values.

Finally, the CallonCentrality and CallonDensity measures, used for exploring the research dynamics of future studies (Di Zio et al., 2023), highlight the dominance of deep learning in the field, but the relative lower density of the artificial *intelligence* cluster points to the challenges in managing a wide range of AI technologies with diverse applications. This broad scope makes it difficult to create a cohesive framework that can seamlessly integrate all relevant AI technologies into KMS. The challenge here lies in balancing the diverse capabilities of AI with the need for a unified, strategically aligned KMS. The increasing complexity of AI integration requires organizations to carefully evaluate which technologies best align with their knowledge management objectives while ensuring that they do not overwhelm or complicate the overall system.

5. Discussions

To further explore the integration of AI into knowledge management systems (KMS), bibliometric analysis has provided valuable insights into both challenges and opportunities in this area. In the following, we discuss the alignment of these challenges with the existing literature, identify new challenges, and highlight opportunities arising from the challenges.

5.1. Challenges Identified from Bibliometric Analysis and Literature

Complexity of deep learning and data processing: The bibliometric analysis emphasized deep learning technologies, such as neural networks and transfer learning, which can automate knowledge processes but also introduce challenges in their complexity and computational demands. This issue aligns with the literature, which discusses the difficulty of implementing deep learning models due to their complexity and high resource requirements (Dalkir, 2023). GenAI applications generate artificial knowledge. Understanding that artificial knowledge has no correspondence with real life or truth and that can be accepted or unaccepted due to its possible hallucinations, constitutes a major challenge for knowledge managers. Another key challenge is the integration process of human knowledge and artificial knowledge within KMS, and decision-making processes. Human knowledge is represented by a spectrum of rational, emotional, and spiritual knowledge (Bratianu and Bejinaru, 2020, 2023) while artificial knowledge is exclusively rational and depends on the complexity of training data (Baker, 2025).

Transparency and interpretability in AI models explainable AI (XAI), identified in the analysis, remains a barrier to AI adoption in KMS, as AI models often function as black boxes. The literature supports this concern, stressing that transparency is essential for trust in AI-based tools (Barredo Arrieta et al., 2020; Adadi & Berrada, 2018). Artificial knowledge is created using syntactic rules, without any connection with semantics or spiritual values. GenAI tools generate texts considering the most probable words to fit a given context, and not like human thinking. They make predictions and not interpretations. Only the human mind gives meaning to artificial knowledge and can integrate it in a decision-making process (Baker, 2025; Russell & Norvig).

Cross-domain knowledge transfer and model adaptation transfer learning pose challenges in applying AI models across different organizational contexts. This challenge is reflected in the literature, where efficient knowledge transfer across diverse datasets and contexts is crucial for successful AI-KMS integration (Nakash & Bolisani, 2024; Weiss et al., 2016).

Ethical oversight and knowledge generation generative AI models present ethical challenges related to data privacy and algorithmic bias. While these models can create new knowledge, the literature emphasizes the need for ethical oversight to ensure AI outputs are reliable and transparent (Harfouche et al., 2023). According to Floridi, digital ethics influences digital regulation and governance by assessing what is considered socially acceptable or desirable from a moral perspective (Floridi, 2023, p. 81). That is a complex challenge for any KMS in making decisions and delivering ethical and moral solutions for organizations and communities.

The bibliometric analysis uncovered also new challenges not extensively discussed in the literature: Saturation of AI research: The rapid increase in AI research publications, with a decline in citations, suggests a saturation of research. This makes it challenging for organizations to identify and apply the most relevant research for KMS.

Integration of emerging AI technologies: The integration of advanced AI technologies, such as GenAI and LLMs, presents challenges related to real-time updates and potential disruption of existing KMS frameworks. The literature has not fully addressed these issues, highlighting a gap in practical integration strategies.

5.2. Opportunities Resulting from Identified Challenges and New Directions for Research

The challenges identified in the bibliometric analysis and the literature also present several opportunities for the advancement of AI-powered KMS:

Development of scalable and accessible AI models: The complexity of deep learning can be addressed by creating modular and scalable AI models that are easier for organizations to implement and manage, reducing the need for specialized expertise. Also, the generation of synthetic data and artificial knowledge contributes directly to the extension of the knowledge space and enhances the power of possible solutions analysis and decision-making. It is an amplification of the potential intellectual capital of the organization with artificial knowledge. However, that amplification may create new knowledge vulnerabilities and knowledge risks (Bratianu et al., 2020).

Establishing ethical guidelines for AI integration: The ethical challenges surrounding AI offer an opportunity to create robust ethical frameworks that ensure AI systems are transparent, trustworthy, and reliable, which would facilitate greater adoption. That is in line with society's efforts to create new legislation able to guard a high standard of ethical working life (Baker, 2025; Floridi, 2023).

AI-driven knowledge personalization: The challenge of managing diverse knowledge types can be addressed through personalized AI systems that tailor knowledge delivery to specific user needs, improving decision-making and knowledge accessibility.

6. Conclusions

In conclusion, this study highlights the transformative potential of AI integration into Knowledge Management Systems (KMS), underscoring both the opportunities and challenges involved. While AI technologies, such as deep learning, GenAI, and transfer learning, provide powerful tools for automating and enhancing knowledge management processes, the implementation of these technologies is not without difficulty, and many barriers coming from inertial thinking, fear of losing control, and some new possible knowledge risks.

The study identifies critical challenges, including the complexity of deep learning models, the need for transparency and interpretability in AI systems, and ethical concerns surrounding AI outputs. These challenges, however, offer valuable opportunities for innovation, such as the development of scalable, transparent AI systems and the creation of ethical guidelines to govern their use in KMS. The generation of artificial knowledge opens new opportunities for enlarging the organizational knowledge spectrum, but induces new knowledge vulnerabilities and knowledge risks.

The findings of the bibliometric analysis, which reveal emerging trends in AI research, further emphasize the dynamic nature of this field and its implications for KMS. The rapid growth in AI research, coupled with the saturation of certain areas, suggests the need for more focused, context-specific studies to bridge the gap between theoretical advancements and practical applications. By addressing the challenges identified, organizations can better integrate AI into their KMS, fostering greater knowledge discovery, collaboration, and decision-making. Ultimately, the integration of AI into KMS offers substantial opportunities for improving organizational efficiency, driving innovation, and maintaining a competitive edge in an increasingly data-driven world.

