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Asymmetric Mean Reversion and Dynamic Equilibrium of Global Interbank Rates: A Reassessment in the Era of Unconventional Monetary Policy**

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** This study is an expanded and improved version of the paper with the same title, presented orally at the 11th National Economic Model Congress held between February 7-8, 2026.

Abstract: This article aims to examine the asymmetric adjustment speeds and dynamic equilibrium intervals through the contemporary period, defined by a decade of unprecedented unconventional monetary policies and significant structural market changes. The quadratic mean reversion model (SWING process) is applied to monthly interbank rate data from March 2014 to December 2024. The model parameters, which define the asymmetric adjustment speeds and the bounds of the equilibrium interval, are estimated using the Generalized Method of Moments (GMM). Particular attention is given to structural breaks, notably the transition from LIBOR to SOFR in the United States and the episode of negative interest rates in the Euro area. The findings confirm the persistence of statistically significant asymmetric adjustment speeds across all the studied markets. Nonetheless, the post-2013 period has fundamentally altered the nature of dynamic equilibrium intervals. There is documented compression of the equilibrium interval into negative territory in the Euro area, substantial widening in Turkey reflecting increased volatility, and a structural shift in U.S. market dynamics following the cessation of LIBOR in mid-2023. The Moroccan market demonstrates relative stability but at historically low equilibrium levels. The quadratic mean reversion model remains a robust tool for capturing the complex dynamics of interest rates. The results show that the structural characteristics of interbank markets, profoundly shaped by a decade of central bank interventions, constitute a primary determinant of asymmetric rate adjustments. These findings bear critical implications for the transmission of monetary policy and risk management.

Keywords: Quadratic Mean Reversion, Asymmetric Adjustment, Interbank Interest Rates, Generalized Method of Moments (GMM), Unconventional Monetary Policy, SOFR

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1. Introduction

The decade following the analysis period of previous studies marks a profound departure from the historical norms of global financial markets. This period, spanning from March 2014 to 2024, has been characterized by a succession of monetary policy regimes and structural transformations that challenge traditional models of interest rate dynamics. The central banks of major advanced economies have operated within a low-for-long interest rate environment, implementing zero interest rate policies (ZIRP)[1] and, more assertively, negative interest rate policies (NIRP)[2], particularly in the Euro area. This era of monetary interventionism takes place within a broader context of the secular decline in global real interest rates, a phenomenon extensively documented and analyzed in recent academic literature, attributed to profound structural factors such as the deceleration of productivity growth and demographic changes (eg. Bauer & Rudebusch 2020; Borio et al. 2017; Del Negro et al. 2018).

Concurrently with these macroeconomic changes, the infrastructure of financial markets has been restructured. The most emblematic reform was the gradual phase-out of the London Interbank Offered Rate (LIBOR) (Del Negro et al. 2018), a global benchmark for decades, in favor of new

[1] The term ZIRP is an acronym for Zero Interest Rate Policy.
[2] The term NIRP is an acronym for Negative Interest Rate Policy.

risk-free rates such as the Secured Overnight Financing Rate (SOFR) in the United States. This transition was not merely a technical adjustment but a fundamental transformation in the nature of the benchmark rate, shifting from a credit-sensitive rate to one based on secured overnight financing transactions. Furthermore, the structure of interbank money markets has evolved under the influence of new prudential regulations (such as Basel III) and the increasing prominence of non-bank financial institutions, altering liquidity flows and the interactions among market participants[3].

Within this transformed context, the hypothesis that interest rates adjust toward their equilibrium at differing speeds depending on whether they are rising or falling (asymmetric adjustment) warrants examination in an environment where monetary policies have themselves been strongly asymmetric. Likewise, the notion of an equilibrium defined not by a single point but by an interval, reflecting market frictions, is particularly relevant in a period during which the floors and ceilings on rates imposed by central banks have engendered new zones of passivity within the market.

The main question of our research is: "How have extreme monetary policies (zero/negative rates) and market reforms (transition to SOFR) altered the adjustment speed and equilibrium ranges of global interbank rates (Morocco, USA, Euro area, Turkey) between 2014 and 2024?". In order to answer this question, some sub-questions will be addressed throughout the paper:

Is the nonlinear model (SWING)[4] still robust in capturing the dynamics of rates under extreme conditions (negative levels, volatility, structural breaks)?

Has the asymmetric adjustment of rates (differential speeds in upward versus downward movements) persisted or changed in magnitude since 2014?

How have policies reshaped the equilibrium rate range? (μ_1, μ_2) : negative anchoring (Euro area), post-SOFR narrowing (USA), or widening due to volatility (Turkey)?

What do these changes imply for the efficiency and future calibration of monetary policy?

