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Can Increased Intra-Continental Trade Partnerships Diversify Export Baskets in Africa?

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The study investigates the potential of the African Continental Free Trade Area (AFCFTA) agreement in fostering diversified export baskets through increased intra-continental trade partnerships. It aims to evaluate how these trade partnership influence export diversification within Africa. Using network analysis, it develops three indices to measure the degree, closeness, and prestige of trading partners across 54 African countries from 2000 to 2020. These indices, along with traditional estimators, reveal two key findings. Firstly, the quality of trade partnerships, focusing on 'who' a country trades with, holds more significance than quantity. Secondly, there is a geographical imbalance, where the effect of trade partnerships turns negative for countries with higher product diversification. In conclusion, while intra-continental trade diversification shows promise, more advanced African nations may experience diminishing returns, suggesting a need for expanding trade networks beyond the continent for sustained export diversification.

Key Words: trade partner diversification, product diversification, AFCFTA agreement
JEL *Classification:* C31, C32, C43, F14, F15

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Introduction

Africa, with its vast and diverse resources, has long been viewed as a continent ripe with potential for economic growth and development. However, unlocking this potential has proven to be a complex challenge, particularly in the realm of international trade. The main problem addressed in this research revolves around the need to diversify export baskets in Africa, thereby enhancing economic resilience and sustainability. By addressing this issue, this study aims to shed light on the potential of increased intra-continental trade partnerships as a means to address this challenge. Therefore, the primary objective of the study is to investigate the potential impact of increased intra-continental trade partnerships on the diversification of export baskets among African nations. Specifically, the paper aims to assess the influence of these trade partnerships on export diversification within the African context. This involves examining both the quantity and quality of trade relationships to understand their role in fostering diversified export portfolios among African countries.

Historically, one of the primary impediments faced by African countries is the reliance on a restricted set of trading partners. This historical dependence, often rooted in colonial legacies and post-colonial relationships, exposes African economies to external shocks and constrains their ability to explore diversified export destinations (United Nations Conference on Trade and Development 2019). Recognizing the vulnerability associated with such dependence, concerted efforts have been made to broaden the scope of trading relationships.

In the past, many developing nations pursued inward-looking import substitution policies to address economic challenges, but the oil shocks of the 1970s rendered these strategies unsustainable. This led to a shift towards more liberalized trade regimes, notably through programmes like the Structural Adjustment Programme. Export promotion gained traction in the 1980s, inspired by the success of the 'Asian Tigers', aiming to catalyse economic growth through international trade. However, the outcomes of export-oriented policies varied among developing countries, prompting nuanced examination. In Africa, low intra-African trade levels persist despite efforts at regional economic cooperation since the 1970s. Aid for Trade initiatives introduced by the World Trade Organization sought to enhance developing countries' participation in global trade, yet progress in diversifying economies through international commerce remains uneven. The African Continental Free Trade Area (AFCFTA), established in 2018, holds the potential to enhance intra-African trade and economic integration, offering opportunities to diversify export markets and goods produced across the continent.

The AFCFTA agreement is the largest FTA since the formation of the General Agreement on Tariffs and Trade (GATT) and is considered as a resurrection of previous attempts to economically unify Africa through terms of trade (Leshoele 2020). At the core of the agreement is the agenda of increased intra-continental trade partnerships which is envisioned as necessary to decolonize the African trade system and subsequently overcome the lingering effects of slavery, colonialism and neo-colonialism (Obeng-Odoom 2020). Whilst several authors have used Computable General Equilibrium (CGE) and Partial Equilibrium (PE) models to document the potential economic gains from the zero-tariffs policy proposed by the agreement (Abrego et al. 2019; Fofack et al. 2021; Bayale et al. 2022), these studies do not offer insights into the economic impact of increasing the number and variety of trade partnerships.

The hypotheses driving this research are twofold: firstly, that fostering trade partnerships within Africa will lead to greater diversification of export baskets among its nations, and secondly, that such diversification will result in increased economic stability and growth for participating countries. These hypotheses are grounded in the belief that reducing reliance on a limited set of exports and broadening the range of traded goods can mitigate risks associated with market volatility and external shocks.

Our study seeks to investigate whether the AFCFTA's primary objective of improved intra-trade partnerships can stimulate diversification in trade products. In theory, the configuration of trade networks is fundamentally shaped by competitive dynamics and the drive for survival among heterogeneous firms, compelling them to adapt and seek heightened productivity by venturing into new markets (geographical trade margins) and expanding the array of products they offer (extensive trade margins) (Melitz 2003; Chaney 2008; Helpman et al. 2008). In practice, insights drawn from the 'Asian growth miracle' demonstrate the significance of cultivating more sophisticated export portfolios and forging new trade alliances, as these elements can enhance a nation's trade standing and fully harness the potential of trade activities (Stiglitz 1996).

In alignment with these theoretical underpinnings and practical insights, our study scrutinizes whether the prospect of augmenting Africa's intra-continental geographical trade margins will increase the extensive trade margins of its products and produce a more diversified export portfolio.

The main element of complexity in our research lies in formulating a measure for trade partnerships. While existing literature suggests metrics such as the actual number of trading partners (Shepard 2010) or the trade partner concentration index formulated by Babones et al. (2011), and Babones and Farabee-Siers (2012), which gauges the proportion of a country's exports routed to its foremost trading partners, we adopt the network coding system devised by Önder and Yilmazkuday (2016). This network system produces three indices of trade partner diversification (TPD) encompassing (i) the degree or number of export partners), (ii) the proximity of these export partners, and (iii) the prestige of trading partners, which delineates the interconnectedness of a country's trading associates. Notably, these indices encapsulate pivotal dimensions of trade within the partnership network, encompassing facets such as intermediate-input trade, participation in global value chains, and considerations related to transportation costs (Önder and Yilmazkuday 2016).

We compile a comprehensive TPD dataset spanning 54 African countries over the period from 2000 to 2020. Subsequently, we employ this dataset to scrutinize the relationship between geographical trade margins and trade product diversification across the African continent using traditional POLS and more advanced panel quantile regressions which can capture location asymmetries in trade relationships (Ngondo and Phiri 2024). Our findings unveil a 'semi-hump-shaped' association between partner diversification and export diversification, signifying that the AFCFTA's pursuit of augmented intra-trade partnerships can catalyse the development of novel products for new markets, albeit up to a certain threshold limit.

The study overcomes the constrictions of relying on a few trading partners, enabling policymakers and businesses to develop strategies for diversification and reducing dependence. Despite its significance, this research is not without limitations. One such limitation is that the study may face challenges in accounting for the diverse economic, political, and social contexts across different African countries, which could impact the generalizability of its findings. Furthermore, the complex nature of trade dynamics entails that the outcomes of increased intra-continental trade partnerships may vary depending on a range of contextual factors.

The rest of the paper is structured as follows: the second section presents a literature review, the third section outlines the measures of trade partner diversification, the fourth section presents the empirical framework, the fifth section presents the results and the sixth section concludes the study.

Literature Review

Our study relates to a strand of research which examines the influence of a country's trade partners on economic growth, employing various proxies to measure trade partnerships. Arora and Vamvakidis (2005) were among the pioneers in investigating the impact of a country's trading partners on domestic economic growth. Analysing a sample of 101 countries from 1960 to 1999, they found that the growth and income levels of trading partners significantly affect a country's growth rates, suggesting that developing countries can benefit from industrialized economies, while industrialized countries can benefit from rapidly growing emerging economies.

Brenton and Newfarmer (2007), along with Amurgo-Pacheco and Pierola (2008), introduced a formal measure of the geographic extensive margin, emphasizing the importance of exporting to new geographical destinations for developing countries. Rondeau and Roudaut (2014) and Didier (2017) extended these concepts, developing similar measures of trade geographic diversification for samples of 64 developing countries and BRICS countries, respectively. Rondeau and Roudaut (2014) found that partner diversification can benefit poorer countries more than richer ones, while Didier (2017) highlighted the role of bilateral trade between Sub-Saharan Africa (SSA) and BRIC (Brazil, Russia, India and China) countries in diversifying export destinations within intra-Africa trade.

Shepard (2010) presented a simpler measure of trade partner diversification for 117 developing countries, counting the number of countries to which the exporting country has strictly positive export flows. The study used POLS and GMM estimators to identify factors influencing export partner diversification, finding that reductions in export costs, tariffs, and international transport costs positively impact geographical export diversification.

Babones et al. (2011), and Babones and Farabee-Siers (2012), created trade partner concentration indices for a sample of 128 countries from 1981 to 2006, measuring the percentage of a country's exports allocated to its top trading partners. They found that while the patterns of export trade concentration shifted over decades, Latin America and Africa maintained historically high levels of trade partner concentration.

In a study closely related to ours, Önder and Yilmazkuday (2016) created a panel dataset of export partner diversification for 83 countries, considering the degree, closeness, and prestige of export partners. Their growth regressions revealed that trade partnership is a significant growth determinant for countries characterized by low financial depth, high inflation, and low levels of human capital.

Our study extends Önder and Yilmazkuday's work by creating a trade partner diversification dataset exclusively for a network of African countries, using a more recent time span (2000 - 2020). Moreover, we deviate from the conventional focus on economic growth and investigate the trade partnership-export diversification relationship. This departure is motivated by recent literature questioning the utility of economic growth as a welfare measure, emphasizing the importance of diversified export portfolios in reflecting a more diversified industrial structure, which, in turn, is directly linked to improvements in standards of living (Siswana and Phiri 2021).

Measures of Trade Partner Diversification

We now detail the steps taken to create the time series indices of trade partner diversification for 54 African countries. We use information from the World Integrated Trade Solution (WITS) database to identify the export trading partners of each African country in the network and follow the three-stage procedure, described in Önder and Yilmazkuday (2016), to construct the indices.

Firstly, we create an Adjacency matrix A(t) of binary digits describing the bilateral trade links between African countries, with the trade elements (i.e. TRD (t):

$$A(t)_{ij=}\begin{cases} 1, \textit{ if country } i \text{ exp}\textit{orts to contry } j \\ 0, \textit{ otherwise} \end{cases}. \tag{1}$$

From matrix A(t), trade partner degree (TPD) is measured as the number of trade links a country has relative to the total number of possible links in the binary network.

$$TPD(t)_i = \frac{\sum_j \exp(t)_{ij}}{N - 1}, \tag{2}$$

where $0 < \text{TPD}(t)i < 1$, such that when TPD = 1, then country i trades with every African country in the network, whereas if TPD = 0, then country i does not export to any country.

Secondly, we extend the binary A(t) matrix into a non-binary D(t) matrix whose non-diagonal elements measure the geodesic distance between two countries, that is, the shortest path between two nodes in the network (Han et al. 2022). For cases in which the countries in the network are not connected and their geodesic distance is assumed to be infinity, we follow Önder and Yilmazkuda (2016) and assign the value 10 in the corresponding elements of the distance matrix D(t). All in all, the closeness centrality shows how far or close a country is to its trade partners or how directly accessible a country is by other countries, and thus reflects dimensions of intermediate-input trade and global value chains as well as transportation costs within the network (Önder and Yilmazkuday 2016). The elements 'TPC(t)ij' within the D(t) matrix are computed as:

$$TPC(t)_i = \frac{N-1}{\sum_j d\exp(t)_{ij}}, \tag{3}$$

wher $0 < \text{TPC}(t)i < 1$, such that values close to 0 indicate that a given country is 'far' from other countries (trade partners) in the network, whereas a value close to 1 indicates that a given country is 'close' to its trade partners. In other words, in the trade network, the higher the closeness centrality of a country, the closer its trade connection with other countries in the trade network.

Lastly, we create an index of a country's trade prestige by computing the eigenvectors for each country in the international trade network which measures how crucial, influential, and clustered a country's trading partners are. The eigenvector centrality is computed using the Power-Iteration Method in which we (i) initialize all the centralities to one, (ii) normalize the vector, and (iii) repeat the multiplication-normalization steps until convergence is reached (Abdi and Shakeri 2019). The trade partner eigenvalue - TE(t) - values range from a hypothetical 0 (a country does not have trading partners) to 1 (all of a country's trading partners trade with all other partners in the network) and countries with higher (lower) eigenvectors are more (less) connected to countries which are well connected to other countries in the network.

We now provide insight to some stylized facts on the trade partner diversification dataset by summarizing the rankings of the countries based on degree, closeness, and prestige, and further evaluate the evolution of time series plots for the individual countries. To keep the discussion concise, we focus on countries in the top five and bottom five of the rankings.

From the summary of the rankings in table 1, we observe that higher income countries such as South Africa, Egypt, and Morocco occupy the top rankings of all partnership indices (panel A), whilst poorer con-

TABLE 1 Summary of Top 5 and Bottom 5 Trade Diversification Ranking

Rank	Export Degree (ED)	Export Concentration (EC)	Export Prestige (EE)
Panel A: top-ranked countries			
1	South Africa (0.94)	South Africa (0.95)	South Africa (0.20)
2	Egypt (0.91)	Egypt (0.92)	Egypt (0.20)
3	Kenya (0.91)	Kenya (0.92)	Kenya (0.19)
4	Côte d'Ivoire (0.87)	Morocco (0.89)	Côte d'Ivoire (0.19)
5	Morocco (0.87)	Côte d'Ivoire (0.88)	Morocco (0.19)
Panel B: bottom-ranked countries			
1	Guinea-Bissau (0.26)	Guinea-Bissau (0.57)	Guinea-Bissau (0.06)
2	Comoros (0.230	Comoros (0.57)	Comoros (0.06)
3	Cabo Verde (0.19)	Cabo Verde (0.55)	Cabo Verde (0.04)
4	Sao Tome and Principe (0.14)	Sao Tome and Principe (0.54)	Sao Tome and Principe (0.03)
5	South Sudan (0.03)	South Sudan (0.38)	South Sudan (0.01)

NOTE Index values reported in parentheses ().

flict-prone economies and islands such as South Sudan, Somalia, Guinea-Bissau, and Eretria are at the bottom of these rankings (panel B).

The time series plots of the trade partner indices are presented in figure 1 for the top 5 (South Africa, Egypt, Kenya, Côte d'Ivoire, Morocco) and bottom 5 (Guinea-Bissau, Comoros, Cabo Verde, Sao Tome and Principe, South Sudan) ranked countries.

Two striking features are observed from the evolution of the time series. Firstly, the indices appear to be correlated with business cycle fluctuations. For instance, during the commodity boom of 2003-2005, we observe an increasing trend in most trade partnership indexes, whereas around the 2008-09 financial crisis and the resulting global recession period of 2009-2010, as well as the more recent COVID-19 pandemic, the indexes experience slumps. Secondly, in the post-2010 recession period the closeness and prestige indexes have slumped for most lower-ranked countries, whereas a general upward trend is observed for the higher ranked counterparts.

Empirical Framework

To examine the impact of trade partner diversification (TPD) on export product diversification, we estimate the following panel regression model using data spanning from 2000 to 2020:

$$DX_{i,t} = \alpha + \beta_1 TPD_{i,t} + \beta_2 TPD^2_{i,t} + \gamma Z_{i,t} + \delta_i + \delta_t + e_{i,t}\,, \tag{4}$$

where the dependent variable DXt is the modified Finger-Kreinin (1979) index used to capture export diversification computed as:

$$DX_j = \frac{\sum h_{ij} - x_j}{2}, \tag{5}$$

where is the share of commodity i in the total exports of country j and is the share of the commodity in world exports. The vector Zt is the set of conditioning variables inclusive of GDP growth (GDP), human capital (HC), domestic investment (INV), and quality of political institutions (POLITY), whilst δi and δt account for fixed effects.

We also estimate regressions (4) using the quantile regression estimators of Koenker and Bassett (1978), which we use to examine how trade partner diversification and other growth covariates influence the shape, scale and location at different points of the response distribution to export diversification. This involves estimating the dependent variable (Yit) at different quantiles of conditional distribution of the independent variables, Xit, where the conditional quantile for Yit given Xit i is compactly represented as:

$$Q_{y_{it}}(\tau ? X_{it}) = X^{\tau}_{it}\beta_{\tau}. \tag{6}$$

The coefficient estimates obtained from the traditional OLS estimator is based on the following minimization mean function of the form,], the quantile estimator of the conditional mean function of Y on its set of conditioning covariates (X):

$$\min_{\beta}\,[\theta\sum|Y_t - X_t\beta| + (1+\theta)\sum|Y_t - X_t\beta|]\{t{:}FS_t \geq X_t\beta\}\{t{:}\ FS_t < X_t\beta\}, \tag{7}$$

with $\{Y, t = 1, 2\ldots, T\}$ being a random sample on the regression

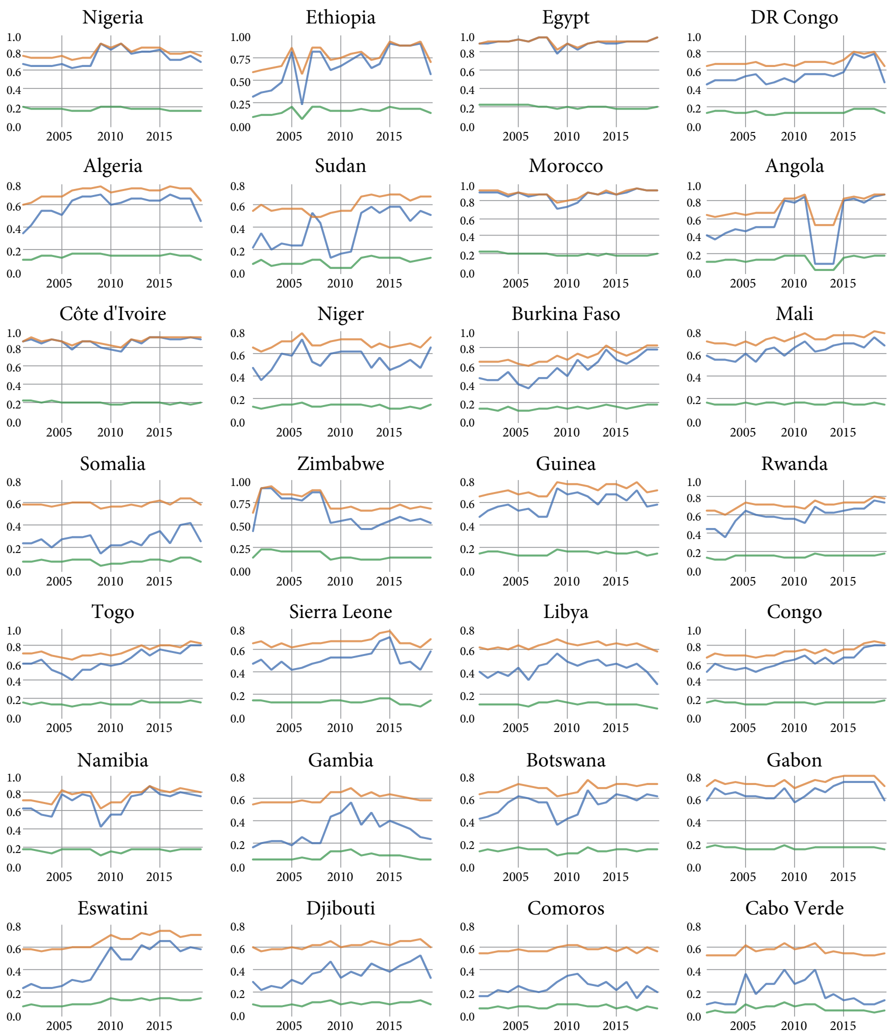
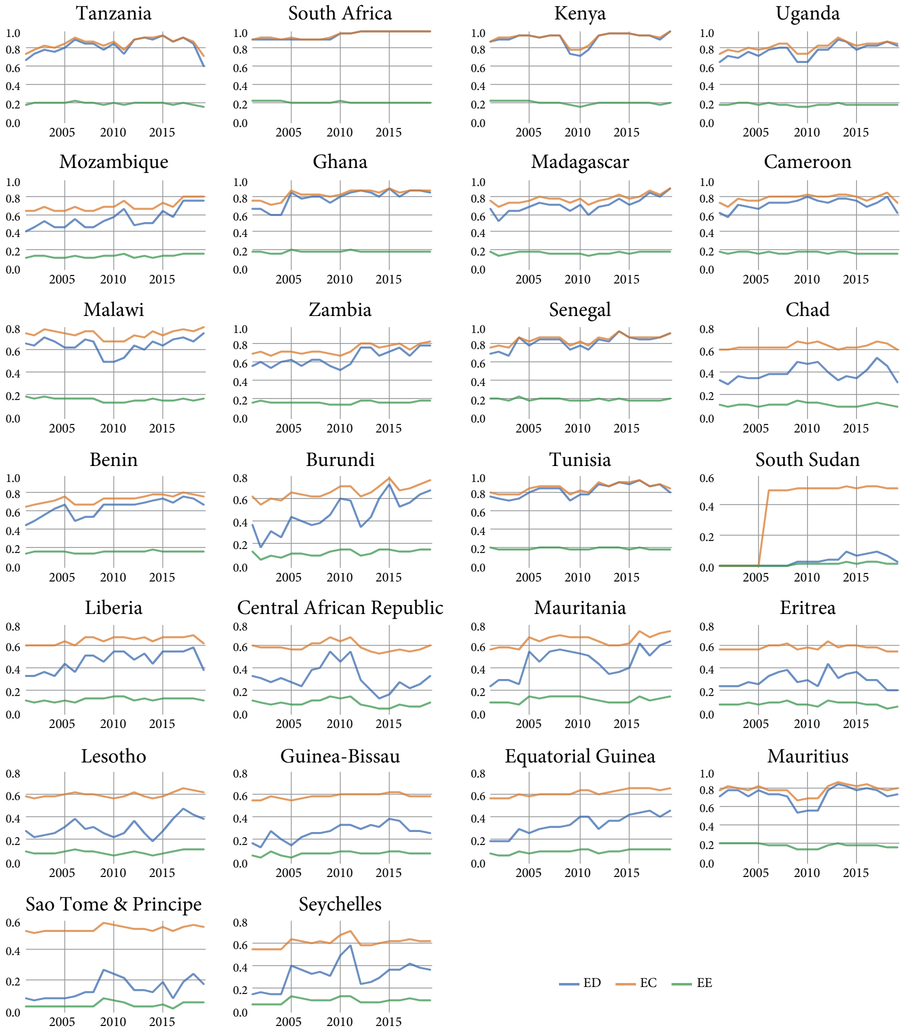


FIGURE 1 Time Series Plots of Trade Partner Diversification Indices

process $Y = {}_t + X_t\beta$, and the conditional distribution function of $F_{Y/X}(y) = F(Y_t \leq GDP) = F(Y_t - X_t\beta)$, and $\{X_{t,}\, t = 1, 2\ldots, T\}$ being the sequences of (row) k-vectors of a known design matrix. The θ^{th} regression quantile, $Q_{Y/X}(\theta)$, $0 < \theta < 1$, is any solution to minimize problems, denotes the solution from which the θ^{th} onditional quantile $Q_{Y/X}(\theta) = x\beta_\theta$. Our study uses 3 'quantiles' within the regression which are designated at the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th quantiles of conditional distribution.



Data Description and Results

The following sub-sections present the empirical findings from our analysis.