This study yields several theoretical contributions to the extensive topic of AI integration in KMS. It reveals the power of the new AI tools like deep learning and large language models and shows how they generate artificial knowledge that should be integrated into the organizational KMS. Artificial knowledge does not replace human knowledge but it complements the actual KMS centred on human knowledge and human intelligence.

References

Adadi, A. and Berrada, M., 2018. Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access*, 6, pp.52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052

Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Amidie, M. and Farhan, L., 2021. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, 8(1), p.53. https://doi.org/10.1186/s40537-021-00444-8

Baker, P. (2025). *Generative AI for dummies*. Hoboken: John Wiley & Sons.

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Chatila, R. and Herrera, F., 2020. Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, pp.82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Ben Chouikha Zouari, M. and Dakhli, S.B.D., 2018. A multi-faceted analysis of knowledge management systems. *Procedia Computer Science*, 138, pp.646–654. https://doi.org/10.1016/j.procs.2018.10.087

Bratianu, C., 2022. *Knowledge strategies*. Cambridge: Cambridge University Press.

Bratianu, C. and Bejinaru, R., 2020. Knowledge dynamics: A thermodynamics approach. *Kybernetes*, 49(1), pp.6–21. https://doi.org/10.1108/K-02-2019-0122

Bratianu, C. and Bejinaru, R., 2023. From knowledge to wisdom: Looking beyond the knowledge hierarchy. *Knowledge*, 3(2), pp.196–214. https://doi.org/10.3390/knowledge/3020014

Bratianu, C., Agapie, A., Orzea, I., and Agoston, S. (2011). Inter-generational learning dynamics in universities. *Electronic Journal of Knowledge Management*, 9(1), 10-18. [online] Available at: www.ejkm.com [accessed 25 January 2025].

Bratianu, C., Nestian, A.S., Tita, S.M., Voda, A.I. and Guta, A.L. (2020). The impact of knowledge risks on sustainability of firms. *Amfiteatru Economic*, 22(55), 639-652. https://doi.org/10.24818/EA/2020/55/639

Dalkir, K., 2023. *Knowledge management in theory and practice*. Cambridge, MA: MIT Press.

Di Zio, S., Tontodimamma, A., del Gobbo, E. and Fontanella, L., 2023. Exploring the research dynamics of futures studies: An analysis of six top journals. *Futures*, 153, p.103232. https://doi.org/10.1016/j.futures.2023.103232

Erkan, G. and Radev, D.R., 2004. LexRank: Graph-based lexical centrality as salience in text summarization. *Journal of Artificial Intelligence Research*, 22, pp.457–479. https://doi.org/10.1613/jair.1523

Floridi, L. (2023). *The ethics of artificial intelligence: Principles, challenges, and opportunities*. Oxford: Oxford University Press.

Harfouche, A., et al., 2023. Artificial intelligence (AI) and information systems: Perspectives to responsible AI. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-023-10145-8

Hill, D. (2008). *Emotionomics: Leveraging emotions for business success*. Revised Edition. London: Kogan Page.

Khan, A., Sohail, A., Zahoora, U. and Qureshi, A.S., 2020. A survey of the recent architectures of deep convolutional neural networks. *Artificial Intelligence Review*, 53(8), pp.5455–5516. https://doi.org/10.1007/s10462-020-09825-6

Ghorbani, B.D., 2024. Bibliometrix: Science mapping analysis with R Biblioshiny based on Web of Science in applied linguistics. In: H. Meihami and R. Esfandiari, eds. *A scientometrics research perspective in applied linguistics*. Cham: Springer, pp.197–234. https://doi.org/10.1007/978-3-031-51726-6_8

Liben-Nowell, D. and Kleinberg, J., 2007. The link-prediction problem for social networks. *Journal of the American Society for Information Science and Technology*, 58(7), pp.1019–1031. https://doi.org/10.1002/asi.20591

Majumder, S. and Dey, N., 2022. A bibliometric analysis of artificial intelligence in knowledge management. In: N. Dey, ed. *AI-empowered knowledge management*. Singapore: Springer, pp.93–108. https://doi.org/10.1007/978-981-19-0316-8_7

Minkkinen, H., et al., 2023. Technological frames and responsible AI: Shaping expectations in the European ecosystem. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-023-10148-5

Nahash, M. and Bolisani, E. (2024). Knowledge management meets artificial intelligence: A systematic review and future research agenda. *Proceedings of the 25th European Conference on Knowledge Management*, Pannonia University, Hungary, ECKM 25(1), 544-552.

Papagiannidis, S., et al., 2023. AI governance in organizations: A case study from the energy sector. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2023.101349

Rahman, A., Raj, A., Tomy, P. and Hameed, M.S., 2024. A comprehensive bibliometric and content analysis of artificial intelligence in language learning: Tracing between the years 2017 and 2023. *Artificial Intelligence Review*, 57(4), p.107. https://doi.org/10.1007/s10462-023-10643-9

Russell, S. and Norvig, P. (2022). *Artificial intelligence: A modern approach.* 4th Edition. Upper Saddle River: Pearson.

Shaikh, A.K., Alhashmi, S.M., Khalique, N., Khedr, A.M., Raahemifar, K. and Bukhari, S., 2022. Bibliometric analysis on the adoption of artificial intelligence applications in the e-health sector. *Journal of Digital Health*. https://doi.org/10.1177/20552076211022213

Taherdoost, H. and Madanchian, M., 2023. Artificial intelligence and knowledge management: Impacts, benefits, and implementation. *Computers*, 12(4), p.72. https://doi.org/10.3390/computers12040072

Turney, P.D. and Pantel, P., 2010. From frequency to meaning: Vector space models of semantics. *Journal of Artificial Intelligence Research*, 37, pp.141–188. https://doi.org/10.1613/jair.2934

Wu, Z., Pan, S., Chen, F., Zhang, C. and Yu, P.S., 2021. A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), pp.4–24. https://doi.org/10.1109/TNNLS.2020.2978386