The contribution of our study is threefold: firstly, it provides a crucial empirical update on the dynamics of interbank rates (Morocco, United States, Euro area, Turkey) by extending the analysis over more than a decade. Secondly, it constitutes a robustness test of the quadratic mean reversion model under extreme market conditions (negative rates, high volatility). Thirdly, it offers a contextual reinterpretation of the results in light of recent academic advances to derive updated policy and theoretical implications.

The reminder of this article is structured as follows: in section 2 we provide a comprehensive literature review, in section 3 we detail data and the used methodology. The section 4 will focus on the analysis of the main results, and a discussion will be provided in section 5. The section 6 will wrap the paper.

2. Literature Review

This literature review aims to bridge the theoretical foundations of Interest rates with major academic developments over the past decade. It establishes the conceptual framework necessary to interpret the results of our updated analysis, incorporating new perspectives on macroeconomic dynamics, market microstructure, and modeling methodologies.

2.1. Foundations: Interest rates in the global economy

In the global Economy, Interest rates remain a pivotal mechanism for shaping economic outcomes in the contemporary global landscape, serving as a primary lever of monetary policy wielded by central banks to manage inflation, stimulate growth, and ensure financial stability. The interconnectedness of global financial markets means that the policies of one major economy inevitably create spillovers that influence others, creating a complex web of synchronized and divergent actions.

In recent periods, major central banks have largely moved in concert to either tighten policy in response to post-pandemic inflationary pressures or, more recently in 2025, initiate rate cuts as inflation moderates (Federal Reserve, 2025). These decisions are fundamentally driven by domestic economic conditions, primarily the dual mandate of price stability and maximum employment, their impact extends internationally. For instance, U.S. interest rate changes often affect global capital flows and the strength of the dollar, influencing borrowing costs for emerging markets (IMF, 2024).

Based on Islamic Economic Principles, Baş (2005) suggested another point of view when he suggested his National Economy Model (NEM). Baş's model states that sources are boundless, but human needs are limited. The NEM suggests a third way between socialism and capitalism, posits a critical stance on conventional interest-based systems and advocates for an interest-free economy, by focusing on Consumption over Interest rate.

[3] https://www.newyorkfed.org/markets/reference-rates/sofr (accessed: 11/11/2025)
[4] The SWING model is a stochastic interest rate model, also referred to as the Quadratic Mean Reversion Model (Quadratic Interest Rate model - QIR).

Contrary to commonly held beliefs, The model considered that it is not inflation that pulls interest rates up, but it is interest rates (costly money) that increase production costs, which results in inflation in the end. Interest gives rise to inflation and inflation fosters interest policies on account of inappropriate money policies ». In the light of Baş (2005)'s Model, interest rates create cost-push inflation and inhibit growth. Therefore, increasing interest rates increases costs and, consequently, inflation, which in turn inhibits growth. This cost-inflation loop can be used as an explanation of the « Gibson Paradox » raised a century ago.

2.2. Stochastic interest rate models and asymmetric adjustment

The modeling of short-term interest rates has historically been based on mean-reverting processes. Classical one-factor models, such as those of Vasicek (1977); Cox et al. (1985), posit that the interest rate oscillates around a unique long-term mean with a constant mean reversion speed. These models, although fundamental, assume symmetric behavior and a point equilibrium.

The quadratic reversion model (SWING process) constitutes a significant advancement by relaxing these two assumptions. It introduces two major theoretical innovations. First, the equilibrium is no longer a point, but an interval. $[\mu_1, \mu_2]$ (Hamzaoui & Bousalam 2015). This conceptualization is economically more intuitive, as it incorporates the existence of market frictions, such as transaction costs. Rational agents will not adjust their positions as long as the deviation from equilibrium does not justify the incurred costs. Second, the speed of return to this equilibrium interval is asymmetric. The model specifies two distinct speeds, ϑ_1 and ϑ_2, depending on whether the rate lies above or below the interval. This asymmetry is justified by the nature of the information available in the market, which may differ depending on whether agents are predominantly buyers or sellers. The persistence of asymmetric adjustment in interest rates remains an active area of research, with explanations ranging from client reactions and information asymmetry (adverse selection issues) to the intrinsic nature of monetary policy shocks (Aastveit & Anundsen 2022; Stiglitz & Weiss 1981).

2.3. The macroeconomic context since 2014: secular decline and the role of global factors

The post-2013 period is closely linked to the academic debate on the secular decline of global real interest rates (Bauer & Rudebusch 2020; Borio et al. 2017; Christensen & Rudebusch 2019). Extensive research has identified several structural factors driving this trend: the slowdown in productivity growth, demographic changes (population aging), and a global imbalance between saving and investment, often referred to as the global saving glut (Borio et al. 2017; Rogoff et al. 2022). A particularly notable conclusion from this literature is the rise in global demand for safe and liquid assets, which is reflected in an increase in the convenience yield of these assets. This implicit yield, representing the premium investors are willing to pay for safety and liquidity, has significantly contributed to the decline in interest rates on sovereign bonds of advanced economies (Borio et al. 2017).