SUMMARY STATISTICS, CORRELATION MATRIX AND UNIT ROOT TESTS

In this section of the paper, we present the summary statistics, unit root tests, and correlation matrices of the panel series, as reported in tables 2,

TABLE 2 Summary Statistics and Unit Root Tests

	DX	EC	ED	EE	INV	HC	GDP	POLITY
MEAN	0.759	0.705	0.548	0.126	-1.88	0.185	4.074	0.351
MEDIUM	0.782	0.697	0.566	0.133	-2.379	0.195	4.337	0.00
MAXIMUM	0.937	1.00	1.00	0.224	0.00	0.468	6.083	1.00
MINIMUM	0.453	0.00	0.00	0.00	-5.231	0.00	0.00	0.00
STD. DEV.	0.089	0.127	0.238	0.049	1.506	0.137	1.333	0.399
SKEWNESS	-1.15	-0.489	-0.211	-0.475	0.187	0.039	-1.902	0.378
KURTOSIS	4.04	6.27	2.19	2.54	1.52	1.84	6.77	1.31
JARQUE-BERA	273.47	499.70	35.66	47.76	99.37	57.13	1228.08	145.51
P-VALUE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

NOTES DX – export diversification; EC – Export closeness, ED – Export degree; EE – Export prestige, INV – investment; HC – human capital; GDP – gross domestic product growth; POLITY – political institutions.

3, and 4, respectively. It is essential to note that all time series variables have been logged for empirical purposes.

From table 2, we observe high (low) average values on the export diversification and trade partner concentration indices (trade partner diversification and prestige), implying that while African countries have a high number of trading partners, these countries also have relatively low-quality trading partners. Skewness and kurtosis statistics reveal that the trade partnership indices are slightly negatively skewed with fat tails, indicating a non-normal distribution of the series. This justifies the use of quantile regression, which can capture the relationship between a set of time series at different levels of conditional distribution, including tail-end co-movements.

In table 3, the reported correlation coefficients demonstrate the expected positive correlation between all measures of trade partner diversification and export diversification, as indicated by previous studies (Brenton and Newfarmer 2007; Amurgo-Pacheco and Pierola 2008; Shepard 2010; Babones et al. 2011; Babones and Farabee-Siers 2012; Didier 2017). Based on these preliminary findings, we formulate the hypothesis of a positive trade partner–export diversification relationship for all partnership indices, which we subsequently evaluate in our main empirical analysis. Moreover, none of the reported correlation coefficients exceeds 0.8, a result that safeguards against possible multicollinearity among the variables.

Finally, the LLC and IPS unit root test results in table 4 reject the unit root null hypothesis for at least one of the performed tests for each of

TABLE 3 Correlation Matrix

	DX	EC	ED	EE	INV	HC	GDP	POLITY
DX	1.00							
EC	0.04	1.00						
ED	0.07	0.96	1.00					
EE	0.06	0.92	0.97	1.00				
INV	0.05	−0.06	−0.05	−0.05	1.00			
HC	0.09	0.60	0.63	0.62	−0.10	1.00		
GDP	0.08	0.63	0.64	0.63	−0.20	0.58	1.00	
POLITY	0.05	0.16	0.15	0.15	−0.12	0.23	0.16	1.00

NOTES DX – export diversification; EC – Export closeness, ED – Export degree; EE – Export prestige, INV – investment; HC – human capital; GDP – gross domestic product growth; POLITY – political institutions.

the panel time series. This implies that all variables are mutually I(0) stationary processes and are thus suitable for estimation using POLS and quantile estimators.

BASELINE ESTIMATORS

Table 5 presents the baseline regression outcomes from the POLS, fixed effects, and random effects estimators. Notably, all three trade partner diversification indices yield positive and statistically significant estimates, indicating the importance of the degree, closeness, and prestige of trading partners in trade product diversification. It is noteworthy that both prestige and closeness indices result in higher coefficient estimates

TABLE 4 Unit Root Tests

	Levin, Lin, and Chu (LLC)		Im, Pesaran, and Shin (IPS)	
	levels	First differences	Levels	First differences
DX				
ED	−2.04**	−9.48***	−1.84**	−13.68***
EC	−1.46*	−9.98***	−1.37*	−13.74***
EE	−3.77***	−8.88***	−4.59***	−13.99***
INV	−5.59***	−5.63***	−1.23	−5.27***
HC	−0.21	−3.95***	−1.51*	−3.59**
GDP	−7.57***	−17.57***	−7.63***	−22.79***
POLITY	45.77***	−37.42***	−14.61***	−12.28***

NOTES '***', '**', '*' denote 1%, 5%, 10% significance levels, respectively. DX – export diversification; EC – Export closeness, ED – Export degree; EE – Export prestige, INV – investment; HC – human capital; GDP – gross domestic product growth; POLITY – political institutions.

compared to the degree of trading partners. This aligns with the findings of Brenton and Newfarmer (2007), Amurgo-Pacheco and Pierola (2008), and Önder and Yilmazkuday (2016), underscoring that the type of trading partner holds more significance than the sheer number of trading partners. For instance, countries with an equal number of trading partners may exhibit different levels of development based on the nature of their trade partnerships (Babones et al. 2011; Babones and Farabee-Siers 2012). Moreover, from an economic standpoint, establishing international trade connections with a larger and/or better-connected array of countries is positively and significantly associated with higher levels of export diversification, all else being equal. This implies that fostering such connections should be considered crucial for achieving greater export diversification, thereby potentially leading to higher levels of economic growth and development. Policymakers should therefore prioritize initiatives aimed at fostering diverse and robust trade partnerships, both regionally and internationally. While efforts to increase the number of trading partners are important, policymakers should also focus on strengthening ties with economically advanced and geographically proximate countries. This balanced approach to diversifying trade partnerships can amplify efforts towards export diversification and contribute positively to overall economic development.

Furthermore, most control variables (investment, human capital, and GDP growth) consistently yield positive and statistically significant estimates, consistent with prior studies by Agosin et al. (2012), Fonchamnyo and Akame (2017), Swathi and Sridharan (2022), and Zarach and Parteka (2023). These variables are recognized as plausible determinants of export diversification. An exception is the political institution (POLITY) variable, which predominantly produces negative and significant estimates. This could occur when political institutions fail to create an environment conducive to fostering diversification of productive capabilities, particularly in resource-intensive countries, i.e. the resource curse (Omgba 2014; Olander 2019).

QUANTILE ESTIMATORS

Table 6 presents the coefficient estimates from quantile regression across 10 distributional quantiles. For the trade partner degree and closeness measures, positive and statistically significant estimates are evident between the 20th and 80th quantiles. Conversely, the coefficient estimates for the prestige measure are significantly positive across all quantiles.

TABLE 5 Baseline Estimators

	POLS			Fixed effects			Random effects		
ED	0.05			0.04			0.03		
	(0.00)***			(0.00)***			(0.00)***		
EC		0.16			0.16			0.14	
		(0.00)***			(0.09)*			(0.06)*	
EE			0.18			0.17			0.17
			(0.01)**			(0.01)**			(0.01)**
INV	0.005	0.005	0.005	0.004	0.004	0.04	0.008	0.007	0.007
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
HC	0.07	0.09	0.04	0.11	0.10	0.08	0.06	0.04	0.03
	(0.00)***	(0.00)***	(0.09)*	(0.09)*	(0.14)	(0.24)	(0.30)	(0.34)	(0.25)
GDP	0.01	0.01	0.005	0.02	0.03	0.03	0.003	0.005	0.005
	(0.00)***	(0.00)***	(0.06)*	(0.07)*	(0.02)**	(0.02)**	(0.69)	(0.46	(0.52)
POLITY	0.009	0.01	0.009	−0.02	−0.015	−0.01	−0.01	−0.015	−0.015
	(0.18)	(0.15)	(0.20)	(0.01)**	(0.02)**	(0.02)**	(0.01)**	(0.00)***	(0.00)***

NOTES '***', '**', '*' denote 1%, 5%, 10% significance levels, respectively. DX – export diversification; EC – Export closeness, ED – Export degree; EE – Export prestige, INV – investment; HC – human capital; GDP – gross domestic product growth; POLITY – political institutions.

Similar to the traditional estimators, the trade partnership closeness and prestige variables yield larger regression coefficients compared to the partnership degree across all quantiles. This aligns with prior literature, emphasizing that the quality of trading partners holds more significance than the sheer quantity (Brenton and Newfarmer 2007; Amurgo-Pacheco and Pierola 2008; Önder and Yilmazkuday 2016). Therefore, trade policies should focus on nurturing relationships with partners characterized by high prestige and closeness, as they are likely to yield larger benefits in terms of export diversification for more developed AFCFTA member countries.

Upon closer examination, the coefficient estimates for all three measures of Trade Partner Diversification (TPD) increase in magnitude until the 50th median quantile, after which the magnitude decreases at higher quantiles. This suggests a semi-humped-shaped relationship between partnership and export diversification, indicating that the marginal benefits of increasing trade partnerships exist primarily for countries with low to medium levels of product diversification. Conversely, diminishing returns are observed for countries with more developed trade industries at higher quantiles.

The control variables generate positive and statistically significant estimates at various quantiles. For the investment, human capital, and GDP

TABLE 6 Quantile Regression Estimators

		Export Degree		Export Closeness		Export Prestige	
	τ	estimate	p-value	estimate	p-value	estimate	p-value
TPD	0.1	0.02	0.93	0.29	0.66	0.05	0.00***
	0.2	0.08	0.06*	0.13	0.00***	0.09	0.75
	0.3	0.07	0.00***	0.14	0.00***	0.11	0.29
	0.4	0.06	0.00***	0.14	0.00***	0.14	0.04*
	0.5	0.06	0.00***	0.16	0.00***	0.18	0.03*
	0.6	0.05	0.00***	0.14	0.00***	0.19	0.02**
	0.7	0.05	0.00***	0.13	0.00***	0.17	0.04*
	0.8	0.04	0.01**	0.12	0.00***	0.15	0.09*
	0.9	0.01	0.54	0.06	0.14	0.003	0.07*
INV	0.1	0.009	0.13	0.009	0.04*	0.003	0.45
	0.2	0.01	0.00***	0.008	0.12	0.006	0.03*
	0.3	0.007	0.00***	0.007	0.00***	0.006	0.00***
	0.4	0.006	0.00***	0.007	0.00***	0.008	0.00***
	0.5	0.005	0.00***	0.005	0.00***	0.007	0.00***
	0.6	0.004	0.00***	0.005	0.00***	0.005	0.00***
	0.7	0.003	0.03*	0.003	0.01**	0.003	0.04*
	0.8	0.003	0.09*	0.004	0.04*	0.003	0.07*
	0.9	0.004	0.07*	0.005	0.00***	0.004	0.05*
HC	0.1	−0.44	0.15	−0.18	0.78	−0.56	0.00***
	0.2	0.153	0.14	0.20	0.04*	0.003	0.98
	0.3	0.136	0.00***	0.18	0.00***	0.08	0.09*
	0.4	0.146	0.00***	0.16	0.00***	0.133	0.00***
	0.5	0.161	0.00***	0.17	0.00***	0.137	0.00***
	0.6	0.123	0.00***	0.12	0.00***	0.111	0.00***
	0.7	0.076	0.00***	0.08	0.00***	0.075	0.00***
	0.8	0.078	0.00***	0.09	0.00***	0.061	0.00***
	0.9	0.075	0.00***	0.09	0.00***	0.072	0.00***
GDP	0.1	0.03	0.12	0.05	0.00***	0.01	0.09*
	0.2	0.012	0.14	0.02	0.42	0.01	0.26
	0.3	0.014	0.00***	0.01	0.00***	0.01	0.01**
	0.4	0.012	0.00***	0.01	0.00***	0.008	0.06*
	0.5	0.005	0.23	0.008	0.09*	0.002	0.44
	0.6	0.002	0.21	0.003	0.08*	0.001	0.43
	0.7	0.004	0.03*	0.004	0.00***	0.003	0.06*
	0.8	0.005	0.00***	0.005	0.00***	0.004	0.01**
	0.9	0.005	0.00***	0.006	0.00***	0.005	0.00***

Continued on the next page

TABLE 6 *Continued from the previous page*

		Export Degree		Export Closeness		Export Prestige	
	τ	estimate	p-value	estimate	p-value	estimate	p-value
POLITY	0.1	0.0002	0.99	−0.0002	0.99	0.017	0.33
	0.2	0.0004	0.97	0.002	0.90	0.004	0.80
	0.3	−0.004	0.63	−0.002	0.82	−0.004	0.63
	0.4	−0.001	0.81	−0.001	0.82	−0.002	0.70
	0.5	−0.002	0.75	−0.001	0.80	−0.003	0.62
	0.6	0.002	0.74	0.005	0.43	0.0009	0.98
	0.7	0.014	0.03*	0.017	0.00***	0.009	0.18
	0.8	0.007	0.29	0.007	0.28	0.01	0.11
	0.9	0.14	0.04*	0.012	0.06*	0.02	0.02**

NOTES '***', '**', '*' denote 1%, 5%, 10% significance levels, respectively. DX – export diversification; EC – Export closeness, ED – Export degree; EE – Export prestige, INV – investment; HC – human capital; GDP – gross domestic product growth; POLITY – political institutions.

variables, the coefficients are significant across the 20th to 90th quantiles. Meanwhile, the political institution (POLITY) variable produces significant estimates at the 70th and 90th quantiles.

Conclusions

We examine whether the increased intra-continental trade partnerships resulting from the recent AFCFTA agreement can contribute to diversifying export baskets. To this end, we employ network analysis to construct three novel indices measuring the degree, closeness, and prestige of a country's trading partners for 54 African countries from 2000 to 2020. This dataset enables us to explore the impact of trade partnerships on export diversification using both traditional and quantile estimators.

Despite the potential benefits of AFCFTA and increased intra-continental trade, there is a gap in the literature regarding its specific impact on export diversification within the African context. While some studies have explored the determinants of export diversification at the country level, few have examined the role of trade partnerships in shaping export portfolios across the continent. Our contribution to the literature therefore lies in demonstrating that a country's position within the international trade network significantly and positively influences the level of export diversification regressions, even when considering other standard control variables. Traditional estimators indicate that all trade indices are positively associated with product diversification. Notably, the closeness and prestige of trading partners exhibit more significant effects compared to the sheer number of trading partners. However, quantile regressions reveal a semi-humped-shaped partnership-export diversification schedule, suggesting that the marginal effects of enhanced intra-continental trade partnerships turn negative at higher quantiles of distribution.

Our findings yield two key policy implications. Firstly, the 'type' of a country's trading partners holds greater significance than the sheer quantity. Countries with the same number of trading partners may differ in industry structure and development based on the quality of their trading partners. Secondly, African countries with high (low) levels of product diversification will benefit less (more) from increased intra-continental trade partners. Hence, for the success of the AFCFTA agreement, policymakers should not only emphasize strengthening intra-continental ties but also consider boosting international trade connections, especially for more developed African countries unable to diversify trade baskets with less 'sophisticated' trading partners.

Based on the findings, the paper suggests that fostering intra-continental trade partnerships through initiatives like the AFCFTA can indeed contribute to diversifying export portfolios. Policymakers can leverage this insight to prioritize efforts aimed at strengthening regional trade integration. Therefore, a prudent trade policy for these countries would entail fostering strategic alliances with prestigious and economically robust trading partners, as emphasized in prior literature. By doing so, they can optimize their export diversification efforts and enhance their competitiveness within the AFCFTA framework.

African countries vary significantly in terms of geographical, economic, and institutional characteristics, which could affect the generalizability of the findings. To account for this heterogeneity, the study could have conducted subgroup analyses or sensitivity tests to assess the robustness of the results across different country groupings or economic classifications.

While the current study provides valuable insights into the relationship between intra-continental trade partnerships and export diversification in Africa, there are several avenues for further research that could expand upon the findings. Conducting comparative studies with other regions or countries outside of Africa could provide valuable insights into the unique challenges and opportunities faced by African nations in diversifying their export portfolios. By benchmarking against global trends and best practices, researchers can identify lessons learned and potential policy recommendations for enhancing export diversification efforts.

Given the novelty of our dataset, we encourage researchers to utilize it (available upon request) for further empirical research on intra-continental partnerships under the AFCFTA agreement. The time series format of the data facilitates country-specific or regional analyses for researchers and policymakers. Future studies can use the dataset to explore issues related to regional-value-chains, small business and tourism development, female participation and environmental sustainability.

In essence, our findings highlight the potential of intra-continental trade partnerships under the AFCFTA agreement to foster export diversification in Africa, offering a pathway towards sustainable economic growth and development.

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Appendix

List of Countries

Countries			
1	Algeria	28	Madagascar
2	Angola	29	Malawi
3	Benin	30	Mali
4	Botswana	31	Mauritania
5	Burkina Faso	32	Mauritius
6	Burundi	33	Morocco
7	Cameroon	34	Mozambique
8	Cape Verde	35	Namibia
9	Central African Republic	36	Niger
10	Chad	37	Nigeria
11	Comoros	38	Republic of the Congo
12	DR of the Congo	39	Rwanda
13	Djibouti	40	Sao Tome and Principe
14	Egypt	41	Senegal
15	Equatorial Guinea	42	Seychelles
16	Eritrea	43	Sierra Leone
17	Eswatini	44	Somalia
18	Ethiopia	45	South Africa
19	Gabon	46	South Sudan
20	Ghana	47	Sudan
21	Guinea	48	Tanzania
22	Guinea-Bissau	49	The Gambia
23	Côte d'Ivoire	50	Togo
24	Kenya	51	Tunisia
25	Lesotho	52	Uganda
26	Liberia	53	Zambia
27	Libya	54	Zimbabwe

Assessing the Impact of Emotional Intelligence on Employee Performance: Toward an Integrated Emotional Intelligence Framework

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Emotional intelligence has garnered significant attention in the field of business management. It encompasses a range of interpersonal and intrapersonal skills that profoundly impact multiple aspects of human behaviour, relationships, and general well-being. Emotional intelligence has been demonstrated to be a pivotal element in shaping workplace dynamics, maintaining the well-being of employees, and improving organisational performance. Therefore, this paper aims to investigate and analyse the impact of emotional intelligence on employee performance. A survey was conducted in the business process outsourcing sector in Mauritius. Results demonstrated that factors including years of experience, educational level, age group, motivation and job roles positively influence emotional intelligence and employee performance. In addition, an emotional intelligence framework was proposed to mediate conflicts between higher management and employees. Finally, relevant recommendations have been put forward on how to improve performance and also how to reduce conflicts.

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Introduction

Emotional intelligence (EI) has garnered significant attention in the fields of psychology, education and business management (Jawaheer 2022).

EI involves the ability to recognise, understand, manage, and effectively use one's own and others' emotions in shaping workplace dynamics and outcomes (Goleman 1995). It encompasses a range of interpersonal and intrapersonal skills that profoundly impact multiple aspects of human behaviour, relationships, and general well-being. The concept of EI emerged as an answer to the realisation that cognitive intelligence did not fully record the complexities of human interactions and success. EI embraces components such as self-awareness, self-regulation, motivation, empathy, social skills, social awareness and relationship management (Dessler 2020). All these are crucial for decision-making. EI has a deep impact on multiple facets of life, varying from personal relationships to professional success (Khalid et al. 2018).

Different people come with different emotions and behaviours. Managers and leaders make decisions based on their feelings and emotions without assessing the impact on the feelings and emotions of other employees in the organisations. This has an impact on employee performance reducing the effectiveness and efficiency with which an employee fulfils job responsibilities and commits to organisational goals (Dhungana and Kautish 2020).

The implementation of EI in an organisation is also influenced by factors like age groups, mentalities, opinions and different backgrounds. Not everyone will have the same reactions to a decision taken by the firm. To some, it may seem favourable and suitable, but to others, it can have an adverse impact which eventually leads to disagreements between colleagues. Therefore, this study aims to investigate the effect of emotional intelligence on employee performance in a Small Island Developing State (SIDS) such as Mauritius. The influence of demographic factors, such as education level, years of experience, age group and job roles on EI will also be investigated, as well as practical recommendations for BPO (Business Process Outsourcing) organisations to optimise their workforce's EI and enhance performance outcomes.

This paper is organised into 7 parts. The first section outlines the background, aim and objectives of the research work. The second section summarises the main literature on emotional intelligence, while the third section develops a framework connecting emotional intelligence and employee performance. The fourth section explains the data collection phase as well as the methodology used. The fifth section presents the results of the study, followed by a general discussion in the sixth section. The seventh section concludes with some areas for future research.

Theoretical Background

EMOTIONAL INTELLIGENCE

EI is the ability to monitor one's own and others' feelings and emotions, to discriminate among them, and to use this information to guide one's thinking and actions (Salovey and Mayer 1990). Goleman (1995) defined EI as an individual's ability to understand and manage their feelings so that they are expressed appropriately and effectively. Mayer and Salovey (1997) argued that EI is an ability that someone can have instead of a trait since it can be mastered with age and experience.

EI consists of four components, namely self-awareness, self-management, social awareness, and relationship management (Noorafshan and Jowkar 2013). Self-awareness refers to understanding our own emotions and the way that they can affect our behaviours, thoughts, and performance. It is defined as a skill that needs to be worked on with repetitive reflection on one's continuous actions, to question one's behaviour and think about the answer without a prior judgment of being perfect (London et al. 2023). Individuals with high EI are skilled at managing stress. They can recognise when stress levels are rising and apply coping strategies to maintain their well-being (Sharma 2008). Emotionally intelligent individuals excel at managing their own emotions, especially in high-pressure situations. It prevents emotional outbursts that could negatively impact their work. Employees can remain composed, make rational decisions, and maintain focus on tasks, resulting in consistent and productive performance. Employees who possess EI not only perform well but also commit to the job (Biza and Irbo 2020; Sujatha et al. 2013).

Furthermore, EI contributes enormously to conflict management. Wall and Callister (1995) defined conflict as a proceeding in which one party discerns that its interest is different and contradicted by another individual. Conflict occurs due to different goals, expectations, principles, and outlooks on handling a situation. Different interests cause a divergence in opinions, leading to conflict (Chen et al. 2019). Thus, individuals with high levels of EI would have higher abilities to deal with these situations. Goleman (1995) stated that conflict resolution relies on an individual's level of EI. If an individual has mastered EI, he will be able to have better conflict management skills. Navigating conflicts with empathy and understanding contributes to a harmonious work environment. This, in turn, reinforces commitment, as employees perceive the organisation as a place where differences are resolved with respect (Oyoru and Ambali 2022).

EMOTIONAL INTELLIGENCE MODELS

While Salovey and Mayer (1990) explain EI as the ability to study one's own and others' emotions, Petrides and Furnham (2001) defined EI as a quality and a set of emotional insights that are located at the bottom of the personality ladder. These definitions have resulted in the culmination of three different models, namely, the ability model, the trait model, and the mixed model.

The ability model of EI was developed by Mayer and Salovey (1997). It is categorised into four dimensions of emotion-processing mental abilities, starting from the bottom line to the higher-level ability. The dimensions include (1) Perception, appraisal and expression of emotions, (2) Emotional facilitation of feelings, (3) Comprehension and analysis of emotions, (4) Reflection synchronisation of emotions.

The trait model as shown in figure 1 was explained by Petrides and Furnham (2001), wherein they defined EI as the ability to be self-aware and prone to behave well. According to these theorists, the personality dimension should be used to evaluate EI and, eventually, come up with the trait model of EI. This has been categorised into fifteen emotional aspects that have been assimilated under four main components, namely well-being, self-control, emotions, and sociability.

The mixed model of EI by Bar-On (1997) integrates emotional and social competencies to predict personal well-being and performance. It encompasses five key areas: intrapersonal skills (self-awareness and self-expression), interpersonal skills (social awareness and interpersonal relationships), adaptability (managing change and solving problems), stress management (emotional regulation and stress tolerance), and general mood (optimism and happiness). The Bar-On model assesses these competencies to help individuals improve emotional and social functioning to enhance mental health and life success. A summary of the model is found in figure 2.