Bio-note

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THE IMPACT OF ECONOMIC INFRASTRUCTURE INVESTMENT ON FOREIGN TRADE FLOWS: THE CASE OF SOUTH AFRICA

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Abstract: *A well-functioning economic infrastructure is fundamental for sustainable economic growth in both developing and developed countries. It can be an effective tool for addressing economic and socioeconomic challenges and improving a country's competitiveness. It is therefore critical to understand how economic infrastructure investment affects different aspects of economic growth. This would assist policymakers in ensuring that there is proper alignment between policies on infrastructure development and policies pertaining to economic development. Although many studies have been conducted on the impact of infrastructure development on economic development, literature focusing on the foreign trade aspect is scant. This study, therefore, bridges this gap by examining the impact of economic infrastructure investment on foreign trade flows in South Africa in the long run and short run. To examine this linkage, the study applied the autoregressive distributed lag (ARDL) bounds test on annual data for the period 1986 - 2022 and estimated two models. Model 1 investigates whether economic infrastructure investment has a significant impact on exports, while Model 2 examines the impact of economic infrastructure investment on imports. The findings of the study confirmed that economic infrastructure investment has a positive impact on exports both in the long run and short run, while it has no significant impact on imports. On the control variable, the findings confirmed that economic growth only has a long-run positive impact on exports, while it has a long-run and short-run positive impact on imports. It was found that trade openness and real effective exchange rates have positive effects on foreign trade flows regardless of the proxy used. The results confirmed that human capital has a negative effect on exports in the long run and short run, while it only has a positive long-run impact on imports. Furthermore, the findings show that money supply does not affect exports, while it negatively drives imports both in the long run and short run. Based on the main findings, the study recommends that governments should design policies that support investment in improving the country's geographical conditions and connectivity. Furthermore, it is recommended that the South African government should prioritize the establishment and maintenance of functional economic infrastructure to create a conducive environment for local productivity and exports.*

Keywords: ARDL Model, Economic Infrastructure Investment, Foreign Trade Flows, Imports, South Africa, Exports

JEL codes: F14, H54

1. Introduction
Worldwide, foreign trade is viewed as a long-run and short-run catalytic agent for economic growth and integration of developing economies into the world economy. It provides poor

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and resource-constrained countries with access to capital from developed countries and promotes efficient allocation of resources through a comparative advantage (Chang et al, 2009). Furthermore, foreign trade provides easy access to economies of scale and international specialization for developing and developed countries (Suriaganth and Abdullah, 2021). Estimates from the World Bank (2023) confirm that foreign trade contributes significantly to economic growth, accounting for 63% of the world's gross domestic product.

In the case of South Africa, foreign trade also plays a critical role in boosting economic growth and integration. Since democracy, the country has made significant strides in integrating itself into the world trading system by signing various multilateral and bilateral agreements with multiple regions and individual countries. These agreements have boosted the contribution of foreign trade to the country's economy by reducing trade costs and integrating the country into the world supply chain. This can be seen through the increases in foreign trade as a share of GDP since democracy from 37% in 1994 to 66% in 2023 (World Bank, 2023). Although the contribution of foreign trade has increased over the years, the country's trade account faced chronic fluctuations for a long time, with trade deficits dominating. In 2016, the country started continually recording a trade surplus, however, the magnitude of this surplus has started diminishing in recent years. According to the estimates from the World Bank (2023) South Africa's trade surplus as a share of national output declined from 6.1% in 2021 to 0.3% in 2023.

South Africa's inability to maintain a healthy trade account raises questions on the country's ability to create a conducive environment for trade, especially, exports. Existing literature points out the cost of trade emanating from the geographical position of the African continent as one of the biggest factors undermining foreign trade in African countries, as it makes the continent economically remote from the world markets (African Bank, 2010). According to Etensa. *et al,* (2022) a sustainable and effective solution to this challenge would be securing and maintaining a functional economic infrastructure as it reduces transport costs, improves connectivity, and boosts productivity. A functional infrastructure reduces trade costs, improves a country's comparative advantages, and promotes the country's intraregional trade to the world economy (Brooks, 2018 cited in Ahmad, 2016). Furthermore, enhanced infrastructure reduces both bilateral and multilateral trade costs (Donaubauer, 2018).

The current study explores the impact of economic infrastructure investment on foreign trade flows in South Africa. It particularly focuses on whether economic infrastructure investment drives foreign trade and impacts the different components of foreign trade differently. Although previous studies have extensively examined the role of economic infrastructure investment in promoting different aspects of economic growth, literature on its role in promoting foreign trade activities remains scant. As far as we understand, no study has examined the effects of economic infrastructure investment on foreign trade flows in the case of South Africa.

The remaining sections are structured as follows: sections 2 and 3 present the literature review examining infrastructure development's impact on foreign trade and model specifications and the econometric methodology employed in the study, respectively. The empirical results and conclusion of the study are presented in sections 4 and 5, respectively.

2. Literature Review

The impact of economic infrastructure investment on foreign trade has been explored in numerous studies for both developing and developed countries. The findings from these studies are inconclusive, as some studies confirmed a positive link, while some confirmed a negative link or no significant link between the two variables. For example, Shepard and Wilson (2007) examined the impact of infrastructure quality of interregional trade in countries of Europe and Central Asia using the ordinary least squares method and the Pseudo Poisson

Maximum Likelihood (PPML). The study employed annual data covering the period from 1995 to 2004, and the findings confirmed that proper infrastructure has a positive impact on trade flows. A similar study was conducted by Albarran *et al.* (2013) for Spanish firms using the probit pooled model and annual panel data for the period 1990 - 2005. The results confirmed that transport infrastructure leads to an increase in a firm's probability of exporting. For Malaysia, Ahmad *et al.* (2016) employed the fixed effect model to examine the impact of infrastructure development on trade flows. The study employed annual data for the period 1980-2013 and found that infrastructure development positively impacts export volume.