In this globalized context, United States monetary policy plays a predominant role. Recent studies employing high-frequency data have shown that a substantial portion of the secular decline in long-term interest rates *globally* occurred during very narrow time windows surrounding Federal Open Market Committee (FOMC) announcements (Hillenbrand 2025). These findings suggest that news regarding U.S. monetary policy not only influence domestic markets but also serve as a key determinant of global financial conditions. This observation has a direct implication for our comparative study: the U.S. rate should not be regarded merely as a peer among other rates but potentially as a driver of their dynamics.

2.4. Microstructure context since 2014: a transformed interbank market

Beyond macroeconomic trends, the infrastructure of the financial system has undergone profound changes. Traditional interbank money markets, central to the 2008 financial crisis, have witnessed reduced activity in favor of secured transactions and the increasing participation of non-bank actors and central clearing counterparties (CCPs). Post-crisis regulatory measures, notably Basel III leverage and liquidity ratios, have altered banks' incentives, leading them to favor financing modalities that are less balance sheet-intensive.

This evolution has facilitated a transition from anonymous over-the-counter transactions toward more stable and concentrated lending relationships. In response to heightened uncertainty regarding counterparty risk, banks have developed enduring bilateral relationships to secure their access to liquidity. This structural shift toward a more relational market reinforces the pertinence of models grounded in informational asymmetry. If the market has reorganized to better manage informational frictions, it is plausible to hypothesize that the behavioral phenomena underpinning asymmetric adjustment may be consequently intensified.

2.5. Methodological advances in modeling and estimation

Research in interest rate modeling has similarly advanced to accommodate evolving market realities. The emergence of negative interest rates in multiple jurisdictions has presented a significant challenge to traditional quadratic models, which typically ensure the positivity of rates. Recent innovations have proposed overcoming this limitation by introducing a stochastic lower bound, modeled, for instance, via a Brownian bridge, to explicitly account for periods of Unconventional Monetary Policy (Kikuchi 2024). While our study maintains the original SWING model to preserve comparability, knowledge of these advancements facilitates a more precise assessment of its strengths and potential limitations.

From an estimation standpoint, the Generalized Method of Moments (GMM) remains a benchmark methodology for stochastic volatility models. The literature has, however, underscored the delicate trade-off between efficiency (achieved by including additional moment conditions) and the precision of estimates in small samples, where a misestimated weighting matrix may introduce substantial biases Andersen & Sorensen (1996). Contemporary methodologies, such as outlier-robust GMM or the incorporation of realized volatility as supplementary information, have been formulated to enhance estimator performance (Chaussé & Xu 2018). Our study facilitates a direct and coherent extension of these findings, simultaneously recognizing these methodological advances as promising directions for future robustness analyses.

3. Data and Methodology

This section formally presents the analytical framework employed in the study. It details the stochastic model, the nature of the data collected for the updated period, and the econometric estimation procedure.

3.1. The Quadratic Mean Reversion Model (SWING)

The foundation of the analysis lies in the assumption that the evolution of the interbank interest rate, denoted r_t , follows a mean-reverting stochastic process described by the following stochastic differential equation (SDE):

$$\boldsymbol{dr_t = [v_1(\mu_1 - r_t) + v_2(\mu_2 - r_t)]t + \sigma\sqrt{1 - r_t}\, dw_t} \qquad \textbf{(1)}$$

where:

$\boldsymbol{r_t}$ denotes the level of the interest rate at time t.

$(\boldsymbol{\mu_1}, \boldsymbol{\mu_2})$ denote the lower and upper bounds of the equilibrium interval.

$\boldsymbol{v_1}$ *et* $\boldsymbol{v_2}$ are the adjustment speeds (restoring forces) towards the equilibrium bounds, representing the downward and upward forces, respectively.

$\boldsymbol{\sigma}$ is the volatility parameter.

$\boldsymbol{dw_t}$ is the increment of a standard Wiener process, following a normal distribution **N(0, dt)**.

For the purposes of econometric estimation, this continuous-time SDE is discretized. A discrete form is obtained, corresponding to a second-order autoregressive process:

$$\boldsymbol{\xi_t = v\xi_{t-1}^2 + \beta^*\xi_{t-1} + \alpha + \epsilon_t} \qquad \textbf{(2)}$$

With $\boldsymbol{\beta^* = \beta + 1}$. The variable $\boldsymbol{\xi_t}$ represents the standardized values of the interest rate, defined by $\boldsymbol{\xi_t} = \frac{r_t}{\sigma_{r_t}}$, where $\boldsymbol{\sigma_{r_t}}$ is the standard deviation of the rate series. $\boldsymbol{r_t}$. This transformation removes the unit of measurement and renders parameters comparable across different markets.