Development of an Integrated Emotional Intelligence Framework

One contribution of this research work is to develop an Emotional Intelligence Model (EIM) compatible with Mauritius as a SIDS country. The literature fails to connect the existing framework to the test case

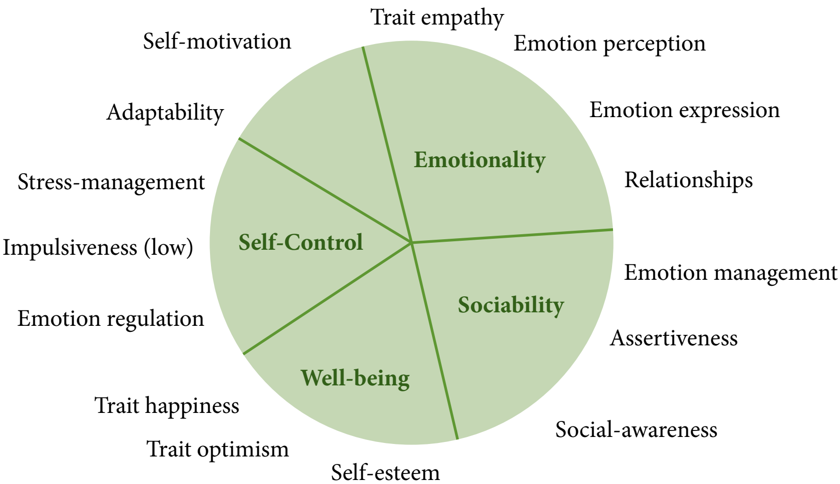

FIGURE 1 Trait Model of Emotional Intelligence Source Adapted from Petrides and Furnham (2001)

<table>
<tr><td colspan="3">Intrapersonal
Self-regard, emotional self-awareness, assertiveness, self-actualisation, independence</td><td colspan="3">Interpersonal
Empathy, social responsibility, interpersonal relationships</td></tr>
<tr><td colspan="2">Adaptability
Problem-solving, flexibility, reality testing</td><td colspan="2">Stress Management
Stress tolerance, impulse control</td><td colspan="2">General Mood
Happiness, optimism</td></tr>
</table>

FIGURE 2 Mixed Model of Emotional Intelligence
SOURCE Bar-On (1997)

country. Though popular amongst researchers, the trait model does not always concur with real-world empirics. Employees with high EI may find it difficult to sort conflicts effectively due to external factors, power dynamics, and the nature of the conflict itself. The ability model on the other hand does not address the behavioural aspects of conflict management. It provides insight into an individual's ability to understand emotions but does not directly explain how these abilities change into effective conflict resolution strategies and behaviours. The complexity of the mixed model makes it less practical for organisations to use in assessing employees for conflict management skills. The latter model may not cover specific conflict resolution styles such as collaboration,

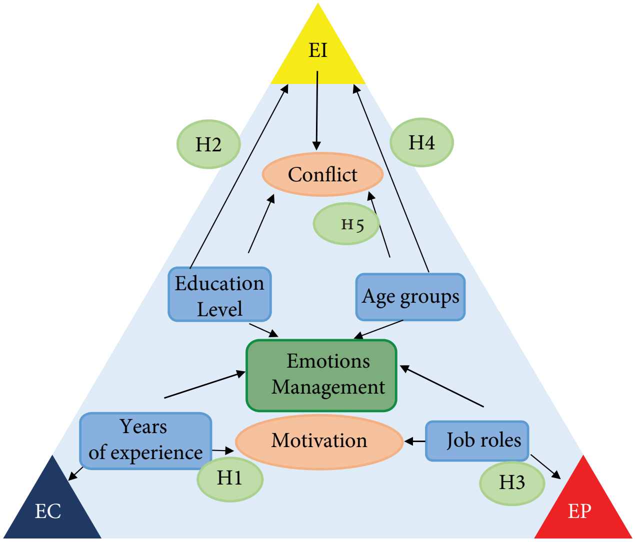

FIGURE 3 Proposed Emotional Intelligence Framework

compromise, or avoidance (Kanesan and Fauzan 2019). As a result, a conceptual framework was developed to cater for the above-mentioned weakness, which includes variables such as Employee Performance (EP) and Employee Commitment (EC). The model integrates internal factors such as conflict, emotional management and motivation, as well as external factors such as education level, age groups, years of experience and job status, as illustrated in figure 3.

INTERNAL FACTORS

Conflict in workplaces is still a concern for any organisation. It has serious impacts, disrupts peace at work, and leads to disagreements between employees and management. In certain instances, some employees go out of their way to make their colleagues' lives hell. It generates a toxic work environment where everyone is working just for the sake of getting a salary, and no sense of commitment can be seen in their work. This eventually affects productivity, both in terms of quality and quantity (Vashisht et al. 2018).

Motivation in many organisations is another important aspect that is needed to keep employees' performance at a high level (Munir and Azam 2017). When employees are less motivated to work, they tend to neglect work, which can lead to an increase in the rate of absenteeism. Different employees have different mindsets; however, with more work experience, employees tend to know better how to manipulate their emotions and eventually better commit to the organisation. Repeating the same work daily with poor management, where employees do not feel valued and heard, leads to a lack of motivation to work. Thus, managers should be made aware of their managing styles to avoid miscommunication and act upon any difficulty that employees are facing. Self and team motivation is equally important for EI to work. Otherwise, not only employees but the organisation will suffer. In an organisation, there are various job roles – senior positions, recruits, caretakers, etc. Neither does everyone have the same performance, it differs for everyone (Shooshtarian et al. 2013). It could be due to a lack of motivation to work or because they are unable to manage their emotions. Therefore, Hypothesis 3 will test the relationship between job roles and the level of performance.

External Factors

EI can be related to the education level of employees (Abebe and Singh 2023). Those who have a higher academic qualification tend to understand EI better. In an organisation, there are different age groups with different opinions and different ways of perceiving things (Saulick et al. 2024). EI is considered to increase with age: between an employee aged 18 and one aged 40, there will be a huge difference in their ability to manage their emotions and to reflect on their decisions. Not every employee will be ready to agree to implement EI as a factor to drive job performance (Igbinovia and Popoola 2016). Implementing the performance appraisal is usually done by the HRM team. There is a misconception about performance appraisal that it is mainly for increasing the salary of an employee, but through a strategic Human Resource Management perspective, it helps to drive EP and to provide feedback. Their performance throughout the year is discussed and based on that, they are remunerated. Therefore, employees who possess EI not only perform well but also commit to the job. Eventually, the performance of an employee is no longer related to the job level.

Emotional Intelligence and Managing Conflict

In an organisation, people manage their emotions differently and therefore also handle conflicts differently. Some people are impulsive and people who react abruptly, whereas others are more composed and analyse things first before reacting. EI is important for any organisation to succeed in the long run; indeed, numerous factors bring about a healthy work environment and good relationships among employees. The following hypotheses are used to test the validity of the proposed EIM:

- HYPOTHESIS 1: Years of experience impact the level of employee motivation.
- HYPOTHESIS 2: The level of employee education affects the level of EI.
- HYPOTHESIS 3: Job roles impact employee performance throughout the fiscal year.
- HYPOTHESIS 4: Different age groups will have different levels of EI.
- HYPOTHESIS 5: Different age groups will manage conflict according to their level of EI.

Methodology

To test the proposed hypotheses, a quantitative survey approach was adopted using a self-administered questionnaire. The survey contains seven sections (A to G), as shown in table 1. The detailed components of each section are illustrated in the Appendix.

Section A comprises demographic parameters (summary of questions in table 2), while Sections B to Section G comprise Likert 5-scale questions on EI and EP. The target population for this study comprises employees working within the BPO sector in Mauritius. Respondents were selected using a nonprobability sampling strategy, more specifically, a convenience sampling approach.

A pilot study was conducted to examine the feasibility, design and methodology of the survey instrument. It served as a trial to locate potential issues, refine research methods, and make necessary adjustments before moving forward with the full-scale survey. Five employees were selected for the pilot tests and the questionnaire was sent to them through email. Once the questionnaire was deemed as meeting the research objective, 400 copies were distributed to various actors in the BPO sectors. A total of 350 valid responses were collected, resulting in a response rate of 87.5%. The participants were reminded of the confidentiality of their responses. The demographic profile of respondents is shown in table 2.

Cronbach's alpha is a statistic used to assess the reliability, or internal consistency, of a set of scale or test items. It measures how well a group of items collectively measures a single, unidimensional latent construct. The values of Cronbach's alpha range from 0 to 1, with higher values indi-

TABLE 1 Survey Questionnaire Breakdown

Sections	Description
A	It includes the demographic information of each participant, such as gender, age groups, years of experience in the BPO industry, highest academic qualifications and job role.
B	This will measure how employees view the importance of EI in their organisation.
C	This will explain how EI contributes to EC and whether the EI training will help in increasing EC.
D	This will address EP in the BPO sector and the factors that can influence it.
E	This will show how conflict is dealt with and whether the respondents think that EI can help in managing conflict.
F	This will show the regulations that ameliorate the implementation of EI in BPO sectors.
G	This section will demonstrate whether motivation is a key factor in an organisation and if respondents think motivation drives EC and EP.

TABLE 2 Demographic Characteristics of the Study Population

Characteristics		Frequency		
		Male	Female	Percentage (%)
Gender		163 (46.6%)	187 (53.4%)	100
Age group	18 - 25	85	96	51.7
	26 - 40	65	68	38.0
	41 - 65	13	23	10.3
	Total	163	187	100
Academic performance	School Certificate	20	18	10.9
	Higher school certificate	65	78	40.9
	Bachelor’s degree	70	73	40.8
	Master’s degree	8	18	7.4
	Total	163	187	100
Years of experience	0 - 5 years	85	96	51.7
	6 - 10 years	36	40	21.7
	11 - 15 years	23	34	16.3
	Above 15 years	19	17	10.3
	Total	163	187	100
Job Roles	Associate	82	100	52.0
	Analyst	45	47	26.3
	Manager	15	13	8.0
	Others	21	27	13.7
	Total	163	187	100

TABLE 3 Reliability Analysis

Sections		Cronbach's alpha	Cronbach's alpha based on standardised items	No. of items
B	Emotional Intelligence	0.782	0.752	8
C	Employee Commitment	0.761	0.769	6
D	Employee Performance	0.850	0.861	7
E	Conflict Management	0.796	0.716	7
F	Raising Awareness of EI	0.970	0.971	2
G	Motivation	0.587	0.635	9

TABLE 4 KMO and Bartlett's Test Results

Components	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Bartlett's Test of Sphericity		
		Approx. Chi-square	Df	Sig
Emotional Intelligence	0.525	42.395	15	0
Employee Performance	0.715	2200.902	21	0
Conflict Management	0.627	3153.37	21	0
Raising Awareness of EI	0.500	3.062	1	0.08
Motivation	0.668	3207.12	36	0

cating greater internal consistency (typically, a value of 0.70 or higher is considered acceptable). It is calculated by analysing the average interim correlations and the number of items in the scale. Despite its widespread use, it has limitations, such as assuming unidimensionality and being sensitive to the number of items. Table 3 summarises the Cronbach's alpha coefficient of all the constructs used in the study. They are all above the internal consistency threshold of 0.70.

Results and Discussion

EXPLANATORY FACTOR ANALYSIS

Explanatory factor analysis is used to identify the factor structure of a measure and to calculate its internal reliability. In other words, it is used to simplify the variables and to group them for hypothesis testing. The Kaiser-Meyer-Olkin (KMO) and Bartlett test evaluates all gathered data together. A KMO greater than 0.5 and a significance level for Bartlett's test below 0.05 show that there is a substantial correlation in the data. The following diagram comprises the analysis of the KMO and Bartlett's test. Each component comprises factors grouped for further analysis. Table 4 depicts the results of the KMO and Bartlett's tests. The KMO Measure of

TABLE 5 Influence of Years of Experience and Motivation

Descriptive Statistics	Mean	Std. Deviation	N
Motivation	4.2675	0.35087	350
Years of experience	1.91	1.068	350

Correlations		Motivation	Years of experience
Motivation	Pearson Correlation	1	-0.023
	Sig. (2-tailed)		0.667
	N	350	350
Years of experience	Pearson Correlation	-0.023	1
	Sig. (2-tailed)	0.667	
	N	350	350

Sample Adequateness for Emotional Intelligence has a value of 0.525. It is recommended to have a value that is greater than 0.5, thus the sample is moderate and acceptable. The Bartlett test of sphericity should be below 0.05, and as a result, the significance is 0.000; therefore, this means that there is a relationship among the variables.

Moreover, the KMO value for 'Employee Performance' is 0.715 indicating that the sample is relatively adequate. Bartlett's Test of Sphericity has a significance of less than 0.05, which shows a relationship between the variables.

For the case of conflict management, the KMO value is 0.627 which is acceptable, as it is above 0.5. Bartlett's coefficient test of sphericity has a significance of less than 0.05, which means that there is a relationship between the variables. For raising awareness of EI, the KMO value is 0.5, which is an acceptable figure to conduct the factor analysis. The significance is 0.000, which means that there is a relationship between the variables. Lastly, for the variable 'Motivation', the KMO Measure of Sampling Adequacy is 0.668. Therefore, it is acceptable since it is above 0.5 and the significance is 0.000, which means that there is a relationship between the variables.

INFERENTIAL ANALYSIS

This section presents the inferential analysis of the study. The researcher aims to have the results from factor analysis in a simple structure with the majority of the items having a large loading on one variable and small loadings on other variables. Hypotheses 2, 3 and 4 are analysed using Chi-square tests and Cramer's V, while hypotheses 1 and 5 are analysed through Pearson's Correlation coefficient.

Influence of Years of Experience and Motivation (Hypothesis 1)

Hypothesis 1 was tested using Pearson's correlation. Table 5 illustrates the results. Pearson's correlation coefficient was −0.023, which indicates that both variables move in opposite directions. The level of significance is 0.667, which is above 0.05, showing that motivation and years of experience do not have a significant association.

Findings showed that years of experience do not impact the motivation level of employees. An employee can have more than 20 years of experience in the BPO industry. However, their motivation level does not need to be high. The same goes for someone who just joined a firm and can be demotivated to work, considering the work environment, the values and beliefs of the organisation, and the relationships that higher management maintains with their employees. All of these are factors that generate no relationship between the variables. Another reason why years of experience have no relationship with motivation is that when employees are not remunerated as they should, this leads to a lack of motivation at work. So eventually, years of experience influence employee motivation less when it comes to being remunerated or even being recognised for the quality of work. Thus, managers will need to consider other factors apart from experience to motivate employees and increase efficiency. An effective motivation system helps eliminate alienation, disgust, anger, and sulky and aggressive behaviours (Teker 2016).

Influence of Education Level and Emotional Intelligence (Hypothesis 2)

Hypothesis 2 focuses on finding the association between EI and level of education. Results are illustrated in table 6. The Chi-Square test results in an asymptotic significance of 0.120, indicating a p-value less than 5%. Therefore, there is an association between the level of EI and education level. Cramer's V value yielded a value of 0.185, showing that the resulting association is relatively weak.

Results show that education level does have an impact on an individual's EI. As the education level increases, the level of EI also increases. An employee who has only a secondary education can be seen to have a low

TABLE 6 Influence of Education Level and Emotional Intelligence

Chi-Square Tests				
		Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square		35.766[a]	27	0.120
Likelihood Ratio		41.945	27	0.033
Linear-by-Linear Association		0.016	1	0.901
N of Valid Cases		350		
			Value	Approx. Sig.
Nominal by Nominal	Phi		0.320	0.120
	Cramer's V		0.185	0.120

NOTE [a] 23 cells (57.5%) have an expected count of less than 5. The minimum expected count is 0.07.

TABLE 7 Influence of Job Roles and Employee Performance

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	19.892[a]	24	0.703
Likelihood Ratio	21.239	24	0.625
Linear-by-Linear Association	0.106	1	0.745
N of Valid Cases	350		

NOTE [a] 16 cells (44.4%) have an expected count of less than 5. The minimum expected count is 0.40.

EI. Those who have a bachelor's degree display a higher level of EI. As learners progress in their education, they are faced with different social situations and challenges. These help them to develop their EI. Furthermore, during their educational journey, learners are exposed to different activities that promote self-awareness, improve their interpersonal skills and develop their sense of empathy (Peeraullee et al. 2020). However, results also showed that employees having a master's degree display low levels of EI. This result can be neglected because, among the 350 respondents, only 8 had a master's degree.

The results of this study do not corroborate with that of Kashani et al. (2012) who found no association between university students and EI scores. They argued that EI and its factors do not have a significant relationship with the level of education and they think EI can be regarded as a mediating factor that eases the compatibility of intelligence. They also argued that success depends on numerous intelligences, not only EI. Hence, this leaves scope for further analysis.

Influence of Job Roles and Employee Performance (Hypothesis 3)

Table 7 shows the results for Hypothesis 3 – the influence of job roles and employee performance. The asymptotic significance was 0.703. Therefore the p-value is more than 5%, showing no relationship between EP and job roles in the BPO sector.

From table 7, it can be observed that employees can be outperforming in their jobs while a manager can be working relatively poorly. Therefore, job roles do not contribute to EP; thus it does not matter whether an employee is an associate or an analyst. This analysis can be supported by the study of Shahhosseini et al. (2012). They argued that EP does not relate to job position, and the implementation of EI skills for managers is crucial for the increase in efficiency and better job performance. Moreover, studies like this relate directly to human resource professionals who can implement 'mentoring' amongst employees. Another contributing factor can be the employee's reward system. This can lead to decreased performance if employees are not remunerated well. A workplace culture is equally important if an organisation wishes to achieve high productivity. Productivity and EP are equally affected by work-life balance. For instance, if an employee cannot manage their work and personal life separately, at some point, work suffers. This can be resolved through EI (Shahhosseini et al. 2012). Indeed, emotionally intelligent individuals are optimistic, which is a trait that allows the individual to focus on the resolution of the problem rather than the reasoning of this issue. Hence, EI will contribute positively to productivity and EP (Carmeli 2013).

Influence of Age Group on Emotional Intelligence (Hypothesis 4)

Previous studies show that there is a relationship between EI and age groups. It was reported that EI increased with age and that it demonstrates an amalgamation of early childhood experiences and genetics. As such, Hypothesis 4 has been developed to assess whether age groups have an impact on the level of EI in the BPO sector. The Chi-Square test yields an asymptotic significance of 0.079, indicating a p-value less than 0.5. Therefore, there is a significant relationship between the level of EI and different age groups. However, the strength of the relationship is 0.196, which means the association is weak. Table 8 illustrates the findings.

The results of this study corroborate with that of Extremera et al. (2006). The same findings were interpreted where the scores were pos-

TABLE 8 Influence of Age Group on Emotional Intelligence

Chi-Square Tests

	Value	df	Asymptotic. Sig. (2-sided)
Pearson Chi-Square	26.997[a]	18	0.079
Likelihood Ratio	27.856	18	0.064
Linear-by-Linear Association	0.870	1	0.351
N of Valid Cases	350		

		Value	Approx. Sig.
Nominal by Nominal	Phi	0.278	0.079
	Cramer's V	0.196	0.079

NOTE [a] 16 cells (53.3%) have an expected count of less than 5. The minimum expected count is 0.06.

itively correlated with the age factor. However, it was done mainly for college students. They recommended that further studies should be conducted for various age groups. This was eventually done in this study, where age groups of 18–25, 26–40, and 41–65 years were considered for the Mauritian BPO sector. It could be that employees in the age group 18–25 years have a higher EI and can manage their emotions effectively because nowadays in school there are subjects like social sciences and life skills. The concept of EI could be ambiguous to older people aged between 40–65 years, as this is a stage in a person's life where they already have a career and thus, learning a new thing can make them apprehensive. Therefore, it is a barrier to implementing EI. The same findings were found in the study of Fariselli et al. (2008), where the researchers argued that the relationship between EI and age groups is weak but significant, and the analysis was done through the Six Seconds Emotional Intelligence Assessment. However, it was concluded that EI tends to increase with age, that is, people over 60 years might have a better level of EI.

Influence of Age Group on Conflict Management (Hypothesis 5)

Hypothesis 5 was tested using the Pearson correlation test. Pearson's correlation test shows a value of 0.099 and a significance of 0.064, which does not define a relationship between conflict management and different age groups. These results are presented in table 9.

The literature shows that conflict is managed differently among different individuals. While some think effective communication will resolve a dispute, others might believe that walking out of a situation is a

TABLE 9 Influence of Age Group on Conflict Management

Descriptive Statistics

	Mean	Std. Deviation	N
Conflict management	3.9441	0.22625	350
Age group	1.54	0.613	350

Correlations

		Conflict management	Age group
Conflict management	Pearson Correlation	1	0.099
	Sig. (2-tailed)		0.064
	N	350	350
Age group	Pearson Correlation	0.099	1
	Sig. (2-tailed)	0.064	
	N	350	350

better solution to avoid conflicts. There are people, no matter the age, be they 18 years old or 40 years old, who tend to be impulsive, and this characteristic causes issues not only in workplaces but also in personal life. A group of employees with different age groups can manage conflict either through competing, accommodating, or even compromising. This shows that age groups are not relevant in managing conflicts. However, the study by Beitler et al. (2016) indicates that there is a positive relationship between the two variables, as they argue that an individual's conflict management skills develop over time, and, with increasing age, people tend to improve their social interactions. Therefore, managing conflict does not need to be easy for everyone. Moreover, as per Goleman (1995), when an individual can regulate their emotions and is socially aware, eventually managing conflict becomes easier. This theory was applied in practice, and most of the results were favourable. The values and beliefs are a turning point in the management of conflict. The implementation of EI in organisations will help in managing conflict better since different age groups have no significant relevance to conflict management.

General Discussion

This research aims to investigate the effect of EI on employees in the Mauritian BPO sector. The influence of demographic factors such as years of experience, education level, job roles and age group have been investigated on variables such as employee motivation, employee performance, conflict management and emotional intelligence.

Taking cognisance of the weaknesses of different EI models in the literature, an attempt has been made to develop an Emotional Intelligence Model (EIM) more specifically for the Mauritian context. The model was developed using the above-mentioned demographic factors and variables. Five hypotheses were formulated as illustrated in figure 3.

Hypothesis 1 was about determining the impact of years of experience on employee motivation. Findings showed that years of experience do not impact employee motivation. Reasons put forward were that there are more important factors that need to be considered for motivating employees in the BPO sectors and some of the factors are remuneration; working conditions; values and beliefs of the organisation; and relationship with higher management.

Hypothesis 2 was concerned with education level and emotional intelligence. Results showed that the level of education does affect the emotional intelligence of employees in the BPO sector. The higher the education level, the higher the level of EI. Employees having a tertiary education have a higher level of EI because they are exposed to more self-awareness activities. Their maturity helps them enormously in handling their emotions in different situations.

Hypothesis 3 investigates the impact of job roles on employee performance. It was observed that job roles do not have a significant association with employee performance. Literature also showed similar findings (Shahhosseini et al. 2012; Carmeli 2013). Reasons put forward are that other factors such as the reward system; employee training and workplace culture are aspects which have a higher impact on employee performance.

Hypothesis 4 is concerned with the demographic factor 'age group' and level of EI. Findings showed that there is a significant relationship between age group and level of EI. As age increases, the level of EI increases. This may be because employees become more mature with age. They accumulate a wealth of experiences and face many situations which help them understand and control their emotions and feelings. As people grow, they develop deeper emotional insights and develop more interpersonal dynamics and management skills.