Donaubauer *et al.* (2018) examined the impact of infrastructure on trade in open and emerging economies. The study applied the Pseudo Poisson Maximum Likelihood (PPML) on panel data for the period 1992-2011. The findings confirmed that infrastructure development has a positive impact on trade. For Nigeria, Nwaogwugwu and Olaoye (2018) studied the link between infrastructure development and exports using the ordinary least squares method. The study employed annual data covering the period from 1984 to 2017 and the findings confirmed that infrastructure development has a positive impact on exports. A similar study was conducted by Karymshakov and Sulaimanova (2020) for three Central Asian countries. The study applied the Pseudo Poisson Maximum Likelihood (PPML) estimation method on panel data covering the period from 2010 to 2018. To measure infrastructure, the study used quality and quantity proxies, and the findings confirmed that infrastructure has a positive impact on trade, although the impact diminishes over time. Based on these findings, the authors argued that for a sustainable impact, infrastructure development should be accompanied by supportive government policies.

Rehman *et al*. (2020) confirmed similar findings for Southeast Asian economies. The study applied the pooled mean group, Dynamic ordinary least squares, and the fully modified least squares on panel data for the period 1990 - 2018. Using the same techniques and panel data for the period 1990 - 2017, Rehman *et al.* (2020) confirmed that improved infrastructure promotes exports and reduces trade deficit. A similar finding was confirmed by Vidya and Taghizadeh-Hesary (2021) who examined the impact of infrastructure investment on trade connectivity between ASEAN and three Asian countries. The three countries are India, China, and Japan. The paper employed panel data covering the period from 1990-2018. The findings confirm that foreign trade connectivity is positively influenced by hard infrastructure.

Using the generalized effects of the moments method and annual data covering the period from 2005 to 2019, Zhou *et al*. (2022) examined the impact of broadband infrastructure on international trade in 243 cities. The findings confirmed that infrastructure development has a positive impact on international trade through information efficiency, which in turn reduces trade costs and barriers to trade. For African countries, Ngassam (2023) examined the impact of infrastructure development on export diversification using the Panel Correlated Standard Error (PCSE) and the two-step system Generalized Method of Moments on annual panel data covering the period from 2000 to 2014. The funding confirmed that infrastructure development has a positive impact on export diversification.

Thia and Lopez (2023) examined the impact of infrastructure quality on the trade balance for selected developing countries. The study applied the gravity model on a panel data from 2006-2017 and the findings confirmed that an improvement in infrastructure quality has a positive effect on trade flows. A similar finding was confirmed by Zheng and Hongtao (2022) in the case of OECD countries. The study applied the augmented gravity method to panel data covering the period from 2000 to 2016. The results confirmed that an improved infrastructure plays a critical role in reducing trade costs, which in turn encourages trade.

Mao *et al.* (2024) examined the impact of infrastructure development on international trade in Asian countries. The study applied the cross-sectional autoregressive distributed lags and the augmented gravity model to cross-sectional data covering the period from 2004 to 2020. The findings from this study confirmed that infrastructure development has a positive and significant impact on trade.

3. Research Methodology and Data

This section provides the model, estimation technique, and data used in this study to explore the impact of economic infrastructure investment on exports. The model used in this study is adopted from Rehman *et al.* (2020), who specified trade as a function of economic growth, Human Capital, Infrastructure, exchange rate, and Institutional quality. Due to data limitations, the model is modified in this study to exclude institutional quality and include trade openness and money supply. The inclusion of these variables is supported by empirical studies such as Nwaogwugwu and Olaoye (2018). The study employs two models, that is, Model 1 where the focus is on the export side of foreign trade flows, and Model 2 where imports are used. The empirical model used in this study can be specified as:

$$TRD = f (INFD, GDP, REER, HC, TOP, MS) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(1)$$

$$TRD_{it} = \alpha_0 + \alpha LINFD_{i.t} + \alpha LGDP_{it} + \alpha LREER_{it} + \alpha LHC_{it} + \alpha TOP_{it} + \alpha LMS_{it} + \varepsilon t \dots..(2)$$

Where:

- TRD refers to foreign trade flow, measured through aggregate values of exports and imports.
- INFD refers to the economic infrastructure investment variable
- GDP refers to the economic growth variable measured through gross domestic product
- TOP refers to trade openness,
- MS refers to money supply,
- HC refers to human capital, and
- REER refers to real effective exchange rates.

3.1. The Autoregressive Distributed Lag (ARDL) Cointegration Approach

With the ARDL technique, the pretesting of the unit root in variables used is not required. However, it is important to conduct the unit root tests as time series data is commonly associated with unit root problems, which may result in false results. For the unit root testing, the Dickey-Fuller Generalised Square (DF-GLS) and Phillips-Parron were used. After confirming the stationarity of the variables, the study explores the impact of economic infrastructure investment on different proxies of foreign trade flows using the ARDL technique. This technique was proposed by Pesaran and Shin (1999) and has various advantages over other cointegration techniques. The advantages are that: (i) it can be applied regardless of whether the regressors are integrated of I(0) or I(1), as long as the order of the regressors integration is equal to one or less (Arize, 2017). (ii) Through a simple linear transformation, it allows for the derivation of the Error Correction Model, which integrates adjustments in the short run with equilibrium in the long run without losing information (Thao and Hua, 2016). (iii) The error correction representation becomes relatively more efficient when there is a single long-run equation and small or infinite data sample size (Nkoro and Uko, 2016; Arize, 2017). The ARDL function for trade is specified as :

$$
\Delta LTRD_t
$$
$$
= \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta LTRD_{t-i} + \sum_{i=0}^{n} \beta_{2i}\Delta INFD_{t-i} + \sum_{i=0}^{n} \beta_{3i}\Delta LGDP + \sum_{i=0}^{n} \beta_{4i}\Delta LLF_{t-i} + \sum_{i=0}^{n} \beta_{5i}\Delta REER
$$
$$
+ \sum_{i=0}^{n} \beta_{6i}\Delta LTOP_{t-i} + \sum_{i=0}^{n} \beta_{7i}\Delta LMS_{t-i} + \sum_{i=0}^{n} \beta_{8i}\Delta LHC_{t-i} + \pi_1 LTRD_{t-1} + \pi_2 LINFD_{t-1}
$$
$$
+ \pi_3 LGDP_{t-1} + \pi_4 LLF_{t-1} + \pi_5 LREER_{t-1} + \pi_6 LTOP_{t-1}
$$
$$
+ \pi_7 LMS_{t-1} + \pi_8 LHC_{t-1} u_t \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (3)
$$