The estimated parameters of the discrete model $(\boldsymbol{v}, \boldsymbol{\beta}, \boldsymbol{\alpha})$ are related to the structural parameters of the continuous model $(\boldsymbol{\mu_1}, \boldsymbol{\mu_2}, \boldsymbol{v_1}, \boldsymbol{v_2})$ by the following system of linear equations:

$$\begin{cases} \boldsymbol{v_2 - v_1 = -v} \\ \boldsymbol{\mu_1 v_1 - \mu_2 v_2 = \alpha} \\ \boldsymbol{\mu_2 v_2 = \beta} \end{cases} \qquad \textbf{(3)}$$

This system consists of three equations with four structural unknowns, thereby creating an identification problem. To address this, one approach involves fixing the value of one parameter (specifically $\boldsymbol{v_2}$) and solving for the remaining three. By varying $\boldsymbol{v_2}$ over a plausible interval, it is possible to delineate a spectrum of solutions, namely the set of equilibrium intervals $(\boldsymbol{\mu_1}, \boldsymbol{\mu_2})$ associated with each potential adjustment speed.

3.2. Data and analysis period

This analysis extends the time series, covering the period from March 2014 to December 2024. This adds 129 monthly observations, enabling a robust analysis of interest rate dynamics within a substantially altered economic environment.

Morocco: The benchmark rate is the weighted average rate (WAR) of the interbank market. Given the availability of public data, the policy rate of Bank Al-Maghrib is employed as a closely correlated proxy for the recent period. The data are sourced from Bank Al-Maghrib and financial data providers.[5]

United States: The processing of the U.S. series requires particular attention due to the transition from LIBOR to SOFR. The 3-month USD LIBOR is utilized until its cessation for new contracts at the end of 2021, with historical data applied until its definitive termination in mid-2023[6]. From this date, the 90-Day Average SOFR rate (*90-Day Average SOFR*) is employed as its successor. The analysis is conducted over sub-periods to explicitly test for structural breaks in the model parameters.[7]

Euro area: The 3-month EURIBOR, a series of particular interest due to its prolonged period of negative rates, thus providing a robustness check for the model. The data are sourced from the European Central Bank (ECB) data portal.[8]

Turkey: The 3-month TRLIBOR is utilized to represent the Turkish market. The data are collected from the Central Bank of the Republic of Turkey and financial data providers.[9]

Prior to estimation, each rate series $\boldsymbol{r_t}$ is transformed into its standardized counterpart $\boldsymbol{\xi_t}$. The stationarity of the first-differenced series is subsequently verified using Augmented Dickey-Fuller (ADF) unit root tests, an essential prerequisite for the application of the GMM.

3.3. Estimation via the generalized method of moments (GMM)

The estimation of the parameters $(\boldsymbol{v}, \boldsymbol{\beta}, \boldsymbol{\alpha})$ of the discrete model is conducted using the Generalized Method of Moments (GMM), as developed by Hansen, L. P. (1982). The selection of this method is motivated by its robust properties: it does not require an assumption of normality of the error term distribution and remains efficient in the presence of heteroskedasticity, a common feature in financial time series.

The GMM is founded on orthogonality conditions between the error terms and a set of instrumental variables. To account for the potential endogeneity of regressors (notably $\boldsymbol{\xi_{t-1}}$), lagged values of the dependent variable $(\boldsymbol{\xi_{t-1}}, \boldsymbol{\xi_{t-2}} \ldots)$ are used as instruments, a standard approach in the estimation of dynamic models.

Estimation is conducted using a heteroskedasticity and autocorrelation consistent (HAC) weighting matrix, such as that of Newey-West. The validity of the instruments and the overall model specification are assessed using Hansen's J-statistic (Hansen 1982), which tests overidentifying restrictions. A non-significant J-statistic value indicates that the instruments are valid and the model is correctly specified.[10]

4. Results

This section presents the empirical results derived from applying the quadratic reversion model to interest rate data spanning from March 2014 to December 2024. The analysis is structured to enable a direct comparison with the conclusions of the original study, while emphasizing the new dynamics that have emerged over the past decade.