Lastly, hypothesis 5 was about finding the relationship between age group and conflict management. Results showed there is no relationship between the two variables. This is because the management of conflict is not affected by age group in the BPO sector. Each individual has his/her way of dealing with or getting out of conflicting situations. Thus, the implementation of EI in organisations can help in managing conflict better since different age groups have no significant relevance to conflict management.

Conclusion and Future Research

The purpose of this study was to assess the relationship between EI and EP, and how external factors affected this relationship. However, psychological theories and emotions management of different individuals are far more complex, hence this limits this study to only the BPO sector, although EI exists in almost every field, even at a school or a kindergarten. A proposed EIM was developed to assess the prevalent issues that exist in large organisations nowadays, that is, conflict management. Previous models like Goleman's theory were tested and a new one was derived and analysed through hypothesis testing.

All the objectives of this study were achieved. This study will help managers and team leaders to understand and adapt to the different mindsets of employees, and team managers will have better-suggested strategies to implement in their daily tasks to achieve their monthly and yearly goals. Employees, on the other hand, will understand how to identify their emotions and manage their relationships with their colleagues. This will eventually lead to a healthier work environment.

However, there is still scope for future research. It can be noted that not all dimensions of the conceptual framework have been tested due to the narrow scope of the study. Endogenous relationships between variables such as 'conflict', 'emotional intelligence', and 'motivation' open the door for future work. Other avenues also include the necessity to cater for potential cultural differences between organisations as well as differences in business etiquette.

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Appendix

Section	Code	Statements
B	EI 1	I am aware of my own emotions.
	EI 2	I understand and empathise with the emotions of others.
	EI 3	I can easily build positive relationships with colleagues and clients.
	EI 4	Do you believe if you can manage your emotions, then stress management at work will be easier?
	EI 5	Do you believe you can resolve conflicts through effective communication?
	EI 6	How would you rate your own level of EI when it comes to managing conflicts in the workplace?
	EI 7	Do you think employees with more than 20 years of working experience are more aligned with their emotions and decision-making skills?
	EI 8	Do you think someone with high EI in the age group 18-25 will fit a leading job position?
C	EC1	How far do you think emotional intelligence will contribute to a stronger emotional attachment to an organisation?
	EC2	How firmly do you believe emotional intelligence will help employees in believing in the values and goals of their organisation?
	EC3	How likely are you to be willing to work overtime when the business is struggling to meet the required expectations?
	EC4	How likely are you to be willing to work in the same organisation for the next five years?
	EC5	How proud do you feel when talking about the company that you work for?
	EC6	Do you think implementing emotional intelligence can help in reducing the rate of absenteeism at work?
D	EP1	Do you think being emotionally attached to your organisation will improve your performance at work?
	EP2	Do you always seek opportunities for improvement and growth?
	EP3	Are you open to feedback from your team leads and use them to improve your performance?
	EP4	Do you think that you contribute positively to the overall success of your team?
	EP5	Is your work output meeting the team's expectations?
	EP6	Do you think there is a relationship between emotional intelligence and career advancement within the organisation?

Section	Code	Statements
	EP7	Which of the possible factors can impact employee performance other than motivation?
E	CM1	Do you believe impulsiveness leads to conflict amongst employees?
	CM2	According to you, is an employee who is too shy to express his opinions, more prone to be submissive to wrong decisions by the management?
	CM3	Is a lack of expression of opinions at work an obstacle to getting a promotion?
	CM4	Can you manage your emotions effectively during challenging situations?
	CM5	How do you handle disagreements with team members or colleagues who have different emotional responses to the conflict?
	CM6	Do you think work environments would be a better place if everyone knew how to align their emotions with their decision-making skills?
	CM7	Do you think different age groups lead to divergence in opinions?
F	TAEI1	Do you think training employees in managing their emotions will lead to a healthy work environment?
	TAEI2	Have you participated in any emotional intelligence training or workshops provided by your organisation?
G	M1	Does motivation influence your commitment to your organisation?
	M2	Do you think managers should motivate their employees regularly?
	M3	Does motivation bring about a healthier workplace?
	M4	Please indicate your level of agreement with the following statement: "I feel highly motivated in my current role."
	M5	How important is a sense of purpose and alignment with the organisation's mission and values in motivating you and fostering your commitment?
	M6	Do words of motivation from your managers improve your performance at work?
	M7	Do you believe that setting personal goals and milestones at work contributes to your motivation and job performance?
	M8	How often does a lack of motivation lead to decreased job performance for you?
	M9	Please rate your level of motivation in your current role.

List of Acronyms
EI – Emotional Intelligence
EC – Employee Commitment
EP – Employee Performance
CM – Conflict Management
TAE – Training and Work environment
M - Motivation

Does Financial Development Drive Entrepreneurship in Africa? A Panel Data Analysis

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Entrepreneurship in Africa faces a multitude of challenges, with financial issues being prominently discussed in scholarly literature. Thus, this study explores how financial development plays a crucial role in encouraging entrepreneurship in Africa, analysing both short- and long-term impacts alongside the direction of causality within the continent. The study utilises panel data regression techniques to analyse data from 28 African countries, spanning from 2006 to 2020. The analysis reveals that financial development, alongside the growth of financial institutions and markets, consistently boosts entrepreneurship development in both time frames. Even though this is more pronounced in the long run, this suggests that the influence of financial development and its components is uniformly positive, with no significant differential impacts observed in either the short or long run. Causality results establish unidirectional causality between entrepreneurship, financial development, and its components, flowing from financial development and its components to entrepreneurship development. Given these insights, the study underscores the necessity for policymakers to focus on sustainable financial development strategies that enhance stability and inclusivity within financial markets.

Keywords: Africa, entrepreneurship, financial development, panel regression

JEL *Classifications:* F3, G2, M13, N27

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Introduction

Entrepreneurship has emerged as a significant global phenomenon, gaining prominence since 1990. However, its scope, features, and socioeconomic impact vary across different contexts. Recent evidence, facilitated by the accessibility of public datasets, indicates that entrepreneurship is flourishing more prominently in emerging economies, including Africa

(Bruton et al. 2008; Omri 2020). These economies are characterized by lower entry barriers, an increasing focus on the market, and an expansion of economic activity. Despite this, the potential of entrepreneurship to promote sustainable, long-term economic development and growth has not yet been completely realized in African countries. Some obstacles, including legislative barriers, market accessibility issues, competition, skill shortages, and inadequate infrastructure, are impeding the growth of entrepreneurship in Africa. Nonetheless, the issues of access to funds is seen as one of the key elements mentioned in the literature, which creates a vicious cycle of poverty by lowering production and earnings (Abubakar 2015; Bayar et al. 2018; Ojonta and Ogbuabor 2021).

Generally speaking, it is thought that an effective financial system should encourage the growth of entrepreneurship; nevertheless, the degree of financial development, particularly in African nations, is concerning. For example, even though the African financial system has undergone financial reforms in the past, ranging from financial diversification to financial integration to permit unrestricted inflows of foreign capital into the economy, the system's development status is still low. Global analysis of financial development reveals that African nations do badly in terms of total financial development (Internation Monetary Fund n.d.; Noah 2023; Noah et al. 2023).

To address finance-related issues impeding entrepreneurship development, a number of empirical researches have examined the relationship between finance and entrepreneurship (Dutta and Meierrieks 2021; Gaies et al. 2023; Léon 2019; Ojonta and Ogbuabor 2021). However, with a few notable exceptions, such as the works of Ajide and Ojeyinka (2022) and Babajide et al. (2020), these studies primarily concentrate on developed and emerging economies outside of Africa, particularly at the macro level. Individual, corporate, regional, and national levels are all included in the examination of entrepreneurship (Kraus et al. 2021). For example, risk preferences, education, experience, age, and other employment opportunities may be individual-level factors that affect entrepreneurial decisions (Brachert et al. 2020). On the other hand, competition, market size, firm size, and business culture are important factors at the firm or industry level (Silwal 2022).

On the relationship between entrepreneurship and financial development at the national level in Africa, there is, however, limited research. Concerning the distinct political, cultural, and economic environments of African countries, this gap suggests a partial understanding of the true impact of financial development on entrepreneurship in Africa. In addition, a thorough analysis of the body of research indicates conflicting results about the relationship between finance and entrepreneurship. While some studies suggest a positive association between financial development and entrepreneurial success , others contend that various financial sector constraints, economic challenges, institutional shortcomings, inequality, and imperfect markets can all work against financial development and impede entrepreneurship, especially in developing economies (Amin et al. 2023). This ongoing discussion emphasizes the need for more research, especially in the African setting, to determine the true effects of financial development on entrepreneurship.

Comprehending the efficacy of domestic financial development is vital to grasping the development of entrepreneurship in Africa. Remarkably, this field has not gotten nearly enough attention in the pertinent literature, especially at the national level, where the current study is highly relevant. By investigating the effects of financial development and its components (financial markets and institutions) on the growth of entrepreneurship in the African environment, the study contributes to the body of literature. Except for the research by Ajide and Ojeyinka (2022) and Babajide et al. (2020), previous panel studies largely exclude Africa. However, these two studies also have their limitations. For instance, Babajide et al. (2020) focused solely on financial stability and encountered methodological constraints, including issues of endogeneity and cross-sectional dependence. Ajide and Ojeyinka (2022) addressed some of these limitations by adopting a broader measurement of financial development and the generalized method of moments (GMM) methodology but paid less attention to the causality and long-term effects of financial development on entrepreneurship.

Considering the potential differential impacts of short- and long-term credit on entrepreneurship, as highlighted by Léon (2019), our study investigates both periods and explores potential differential effects to address the mixed results in the financial-entrepreneurship development nexus. We also analyse the differential effects of financial development and its components, as well as the control variables during these periods. In addition, existing theories like Schumpeter's theory contend that financial development encourages entrepreneurship by supplying the capital required. But there is also potential for the link to go the other way: strong entrepreneurship can stimulate the demand for a range of financial services and products, which in turn can propel financial development. Understanding the causality in this relationship within the African context is theoretically challenging and underexplored. Additionally, there is a dearth of empirical studies that are particularly concentrated on Africa and which thoroughly investigate the causal relationships between financial development and entrepreneurship.

Furthermore, neglecting cross-sectional dependency and slope heterogeneity in panel data may introduce bias and inconsistency in estimations in these studies, given the interconnectedness of nations in trade, economics, and finance. Therefore, it is necessary to test for cross-sectional dependency in the panel to select appropriate estimation techniques if this issue is identified in the panel data. Additionally, our study differs in terms of measurements of financial development. The measurement of financial development in the present study includes the overall financial development in terms of accessibility, efficiency, and depth, in contrast to nearly all previous research that only used one indicator or component. Similarly, this study employs a superior measurement of entrepreneurship from the World Bank dataset, termed 'new entry density', capturing the essential aspect of entrepreneurial venturing and available for the selected African countries, ensuring robust estimations.

The primary aim of this study is to address these gaps by investigating how financial development and its components (financial institutions and markets) affect entrepreneurship development in Africa. Specific objectives entail assessing the impacts of financial development and its components over both short and long durations. Employing the system SGMM, panel-corrected standard error (PCSE), and Dumitrescu-Hurlin Granger causality methodologies, the study further explores the varying effects of financial development and its components on entrepreneurship development, as well as the causal link between entrepreneurship development and financial development.

This empirical study also contributes significantly to the body of knowledge on financial development and entrepreneurship from a theoretical standpoint. First of all, it makes clear how different financial development and its elements affect entrepreneurship in both short- and long-term scenarios. Second, the study improves our understanding of how financial systems influence entrepreneurship by identifying the direction of causality between financial development, its components, and entrepreneurial activity in Africa. This contradicts earlier theories that would have assumed a more reciprocal or context-dependent relationship between the two. Furthermore, by taking into account the varying impacts of control variables, the research expands on our understanding of how particular policy contexts and economic circumstances affect the evolution of entrepreneurship across time. All things considered, this study contributes to the theoretical conversation by providing a more thorough and nuanced understanding of the elements that propel entrepreneurship in Africa.

The subsequent sections of the study are divided into five sections, where the second section reviews the related literature and theories, the third section presents the methodology, empirical results are presented and discussed in the fourth section, and the fifth section concludes the study.

Literature and Theoretical Review

As the field of entrepreneurship continues to expand, numerous opportunities emerge to further develop and refine its concepts (Chrisman et al. 2023). One of the earlier definitions of entrepreneurship is the one proposed by Wennekers and Thurik (1999), who defined entrepreneurship as the ability and readiness of individuals to identify and cultivate novel business opportunities and to communicate their ideas to potential stakeholders in the market effectively. This process often requires individuals with enterprising qualities, who may not fit the traditional mould of entrepreneurs but act as agents of change. An entrepreneur can be described as a forward-thinking individual who identifies emerging opportunities and is proactive in pursuing them to establish new ventures (Thompson 1999). Entrepreneurship, encompassing both high-growth ventures and self-employment, plays a crucial role in wealth creation for individuals and society as a whole (Sun et al. 2024).

The International Monetary Fund (Internation Monetary Fund n.d.) also classifies financial development into two main categories: market development and institutional development, which encompass the accessibility of financial services to individuals and businesses, market depth (size and liquidity), and efficiency (cost-effective delivery of financial services and sustainable revenues, as well as capital market activity). As noted by Čihák et al. (2012), the relationship between entrepreneurship and financial intermediation is relevant across all dimensions of financial development at the national level. Ayob (2021) adds that the level of economic underdevelopment within an economy influences the impact of financial development on entrepreneurship.

Theoretically, the relationship between the growth of the financial sector and entrepreneurship dates back to Schumpeter's (1912) seminal work, which emphasized the role of the financial system in enabling entrepreneurs to obtain loans and other financial resources. According to Schumpeter's theory, a dynamic economy needs a force that can explain both long-term growth and development and technological advancements. He maintained that the entrepreneur is the embodiment of this power. According to him, entrepreneurship is 'the carrying out of new combinations'. He described the entrepreneur as 'the agent of innovation' and 'the pivot on which everything turns' (Schumpeter 1912). He further stated that an entrepreneur innovates rather than invents. He clarified that the rate of capital expansion and whether or not it will entail innovation and change are determined by the calibre of entrepreneurial activity (Schumpeter 1912).

The aforementioned viewpoint is corroborated by later researchers who highlight the crucial role the financial sector plays in fostering entrepreneurial endeavours (Goldsmith 1969; Gurley and Shaw 1967; Patrick 1966). Meanwhile, Gerschenkron (1962) demonstrates that the degree of an economy's economic regression determines the influence of financial development on that sector. Furthermore, the four perspectives covered by Verheul et al. (2000) eclectic theory of entrepreneurship (ETE) includes the disciplinary approach, level of analysis, differentiation based on supply and demand, and differentiation between the short- and long-term equilibrium levels of entrepreneurship. Even though individual decisions are made while starting a business, supply and demand considerations are crucial in generating chances for new ventures (Ayob 2021).

From the demand side of the ETE, more financial development boosts the nation's entrepreneurial activity since it creates more innovative business chances and has regulations that work (Amin et al. 2023). According to Čihák et al. (2012), financial systems are seen as important for providing risk management, information management, resource allocation, corporate control, mobilizing and pooling funds, and facilitating economic transactions. The Internation Monetary Fund (n.d.) divides financial growth into two main categories: the development of markets and financial institutions. The ability of people and businesses to obtain financial services, their depth (size and liquidity), and their efficiency (the ability of institutions to deliver financial services at cheap cost and with sustainable revenues, and the level of activity of capital markets) are all taken into consideration. As noted by Čihák et al. (2012), the relationship between entrepreneurship and financial intermediation is pertinent to each of these four aspects of financial development at the national level.

There has been extensive theoretical and empirical discourse on the role of entrepreneurship as a significant driver of economic growth and development (Urban and Mgwenya 2024; Matenda and Sibanda 2023; Oyeniran et al. 2015). Given its importance, understanding the factors that influence entrepreneurship development, particularly at the national level, is crucial. However, there remains an ongoing debate on the relationship between financial development and entrepreneurship, characterized by contradictory evidence. For example, Abubakar (2015) highlighted the challenges in access to finance, market access, policy support, and entrepreneurship culture as significant constraints on entrepreneurship in Africa. In contrast, Kar and Ozsahin (2016) found that financial development positively affects entrepreneurship in emerging markets.

Fan and Zhang (2017) used data from 31 provinces and 19 industries in China between 2005 and 2014 to examine the relationship between the development of financial inclusion and the emergence of entrepreneurs. The variables used include the financial inclusion index, business freedom index, GDP per capita, education, urbanization, infrastructure, degree of openness, and government policies, and entrepreneurship is measured by the number of registered enterprises. By lessening information asymmetry in financial transactions, the estimated models utilizing panel ordinary least square (OLS) indicate that the advancement of financial inclusion can lessen credit limitations for entrepreneurial endeavours. Furthermore, this effect is stronger in sectors of the economy where entry barriers are smaller. Furthermore, the impact varies depending on the industry.

Using data from 15 upper-middle-income and high-income nations between 2001 and 2015, Bayar et al. (2018) examined the effects of the development of the financial sector on entrepreneurship, including other variables like foreign direct investment (FDI) inflows, trade and financial openness. The study used domestic credit to the private sector for financial development and total early-stage entrepreneurial activity for entrepreneurship. According to the results of the random effect estimation, the expansion of the banking industry and capital markets, FDI inflows, and trade openness all have a positive impact on the overall amount of early-stage entrepreneurial activity. In addition, in their investigation of the relationship between human capital and entrepreneurship, Dutta and Sobel (2018) used data from the Global Entrepreneurship

Monitor (GEM) to clarify the mixed findings. The variables considered in the study include labour force participation, GDP per capita, urbanization, polity, financial development, and student enrolment. Business entities were employed as a measure of entrepreneurship. The results of the study, which used both the difference and system GMM, indicated that entrepreneurship gains most from an increase in tertiary enrolment when financial development is low. In comparison to nations with lower levels of financial development, the impact of tertiary enrolment on entrepreneurship is still beneficial for greater levels of financial development, but it is much smaller.

Léon (2019) looked into how business entry was impacted by short- and long-term financing in 85 different countries between 1995 and 2014. The study used household credits, business contracts and laws, GDP per capita, and both the Total Entrepreneurial Activity (TEA) and GEM measurements as proxies for entrepreneurship. According to the econometric results (fixed and random effect estimations), short-term credit had a positive relationship with the creation of firms from the point of birth to registration, but long-term credit did not encourage company entry. Also, in 19 emerging economies between 2001 and 2014, Omri (2020) showed how the relationship between financial development and good governance influences formal and informal entrepreneurship differently. Formal entrepreneurship was quantified in the study by counting the number of newly registered firms as a percentage of working-age individuals (registered enterprises). On the other hand, informal entrepreneurship was measured by the number of new unregistered businesses per 1,000 working-age adults. The results of the two-step GMM method demonstrated that financial development has a significant positive influence on formal, while negatively influencing informal entrepreneurship.

Between 2004 and 2017, Dutta and Meierriecks (2021) also looked into how financial development affected entrepreneurship across a panel of 136 nations. The study used business density to proxy entrepreneurship, and domestic credit to the private sector to proxy financial development. Indicators of governance, population, GDP per capita, trade openness, tax burden, and education are other variables considered. The study's findings from the instrumental-variable approach showed that higher levels of financial development cause higher levels of entrepreneurial activity, particularly in the presence of strong political and economic institutions.

Using data from 20 specifically chosen African countries between 2006 and 2017, Ajide and Ojeyinka (2022) investigated the effect of financial development on entrepreneurship in the continent. As proxies for financial development and entrepreneurship, they used the business entity and financial development index. The study also takes into account other factors including infrastructure, GDP growth rate, inflation rate, FDI inflow, financial stability, and the regulatory climate of the nation. They used the dynamic panel threshold approach and system GMM. Their results showed that financial development in Africa did not promote entrepreneurship. They went on to say that there is a threshold beyond which financial development raises the degree of entrepreneurship in Africa.

Amin et al. (2023) investigated whether financial development influences entrepreneurship and how financial openness moderates this relationship using panel data made up of 781 country-year observations of 48 Asian nations from 2001 to 2018. As a proxy for financial development, the study employed domestic lending to the private sector. Other factors included in the study are GDP growth, population growth, primary, secondary, and tertiary education levels, foreign investment, unemployment, and innovation. The study's conclusions showed that the nation's entrepreneurial activity is increased by efficient resource allocation and simple transaction processes. Furthermore, the laxer regulations that permit international trade also make more capital available to entrepreneurs, spurring their creativity and the launch of new ventures. In addition to finding a U-shaped association between financial depth and emerging entrepreneurship in European nations, Gaies et al. (2023) concluded that financial stability, rather than banking intermediation or venture capital, drives new business growth at a macro level. These diverse perspectives highlight the complexity of the financial development-entrepreneurship nexus and underscore the need for further research to elucidate its mechanisms and implications.

This study's hypotheses are supported by a substantial body of theoretical and empirical research that emphasizes how important entrepreneurship is for promoting economic development and progress (Matenda and Sibanda 2023; Urban and Mgwenya 2024). The relationship between financial development and entrepreneurship has been the subject of numerous researches, although the results are still conflicting and situational. For example, whilst one of the early studies, Abubakar (2015), highlights barriers like financial access in Africa, others such as Kar and Ozsahin (2016) find benefits of financial development in emerging markets. Studies such as those conducted by Bayar et al. (2018), and Fan and Zhang (2017) strengthen the case for financial infrastructure's promotion of entrepreneurship through lending availability or financial inclusion. The importance of financial markets and institutions is also highlighted because they supply vital resources that make it possible for new businesses to succeed (Dutta and Sobel 2018; Léon 2019).

In light of this, this study's hypotheses suggest that financial development, institutions, and markets positively influence entrepreneurship in Africa. These hypotheses, which are backed by empirical evidence from several locations, are in line with Schumpeter's theory, which contends that financial systems are crucial to the success of entrepreneurs. The study fills gaps in the literature by examining these links in the African setting, paying particular attention to the region's distinct institutional and economic structure. Therefore, the hypothesis claims as follows:

H_1 *Financial development and its components – financial institutions and financial markets – positively promote entrepreneurship in Africa.*

In addition, although several studies have examined the impact of financial development on entrepreneurship, very few have considered the impact of entrepreneurship on financial development. Entrepreneurship development plays a crucial role in enhancing financial development by driving economic growth and development (Kraus et al. 2021; Matenda and Sibanda 2023). When entrepreneurs establish new businesses, they contribute to the creation of new jobs, which in turn increases household incomes and stimulates demand for goods and services. This job creation helps reduce unemployment and poverty, which are key indicators of financial development. Moreover, as businesses grow, they often need to secure financing, leading to the development of financial institutions and markets, which further supports financial inclusion (Yang and Zhang 2020).

Entrepreneurship also contributes to financial development by encouraging innovation and competition. New businesses often introduce innovative products, services, and technologies that can enhance productivity and efficiency across the economy. This innovation leads to increased economic output, which boosts national income and expands the financial resources available for investment in further development (Surya et al. 2021). Furthermore, entrepreneurship development can enhance financial development by promoting financial inclusion. Entrepreneurs often target underserved markets or develop solutions that make financial services more accessible to a broader population. Thus, countries with high levels of entrepreneurial activity tend to experience faster economic growth and greater financial development (Cervelló-Royo et al. 2020). From the foregoing, we can therefore test for the directional causality between entrepreneurship and financial development in the context of Africa to clarify their causal relationship. We therefore state the second and third hypotheses as follows:

- H_2 *Financial development and its components cause entrepreneurship in Africa.*
- H_3 *Entrepreneurship activities cause financial development and its components in Africa.*

Methodology

DATA SOURCES AND MEASUREMENTS

The primary aim of this study is to investigate the extent to which the financial sector, including financial institutions and markets, influences entrepreneurship development across a panel of 28 African countries. These countries encompass Algeria, Botswana, Burkina Faso, Democratic Republic of the Congo, Egypt, Ethiopia, Gabon, Ghana, Guinea, Kenya, Lesotho, Madagascar, Malawi, Mauritius, Morocco, Namibia, Niger, Nigeria, Rwanda, São Tomé and Príncipe, Senegal, Sierra Leone, South Africa, South Sudan, Togo, Tunisia, Uganda, and Zambia. Spanning from 2006 to 2020, data sourced from the World Bank and IMF databases are used to measure both entrepreneurship and financial development.