Where: *L* represents the logarithm, i represents the number of lags, Δ is the first difference, u_t represents the white noise error term, β_0 is a constant, $\beta_1 - \beta_8$ are the coefficients of the long-run ARDL model, $\pi_1 - \pi_8$, are short-run coefficients. To estimate the short-run relationship between foreign direct investment and exports, the short-run model is specified as follows. The Error correction model is specified as:

$$
\Delta LTRD_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta LTRD_{t-i} + \sum_{i=0}^{n} \beta_{2i}\Delta INFD_{t-i} + \sum_{i=0}^{n} \beta_{3i}\Delta LGDP + \sum_{i=0}^{n} \beta_{4i}\Delta LLF_{t-i}
$$
$$
+ \sum_{i=0}^{n} \beta_{5i}\Delta REER + \sum_{i=0}^{n} \beta_{6i}\Delta LTOP_{t-i} + \sum_{i=0}^{n} \beta_{7i}\Delta LMS_{t-i} + \sum_{i=0}^{n} \beta_{8i}\Delta LHC_{t-i}
$$
$$
+ \alpha_1 ECM_{t-1} + u_t \dots \dots \dots . (4)
$$

3.2 Data and definition of variables

Table 1: Description of variables

Notation	Description	Data source
EX	The aggregate value of exports	World Bank database
IM	The aggregate value of imports	World Bank database
INFD	Economic infrastructure investment is measured through gross fixed capital formation on economic infrastructure as a share of GDP. This variable is expected to have a positive impact on foreign trade and has been confirmed to be a determinant of foreign trade in studies such as Hassan *et al* (2022).	South African Reserve Bank
GDP	GDP represents gross domestic product and is used to measure economic growth. This variable is measured through GDP per capita at a constant price.	World Bank database
HC	HC represents human capital. In this study, this variable is measured through life expectancy which measures the production capacity of human beings. Life expectancy has been used in several studies as a measure of human capital. It is expected to have a positive impact on trade (Akpolat, 2014).	World Bank database

REER	REER stands for real effective exchange rate. The theoretical expectation for this variable is that it should positively affect exports and negatively affect imports. The relationship between REER and trade has been tested in studies such as Hassan *et al.* (2022); Matlasedi (2017)	World Bank database
TO	TO represents trade openness. This variable is measured as total foreign trade as a share of GDP. This variable is expected to have a negative effect on foreign trade.	World Bank database
MS	MS represents the money supply. This variable is measured through broad money as a share of GDP. Theory suggests that this variable should negatively influence foreign trade flows regardless of the proxy used. The inclusion of this variables is supported by studies such as Nwaogwugwu and Olaoye (2018).	South African Reserve Bank

4. Empirical Analysis and Results

This section provides an analysis and discussion of the results on the impact of economic infrastructure investment on foreign trade flows. Table 2 presents the stationarity results from two techniques, that is. Phillips Parron and Dickey-Fuller Generalized Square.

Table 2: Unit root results

	Levels			
Variables	**DF-GLS Test**		**Phillips Parron**	
	Without Trend	With Trend	Without Trend	With Trend
LEXPORTS	0.075682	-2.499615	-0.094264	-2.389906
LIMPORTS	-0.500934	-5.785723***	-2.156985	-5.081716***
LINFD	-1.729684*	-2.804577	-1.945578	-2.649907
LREER	-0.923064	-3.397979*	-1.063980	-2.342673
LMS	0.230606	-1.167028	4.468962	-1.077575
LHC	0.240496	-2.644121	-0.997211	-2.490952
LGDPCS	-3.776266***	-4.018498***	-3.752938***	-3.580772**
LTO	-2.415726	-4.101344***	-2.394767	-3.909928
	First Differenced			
	DF-GLS Test		**Phillips Parron**	
	Without Trend	With Trend	Without Trend	With Trend
LEXPORTS	-4.888525 ***	-4.777152 ***	-4.855729***	-4.795646***
LIMPORTS	-9.050151***	-8.947260***	-5.081716***	-15.61111***
LINFD	-7.030208***	-7.036577***	-6.999061***	-7.176745***
LREER	-4.483527***	-4.879342***	-6.508216***	-8.861221***
LMS	-1.897562	-3.759710***	-1.875060	-3.500590***
LHC	-6.329113***	-6.418443***	-6.282626***	-6.264940***
LGDPCS	-5.680259***	-5.843968***	-11.06018***	-11.72985***

| LTO | -7.318916*** | -7.331703*** | -13.76537*** | -14.93748*** |

*** refers to statistical significance levels at 1%

The results from both the DF-GLS and Phillips Parron tests confirm that all the variables used are stationary after first differencing and including a trend. Given that the variables are stationary, the study proceeds to examine the impact of infrastructure development on foreign trade using the ARDL cointegration technique. Table 3 presents the F statistics for both models 1 and 2, and the critical values.

Table 3: Cointegration results

Dependent Variable	Function		F-Statistics	Cointegration Status	
LEX	$F(EX\mid INFD, GDPC, REER, MS, TO, HC)$		8.281*	Cointegrated	
LIN	$F(IN\mid INFD, GDPC, REER, MS, TO, HC)$		5.712**	Cointegrated	
Asymptotic Critical Values					
Critical Values	1%		5%		10%	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
	4.270	6.211	2.970	4.499	2.457	3.797

**,* refers to statistical significance levels at 5%, 10%.

The results from the bounds test are presented in Table 3, and they confirm that there is cointegration between economic infrastructure investment and foreign trade flows, regardless of the proxy used. The F-statistics for models 1 and 2 are 8.281 and 5.712, respectively. Having confirmed the cointegration between the variables, the study examines the long-run and short-run impact of economic infrastructure investment on foreign trade flows with a particular focus on the imports and exports. Table 4 presents the results for the long run cointegration.