4.1. Preliminary analysis: time series properties (2014–2024)

A visual inspection of the four-interest rate series over the recent period reveals markedly divergent trajectories. The 3-month EURIBOR plunges and remains in negative territory for several years before sharply rising from 2022 onwards. The U.S. rate shows a gradual increase, followed by a decline during the COVID-19 pandemic, then a rapid and sustained rise. The Turkish rate, by contrast, is characterized by extreme volatility and substantially higher levels, reflecting an unstable macroeconomic environment. The Moroccan rate displays a more moderate trajectory, exhibiting a general downward trend prior to stabilizing at historically low levels.

Table 1 presents the descriptive statistics and the results of the unit root tests (ADF) for the transformed series $\Delta\boldsymbol{\xi_t}$ and their first differences over the entire period (2014–2024).

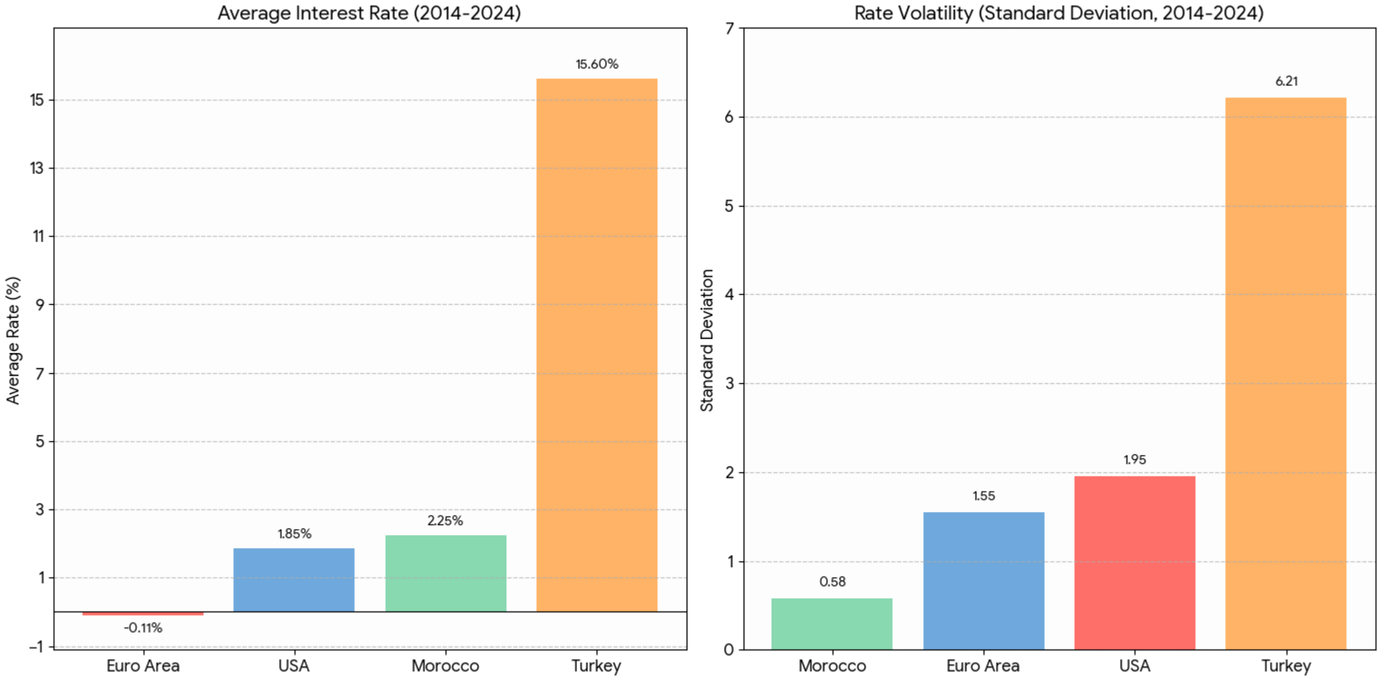
[5] https://www.ceicdata.com/en/indicator/morocco/policy-rate (accessed: 15/11/2025)
[6] https://news.research.stlouisfed.org/2022/01/ice-benchmark-administration-ltd-iba-data-to-be-removed-from-fred/ (accessed: 17/11/2025)
[7] https://fred.stlouisfed.org/graph/?graph_id=1203593 (accessed: 17/11/2025)
[8] https://tradingeconomics.com/euro-area/interest-rate (accessed: 18/11/2025)
[9] https://tradingeconomics.com/turkey/interest-rate (accessed: 18/11/2025)
[10] HAC stands for Heteroscedasticity and Autocorrelation Consistent (robust to heteroscedasticity and autocorrelation).