The financial development measure adopted here is a composite index that encompasses various dimensions of financial development, ranging from 0 to 1, where 0 signifies weak financial development and 1 indicates greater financial development. Unlike most of the previous studies that often use a single indicator or component, this measurement includes dimensions such as financial deepening, stability, and growth, encompassing both financial institutions and markets development. Specifically, it examines aspects like depth (size and liquidity), access (availability of financial services), and efficiency (cost-effectiveness of financial services provision and capital market activity). This approach aligns with studies such as those of Munemo (2018; 2022). The financial development and its components are sourced from the IMF database. In contrast, the new business entry density metric, which measures the number of registered businesses per 1,000 working adults, is used to quantify entrepreneurship. The extensively used measure provides thorough coverage across nations, periods, and variables, in line with earlier studies by Chambers

TABLE 1 Related Reviewed Studies

Review	Focus	Method	Findings
Dutta and Sobel (2018)	Examined the role of financial development on human capital-entrepreneurship nexus in 28 countries (Schumpeter's theory).	System generalized method of moment (SGMM) and Random Effect Model (REM)	Human capital benefits entrepreneurship in countries with lower financial development than in those with higher financial development.
Munemo (2018)	Examined the relevance of financial development and FDI in Entrepreneurial Success in 28 African countries (Bjørnskov and Foss 2013).	Fixed effect model (FEM), dynamic GMM (DGMM), and SGMM	Developed financial institutions and markets enhance entrepreneurial success in African countries.
Bayar et al. (2018)	Investigated the influence of financial sector development, FDI inflows, and trade and financial openness on entrepreneurship in 15 upper-middle-income and high-income countries.	REM	The banking sector and capital market development affect the total early-stage entrepreneurial activity positively.
Léon (2019)	Examined the impact of long-term finance on entrepreneurship in 85 countries (King and Levine 1993).	REM, FEM, and IV-FEM	Long-term credit does not stimulate firm entry but short-term credit does.
Jiang et al. (2019)	Investigated the impact of inclusive financial development index on farmer entrepreneurship in China (Sarma and Pais 2011).	SGMM	Improving the inclusion development level of inclusive finance can better promote farmers' entrepreneurship.
Babajide et al. (2020)	Examined the relationship between financial stability and entrepreneurship development in 24 Sub-Sahara Africa economies (Schumpeter's theory).	Pooled ordinary least squares (OLS) and RE techniques	Financial stability has a significant positive effect on entrepreneurship development.
Omri (2020)	Examined the roles of governance and the financial sector in formal and informal entrepreneurship in 19 emerging economies (Schumpeter's and the eclectic theories).	SGMM	There exists a positive (negative) impact of financial development on formal (informal) entrepreneurship.

Review	Focus	Method	Findings
Ajide and Ojeyinka (2022)	Examined the impact of financial development on entrepreneurship in 20 African countries (Schumpeter's theory).	SGMM and dynamic panel threshold based on dynamic panel GMM.	Financial development does not spur entrepreneurship in Africa, but only at a threshold level.
Dutta and Meierrieks (2021)	Investigated the effect of financial development on entrepreneurship in 136 countries (Schumpeter's theory).	FEM	Financial development beneficially contributes to entrepreneurial activity.
Gaies et al. (2023)	Examined the impact of financial development on nascent entrepreneurship in 22 European economies (Schumpeter's theory; King and Levine 1993).	FEM, REM, and Panel Generalized Least Square (Panel GLS)	With a high level of financial deepening, the banking sector only favours established businesses and nascent entrepreneurship.
Amin et al. (2023)	Examined whether financial development affects entrepreneurship, and how financial openness moderates the relationship, using the eclectic theory of entrepreneurship in 48 Asian countries (Schumpeter's and the eclectic theories).	GMM and SGMM	Effective allocation of resources and ease of transactions increase the entrepreneurial activities in the country.

and Munemo (2019), and Klapper et al. (2004). The data on the new business entry density metric which measures the number of registered businesses per 1,000 working adults is sourced from the World Bank's World Development Indicators

Furthermore, in line with previous studies, we incorporate control variables that are all obtained from the World Bank database. These variables include the GDP per capita, population growth, urbanization, institutional quality, economic openness, inflation rate, labour force participation, and business start-up regulations. GDP per capita (Current US$) serves as a proxy for the country's income level, which has been demonstrated to regulate the establishment of new businesses (Gaies et al. 2023; Omri 2020). Population growth rate and urbanization, measured by the ratio of urban population to the total population, are expected to positively influence entrepreneurship, as they offer entrepreneurs more opportunities and choices (Amin et al. 2023; Fan and Zhang 2017; Gaies et al. 2023; Jiang et al. 2019).

Economic openness, represented by the ratio of total import and export to GDP, indicates a more developed financial environment, fostering entrepreneurship (Bayar et al. 2018; Fan and Zhang 2017; Gaies et al. 2023). The inflation rate, measured by the GDP deflator, reflects price stability, which is crucial for entrepreneurial success (Kar and Ozsahin 2016). The number of start-up procedures to register a business serves as a measure of business start-up regulations, with mixed effects on entrepreneurship: bureaucratic regulations may deter entrepreneurship (Munemo 2022), while favourable regulatory environments can encourage it (Omri 2020). However, it is expected to promote entrepreneurship development in this study. Institutional quality, measured by a governance index comprising six indicators, is identified as a driver of entrepreneurship development, supported by eclectic theory and recent studies (Amin et al. 2023; Ayob 2021). Theoretical justifications and empirical findings support the *a priori* expectations that all explanatory variables (except the inflation rate) influence entrepreneurship development in Africa positively.

MODEL SPECIFICATION

Based on the theoretical and previously mentioned relevant study justifications, we apply panel data analysis to accurately achieve the objectives, with a primary focus on the impact of financial development and its components on the development of entrepreneurship in Africa. This is because panel data analysis offers a better modelling capacity of economic reality, particularly by capturing variations both between and within countries, allowing us to analyse the individual and temporal dynamics of African countries. The theoretical foundation for this study is rooted in Schumpeter's theory of economic development and the eclectic theory of entrepreneurship. Together, these theories highlight how financial development supports entrepreneurship by facilitating access to the capital and resources necessary for business creation and growth. However, since these theories lack a mathematical foundation, we choose panel data analysis in response to a number of recent macro-level assessments of entrepreneurship, including those by Dutta and Meierrieks (2021) and Gaies et al. (2023) with modifications to achieve the objectives of this study. As a result, we develop the following panel data model:

$$EEP_{it} = \vartheta_0 + \vartheta_1 OFD_{it} + \vartheta_2 X_{it} + \varepsilon_{it}, \tag{1}$$

where *EEP* stands for the national level of entrepreneurship development in country i ($i = 1, 2 \ldots 28$) and in year t ($t = 2006 \ldots 2020$), *OFD* stands for financial development, *X* stands for the explanatory control variables (GDP per capita - *GGR*, institutional quality - *GOP*, labour force participation - *LFP*, inflation rate - *IFG*, population growth - *POG*, urbanization - *UBT*, economic openness - *EOP*, and business start-up regulations - *REG*), ϑ_0 is the slope, ϑ_1 - ϑ_n are the coefficients of explanatory variables, and ε represents the error terms.

To clarify the relationship between financial development and entrepreneurship, this study further performs the Granger causality test to determine the direction of causality between financial development and entrepreneurship. Thus, the specific Granger equations for entrepreneurship, financial development, and its components are specified as follows:

$$\begin{aligned} EEP_{it} = \pi_{1j} &+ \sum_{j=i}^{k_1} \gamma_{1ij} EEP_{it-j} + \sum_{j=i}^{k_2} \tau_{1ij} OFD_{it-j} \\ &+ \sum_{j=i}^{k_3} \delta_{1ij} OFI_{it-j} + \sum_{j=i}^{k_4} \psi_{1ij} OFM_{it-j} + \mu_{1it} \end{aligned} \tag{2}$$

$$\begin{aligned} OFD_{it} = \pi_{2j} &+ \sum_{j=i}^{k_1} \gamma_{2ij} OFD_{it-j} + \sum_{j=i}^{k_2} \tau_{2ij} EEP_{it-j} \\ &+ \sum_{j=i}^{k_3} \delta_{2ij} OFI_{it-j} + \sum_{j=i}^{k_4} \psi_{2ij} OFM_{it-j} + \mu_{2it} \end{aligned} \tag{3}$$

$$OFI_{it} = \pi_{3j} + \sum_{j=i}^{k_1} \gamma_{3ij} OFI_{it-j} + \sum_{j=i}^{k_2} \tau_{3ij} EEP_{it-j} + \sum_{i=i}^{k_3} \delta_{3ij} OFD_{it-j} + \sum_{i=i}^{k_4} \psi_{3ij} OFM_{it-j} + \mu_{3it} \tag{4}$$

$$OFM_{it} = \pi_{4j} + \sum_{j=i}^{k_1} \gamma_{4ij} OFM_{it-j} + \sum_{j=i}^{k_2} \tau_{4ij} EEP_{it-j} + \sum_{i=i}^{k_3} \delta_{4ij} OFD_{it-j} + \sum_{i=i}^{k_4} \psi_{4ij} OFI_{it-j} + \mu_{4it}, \tag{5}$$

where *OFI* is financial institution development, *OFM* is financial market development, k_1 - k_4 is lag lengths, and μ_1- μ_4 are the stochastic error terms; all other variables are as defined. We employed Dumitrescu and Hurlin's (2012) panel causality technique because it is a dynamic panel test, which is more reliable and effective in terms of estimation.

ANALYTICAL TECHNIQUES

The data analysis methods encompass descriptive analysis, simple correlation, and panel data regression techniques. The long-term association between financial and entrepreneurship development is examined utilizing the PCSE in the panel data regression analysis. The study additionally performs the pre-estimation tests to ensure the validity of conclusions taken from the findings of the estimated regression models. The PCSE estimate technique is more reliable than panel OLS, fixed, and random effect models due to its adaptability in managing possible problems with serial correlation, heteroscedasticity, and cross-sectional dependency. Although feasible generalized least squares (FGLS) can also be employed, PCSE is more appropriate in this study since the number of periods *(T)* is fewer than the cross-sectional dimension *(N)* (Beck and Katz 1995; Reed and Webb 2010).

A significant concern is the possibility of endogeneity, which could result from the theories and empirical research suggesting a bidirectional causal relationship between the development of finance and entrepreneurship. Consequently, the model is estimated in the study using the GMM in addition to the static panel analysis. When there is a connection between the lagged dependent variables and the unobserved panel-level effects, GMM provides a consistent estimator for the model's parameters. It is also optimized for panel datasets with a bigger nation dimension and a shorter time dimension, like the one used in the present study, and it is more efficient when there is autocorrelation, heteroscedasticity, and endogeneity. We employ the first lagged level of the dependent variable, which is produced automatically by the over-identifying restriction technique, as instruments in the estimate process. The over-identifying limits would change depending on how many instruments were used (Roodman 2009). Therefore, to verify the validity of the instruments and the dependability of the estimations, we perform the Arellano-Bond and Sargan tests.

Presentation and Discussion of Results

DESCRIPTIVE AND CORRELATION ANALYSES

Table 2 presents the findings of the descriptive analysis. It indicates that the average number of entrepreneurs per 1,000 people is 1.972, with a maximum value of 20.091, a minimum value of 0.022, and a standard deviation of 3.441, which appears to be reasonable. These suggest that there is a wide differential in the number of entrepreneurs among African countries.

Additionally, the financial development index's average, maximum, minimum, and standard deviation values are 0.188, 0.593, 0.035, and 0.129, respectively. Although the standard deviation indicates that financial development is not significantly different across African countries, the index's value range indicates that financial development is low in the continent. Except for labour force participation, urbanization, and economic openness, which all exhibit significant variation, this also applies to all other explanatory variables, with the GDP per capita showing the most deviation. Table 2's correlation analysis shows that entrepreneurship has a positive relationship with financial development, GDP per capita, institutional quality, urbanization, and economic openness.

It has a negative relationship with population growth, but not with labour force participation or business start-up regulations. Furthermore, there was no evidence of a multicollinearity issue in our sample because the correlation coefficients were all less than 0.7. The values of the variable's variance inflation components also corroborate this. However, as correlation coefficients simply show how strongly the variables are linearly related to one another, a more succinct and detailed examination of the causal effects is required for this intuitive claim. To test this hypothesis further, the study creates multivariate models using the PCSE and system GMM techniques.

A panel series must also be checked for unit-roots and stationarity because discontinuities can significantly affect econometric estimations. In

TABLE 2 Descriptive Statistics and Correlation Matrix

Variables	EEP	OFD	GGR	GOP	LFP	IFG	POG	UBT	EOP	REG
Mean	1.972	0.188	2592.093	−0.933	62.013	6.053	2.202	43.507	71.456	8.302
Maximum	20.091	0.593	16851.12	2.143	89.450	85.353	3.867	90.092	168.971	17.000
Minimum	0.022	0.035	191.751	−4.106	42.057	−18.075	−0.033	16.208	24.006	2.000
Std. dev.	3.441	0.129	2981.923	1.255	11.446	8.487	0.931	17.929	27.051	2.955
EEP	1.000									

OFD	0.594^a	1.000								
	(0.000)	-----								
GGR	0.604^a	0.675^a	1.000							
	(0.000)	(0.000)	-----							
GOP	0.679^a	0.679^a	−0.071	1.000						
	(0.000)	(0.000)	(0.156)	-----						
LFP	−0.031	−0.184^a	0.158	0.006	1.000					
	0.542	(0.000)	(0.002)	(0.907)	-----					
IFG	−0.085^c	−0.054	0.073	−0.043	0.115^b	1.000				
	(0.091)	(0.281)	(0.147)	(0.392)	(0.022)	-----				
POG	−0.479^a	−0.599^a	0.239	−0.578^a	0.305^a	0.069	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.173)	-----			
UBT	0.327^a	0.358^a	−0.242	0.264^a	−0.529^a	−0.122^b	−0.247^a	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)	-----		
EOP	0.324^a	0.249^a	−0.135	0.427^a	−0.263^a	−0.049	−0.590^a	0.232^a	1.000	
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.333)	(0.000)	(0.000)	-----	
REG	−0.052	−0.090^c	0.044	−0.049	0.098^c	0.186^a	0.001	−0.080	−0.053	1.000
	(0.303)	(0.073)	(0.384)	(0.325)	(0.052)	(0.000)	(0.987)	(0.109)	(0.292)	-----
Source	WDI	IMF	WDI	WDI	WDI	WDI	WDI	WDI	WDI	WDI

NOTES Values in parentheses ( ) are the *p*-values of the test statistic; '*a*', '*b*', and '*c*' imply significance at 1, 5, and 10 percent, respectively. EEP is entrepreneurship development, OFD is overall financial development, GGR is GDP per capita, GOP is institutional quality, LFP is labour force participation, IFG is inflation rate, POG is population growth, UBT is urbanization, EOP is economic openness, REG is business start-up regulations, WDI is World Development Indicators (Doing Business database), and IMF is International Monetary Fund.

addition, a panel series must be examined for stationarity or unit-roots because discontinuities can seriously impair econometric estimates. We conducted panel unit root tests to assess the variables' integration order. Table 3 displays the results of the PP-Fisher, ADF-Fisher, Levin, Lin, and Chu (LLC), and Im, Pesaran, and Shin (IPS) stationarity tests. The null hypothesis of all the stationarity tests is that the panel series contains a unit root. The results show that entrepreneurship (EEP), financial development (OFD), economic growth (GGR), institutional quality (GOP), labour force participation (LFP), and urbanization (UBT) are integrated

TABLE 3 Panel Unit Roots Test Results

Series	Stationarity	PP-Fisher	ADF- Fisher	LLC	IPS	Decision
EEP	Level	72.656 (0.456)	70.376 (0.532)	−0.809 (0.209)	1.206 (0.886)	I(1)
	First difference	144.583[a] (0.000)	227.289[a] (0.000)	−3.297[a] (0.001)	−4.856[a] (0.000)	
OFD	Level	104.632[a] (0.007)	82.386 (0.189)	−2.707[a] (0.003)	−0.485 (0.314)	I(1)
	First difference	-	188.863[a] (0.000)	-	−7.337[a] (0.000)	
GGR	Level	108.086[a] (0.004)	54.333 (0.940)	−2.400[a] (0.008)	1.346 (0.911)	I(1)
	First difference	-	114.645[a] (0.000)	-	−2.3393[a] (0.009)	
GOP	Level	96.556[b] (0.028)	85.728 (0.129)	−6.493[a] (0.000)	−1.099 (0.136)	I(1)
	First difference	-	205.107[a] (0.000)	-	−5.206 (0.000)	
LFP	Level	67.519 (0.562)	37.433 (0.999)	−0.793 (0.214)	6.440 (1.000)	I(1)
	First difference	181.952[a] (0.000)	105.593[a] (0.004)	−2.452[a] (0.007)	−1.319[c] (0.093)	
IFG	Level	186.897[a] (0.000)	142.235[a] (0.000)	−7.769[a] (0.000)	−5.206[a] (0.000)	I(0)
	First difference	-	-	-	-	
POG	Level	113.111[a] (0.001)	102.253[b] (0.011)	−4.644[a] (0.000)	−1.806[b] (0.036)	I(0)
	First difference	-	-	-	-	
UBT	Level	158.150[a] (0.000)	128.060[a] (0.000)	1.653 (0.951)	−0.188 (0.425)	I(1)
	First difference	-	-	−3.405[a] (0.000)	−3.209[a] (0.001)	
EOP	Level	318.961[a] (0.000)	208.959[a] (0.000)	−11.910[a] (0.000)	−9.492[a] (0.000)	I(0)
	First difference	-		-	-	
REG	Level	129.608[a] (0.000)	114.351[a] (0.000)	−18.884[a] (0.000)	−6.620[a] (0.000)	I(0)
	First difference	-	-	-	-	

NOTES Values in parentheses ( ) are the p-values of the test statistic, 'a' and 'b' imply significance at 1 and 5 percent, respectively. EEP is entrepreneurship development, OFD is overall financial development, GGR is GDP per capita, GOP is institutional quality, LFP is labour force participation, IFG is inflation rate, POG is population growth, UBT is urbanization, EOP is economic openness, REG is business start-up regulations.

TABLE 4 Kao-Engle-Granger Panel Cointegration Results

Tests	Statistic	p-value	Conclusion (H_0)
Modified Dickey-Fuller	2.771[a]	0.003	Reject
Dickey-Fuller	2.449[a]	0.007	Reject
Augmented Dickey-Fuller	1.541[c]	0.062	Reject

NOTE H_0: No cointegration, '*a' implies significance at 1 percent and H_0 is rejected*

TABLE 5 Cross-sectional Dependence Test

Test	Statistic	Prob.
Breusch-Pagan LM	2321.311[a]	0.000
Pesaran scaled LM	46.633[a]	0.000
Pesaran CD	2.800[a]	0.005

NOTE: 'a' implies significance at 1 percent

of order one or I(1). In contrast, inflation rate (IFG), population growth (POG), economic openness (EOP), and business start-up regulations (REG) are integrated of order zero or I(0). The results of the stationarity tests clearly show that the panel series' integration sequence varies. It is evident from the stationarity tests that there are differences in the integration sequence of the panel series.

The cointegration test is also required to verify whether there is the existence of a long-term relationship between the variables once the unit root tests have been completed. This is determined by the Kao-Engle Granger test displayed in table 4. The reason for using this method is that it can handle a larger number of regressors than the restricted Pedroni and Westerlund cointegration tests. The Kao cointegration test findings show that each panel series is cointegrated, and every statistic at the one percent significance level supports this.

Table 5 presents the results of the cross-sectional dependency tests utilizing the Pesaran and Breusch-Pagan LM tests. The results validate the presence of cross-sectionally dependent factors among the variables at the one percent significance level. This issue is intensified by the high level of economic interconnectedness among African countries. Ignoring this could cause the study's findings to be distorted and contradictory. At the one percent significance level, the findings confirm the existence of cross-sectionally dependent factors among the variables. The greater degree of economic interdependence among the African nations makes this worse. Ignoring this could lead to skewed and contradictory findings

TABLE 6 PCSE and SGMM Estimations

Variables	PCSE			SGMM		
	(1)	(2)	(3)	(4)	(5)	(6)
L.EEP	—	—	—	0.080[a]	0.081[a]	0.082[a]
				(17.90)	(32.54)	(12.53)
OFD	7.701[a]	—	—	2.761[a]	—	—
	(8.638)			(5.574)		
OFI	—	5.752[a]	—	—	4.033[a]	—
		(6.670)			(11.00)	
OFM	—	—	6.146[a]	—	—	1.025[a]
			(7.132)			(4.413)
GGR	0.004[a]	0.005[a]	0.005[a]	−0.035[a]	−0.0342[a]	−0.032[a]
	(6.548)	(6.107)	(7.509)	(−15.57)	(−30.24)	(−9.136)
GOP	1.842[a]	1.916[a]	2.169[a]	0.188	−0.046	0.413
	(6.761)	(6.742)	(8.938)	(0.804)	(−0.329)	(1.477)
LFP	0.048[a]	0.043[a]	0.051[a]	0.114[a]	0.117[a]	0.117[a]
	(10.54)	(9.107)	(12.09)	(15.89)	(38.22)	(14.33)
IFG	−0.009	−0.002	−0.015[c]	0.003[a]	0.003[a]	0.003[a]
	(−1.175)	(−0.286)	(−1.799)	(2.980)	(4.246)	(3.090)
POG	−0.245[a]	−0.309[a]	−0.396[a]	−0.215[a]	−0.160[a]	−0.269[a]
	(−2.551)	(−3.018)	(−3.969)	(−2.833)	(−3.563)	(−4.200)
UBT	0.026[a]	0.028[a]	0.028[a]	0.088	0.079	0.094
	(5.819)	(6.897)	(5.750)	(7.805)	(9.626)	(8.476)
EOP	0.013[a]	0.008[b]	0.014[a]	0.023[a]	0.025[a]	0.021[a]
	(4.458)	(2.560)	(4.577)	(11.83)	(29.82)	(8.325)
REG	0.039	0.012	0.063[b]	0.031[a]	0.021[b]	0.031[a]
	(1.572)	(0.494)	(2.221)	(4.050)	(2.474)	(3.911)
Constant	−3.257[a]	−2.547[a]	−2.392[a]	−12.27[a]	−12.87[a]	−11.99[a]
	(−5.247)	(−3.468)	(−4.024)	(−12.24)	(−42.90)	(−10.52)
R-squared	0.522	0.515	0.522			
Wald χ^2 –statistic	843.18	526.29	995.38	369791.36	401655.16	280419.89
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
AR1	—	—	—	-1.410	-1.439	-1.423
	—	—	—	{0.158}	{0.150}	{0.155}
Sagan	—	—	—	25.817	26.812	26.877
	—	—	—	{1.000}	{1.000}	{1.000}
Multicollinearity (VIF)	1.81	1.95	1.63	1.68	1.77	1.59

NOTES Figures between ( ) and { } are z-statistic and probability values respectively. 'a', 'b', and 'c' imply significance at 1, 5, and 10 percent, respectively. L.EEP is the first lag of entrepreneurship development, OFD is overall financial development, OFI is financial institutions development, OFM is financial market development, GGR is GDP per capita, GOP is institutional quality, LFP is labour force participation, IFG is inflation rate, POG is population growth, UBT is urbanization, EOP is economic openness, and REG is business start-up regulations.

in the study. This is one of the explanations, as previously acknowledged, for using the PCSE technique in this study, which is suitable for dealing with these kinds of issues and related ones.