Table 4: Long-run Cointegration

Model 1: Impact of Economic Infrastructure Investment on Exports of Goods and Services				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINFD	1,580**	0,607	2,604	0,014
LGDP	0,291**	0,136	2,138	0,041
LREER	1,152**	0,420	2,744	0,010
LMS	0,291	0,338	0,863	0,395
LTO	0,597	0,430	1,388	0,175
LHC	-3,425**	1,667	-2,055	0,048
C	1,256	2,521	0.498	0.623
Model 2: Impact of Economic Infrastructure Investment on Imports of Goods and Services				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINFD	-0,066	0,203	-0,323	0,749

LGDP	0,187*	0,039	4,850	0,000
LREER	0,388**	0,172	2,254	0,031
LMS	-0,437**	0,165	-2,658	0,012
LTO	1,283*	0,159	8,061	0,000
LHC	-0,026	0,434	-0,060	0,952
C	-5.214	0.938	-5.559	0,000

, refers to statistical significance levels at 5%, 10%.*

The results shown in Table 4, Panels 1 and 2 suggest that economic infrastructure investment has a positive significant long-run impact on foreign trade flows when exports are used as a proxy, while it has no significant effect when imports are used. The coefficient of this variable confirms that a 1 percent increase in infrastructure development leads to a 1.580 percent rise in exports in the long run. The findings are in line with the outcome predicted by theory. Economic growth and real effective exchange rates are found to positively impact foreign trade flows regardless of the proxy used. The coefficients of economic growth suggest that a 1 percent increase in this variable leads to a long-run increase of 0.291 percent in exports and 0.187 percent in imports. For the real effective exchange rate variable, the coefficients confirm that a 1 percent increase in real effective exchange rates leads to an increase of 1.152 percent and 0.388 percent in exports and imports, respectively. The positive coefficient of the real effective exchange rate on imports contradicts the theoretical expectations but is supported by the findings in studies such as Kemal and Qadir (2005). Money supply and trade openness are found to have no significant long-run impact on exports, while they negatively and positively impact imports, respectively. The coefficients of these variables suggest that a 1 increase in money supply and trade openness leads to a 0.437 percent decline and a 1.283 percent increase in imports, respectively. Human capital is found to have a negative long-run impact on exports, while it has no significant impact on imports. The findings suggest that a 1 percent increase in human capital results in a 3.425 percent decline in exports. The sign carried by the coefficient of this variable contradicts the theory, however, it is supported in studies by the results from a study by Ayeni and Akeju (2023), who argued that human capital does not increase trade. The short-run findings are presented in Table 5.

Table 5: Short-run results

Model 1: Impact of Economic Infrastructure Investment on Exports of Goods and Services				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECM	-0,545	0,064	-8,549	0,000
DLINFD	2,340***	0,541	4,325	0,000
DLINFD(-1)	-0,946***	0,540	-1,753	0,090
DLGDP	0.159	0115	1.380	0.181
DLREER	1,278***	0,088	14,469	0,000
DLMS	0,159	0,199	0,800	0,432
DLTO	1,185***	0,091	13,073	0,000
DLHC)	-1,950**	0,765	-2,548	0,016
DLHC(-1))	3,377***	0,743	4,546	0,000
R-Squared	0,861	Serial Correlation	1,482[0,240]	

DW-statistic	2.337	Normality	0,343[0.842]	
F-Statistics	33,333	Heteroskedasticity	0,869[0.589]	
Model 2: Impact of Economic Infrastructure Investment on Imports of Goods and Services				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ECM	-1,085	0,100	-10,834	0,000
DLINFD	0,098	0,181	0,541	0,594
DLINFD(-1)	0,662***	0,229	2,887	0,008
DL(GDP)	0,341***	0,092	3,716	0,001
DLGDP(-1)	0,552***	0,123	4,488	0,000
DLREER	0,090***	0,029	3,065	0,006
DLREER(-1)	-0,162***	0,047	-3,461	0,002
DLMS	-0,156***	0,049	-3,195	0,004
DLMS(-1)	0,469***	0,068	6,912	0,000
DLTO	1,001***	0,036	27,978	0,000
DLTO(-1)	-0,192***	0,051	-3,748	0,001
DLHC	1,227***	0,353	3,479	0,002
DLHC(-1)	-0,624**	0,258	-2,418	0,024
R-Squared	0.987	Serial Correlation	0.015[0.985]	
DW-statistic	1.994	Normality	1.293[0.524]	
F-Statistics	214.717	Heteroskedasticity	1.357[0.281]	

***,**refers to statistical significance levels at 1%, 5%.

The short-run findings presented in Table 5, panels 1 and 2, suggest that economic infrastructure investment has a positive impact on trade when exports are used as a proxy, while it has no significant short-run effect when imports are used. The coefficient of this variable suggests that a 1 percent increase in economic infrastructure investment leads to a 2.340 percent increase in exports. The positive coefficient of this variable is in line with the theoretical expectations. On the contrary, the results show that the lagged values of economic infrastructure investment negatively affect aggregate exports and positively affect aggregate imports.

In terms of the control variables, the findings confirm that economic growth measured through GDP has a positive short-run impact on imports and has no significant impact on exports. The coefficient of this variable suggests that a 1 percent increase in economic growth leads to a 0.552 percent increase in imports. It was also confirmed that real effective exchange rates and trade openness positively affect foreign trade regardless of the proxy used. The coefficients for these variables suggest that a 1 percent increase in each of the variables results in a 1.279 percent and 1.185 percent increase in exports, while it leads to a 0.090 percent and 1.001 percent increase in imports, respectively. The positive impact of exchange rates on imports is inconsistent with the theoretical expectations but is in line with Ndou (2021), who found that an increase in exchange rates leads to a deterioration in net trade, which could be a result of an increase in imports. The results confirmed that the money supply has no significant impact on exports and a negative impact on imports. Human capital was found to positively drive imports and negatively drive exports. The negative effect of human capital on exports contradicts theory but is supported by studies such as Ayeni and Akeju (2023), who argued that human capital does not increase trade.

The error correction terms are statistically significant at 1% and have negative signs both when exports and imports are used as proxies for trade flows. This also confirms that there

is a long-run relationship between economic infrastructure investment and foreign trade flows.