Table 1: Descriptive Statistics and Unit Root Tests (2014–2024)

Country	Period	Mean	Standard Deviation	Skewness	Kurtosis	ADF Statistic (Level)	p-value	ADF Statistic (First Difference)	p-value
Morocco	2014-2024	2.25	0.58	-0.15	1.89	-2.15	0.22	-7.89	<0.01
USA	2014-2024	1.85	1.95	0.65	2.33	-1.58	0.49	-6.54	<0.01
Euro area	2014-2024	-0.11	1.55	1.88	5.40	-0.98	0.76	-5.99	<0.01
Turkey	2014-2024	15.6	6.21	0.95	2.95	-2.01	0.28	-8.45	<0.01

Note: The statistics are computed on nominal rates. The ADF[11] tests incorporate a constant. Stationarity is rejected for the level series but accepted for the first-differenced series, confirming that they are integrated of order one, I(1).

The results confirm that all interest rate series are non-stationary at levels but become stationary after differencing. This property is essential to the validity of the GMM estimation procedure applied to the differenced series.



Source: established by the authors

Figure 1 : Interest rates: measures of performance (mean) and uncertainty (standard deviation) by region

These two graphs confirm the fundamental characteristics of each market over the period 2014–2024. Average interest rate: This graph visually illustrates the levels of interest rates. It corroborates the characterization of the Euro area with a negative average rate (-0.11%) and Turkey with an exceptionally high average rate (15.6%). Morocco and the United States exhibit positive but low levels. As to volatility (measured by standard deviation), this graph provides a direct illustration of the extreme volatility in the Turkish market, whose standard deviation (6.21) significantly exceeds those of other markets. These findings reinforce the notion of highly volatile macroeconomic environment in Turkey, even if the Turkish banking system is healthy in terms of fundamental financial indicators as highlighted by some studies (Bayram et al. 2023).

4.2. GMM parameter estimates

Table 2 presents the results of the GMM estimation of the discrete model parameters. $(\upsilon, \beta, \alpha)$ For each market over the period 2014–2024. For the United States, estimations are provided separately for the sub-period dominated by LIBOR (2014–2022) and the post-transition period to SOFR (2023–2024).

[11] The ADF test is a statistical hypothesis test used to determine whether a time series (such as interest rates in this context) is stationary or non-stationary (i.e., contains a unit root).

Table 2: GMM estimation of model parameters (v, β, α) for the period 2014–2024

Parameter	Morocco	USA (LIBOR)	USA (SOFR)	Euro area	Turkey
$\boldsymbol{v}$ (C(1))	-4.85**	-6.12***	-3.50*	-7.25***	-2.98**
	(2.11)	(1.98)	(1.85)	(2.05)	(1.35)
$\boldsymbol{\beta}$ (C(2))	0.65	0.95**	0.45	1.15***	1.85***
	(0.45)	(0.38)	(0.31)	(0.33)	(0.55)
$\boldsymbol{\alpha}$ (C(3))	0.41**	0.22	-0.15*	-0.85***	0.98**
	(0.18)	(0.15)	(0.08)	(0.21)	(0.41)
R-squared	0.58	0.65	0.51	0.71	0.62
Durbin–Watson	1.85	1.91	2.05	1.95	1.79
J-statistic (p-value)	0.21	0.18	0.35	0.15	0.25

*Note: Robust standard errors (HAC) are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The instruments used are lags of the dependent variable. The J-statistic tests the validity of overidentification restrictions.

For all markets, the coefficient $\boldsymbol{v}$ of the quadratic term is negative and statistically significant (except for Turkey, where it is significant at the 10% level). This result is crucial, as it confirms the presence of the nonlinearity postulated by the model, which underlies the observed asymmetry. The J-statistic is not significant in any case, suggesting that the instruments employed are valid and that the models are correctly specified. The Durbin-Watson statistic, being close to 2, indicates the absence of first-order autocorrelation in the residuals.