PRESENTATION AND DISCUSSION OF EMPIRICAL RESULTS

The findings from the PCSE regarding the long-run effects of overall financial development, its components, and the control variables on entrepreneurship are presented in columns (1), (2), and (3) of table 6, respectively. As part of a robustness analysis aimed at verifying potential factors responsible for the differential effects of financial development on entrepreneurship, we further employed the system GMM (SGMM) method to examine the short-run effects of financial development and its components of financial development, as indicated in columns (4), (5), and (6). Importantly, post-estimation tests confirm the robustness of the estimates derived from both the PCSE and SGMM models. The variance inflation factors (VIF) for financial development, financial institutions and markets development models are relatively low, with values of 1.81, 1.95, and 1.63, respectively, indicating no significant multicollinearity among the explanatory variables. The correlation analysis supports this finding. Additionally, the Wald Chi-square (X^2) statistics, all significant at the 1 percent level, and the R-square (R^2) statistics, ranging from 0.524 to 0.513, suggest that the model estimations are reliable and valid for decision-making purposes. Furthermore, results from the SGMM indicate no second-order serial correlation, and the Sargan test confirms the validity of the instruments used for estimation, thus passing diagnostic tests.

Based on the empirical findings derived from the PCSE analysis, the coefficients associated with financial development, financial institutions and markets demonstrate positive and statistically significant relationships at the 1 percent level. This indicates that, considering the direct impacts of financial development, financial institutions, and markets, they positively influence entrepreneurship development over the long run. Specifically, a one percentage increase in financial development, financial institutions, and markets corresponds to a 7.701, 5.752, and 6.146 units increase in entrepreneurship development, respectively.

The observed beneficial relationship between financial development, financial institutions, and markets development and entrepreneurship activities may arise from financial development's role in creating a conducive environment for entrepreneurship. This includes providing access to capital, mitigating risks, facilitating transactions, offering support services, and fostering market confidence. These findings align with previous studies such as those by Amin et al. (2023) and Dutta and Meierrieks (2021), which suggest that improved access to finance promotes entrepreneurial activities. However, this contradicts some earlier research that proposed no significant influence of financial development on entrepreneurship activities due to various complexities (Ajide and Ojeyinka 2022; Gaies et al. 2023).

The empirical findings derived from the SGMM analysis presented in table 6 reveal that the coefficients associated with financial development, financial institutions and markets are all positive and statistically significant at the 1 percent level. This indicates that financial development, financial institutions and markets have a positive impact on entrepreneurship activities in the short run. Specifically, a one percentage point increase in financial development, financial institutions and markets corresponds to a 2.761, 4.033, and 1.025 units increase in entrepreneurship activities, respectively. Moreover, it suggests that the coefficients of financial development and its components are lower in the short run compared to the long run. These results support our first hypothesis.

The observed beneficial relationship between financial development, financial institutions and markets and entrepreneurship activities in the short run may also be attributed to their crucial role in enhancing liquidity, acting as a price discovery mechanism, and establishing institutional infrastructure. This finding is consistent with related studies such as those by Amin et al. (2023), Munemo (2018), and Omri (2020). However, it contradicts the findings of Gaies et al. (2023) and Léon (2019), which indicate that rising borrowing prices and a lacklustre financial sector constitute major obstacles to the expansion of entrepreneurship. Additionally, the results indicate that labour force participation, urbanization, and economic openness positively influence entrepreneurship activities in the long and short run, while population growth and inflation rate negatively impact entrepreneurship activities over both time frames. Furthermore, GDP per capita and start-up business regulations exhibit differential effects on entrepreneurship activities in the short and long run.

The positive effects of labour force participation, urbanization, and economic openness are supported by the findings reported by Dutta and Sobel (2018) and Gaies et al. (2023), while the results of the economic openness and urbanization contradict the results of the study reported by Dutta and

TABLE 7 Causality Between Entrepreneurship and Financial Development

Null Hypothesis:	F-Statistic	Probability value	Decision
OFD does not homogeneously Granger-cause EEP	10.0298[a]	0.0000	Unidirectional
EEP does not homogeneously Granger-cause OFD	0.01008	0.9900	
OFI does not homogeneously Granger-cause EEP	8.23180[a]	0.0003	Unidirectional
EEP does not homogeneously Granger-cause OFI	0.05808	0.9436	
OFM does not homogeneously Granger-cause EEP	6.46435[a]	0.0017	Unidirectional
EEP does not homogeneously Granger-cause OFM	0.07576	0.9271	

NOTE Probability value 'a' implies significant at 1 percent significance level. EEP is entrepreneurship development, OFD is overall financial development, OFI is financial institution development, and OFM is financial market development.

Meierrieks (2021). The positive effects of GDP per capita in the long run are also supported by studies by Dutta and Meierrieks (2021), Gaies et al. (2023), and Omri (2020), while the negative effects of the GDP per capita on entrepreneurship in the short run are supported by Ajide (2022), Amin et al. (2023), and Dutta and Sobel (2018). Notably, the unexpected negative impact of GDP per capita on entrepreneurship activity in Africa may stem from a preference for wage employment over self-employment, wherein higher GDP per capita tends to drive more individuals towards wage employment, making it more appealing than self-employment.

The beneficial short- and long-term effects of financial development, financial institutions and markets on entrepreneurship in Africa may be attributed to the distinct economic environment of the continent and the different phases of financial maturity. Short-term financial development can boost entrepreneurship right away by expanding credit availability and financial services, especially for small and medium-sized businesses (SMEs), which are frequently hampered by inadequate access to funding. If there is more money available to entrepreneurs, more innovative ideas and jobs can be created as they launch and grow their enterprises. Over time, as financial markets and institutions grow more complex and inclusive, they also help to create a more stable economic climate that supports long-term entrepreneurship. Well-developed financial systems eventually lower transaction costs, boost market effectiveness, and offer a wider variety of financial products, all of which are essential for assisting high-growth businesses and drawing in foreign capital. The steady enhancement of financial infrastructure can result in long-term growth in entrepreneurship, economic diversification, and a more robust private sector in Africa, where numerous economies are in the process of forming.

The empirical findings presented in table 7 demonstrate that the development of entrepreneurship is Granger-caused by financial development and its components. However, financial development and its components are not Granger-caused by the growth of entrepreneurship. This demonstrates the unidirectional causal relationship between financial development, entrepreneurship, and its constituent parts. That is, the development of entrepreneurship is causally related to financial development and its components. This lends credence to Schumpeter's argument that entrepreneurial activity is driven by financial development. This supports the idea that entrepreneurship requires access to financial resources, supporting the significance of financial infrastructure in economic theories of development. Nonetheless, it casts doubt on any assumptions about reciprocal causality and emphasizes how important financial institutions are to support entrepreneurial activities. The results of the Granger causality address the second and third hypotheses. This evidence further enhances existing theories and empirical studies by clarifying the direction of causality between financial development and entrepreneurship activity in Africa.

Conclusions

This study validates the impact of financial development and its components on entrepreneurship development across 28 African economies from 2006 to 2020. Its contributions to existing literature lie in examining how financial development influences entrepreneurship and exploring both short- and long-term effects. Utilizing PCSE and SGMM estimations, the study also analyses the differential effects of financial development, financial institutions and markets development as well as other control variables on entrepreneurship development over varying time frames. The study further examines the causal relationship between entrepreneurship, financial development, and its components.

Findings indicate a positive influence of financial development, financial institutions, and markets on entrepreneurship development in both short and long-run contexts. This suggests a consistent relationship without significant differential effects between the two time frames across Africa. Additionally, causality results establish unidirectional causality between entrepreneurship, financial development, and its components, flowing from financial development and its components to entrepreneurship development. Moreover, the results of the control variables reveal positive impacts of labour force participation, urbanization, and economic openness on entrepreneurship development. At the same time, population growth and inflation rates exhibit negative influences over both the short and long term. Only GDP per capita and start-up business regulations demonstrate differential effects on entrepreneurship development in short and long-run scenarios.

The study significantly contributes to existing studies by demonstrating a consistent positive relationship between financial development, financial institutions and markets with entrepreneurship activities in Africa across both short- and long-run contexts. This study suggests that financial development constantly fosters entrepreneurial growth regardless of time, challenging earlier notions about differential consequences over time. Furthermore, the study's demonstration of unidirectional causality, according to which entrepreneurship is driven by financial development and its components, contributes to a more sophisticated comprehension of the dynamic interplay between financial systems and entrepreneurial activity. This emphasizes how important financial development is as an entrepreneurship stimulant.

Drawing from these empirical findings, recommendations emerge to enhance entrepreneurship development in Africa. Firstly, policymakers should prioritize sustainable, long-term financial development through policies promoting stability and inclusivity in financial markets. Emphasis should also be placed on initiatives enhancing access to finance for entrepreneurs by improving financial infrastructure and reducing barriers to financial services. Moreover, fostering conducive environments for entrepreneurship through policies promoting job creation, urban development, and economic diversification is crucial. Measures to control inflation, manage population growth, and promote sustainable economic growth are essential for creating an enabling environment. Finally, the differential effects of GDP per capita and start-up business regulations on entrepreneurship development in the short and long run suggest the need for tailored policy interventions that can promote sustainable economic growth and streamline regulatory processes to facilitate entrepreneurship activities over time.

This empirical study offers insightful information about entrepreneurship and financial development in African economies. Nonetheless, one must also take into account its limitations. First, the study's emphasis on formal entrepreneurship ignores informal entrepreneurship, which may limit how broadly applicable the conclusions can be. Furthermore, the study focuses on the financial development effect on entrepreneurship across African countries, possibly omitting sub-regional differences and the various stages of financial development. Finally, the study's emphasis on unidirectional causality restricts the investigation of possible feedback loops between financial development and entrepreneurship, providing an opportunity for other research to delve deeper into these dynamics.

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Unveiling Organizational AI Adoption Patterns in Italian Companies through the Lens of the Diffusion of Innovations Theory

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This paper investigates the adoption and integration of artificial intelligence (AI) technologies within a sample of 237 Italian enterprises using the Diffusion of Innovations (DOI) theory as the theoretical framework. It examines the characteristics of companies leading in AI adoption, evaluating their alignment with the innovator and early adopter profiles defined by Everett Rogers in 2003 within the DOI framework. The research emphasizes AI's significant role in enhancing operational efficiency, fostering innovation, securing competitive advantage, and driving long-term growth. It also identifies challenges such as lack of skills, data management issues, and ethical concerns. Our findings contribute empirical evidence to the academic literature on the DOI theory, addressing the underexplored context of AI in Italy. The study provides a nuanced perspective on AI's impact on employment and sets a foundation for future research, offering managerial insights for strategically deploying AI.

Keywords: artificial intelligence, diffusion of innovations theory, early adopters, implementation challenges, Italian companies
JEL *Classifications:* L20; M10; O33; O52

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Introduction

Emerging technologies, particularly Artificial Intelligence (AI), are significantly influencing organizational structures (Bailey et al. 2022). The recent widespread availability of Large Language Models (LLMs) has generated curiosity about AI's impact on work. AI technologies drive innovation, efficiency, and competitive advantage by enhancing decision-making, automating routine tasks, and improving customer engagement (Bughin et al. 2017; Agrawal et al. 2019; Davenport and Ronanki 2018). However, successful AI adoption requires careful consideration of ethical implications, workforce reskilling, and robust data governance frameworks (Bostrom and Yudkowsky 2018).

Despite growing global interest in understanding AI adoption across industries (Calvino et al. 2022; Calvino and Fontanelli 2023; IBM Corporation 2022; 2023; Maslej et al. 2023), there is a lack of research on AI adoption in European countries, particularly in Italy. To fill this gap, we adopted the Diffusion of Innovations (DOI) theory (Rogers 2003), providing a theoretical lens to examine AI adoption in Italian companies. This study assesses the alignment of these companies with the innovator and early adopter profiles defined by the DOI framework. We chose this theoretical approach because the DOI theory has been widely used and proven effective in studies investigating AI adoption across various contexts. This is evidenced by its application in numerous recent studies (e.g. Agrawal et al. 2019; Ahituv and Hasgall 2019; Alsheibani et al. 2018; Horani et al. 2023; Lund et al. 2020).

Regarding the Italian context, recent studies have explored the potential impact of AI adoption on Italy's economy and industrial competitiveness. As argued by Saracco (2022), Italy's AI strategy (Programma Strategico Nazionale per l'Intelligenza Artificiale) aims to increase adoption, particularly among small and medium-sized enterprises (SMEs), which form the backbone of the country's industrial landscape (Saracco 2022). AI adoption has been associated with increased productivity, value-added, and higher average wages within adopting firms, although its impact on employment varies by firm size (Bisio et al. 2023). Adopting AI can significantly enhance the competitiveness of firms by improving productivity, customer experience, and problem-solving capabilities (Kinkel et al. 2022). For SMEs, successful AI integration requires addressing four critical dimensions: people, processes, products, and customers (Del Sarto and Piccaluga 2021). Overall, while AI offers significant opportunities for European firms, its effective deployment requires strategic planning and adaptation to maximize benefits while addressing potential challenges, such as ethical considerations and the need for transparent, reliable AI systems (Annoni et al. 2018).

Given the importance of the topic and the identified gap in the existing literature, this study aims to explore AI adoption in Italian organizations, understand predominant AI solutions, measure integration depth, and examine the main implementation challenges.

The research question is: What are the characteristics of Italian companies that are early adopters of AI, and how do these characteristics align with the attributes of innovators and early adopters as defined by the DOI theory?

Our study employed a convenience sampling method, focusing on all the Executive MBA graduates from an Italian Business School. The sample comprises those graduates who voluntarily responded to our web-based survey invitation. This approach allowed us to access a relevant population of business professionals while acknowledging the limitations inherent in convenience sampling (e.g. Alessi and Martin 2010; Schonlau et al. 2009). This approach yielded 237 valid responses for subsequent analysis, revealing multiple perspectives on AI's future in organizational strategy.

Our study reveals a diverse AI adoption landscape in Italy, including both innovators and early adopters, in line with the DOI framework. Increasing AI spending indicates progress along the innovation curve, with early adopters driving mainstream integration. AI is emerging as a critical enabler for Italian companies, driving efficiency, innovation, and competitive advantage. However, challenges such as skills gaps, data management, and ethical concerns require attention.

By understanding the characteristics of leading AI adopters in Italy, this study aims to provide insights that can inform strategies for promoting AI adoption in other contexts. We also offer recommendations for practitioners on effectively using AI to drive business success, gain a competitive edge, and position their organizations as leaders in technological innovation.

The structure of the paper is organized as follows. The second section outlines the theoretical framework and formulates the research question. In the third section, we delineate the employed methodology. After that, in the fourth section, we outline the main results of the study, which are thoroughly discussed in the fifth section, including the implications of the study and subsequent avenues for research. Finally, the conclusion and limitations of the study are presented in the sixth section.

Theoretical Framework

THE DIFFUSION OF INNOVATIONS (DOI) THEORY

The DOI theory, proposed by Rogers (2003), posits that adopting new technologies follows a predictable pattern. It identifies five categories of adopters: innovators, early adopters, early majority, late majority, and laggards. Adopter categories are essential in understanding innovation diffusion within social systems. These categories, derived from empirical data, help to compare and understand innovation adoption. While there are exceptions, they represent a spectrum of innovativeness rather than discrete groups, challenging the notion of a significant 'chasm' between early and late adopters. This perspective views innovativeness as a continuous spectrum, highlighting the differences between categories of adopters and providing insights into their adoption behaviours and motivations (Rogers 2003).

Therefore, these categories efficiently classify individuals based on their innovativeness. Each category shares distinct characteristics, reflecting fundamental differences in how people approach new ideas. Innovators are pioneers who eagerly pursue cutting-edge technologies and are not afraid to take risks when experimenting with them. Early adopters, influential in their own right, play a critical role in spreading innovation to a wider audience. The early majority, a significant segment of the population, carefully observes early adopters before deciding to embrace new concepts. In contrast, the late majority consists of sceptics who adopt innovations only after they have been widely validated. Laggards, the final group, are highly resistant to change and typically adopt innovations only when absolutely necessary. Understanding these categories is essential for organizations and innovators who want to successfully introduce new products, services, or ideas to different segments of society.

In our study focused on AI implementation and early adoption within organizations, we specifically examine the innovators and early adopters. Innovators serve as catalysts for innovation, constantly pushing the boundaries of what is possible in their industries with a relentless pursuit of transformative impact. Their willingness to take risks and engage directly with innovation networks fuels the initial stages of technological advancement. Early adopters complement this momentum by strategically evaluating and swiftly integrating new technologies into mainstream practices. Their role as influential adopters not only validates innovations but also accelerates their widespread acceptance and adoption across industries (Dedehayir et al. 2017).

Together, innovators and early adopters drive the rapid diffusion of innovation, propelling industries forward into new realms of possibility and progress. Therefore, understanding the characteristics of innovators and early adopters is essential for promoting widespread innovation adoption.

The DOI theory highlights the crucial role of innovators and early adopters in technology adoption (Dedehayir et al. 2017). These groups are characterized by their innovative mindset, willingness to take risks, and access to resources. Numerous studies on technology adoption emphasize early adopters due to their significant potential in facilitating organizational uptake of technological innovations and accelerating the digital transformation process effectively. Early adopters demonstrate positive attitudes toward technology, readiness to utilize it, and active involvement in its integration (Ahituv and Hasgall 2019). They also play a crucial role in spreading information through word-of-mouth and serve as benchmarks influencing subsequent market acceptance (Bianchi et al. 2017).

Regarding AI adoption, studies reveal that factors such as relative advantage, compatibility, ease of use, observability, and trialability significantly influence adoption intentions (Raman et al. 2024). Organizations transitioning to Complex Adaptive Systems (CAS) may encourage employees to become early adopters, thereby facilitating effective digital transformation (Ahituv and Hasgall 2019). Understanding the characteristics of innovators and early adopters can expedite innovation uptake for firms and assist policymakers in promoting beneficial technologies (Dedehayir et al. 2017).

Therefore, building on this literature, we argue that in the context of AI, innovators and early adopters recognize AI's potential and invest in its implementation. Since the data collection was conducted in October 2023, during a period of experimentation with AI adoption in organizations, we expected AI adopters in Italy to fall into these adoption categories.

ARTIFICIAL INTELLIGENCE ASCENDANCE

The development of Artificial Intelligence in business has seen remarkable innovations and occasional setbacks. While the 1956 Dartmouth Workshop marked the birth of AI as a formal discipline (Moor 2006), its development soon suffered from early limitations. The resurgence in the 1990s and 2000s was driven by the internet and advances in machine learning and big data, pushing AI into areas such as customer relationship management and business analytics (Zhang and Lu 2021). More recently, AI has experienced rapid growth and today is a transformative force reshaping business strategies and operations across multiple sectors (Gozalo-Brizuela and Garrido-Merchan 2023).

Thus, AI has become one of the most critical technological priorities for companies in recent years, mainly due to the availability of big data and the emergence of sophisticated techniques and infrastructures (Mikalef and Gupta 2021). AI-enabled chatbots and conversational agents, such as ChatGPT, are gaining wide acceptance across various industries to enhance stakeholder relations, engagement, and well-being (Manyika et al. 2017). However, the utilization of AI to enhance business processes was at first predominantly limited to large corporations. These organizations had the necessary big data to train machine learning applications and the financial resources to hire data science experts to develop these applications, along with the requisite technical infrastructure. However, this landscape underwent a significant transformation with the release of OpenAI's ChatGPT in November 2022. As the first widely accessible chatbot powered by a pre-trained neural network, ChatGPT democratized the use of generative AI, offering its capabilities—and inherent limitations—to potentially billions of users (Noy and Zhang 2023).

Owing to the rapid proliferation of AI utilization in both private and public sector entities, the topic of AI has achieved exponential interest among scholars and practitioners. The transformative impact of AI on organizational structures, processes, and employee dynamics has highlighted the growing academic interest in artificial intelligence in organizational studies and the workplace. Recent studies highlight the growing interest in understanding how industries are adopting AI. In the past year, significant research has focused on the impact of AI in various sectors, including manufacturing (Su et al. 2024), banking services (Fares et al. 2023), public sector organizations (Mergel et al. 2023), healthcare (Khan et al. 2023), and pharmaceuticals (Jarab et al. 2023), among others.

This interest spans multiple disciplines investigating how AI is reshaping the paradigm of decision-making, changing the efficiency of operations, and redefining skill requirements and job roles (Davenport and Ronanki 2018; Agrawal et al. 2019; Brynjolfsson and McAfee 2014). However, integrating AI in the workplace requires a comprehensive multidisciplinary approach that comprehensively addresses ethical, legal, and technical considerations. This approach effectively balances the potential benefits and mitigates the associated risks of implementing AI (Wachter et al. 2017).

Despite a wealth of research on the adoption of AI in different industries, our review of the literature reveals a significant gap: there seems to be a lack of studies that specifically investigate the understanding and integration of AI in the Italian context, which is characterized by its specificities, such as the fact that SMEs are the backbone of the Italian economy and there is a massive presence of family businesses. This omission highlights the importance of our study, which aims to fill this critical gap by investigating how AI is perceived and implemented in Italy.

Methodology

A web-based survey was implemented in October 2023, targeting Executive MBA graduates from an Italian business school.

For convenience reasons, the sampling population was represented by all the Executive MBA graduates of the Italian business school who received their degrees by 2023. A total of 2,160 graduates received a link to a web-based questionnaire via email. Out of these, 237 questionnaires were fully or partially filled, resulting in a gross response rate of 11%.

Web-based surveys offer fast, cost-effective data collection, reducing errors associated with physical materials and manual entry (Alessi and Martin 2010). Using Computer Assisted Self-Interviewing (CASI), participants completed the survey via email, providing qualitative and quantitative insights into AI applications and their strategic value across organizations.

Given the rapid evolution and widespread adoption of AI technologies among organizations, we chose to use a convenience sample to quickly gather a sufficient number of responses. The sample consists of graduates who voluntarily responded to our web-based survey invitation. This approach enabled us to reach a significant population of business professionals.

Convenience sampling, a non-probability sampling approach, is widely used in research but has significant limitations (Alessi and Martin 2010; Schonlau et al. 2009). While it allows for larger sample sizes compared to single-subject approaches, it falls between such methods and randomized control group studies. Its primary limitation is the potential lack of generalizability due to sample bias (Emerson 2021). Although, as in this study, the larger sample size of convenience sampling permits some degree of generalization beyond single-subject studies, the absence of random selection fundamentally limits the applicability of results to the broader population (Emerson 2021). Therefore, it is crucial to carefully consider and acknowledge these constraints when interpreting and presenting the findings of this study.

The questionnaire was organized into sections on demographic specifics, the current deployment of AI within respondents' companies, the perceived advantages and challenges associated with AI, and the degree of its integration into business operations (see the Appendix).