5. The CUSUM and CUSUMSQ tests

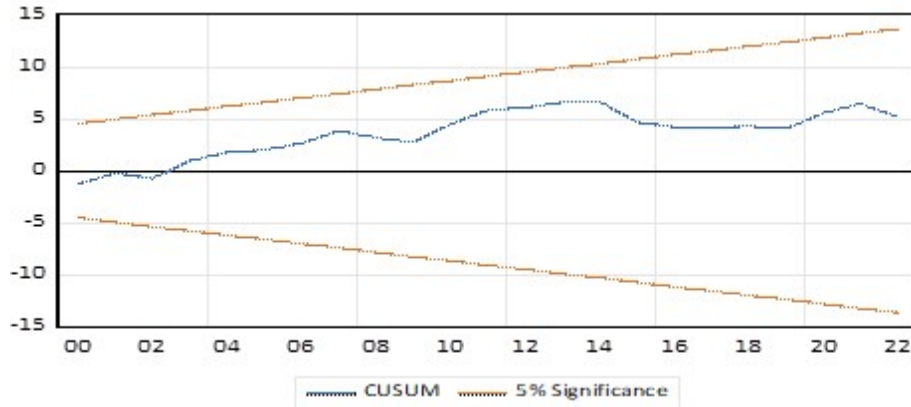Figures 1A-B and 2A-B below present the CUSUM and CUSUMSQ test results.
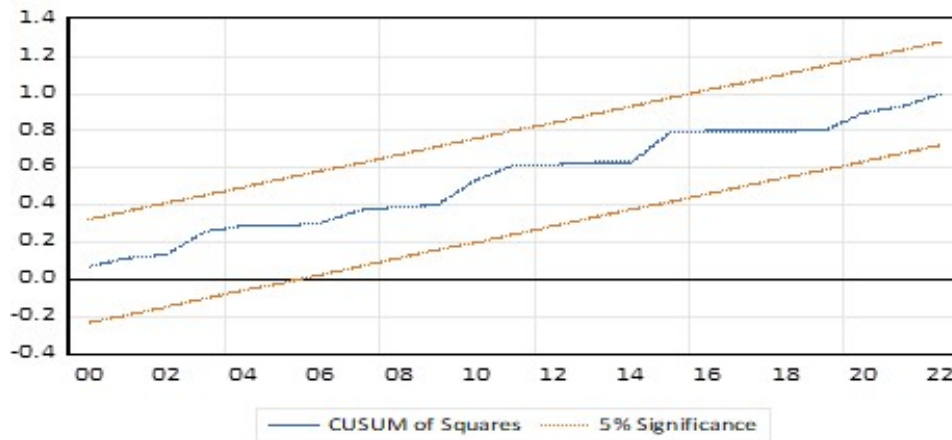

Figure 1A: Model 1: CUSUM

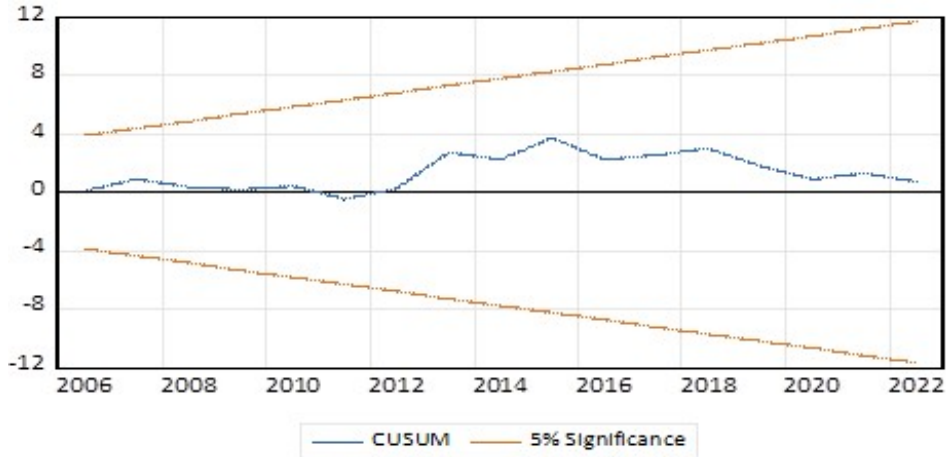**Figure 1B:** Model 1: CUSUM of Squares
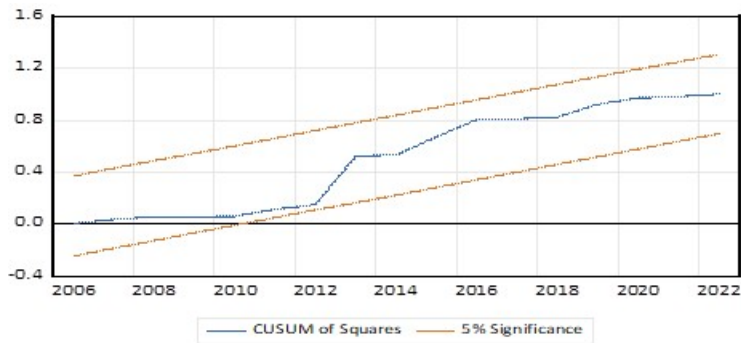
Figure 2A: Model 2: CUSUM

Figure 2B: Model 2: CUSUM of Squares

As shown in Figures 1A-B and 2A-B, the cumulative sum of recursive residuals and the cumulative sum of squares of recursive residual plots are within the critical bounds at 5%, and there are no structural breaks in both models.

6. Conclusion

The study explored the role of economic infrastructure investment in driving foreign trade flows in South Africa for the period of 1986 - 2022. To capture the different aspects of foreign trade, the study employed two models, with Model 1 examining the impact of economic infrastructure investment on exports and Model 2 examining the impact of economic infrastructure investment on imports. The main findings confirm that the nature of the relationship between economic infrastructure investment and foreign trade flows differs depending on the proxy used to measure foreign trade flows. When exports are used, the results confirm that economic infrastructure investment has a positive long-run and short-run impact on foreign trade flows, while it has no significant impact when imports are used. The positive impact of economic infrastructure investment on exports underscores the key role played by economic infrastructure in facilitating trade and improving efficiency. It suggests that investment in economic infrastructure can improve a country's current account, as it promotes local production, import substitution, and exports. The findings of

the study further confirm that the lagged values of economic infrastructure investment negatively influence exports and positively influence imports.