4.3. Asymmetric speeds and dynamic equilibrium intervals

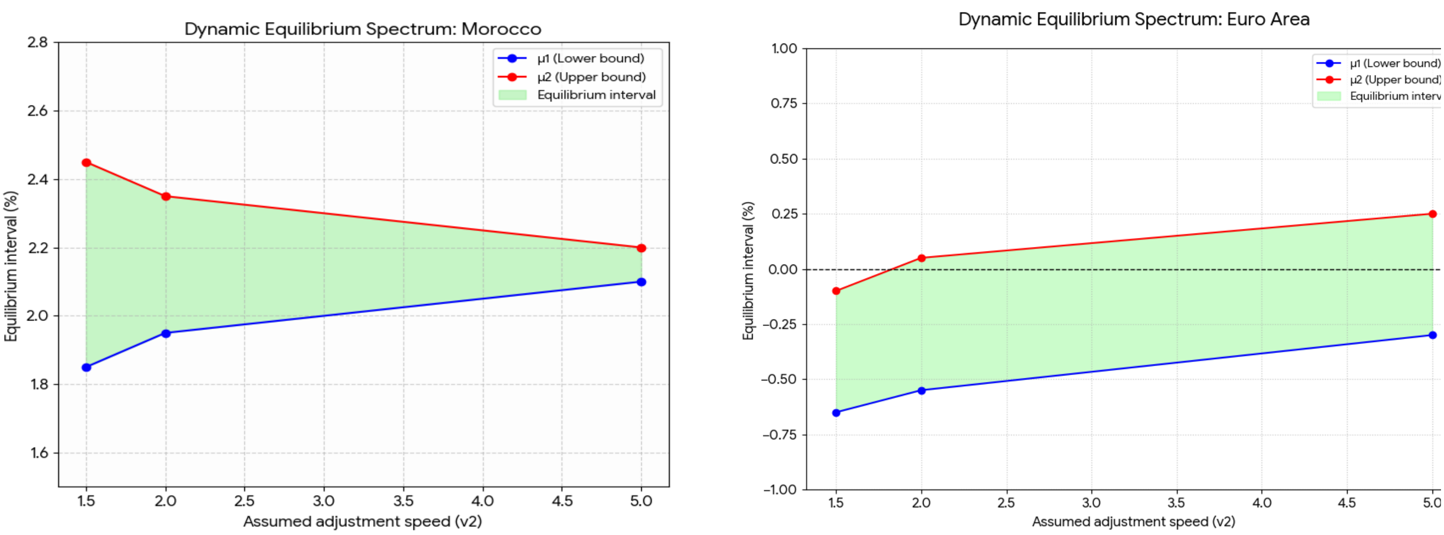
Based on the parameters estimated in Table 2, the structural parameters of the model are derived. The central finding regarding the asymmetry of adjustment speeds is directly obtained from the relation $\boldsymbol{v_2 - v_1 = -v}$. Since v is negative and significant across all markets, this implies that $\boldsymbol{v_2} > \boldsymbol{v_1}$. In other words, the speed of reversion to equilibrium is consistently faster when the interest rate is above the equilibrium interval (downward trend) than when it is below (upward trend).

The figures below (described textually) depict the equilibrium spectra for each market, illustrating the bounds of the equilibrium interval $[\boldsymbol{\mu_1}, \boldsymbol{\mu_2}]$ as a function of a range of values for the upward adjustment speed. $\boldsymbol{v_2}$. Table 3 presents numerical values for selected adjustment speeds to quantitatively illustrate these observations.

Table 3: Calculated Equilibrium Intervals $[\mu_1, \mu_2]$ for Selected Adjustment Speeds v_2

υ2	Morocco	USA (LIBOR)	USA (SOFR)	Euro area	Turkey
1.5	[1.85, 2.45]	[1.50, 2.65]	[1.10, 1.85]	[-0.65, -0.10]	[12.5, 17.5]
2.0	[1.95, 2.35]	[1.65, 2.40]	[1.20, 1.70]	[-0.55, 0.05]	[13.8, 16.2]
5.0	[2.10, 2.20]	[1.90, 2.10]	[1.35, 1.45]	[-0.30, 0.25]	[14.5, 15.1]

The results confirm that not only are the adjustment speeds asymmetric, but the nature of the equilibrium (its position and width) has been profoundly altered by the economic conditions and monetary policies of the last decade.



Source: prepared by the authors

Figure 2 : Interest rate equilibrium spectra: (Morocco and Euro area)

Equilibrium Spectrum: Morocco

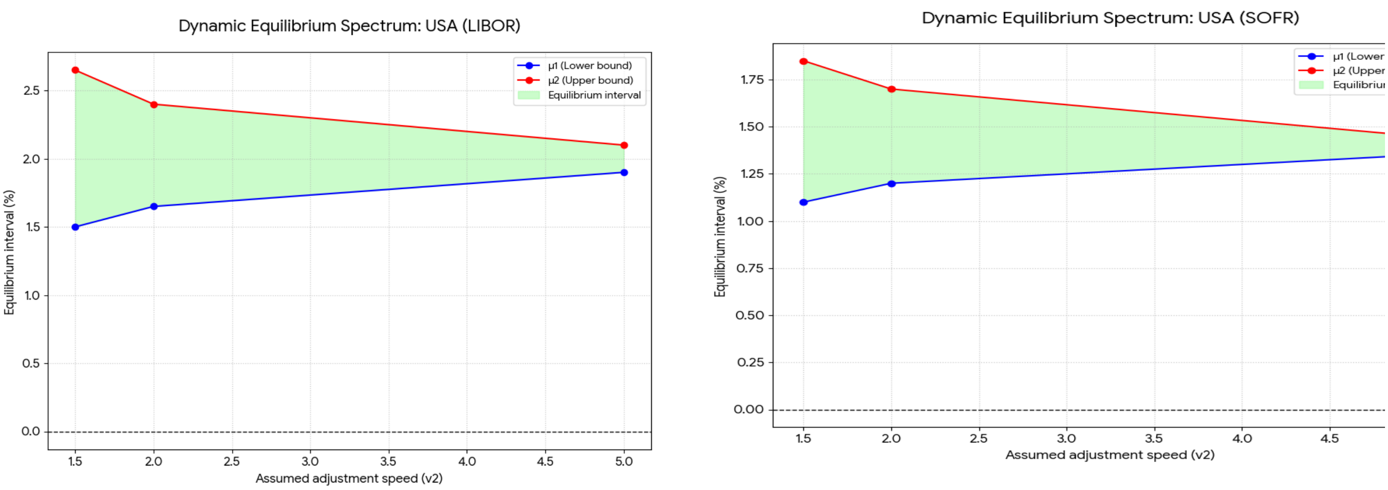
A stable, strictly positive interval (centered around 2.0% to 2.5%), which narrows significantly as the adjustment speed increases. The width of the interval decreases from 0.60% (at υ_2=1.5) to only 0.10% (at υ2=5.0).