Based on the DOI theory, we expected that as the first adopters of AI in Italy (the data were collected in October 2023), they would be classified as innovators or early adopters, as described in Rogers' (2003) seminal article. Therefore, the data collected from the survey were meticulously cleaned and prepared for analysis to address the study's research question: identifying the characteristics of Italian companies that are early adopters of AI and how these characteristics align with the attributes of innovators and early adopters as defined by the DOI theory.

To highlight key findings from our exploratory study, we used distribution frequencies to analyse key aspects identified from survey questions and existing literature. These aspects included, for example, companies' experience with AI technology, motivations driving AI adoption, financial investments in AI in the past and next 12 months, and challenges related to generative AI and its business impact. Through this analysis, we gained valuable insights into the current state of AI adoption and implementation within the Italian companies surveyed.

To address the second part of our research question – alignment with innovators and early adopters as defined by the DOI theory – we conducted a thematic analysis of distribution frequencies derived from our data. This qualitative assessment compared company characteristics identified in our study with the primary traits of innovators and early adopters outlined by Rogers (2003).

The geographical distribution of the 237 valid responses demonstrates nationwide coverage. The organizations surveyed represented a diverse range of sizes, from very small to very large. The majority were small to medium-sized enterprises (SMEs), as evidenced by the median number of employees being 80 – a value more robust than the mean, given the skew of the distribution towards the lower end of the size spectrum.

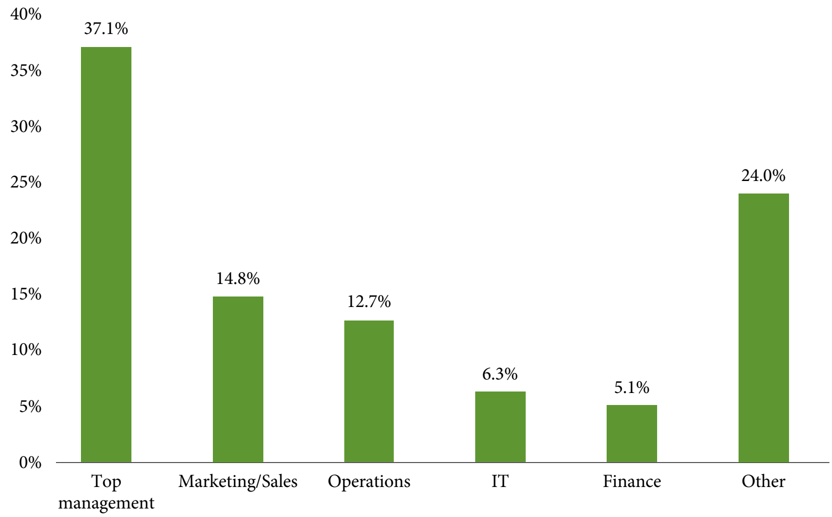

FIGURE 1 Role of Respondents

The majority of respondents (37.1%) were from Top management, followed by Marketing/Sales (14.8%), Operations (12.7%), IT (6.3%), and Finance (5.1%) (figure 1).

Results

OVERVIEW OF AI ADOPTION

Organizations' Level of AI Integration and Experience

Firstly, we classified organizations based on their primary interaction with AI. The responses indicated that 38% of organizations primarily act as end-users, 20.3% as suppliers, 22.8% serve both functions, and 19% do not engage with AI technology in these capacities.

The AI experience levels among surveyed organizations were categorized into four distinct levels. Notably, a significant portion (30%) has over a year of experience with AI, indicating advanced engagement and possible integration into their operations. These companies are likely the innovators of AI in Italy, aligning with Rogers' (2003) characterization of innovators as the first to embrace new technologies and drive industry transformation. Another segment (15.6%) is in the early stages of AI adoption, with experience ranging from six months to a year, suggesting they are scaling up their AI initiatives. These companies could be considered early adopters, as described by the DOI theory. Early adopters are distinguished by their strategic and influential role in validating

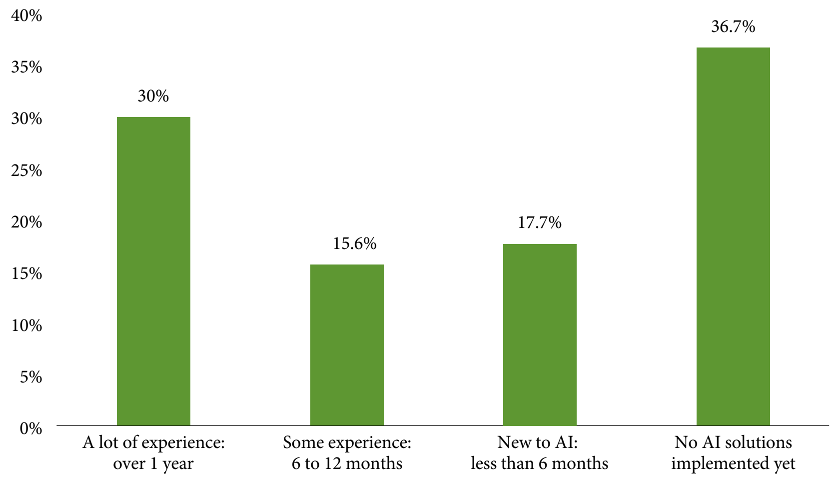

FIGURE 2 AI Experience Level in Companies

new technologies and accelerating their diffusion within the industry, although they may be slightly less mature in their AI adoption than the innovators (Rogers 2003). A slightly larger group is new to AI (17.7%), with less than six months of experience, likely exploring AI's applicability. A significant portion of companies (36.7%) have not yet adopted any AI solutions, likely indicating they are in the early stages of considering AI's potential benefits and challenges or lack the necessary resources, expertise, or strategic direction for AI implementation (figure 2).

A very weak negative correlation (–0.048) between the organization's size and the level of AI adoption suggests that the size of an organization does not significantly influence its AI adoption stage. This counterintuitive result should, however, be treated with caution as the sample of responding companies was self-selected and could, therefore, suffer from selection bias.

Areas of AI Application

The survey uncovers a wide array of AI applications being utilized within organizations, showcasing the diverse spectrum of AI technologies adopted across different sectors. Notably, 'Fraud/security' (55) and 'NLP/Chatbots/Language Processing' (65) applications are particularly prominent, indicating a strong emphasis on using AI to bolster security measures and enhance natural language processing capabilities, which are essential for the improvement of customer services, content engagement and higher security frameworks.

The frequent mention of 'Content creation/creativity' (50 times) underscores a growing interest in Generative AI, suggesting that more individuals and organizations are increasingly recognizing its potential in this field. Additionally, the focus on 'Experimenting/testing AI' (60) within organizations underscores many companies are navigating the discovery or pilot stages of their AI endeavours.

As highlighted by the survey responses, the diverse application of AI technologies illustrates the widespread adoption and integration of AI into various organizational processes and services. It reflects the versatile potential of AI to tackle a broad spectrum of challenges and opportunities. This broad adoption and experimentation signal that organizations are still fine-tuning their strategic priorities and identifying the most impactful technological trends for their AI investments, indicating a landscape of evolving engagement with AI technologies.

Moreover, according to the DOI theory, this substantial portion of organizations actively exploring and testing AI aligns with the behaviour of both innovators and early adopters. Innovators are likely leading the charge with more exploratory projects, while early adopters are beginning to integrate AI in more structured ways across various applications. This broad distribution of AI experimentation points to a growing interest and potential for AI, signalling that the technology is transitioning from early adoption to more widespread, practical use.

DRIVERS AND EXPENDITURES FOR AI ADOPTION

Key Drivers for Embracing AI

The motivations for AI adoption vary among the companies surveyed. The primary motivations behind adopting AI are illustrated in figure 3. These motivations align closely with the characteristics of innovators and early adopters as described in Rogers (2003). This focus on enhancing internal processes is indicative of early adopters, who seek to leverage new technologies to optimize their operations and gain a competitive edge. Early adopters are often motivated by the practical benefits of innovation, using AI to streamline and enhance internal functions, which aligns with their more structured and strategic approach to technology adoption.

On the other hand, the 10.7% of respondents who reported no specific objective for using AI likely represent innovators. This group is characterized by their willingness to explore new technologies without a clear,

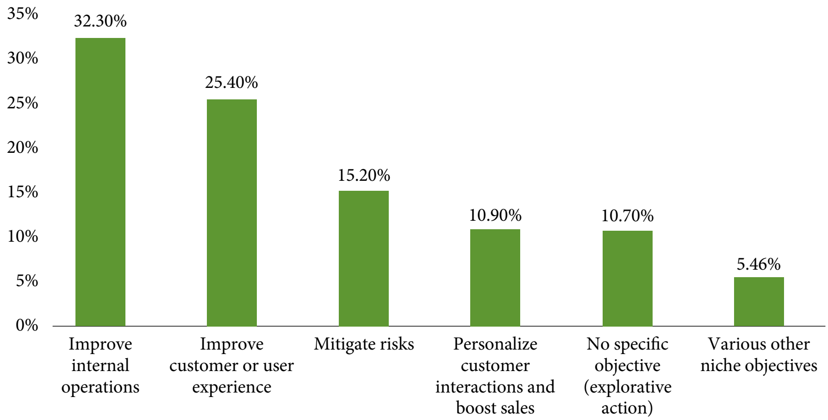

FIGURE 3 Key motivations for AI Adoption

immediate application in mind. Their approach is often experimental, driven by curiosity and the desire to be at the forefront of technological advancements. Innovators are crucial in the diffusion process as they help to identify novel applications and set the stage for broader adoption.

The motivations of other organizations, such as the 25.4% focused on improving customer or user experience, the 15.2% prioritizing risk mitigation, and the 10.9% using AI for personalized customer interactions and sales enhancement, also reflect the traits of early adopters. These companies are actively seeking to apply AI in ways that deliver tangible benefits, whether through enhanced customer engagement, reduced risks, or more personalized services.

The small fraction (5.46%) with niche objectives represents the diversity of AI's potential applications, further illustrating how early adopters are pushing the boundaries of AI usage in specific, targeted ways.

AI Expenditure

We asked the respondents about the changes in AI expenditures in the last 12 months. The findings show a trend where most companies have either maintained or increased their investment in AI technologies, with only a minority reducing their spending (left pie chart in figure 4). Further inquiry into the investment forecasts for the next 12 months reveals a pronounced inclination among companies to either sustain or escalate their AI expenditure, with a significant portion projecting an increase (right pie chart in figure 4).

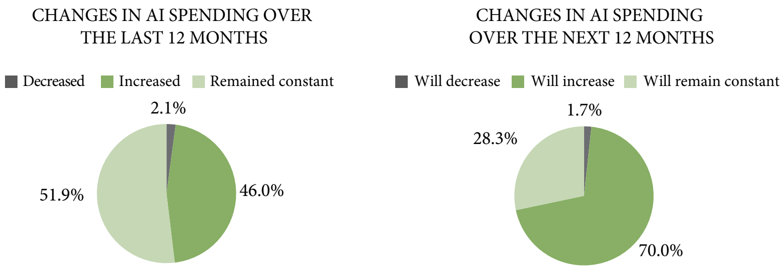

FIGURE 4 Changes in AI Spending

The significant increase in AI investment over the previous year reflects acceleration in adoption, underscoring the strategic importance placed by companies on AI technologies. This trend indicates a shift from viewing AI as a hyped phenomenon to recognizing it as a foundational component of strategic business planning.

Companies increasingly see AI as crucial for future growth, innovation, and competitive advantage. The evolving trend suggests that AI investment will become central to achieving business success and shaping future corporate landscapes.

This pattern of increasing AI expenditures aligns well with the DOI theory's concepts of early adopters and innovators. The majority of companies maintaining or boosting their AI investments reflects the characteristics of early adopters, who strategically invest in technology to enhance productivity and gain a competitive edge.

CHALLENGES AND BARRIERS AND PERCEIVED RISKS TO AI ADOPTION

Primary Challenges in AI Implementation

The survey also probed participants about the primary challenges their company or organization currently faces with AI, aiming to gather insights into the hurdles encountered in harnessing AI's full potential.

The survey reveals that the most pressing challenge faced by organizations in implementing AI is the significant gap in the availability of a skilled workforce (82). This includes not only AI professionals but also individuals with a general data and basic AI literacy, which are crucial for the effective implementation and management of AI projects. Additionally, many companies struggle to identify effective ways to integrate AI into their operations, indicating a lack of strategic clarity (49). The third major challenge is accessing high-quality relevant data, highlighting the essen-

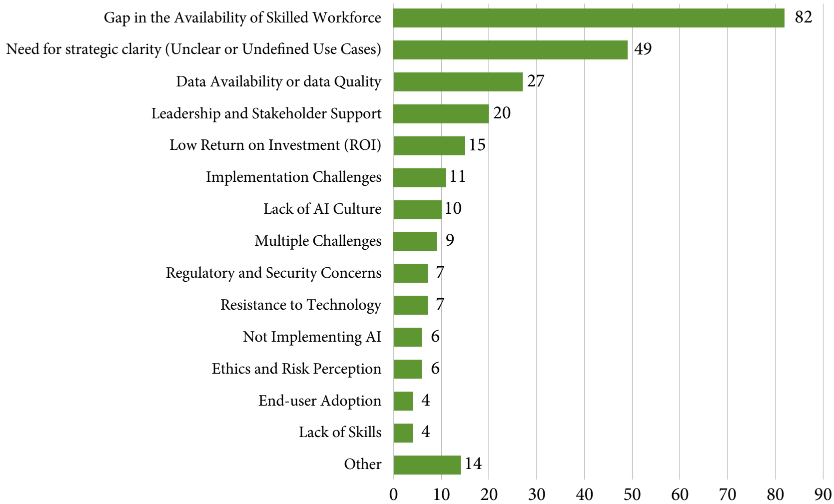

FIGURE 5 Primary Challenges in AI Implementation

tial role of data in maximizing AI's effectiveness (27). A fourth concern is the necessity of securing buy-in from top management and stakeholders, whose support is vital for providing the necessary resources and strategic direction (20). Concerns about the financial outcomes of AI investments also emerged, reflecting the difficulty in measuring and proving the expected benefits (15). Other identified challenges, including regulatory and security concerns (7), resistance to technology (7), and a lack of AI culture within organizations (10), underscore the complex and multifaceted nature of obstacles to AI adoption. Notably, some respondents reported facing multiple challenges (9) or were unable to identify a single predominant issue, illustrating the complexity of AI implementation. Figure 5 illustrates the frequency of these primary challenges in AI implementation.

These findings highlight the need for a multifaceted approach to overcoming challenges in AI adoption and align with the DOI theory, which posits that the adoption of new technologies is frequently impeded by gaps in knowledge and resources. Innovators, who are at the forefront of technology exploration, often encounter difficulties due to a lack of skilled personnel and strategic clarity. Early adopters, while progressing to more structured integration of AI, also face obstacles such as data access and securing management support.

Addressing these challenges is crucial for advancing beyond the initial experimentation phase and fully realizing AI's potential in organizational contexts.

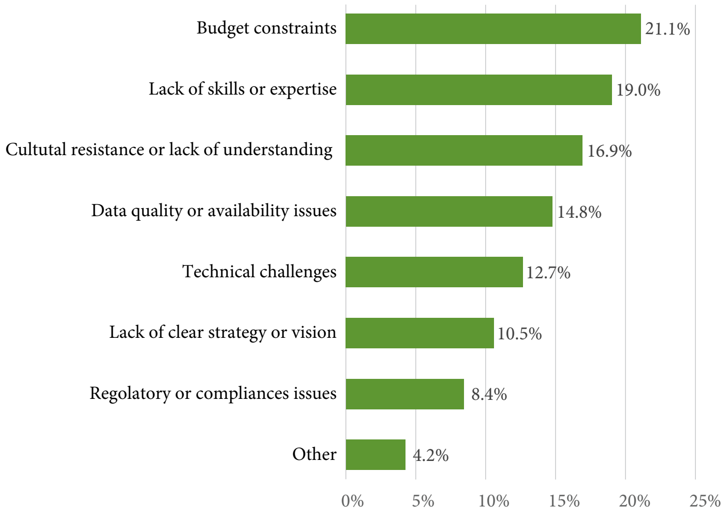

FIGURE 6 Barriers to AI Adoption in Organizations

Barriers to AI Adoption

After asking respondents about the top challenges in AI adoption, we inquired about the primary organizational obstacles they believe their company or organization faces. Analysing these obstacles reveals the various issues companies and organizations may encounter, ranging from financial and cultural to technical hurdles. 'Budget Constraints', cited by 50 respondents, emerge as the primary impediment, spotlighting the substantial financial costs needed for AI adoption activities such as technology procurement, staff training, and system integration. 'Lack of Skills or Expertise', noted by 45 participants, points to a significant deficiency in AI competencies within organizations, highlighting the urgency for targeted education, skills development, and recruitment to bridge this gap.

'Cultural Resistance or Lack of Understanding', mentioned by 40 people, reveals that organizational culture and insufficient comprehension of AI's potential benefits and applications can significantly stall AI adoption efforts. This underscores the necessity for effective change management and educational initiatives to mitigate such resistance. 'Data Quality or Availability issues', acknowledged in 35 responses, stress the critical importance of accessible, high-quality data for successful AI implementation.

'Technical Challenges', identified 30 times, encompass difficulties such as AI integration with legacy systems, scalability concerns, and the inherent complexity of AI technologies. Twenty-five people indicated a 'Lack of Clear Strategy or Vision' as an issue, suggesting that the absence of a coherent strategic framework for AI deployment within the organizational objectives poses a notable barrier to its adoption. 'Regulatory or Compliance Issues', highlighted by 20 participants, reflect the intricate regulatory environment surrounding AI, pointing to privacy, security, and compliance as pivotal considerations (figure 6).

These findings underscore the challenges that both innovators and early adopters face in AI adoption. Innovators often encounter budget constraints and technical challenges as they experiment with new technologies, while early adopters must address issues such as skill deficits and cultural resistance as they integrate AI more systematically.

Perceived Risks Associated with the Use of AI

In terms of concerns about the risks of AI, a significant number (50%) express 'Somewhat concerned' attitudes regarding AI's potential risks, such as biases, inaccuracies, and plagiarism from AI-generated content. This reflects a cautious recognition of the adverse effects AI technologies may pose. Conversely, another group is characterized by 'Extremely concerned' responses (10%), indicating deep apprehension about AI's ethical and operational hazards. This underscores the need for ethical AI development protocols, increased transparency, and stringent regulations to mitigate these concerns. A minority of people are not concerned, suggesting trust in current AI frameworks. According to the DOI theory, the minority who are not concerned could represent the innovators, as they are characterized by their pioneering spirit and willingness to accept higher risks for the sake of advancement. On the other hand, the 50% of respondents who are 'Somewhat concerned' reflect the cautious stance of early adopters. Their concerns suggest they are in the phase of refining their AI strategies and implementing safeguards, which is typical of early adopters who balance innovation with a need for effective risk management.

These findings highlight the importance of ongoing education and policy initiatives to address diverse perceptions and ensure comprehensive engagement in AI development and deployment processes.

GENERATIVE AI

Business Engagement with Generative AI

To assess the current impact of generative AI on Italian companies and organizations, survey participants were queried regarding their entities' engagement with it.

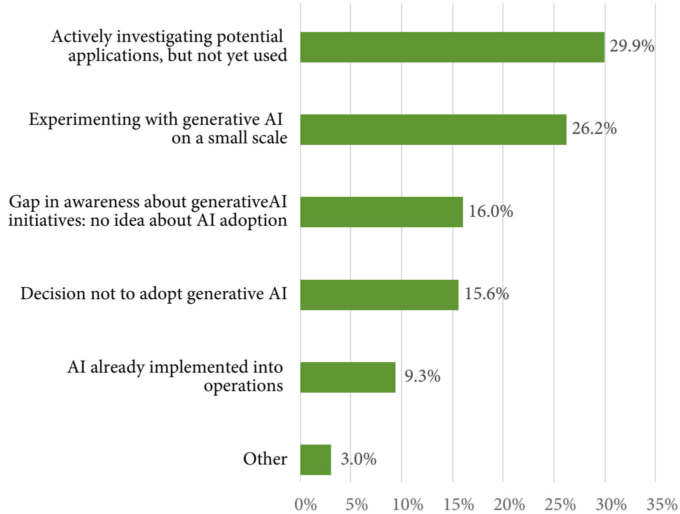

FIGURE 7 Business Engagement With Generative AI

The survey data reveals a varied landscape of engagement with generative AI among Italian companies, painting a dynamic picture of the business sector's relationship with this emerging technology. A small but notable segment, 9.3% of organizations, represents innovators who have already integrated generative AI into their operations, leveraging its potential for competitive advantage and innovation. Early adopters, constituting 26.2% of the sample, are engaging in small-scale experiments, reflecting their proactive approach to understanding and applying AI strategically. Meanwhile, 29.9% of organizations are still in the preliminary stages, exploring AI's potential without yet integrating it into their workflows. The 16% with gaps in awareness and the 15.6% who have opted against adoption due to resource constraints or perceived lack of relevance highlight ongoing challenges in communication and business education about AI technologies (figure 7).

Perceptions about Generative AI

The survey reveals varying levels of engagement with generative AI among participants, which aligns with the DOI theory. The single respondent who identifies generative AI as a fundamental component of their business offering is likely an innovator. Therefore, we can assume that this organization has fully integrated AI into its core operations, reflecting an early and committed adoption of the technology. A notable number, 189 respondents (79.75%), view generative AI as valuable for their organizations, demonstrating an optimistic attitude towards its potential and indicating that these companies are likely in the early adopter phase. This optimism is complemented by a smaller group of 23 participants (9.70%) who see potential benefits but also have concerns about reliability and safety, reflecting a cautious yet proactive approach typical of early adopters. On the other hand, 21 respondents (8.86%) find generative AI irrelevant to their business context, suggesting they may be in the late majority or laggard phases, possibly due to industry-specific constraints or limited relevance. Additionally, 3 respondents exhibit uncertainty or limited knowledge about generative AI, highlighting a need for further education and awareness.

IMPACT AND FUTURE VISION OF AI ADOPTION

AI Implementation across Organizations

The inquiry into the extent of AI implementation across organizations revealed a nuanced landscape of adoption.

Interpreting these results according to the DOI theory, we can assume that the minority of organizations (9) with high levels of AI integration likely represent innovators, as they are at the forefront of AI adoption, having fully embedded AI across multiple operational domains. The 23 organizations (9.70%) pursuing extensive, organization-wide AI integration align with early adopters, demonstrating a proactive approach and readiness to embrace more comprehensive applications despite the associated challenges. In contrast, the substantial group of 118 organizations (49.79%) deploying AI in restricted or departmental contexts may be considered late majority or laggards, reflecting a cautious, exploratory approach to AI adoption. The 87 organizations (36.71%) without AI initiatives are likely laggards, either still contemplating AI adoption or not yet identifying viable applications for the technology.

AI Decision-Makers and Implementers

To explore the AI decision-making process, we asked respondents to examine the governance of AI project budget allocations within their organizations, aiming to identify who holds the authority to make these critical financial decisions and who is involved in the implementation of AI-based innovation projects. Regarding the decision-makers, a significant majority of the responses (181) pointed to the upper echelons of organizational hierarchy as the arbiters of AI project budgets. This underscores the strategic valence attributed to AI investments, which typically necessitate senior management's endorsement, given their considerable implications for organizations' strategic trajectory and resource allocation. Conversely, a minority (35) of participants reported that such budgetary decisions for AI projects are entrusted to line managers. This implies a perception of AI initiatives as departmental endeavours, possibly of a tactical nature, rather than as strategic investments warranting the scrutiny and approval of the organization's top leadership. Additionally, a small fraction of responses was categorized under 'Other/Not Sure' (21), encapsulating those uncertain about the decision-making locus or scenarios that do not conform neatly to the established categories.