In terms of control variables, the findings for Model 1 confirm that economic growth has a positive impact on exports only in the long run, while real effective exchange rates and human capital have a positive and negative long-run and short-run impact on exports, respectively. The results further show a positive short-run effect of that trade openness on exports. For Model 2, the findings confirm that trade openness, economic growth, and real effective exchange rate positively affect imports both in the long run and the short run. Money supply was found to negatively affect imports both in the long run and short run. The findings of the study confirmed negative long-run and positive short-run effects of human capital on imports. Based on these findings, the study recommends that policymakers in South Africa should design policies in a manner that supports the channeling of more resources toward improving geographical conditions and the establishment and maintenance of high-quality infrastructure to create a conducive environment for foreign trade activities.

References

African Bank, 2010. Trade and Trade Costs in Africa: An Overview. [online] available at: *https://www.afdb.org/fileadmin/uploads/afdb/Documents/Publications/African%20Develop ment%20Report%202010_CH%201.pdf.*

Ahmad, N. A., 2016. The Impact of Infrastructure on Trade: The Case of Malaysia. *Journal of Economics and Finance.7(6). 50-53.*

Akpolat, A. G., 2014. The Long-Term Impact of Human Capital Investment on GDP: A Panel Cointegrated Regression Analysis. *Hindawi Publishing Corporation Economics Research International, 2014, 1-10.*

Albarran, P., Carrasco, R and Holl, A., 2013. Domestic Transport Infrastructure and Firms' Export Market Participation. *Small Business Economics. 40.879-898.*

Arize, C. A., 2017. A Convenient Method for the Estimation of ARDL Parameters and Test Statistics: USA trade balance and real effective exchange rate relation. *International Review of Economics and Finance 50(3), 75-84.*

Ayeni, R.K and Akeju, F.K., 2023. Human Capital, Capital Goods Import and Economic Growth in West Africa. *Cogent Economics and Finance, 11.1-14.*

Chang, R., Kaltani, L and Loayza, N., 2009. Openness is Good for Growth: The role of Policy Complementarities. *Journal of Development Economics, 90(1). 33-49.*

Donaubauer, J., Glas. A ., Meyer, B., and Nunnenkamp. P., 2018. Disentangling the Impact of Infrastructure on Trade Using a New Index of Infrastructure. *Review of World Economics. 154:745–784.*

Etensa, T., Taye.L., and Bersisa, M., 2022. Infrastructural Development and Economic Growth in East Africa: Quantity Versus Quality Dimensions Using Panel-ARDL Approach. *International Journal of Empirical Economics 01(04). 1-33.*

Hassan, M.S., Kausarhttps, A and Arshedhttps, N., 2022. Investigating Export Determinants: A Time Series Evidence from Canada. *Sage Open, 12(2).*

Kamguila.B., Ndjakwa and Tadadjeu. S., 2023. Does Infrastructural Development Foster Export Upgrading in Africa? *African Development Review 35 (1).79-94.*

Karymshakov, K and Sulaimanova, B., 2021. The Impact of Infrastructure on Trade in Central Asia. *Asia Europe Journal. 19.5-20.*

Kemar, M.A and Qadir, U., 2005. Real Exchange Rate, Exports, and Imports Movements: A Trivariate Analysis. *The Pakistan Development Review, 44(2)177-195.*

Mao, H., Cui. G., Hussain. Z and Shao, L., 2024. Investigating the Simultaneous Impact of Infrastructure and Geographical Factors on International Trade: Evidence from Asian Economies. *Heliyon 10 (2024) E2379.*

Matlasedi, T.N., 2017. The Influence of the Real Effective Exchange Rate and Relative Prices on South Africa's Import Demand Function: An ARDL Approach. *Cogent Economics and Finance, 5(1).*

Ndou, E., 2021. Exchange Rate Changes, Price Level, and the Income Effects on Trade Balance In South Africa. *SN Business and Economics 1(36). 1-19.*

Ngassam, S.B., 2023. Exports Diversification in Africa: The Role of Infrastructures. *Journal of the Knowledge Economy.*

Nkoro, E and Uko, A.K., 2016. Autoregressive Distributed Lag (ARDL) Cointegration Technique: Application and Interpretation. *Journal of Statistical and Econometric Methods, 5(4), 63-91.*

Nwaogwugwu, I.C and Olaoye. O.O., 2018. Infrastructure Development and Export Trade in Nigeria. *BVIMSR's Journal of Management Research. 10(1). 8-20.*

Pesaran, M. H. and Shin, Y.,1999. An Autoregressive Distributed Lag Modelling Approach to Co-Integration Analysis, in Strom, S. (Ed.): Econometrics and Economic Theory in 20th Century: The Ragnar Frisch Centennial Symposium, Chapter 11, Cambridge University Press, and Cambridge.

Rehman, F., Noman. A. A., and Ding. Y., 2020. Does Infrastructure Increase Exports and Reduce Trade Deficit? Evidence from Selected South Asian Countries Using a New Global Infrastructure Index. *Journal Economic Structures. 9 (10). 1-23.*

Shepherd, B., and Wilson. S.J., 2007. Trade, Infrastructure, and Roadways in Europe and Central Asia: New Empirical Evidence. *Journal of Economic Integration, 22(4),723-747.*

Suriaganth,S and Abdullah, A., 2021. Impact of Foreign Trade on the Economic Growth of India.*Indian Journal of Economics and Business. 20 (1). 1077-1083.*

Thao, D and Hua, Z., 2016. ARDL Bounds Testing Approach to Cointegration: Relationship International Trade Policy Reform and Foreign Trade in Vietnam. *International Journal of Economics and Finance,8(8), 84-94.*

Vidya, C.T and Taghizadeh-Hesary, F., 2021. Does Infrastructure Facilitate Trade Connectivity? Evidence from the ASEAN. *Asia Europe Journal 19(1). S51-S75.*

World Bank database, 2023. World Bank Indicators. [online] available at: http://www.worldbank.org/indicator .

Zheng, H and Hongtao, L., 2022. Transportation Infrastructure and Trade. *Japan and the World Economy, 64. 1-17.*

Zhou, F., Wen. H and Lee, C., 2022. Broadband Infrastructure and Export Growth. *Telecommunication Policy. 46(5). 1-17.*

Bio-note

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