To delve deeper into the practicalities of AI implementation, a hierarchy of involvement has emerged regarding the parties executing AI projects within organizations. Technical teams – comprising IT, AI specialists, and other technical units – are identified as the primary contributors by 170 participants, underscoring the crucial role of technical expertise in leading AI initiatives. Additionally, business and strategy segments, including business development and executive roles, were significantly involved according to 90 mentions, highlighting AI's strategic importance beyond just technical execution.

'External Support' through consultants and specialized individuals accounted for 40 mentions, indicating a dependence on external knowledge for specialized skills or augmented capacity. Thirty participants claimed 'Uncertainty or Lack of Involvement', pointing to a discernible gap in AI project participation or awareness across some organizations. 'Research and Development', alongside 'Specific Functions or Projects' (12) like marketing or quality management, garnered less support, suggesting their more occasional involvement in AI projects. An isolated mention of 'Voluntary or Autonomous Use' hints at informal or individual-led AI explorations.

The survey results underscore a consensus on the importance of integrating business and strategy roles with technical teams in AI project implementation to ensure AI initiatives align with organizational goals.

AI: Unleashing New Frontiers of Creativity

In the context of increasing academic interest in exploring AI's potential to enhance individual creativity, our study invited respondents to assess their perceptions of innovative corporate ideas and creative contributions to organizational practices. The statistical analysis reveals a generally favourable view among participants regarding AI's role in boosting creativity and generating novel beneficial ideas within organizations.

When examining perceptions of the main sources of organizational creativity, the analysis highlighted a predominant belief in the collaborative synergy between human creativity and AI tools (120 respondents). This perspective underscores the potential of human-AI collaboration in creative endeavours. Conversely, another prevalent viewpoint emphasizes the virtues of intrinsic human creativity independently of AI assistance, stressing the enduring value of human ingenuity (80). Finally, a smaller group of respondents expressed uncertainty about the primary contributors to creativity (20), reflecting either indecision or a neutral stance on the issue.

Therefore, while there is growing recognition of the benefits of integrating AI with human creativity, a significant portion of individuals and organizations still prefer traditional methods or remain hesitant to fully adopt AI. According to DOI theory, the successful spread of AI as a creative tool will depend on clearly demonstrating its advantages, compatibility, and ease of use.

Visioning the Future: AI's Impact on the Workforce

The concluding results of the survey delve into participants' perceptions regarding the future impact of AI on the workforce within their organizations. Uncertainty dominates, with a significant number of respondents (44.7%) expressing ambiguity regarding AI's future implications for employment and work procedures. This uncertainty underscores a collective hesitation about predicting AI's effects on the job landscape. However, a subset of 55 participants (23.2%) reveals optimism about AI's capacity to generate new job roles, pointing towards a hopeful stance on AI-driven employment opportunities. Additionally, 40 respondents (16.9%) envision AI as augmenting existing jobs and enhancing efficiency and productivity, which suggests a positive anticipation of AI supporting human work rather than supplanting it. Concerns about the necessity for workforce upskilling and reskilling emerge from 30 mentions (12.7%), indicating an expectation that AI will shift skillset demands.

A nuanced perspective is offered by 25 respondents (10.5%), who recognize AI's dual potential to create and displace jobs, acknowledging the complex and multifaceted nature of AI's impact on employment. Meanwhile, 20 participants (8.4%) voiced concerns over job losses due to automation, highlighting fears of AI-induced redundancy. A minority view held by six individuals (2.5%) posits that AI will not significantly disrupt workforce trends, reflecting either scepticism towards AI's transformative capacity or confidence in the workers' resilience. Interpreting the results through the lens of innovators and early adopters, we can identify the innovators as those respondents who are optimistic about AI creating new job opportunities. Early adopters are those who see AI as a tool to enhance existing jobs and increase productivity. They are not as radical as the innovators but are still proactively integrating AI into their workflows.

Discussion

THEORETICAL CONTRIBUTIONS

This study contributes to the Diffusion of Innovation (DOI) theory (Rogers 2003) by enhancing our understanding of the characteristics and roles of innovators and early adopters within the context of AI adoption. Our research adapts these adopter categories to the AI landscape, aligning with existing literature while offering nuanced insights specific to the Italian setting.

We argue that, in the realm of AI, innovators are defined by their proactive risk-taking and willingness to explore uncharted technological frontiers. These pioneers lead AI adoption by experimenting with the technology in its nascent stages, driven by a quest to discover its potential without immediate practical applications. Their role is crucial in identifying novel uses for AI and setting the stage for broader industry transformation.

Regarding early adopters, we posit that these organizations, while also at the forefront of AI adoption, approach the technology with a more measured evaluation. They play a significant role in assessing the strategic value of AI, often influencing wider industry trends by validating the technology's practical benefits. Early adopters strategically integrate AI to enhance operational efficiency, serving as a bridge between innovation and broader acceptance.

The presence of both innovators and early adopters, comprising approximately half of the sample, enhances the literature on these leading adopter categories (Lund et al. 2020; Raman et al. 2024), stressing their significance in the diffusion of AI technologies. It underscores their distinct roles in driving AI's adoption and integration within the Italian context.

Moreover, this exploratory study addresses a gap in exploring AI knowledge and integration in the Italian context, enriching the academic dialogue on global AI integration strategies. It offers an optimistic perspective on AI's potential impact on employment, predicting net job creation and viewing AI as a tool that will augment existing roles while boosting efficiency and productivity. This implies a belief that AI will support, rather than replace, human work.

Additionally, our study contributes to the literature by demonstrating the progression of AI adoption along the innovation curve. We provide evidence of increasing AI spending, highlighting early adopters and validating AI's critical role in and driving its integration into mainstream business practices. As AI becomes central to business strategy, we expect to see accelerated adoption of these technologies across industries.

Finally, our study advances the literature on innovation and creativity by highlighting AI's role in enhancing creative capabilities. It suggests that AI, in conjunction with human input, can act as a catalyst for both innovation and efficiency. This aligns with and extends existing theories on technology-driven competitive advantage, providing new insights into how AI can be strategically leveraged as a valuable asset in the digital age.

MANAGERIAL IMPLICATIONS

This exploratory study provides valuable insights for managers navigating the complexities of AI implementation and seeking to leverage it for innovation and sustainable competitive advantage. Our research yields the following recommendations:

1. *Strategic* AI *Investment:* Position AI as a core strategic priority, focusing on infrastructure and talent development (Mikalef et al. 2021; Bharadwaj et al. 2013).
2. *Versatile Application:* Explore AI's utility across various business facets, beyond traditional boundaries (Raisch and Krakowski 2021).
3. *Addressing Skills Gap:* Upskill existing employees, attract new talent, and foster interdisciplinary collaboration (Kapoor and Ghosal 2022).
4. AI-*Friendly Culture:* Cultivate an atmosphere encouraging experimentation and creative AI implementation (An et al. 2024).
5. *Robust Data Management:* Establish high-quality data practices, particularly crucial for descriptive and predictive AI (Mikalef and Gupta 2021).

6. *Ethical* AI *Deployment:* Develop guidelines for transparent, accountable, and fair AI use (Bostrom and Yudkowsky 2018).
7. *Workforce Transformation:* Plan for AI-induced changes, including new role creation and reskilling (Brynjolfsson and McAfee 2014; Budhwar et al. 2023).
8. *Cross-Functional Integration:* Ensure seamless AI deployment across departments (Mikalef et al. 2021).

To implement these strategies effectively, organizations should integrate AI into their planning processes, aligning with overall objectives. Addressing skills gaps through targeted training and recruitment is crucial for cultivating a workforce adept at leveraging AI technologies.

Creating an innovation-friendly culture encourages experimentation and learning from both successes and setbacks in AI projects. Robust data management practices are foundational to AI success, while establishing ethical guidelines and governance structures helps mitigate risks and build stakeholder trust.

As organizations prepare for AI-driven transformations, focusing on upskilling, reskilling, and developing complementary roles becomes vital. Fostering cross-functional collaboration supports a more integrated approach to AI implementation, dismantling organizational silos.

By following these recommendations, practitioners can effectively leverage AI to drive business success, gain a competitive edge, and position their organizations as leaders in technological innovation. This comprehensive approach ensures that AI implementation is not merely a technological upgrade but a transformative process enhancing all aspects of the organization.

FUTURE RESEARCH DIRECTIONS

Emerging from our exploratory study, we outline various trajectories for future research that merit deeper investigation to achieve a more comprehensive understanding of AI's transformative impact on organizations. These areas include improving AI skills and training within organizations by exploring effective strategies for closing the AI skills gap; fostering cross-functional collaboration on AI projects by identifying best practices for cross-departmental collaboration; addressing ethical concerns and data quality issues in AI implementation by establishing ethical guidelines for the responsible use of AI; exploring the role of AI in the evolution and creation of jobs; examining the impact of AI on organizational innovation; and tracking trends in AI adoption over time by conducting longitudinal research to monitor evolving trends and their drivers.

Conclusions

In conclusion, our exploratory study of 237 Italian companies uncovers increasing enthusiasm and adoption of artificial intelligence (AI) technologies, marking a significant step towards digital transformation in the Italian business environment.

Our study reveals a heterogeneous landscape of AI adoption in Italy, with both innovators and early adopters present. While most companies are in the initial stages, some have already integrated AI into core operations. This aligns with the Diffusion of Innovation (DOI) framework, strengthening our theoretical grounding. The observed increase in AI expenditures indicates progression along the innovation curve, with early adopters validating AI's utility and driving its integration into mainstream practices.

The study highlights the essential role of AI for Italian companies, not only as a mechanism to improve operational efficiency but also as a key element in driving innovation, securing competitive advantage, and achieving long-term growth. The challenges identified, such as the need to bridge skills gaps, improve data management practices and address ethical concerns, point to crucial areas that require immediate attention and further exploration. These findings suggest that the DOI theory provides a useful framework for understanding the adoption of AI.

As we stand on the cusp of a transformative era in business technology, it is imperative that these issues continue to be explored to ensure that the integration of AI is both impactful and conscientious. This research not only provides a basis for future studies, but also charts a comprehensive course for the ongoing assessment of AI's influence on the evolution of the Italian business landscape.

While this study offers insights into AI adoption in the Italian business sector, it has limitations. The research is confined to Italy, studying a sample of 237 companies, which may limit generalizability. The conventional sampling method could introduce selection bias, potentially not reflecting the broader Italian corporate landscape. Future research should address these issues by expanding the sample size and employing a randomized sampling strategy to enhance representativeness and applicability.

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Appendix: The Survey

The purpose of the survey is to assess the level of adoption of artificial intelligence (AI) technologies, particularly generative AI, and trends for the near future. The estimated time to complete the survey is approximately 10 minutes. The survey is divided into 5 main sections:

1. The first section is dedicated to gathering general information about the organization and the profile of the respondents.
2. The second section is dedicated to understanding the level of adoption of AI technologies.
3. The third section is dedicated specifically to generative AI.
4. The fourth section is dedicated to the implementation aspects of AI.
5. The fifth and final section is dedicated to the organizational aspects of AI.

(1) General information

* Indicates required question

1. Name of the organization/company*
2. Number of employees*
3. Activity code (ATECO)
4. Postal Code*

5. Email (of the person completing the questionnaire if they wish to receive the results of the research)
6. Area (of the person completing the questionnaire)*. *Please select one answer:*

   - Top management
   - IT
   - HR
   - Marketing/Sales Operations
   - R&D
   - Other:

7. Level of responsibility (of the person filling in the questionnaire)*. *Please select one answer:*

   - Apical
   - Head of function
   - Team leader
   - Employee/collaborator
   - External consultant
   - Other:

(2) Knowledge and adoption of AI technologies in your company/organization

8. Which best describes the role of your company/organization with regard to AI technology? *Please select one answer:*

   - My company/organization is mainly an end-user (buyer)
   - My company/organization is mainly a supplier (seller)
   - My company/organization is both end-user and supplier (both)
   - My company/organization is neither end-user nor supplier (none)

9. What is your company/organization's level of experience with AI?
   * *Please select one answer:*

   - We have not yet implemented any AI solutions
   - We are new to AI: less than 6 months
   - We have some experience with AI: 6 to 12 months
   - We have a lot of experience in AI: more than 1 year

10. What are the main goals of using AI in your company/organization? *
    Check all that apply

    - Improve customer/user experience; Improve internal operations
    - Recommend products/services; Mitigate risks
    - We do not have a specific objective
    - Other:

11. Which of the following AI applications do you use in your company/organization? *Check all that apply:*
    - Anti-fraud/security; Artistic vision
    - NLP/chat/messaging/text…
    - Content creation/creativity…
    - Robotic Process Automation…
    - Recommender systems
    - We are experimenting/testing AI; We are not using AI
    - Other:

12. How has your company/organization's AI spending changed in the last 12 months? *Please select one answer:*
    - Has remained constant
    - Has increased
    - Has decreased

13. How do you expect your company/organization's AI spending to change in the next 12 months? *Please select one answer:*
    - Will remain constant
    - Will increase
    - Will decrease

14. What is the main challenge your company/organization faces with AI? *Please select one answer:*
    - Insufficient support from leaders or stakeholders
    - Inadequate availability or quality of data
    - Limited talent or resources
    - Unclear or undefined use cases
    - Low return on investment
    - Other:

(3) Adoption of generative AI (such as ChatGPT, Midjourney, Copilot, Dall-E, Bard, Claude, …) in the enterprise

15. How would you describe the level of involvement of your company/organization with generative AI? *Please select one answer:*
    - No idea
    - None: we are not considering it or have ruled it out
    - We are looking at possible applications, but have not used it yet …
    - We are experimenting with generative AI on a small scale
    - We have implemented generative AI in our operations
    - Other:

16. What are your thoughts on the use of generative AI for your company/organization?* *Please select one answer:*

    - I think it can be useful, with appropriate precautions
    - I think it is not applicable or useful for my business
    - I think it is applicable but not affordable or safe enough for my business
    - Other:

17. Does your organization plan to use generative AI in accessing and exploiting your company/organization's knowledge base? *Please select one answer:*

    - Yes
    - No
    - Maybe
    - Don't know
    - Not applicable

18. If your company/organization uses generative AI, are you using non-proprietary models such as ChatGPT or are you using proprietary models that do not involve sharing company data with others? *Please select one answer:*

    - Mainly non-proprietary models
    - Both types of models
    - Non-proprietary only if from partners
    - Mainly proprietary models
    - Don't know
    - Not applicable

19. Are you concerned about the risks of AI, e.g. bias, accuracy, plagiarism, hallucinations? *Please select one answer:*

    - Extremely concerned
    - Somewhat concerned
    - Not at all concerned

20. How much do you think AI is able to help creativity in the company/organization?*
    Choose an answer from 1 to 7. 1 is "not at all" and 7 is "extremely":

21. Does the use of AI make it possible to produce new and useful ideas for improving processes in the company/organization?
    Choose an answer from 1 to 7. 1 is "not at all" and 7 is "extremely":

22. In general, where do you think the greatest contributions to the creativity of the company/organization can come from? *Please select one answer:*

- From creative people without using AI
- From people using AI
- From AI alone
- Don't know
- Other:

(4) Implementing AI in your company/organization

23. How did you obtain the necessary data for your AI applications?* *Check all that apply:*

    - We used our own data
    - We used crowdsourcing; We used synthetic data
    - We bought it
    - We were unable to obtain the necessary data; We used search engines
    - Other:

24. What are the major findings in preparing the necessary data for AI applications?* *Check all that apply:*

    - Lack of data
    - Lack of structured data
    - Data privacy
    - Data distortion
    - Data normalization
    - Data labelling
    - Data quality
    - Other:

25. Does your company implement AI on a large scale, i.e. integrated throughout the company/organization? *Please select one answer:*

    - We are not implementing AI at all
    - We are implementing AI mainly not on a large scale
    - We are in the process of moving to large-scale AI, but we are not there yet
    - We are implementing AI on a large scale (integrated throughout the company)

(5) Organizational processes and AI in your company/organization

26. Who decides the budgets for AI projects in your company/organization?* *Please select one answer*

    - The executive level (CEO/CTO)
    - The line managers
    - The individual users
    - Other:

27. Who is involved in the implementation of AI projects in your company/organization?* *Check all that apply:*

    - Each line of business
    - The IT team
    - The consultants
    - The AI team
    - Other:

28. In your opinion, who should be involved in the implementation of AI projects in your company/organization? *Check all that apply:*

    - Each line of business
    - The IT team
    - The consultants
    - The AI team
    - Other:

29. How do you think AI will influence the workforce of your company/organization in the future? *Please select one answer:*

    - AI will create more jobs
    - AI will reduce the number of jobs
    - Not sure
    - Other:

30. What do you think are the main organizational barriers to the adoption of AI in your company/organization? *Check all that apply:*

    - Too little sponsorship from the leadership …
    - Lack of skills
    - Few resources
    - Other higher priorities
    - Lack of use cases
    - Lack 4of availability of adequate data
    - Other:

31. What are your general thoughts on the adoption of AI-based technologies, in particular generative AI, and on trends for the near future? *Open question:*

Abstracts in Slovene

Ali lahko povečana trgovinska partnerstva znotraj celine diverzificirajo izvozne košarice v Afriki?

Sibusisiwe Mchani in Andrew Phiri

Študija raziskuje potencial sporazuma o afriškem celinskem prostotrgovinskem območju (African Continental Free Trade Area – AFCFTA) pri spodbujanju raznolikih izvoznih košaric s povečanim trgovinskim partnerstvom znotraj celine. Njen namen je oceniti, kako ta trgovinska partnerstva vplivajo na diverzifikacijo izvoza znotraj Afrike. Z uporabo analize omrežij razvija tri indekse za merjenje stopnje, bližine in prestiža trgovinskih partnerjev v 54 afriških državah od leta 2000 do 2020. Ti indeksi, skupaj s tradicionalnimi ocenjevalci, razkrivajo dve ključni ugotovitvi. Prvič, kakovost trgovinskih partnerstev, ki se osredotoča na to, s kom država trguje, ima večji pomen kot količina. Drugič, obstaja geografsko neravnovesje, kjer je učinek trgovinskih partnerstev negativen za države z večjo diverzifikacijo proizvodov. Skratka, medtem ko diverzifikacija trgovine znotraj celine obeta, utegnejo naprednejše afriške države doživeti zmanjšanje donosov, kar kaže na potrebo po razširitvi trgovinskih mrež zunaj celine za trajno diverzifikacijo izvoza.

Ključne besede: diverzifikacija trgovinskih partnerjev, diverzifikacija izdelkov, sporazum AFCFTA
Klasifikacija JEL*:* C31, C32, C43, F14, F15
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Ocenjevanje vpliva čustvene inteligence na uspešnost zaposlenih: v smeri integriranega okvira čustvene inteligence

Yash Krishna Gaya, Takesh Luckho, Uzma Jannoo in Praveen Saulick

Čustvena inteligenca je pritegnila veliko pozornosti na področju poslovnega upravljanja. Zajema vrsto medosebnih in osebnih veščin, ki močno vplivajo na več vidikov človeškega vedenja, odnosov in splošnega počutja. Čustvena inteligenca se je izkazala za ključni element pri oblikovanju dinamike na delovnem mestu, ohranjanju dobrega počutja zaposlenih in izboljšanju uspešnosti organizacije. Zato je namen tega prispevka raziskati in analizirati vpliv čustvene inteligence na uspešnost zaposlenih. Raziskava je bila izvedena v sektorju zunanjega izvajanja poslovnih procesov na Mauritiusu. Rezultati so pokazali, da dejavniki, kot so leta izkušenj, izobrazbena raven, starostna skupina, motivacija in delovne vloge, pozitivno vplivajo na čustveno inteligen-

co in na uspešnost zaposlenih. Poleg tega je predlagan okvir čustvene inteligence za posredovanje pri konfliktih med višjim vodstvom in zaposlenimi. Na koncu so podana ustrezna priporočila, kako izboljšati uspešnost in kako zmanjšati konflikte.

Ključne besede: čustvena inteligenca, uspešnost zaposlenih, motivacija zaposlenih, obvladovanje konfliktov
Klasifikacija JEL: M12, M14, M50, M52
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Ali finančni razvoj spodbuja podjetništvo v Afriki? Analiza panelnih podatkov

Noah Afees Oluwashina in David Oladipo Olalekan

Podjetništvo v Afriki se sooča s številnimi izzivi, pri čemer so finančna vprašanja pogosto obravnavana v znanstveni literaturi. Zato ta študija raziskuje, kako finančni razvoj igra ključno vlogo pri spodbujanju podjetništva v Afriki, pri čemer analizira tako kratkoročne kot dolgoročne vplive ter smer vzročnosti na celini. Raziskava uporablja regresijske tehnike panelnih podatkov za analizo podatkov iz 28 afriških držav v obdobju od leta 2006 do 2020. Analiza razkriva, da finančni razvoj, skupaj z rastjo finančnih institucij in trgov, dosledno spodbuja razvoj podjetništva v obeh časovnih okvirih. Čeprav je to bolj izrazito na dolgi rok, nakazuje, da je vpliv finančnega razvoja in njegovih komponent enakomerno pozitiven, brez pomembnih diferenciranih vplivov tako na kratki kot na dolgi rok. Rezultati vzročnosti ugotavljajo enosmerno vzročnost med podjetništvom, finančnim razvojem in njegovimi komponentami, ki poteka od finančnega razvoja in njegovih komponent k razvoju podjetništva. Glede na te ugotovitve študija poudarja potrebo, da se oblikovalci politik osredotočijo na trajnostne strategije finančnega razvoja, ki povečujejo stabilnost in vključenost na finančnih trgih.

Ključne besede: Afrika, podjetništvo, finančni razvoj, panelna regresija
Klasifikacija JEL: F3, G2, M13, N2
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Razkrivanje organizacijskih vzorcev sprejemanja umetne inteligence v italijanskih podjetjih skozi prizmo teorije difuzije inovacij

Grazia Garlatti Costa, Francesco Venier in Roberto Pugliese

Ta prispevek raziskuje sprejemanje in integracijo tehnologij umetne inteligence (AI) v vzorcu 237 italijanskih podjetij, pri čemer uporablja teorijo difuzije inovacij (Diffusion of Innovations – DOI) kot teoretični okvir. Proučuje značilnosti podjetij, ki so vodilna pri sprejemanju AI, in ocenjuje njihovo usklajenost s profili inovatorjev in zgodnjih sprejemnikov, ki jih je Everett Rogers opredelil leta 2003 v okviru DOI. Raziskava poudarja pomembno vlogo umetne inteligence pri povečevanju operativne učinkovitosti, spodbujanju inovacij, zagotavljanju konkurenčne prednosti in spodbujanju dolgoročne rasti. Opredeljuje tudi izzive, kot so pomanjkanje veščin, težave z upravljanjem podatkov in etični pomisleki. Naše ugotovitve prispevajo empirične dokaze k akademski literaturi o teoriji DOI in obravnavajo premalo raziskan kontekst umetne inteligence v Italiji. Študija ponuja niansiran pogled na vpliv AI na zaposlovanje in postavlja temelje za prihodnje raziskave, pri čemer ponuja vodstvene vpoglede za strateško uvajanje AI.

Ključne besede: umetna inteligenca, teorija difuzije inovacij, zgodnji uporabniki, izzivi implementacije, italijanska podjetja
Klasifikacija JEL*:* L20; M10; O33; O52
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