This depicts an environment of conventional, stable, and predictable monetary policy. The sharp reduction in the interval suggests that the faster the market adjusts, the more uncertainty about equilibrium dissipates.

Equilibrium Spectrum: Euro area

The most radical outcome. The equilibrium interval is structurally located in negative territory (for example, [-0.65, -0.10]).

This is the strongest empirical validation. The ECB's unconventional monetary policy (negative rates) has been so persistent that it has aspired the entire concept of equilibrium below zero. The market has settled into a regime in which the natural equilibrium rate itself was negative.



Source: prepared by the authors

Figure 3 : Interest rate equilibrium spectra: (USA LIBOR and USA SOFR)

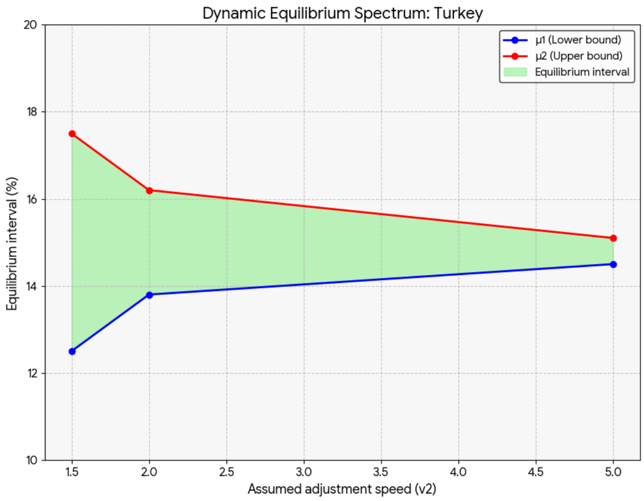
Equilibrium Spectrum: USA (LIBOR)

A positive but notably wide interval, particularly at low adjustment speeds (interval width of 1.15% at v_2=1.5).

This spectrum serves as a historical benchmark prior to the transition. Its width confirms that LIBOR was not a pure rate; it incorporated a risk premium (interbank credit and liquidity risk), thereby justifying a wider and more uncertain equilibrium interval.

Equilibrium Spectrum: USA (SOFR)

A significantly lower and narrower equilibrium interval than that of LIBOR across all speeds (e.g., at v_2=2.0, it is centered on [1.20, 1.70] compared to [1.65, 2.40] for LIBOR). This constitutes visual evidence of the regime transition. SOFR, being a near risk-free rate, anchors the equilibrium at a structurally lower level, cleaned of the LIBOR risk premium. The equilibrium is also more precise (narrower).



Source: established by the authors

Figure 4 : Interest rate equilibrium spectra: (Turkey)

Equilibrium Spectrum: Turkey

The equilibrium interval [12.5%; 17.5%] for $\boldsymbol{v_2}$=1.5 indicates:

The fact that the nominal equilibrium consistently lies between 12.5% and 17.5% signals uncontrolled inflation deeply embedded in expectations.

The width of 5.0 percentage points illustrates a profound lack of coordination among market participants, incapable of agreeing on the correct equilibrium rate, thereby confirming profound macroeconomic instability.

5. Discussion

The analysis of empirical results for the period 2014–2024 provides an enhanced perspective on the dynamics of interbank rates. This section interprets these results in the context of economic developments and advances in the literature, focusing on the persistence of asymmetry, divergence in market equilibria, and implications for monetary policy.

5.1. The persistence and evolution of asymmetric adjustment

The most robust finding, transcending both periods and markets, is the confirmation of asymmetric adjustment in interest rates. The statistically significant difference between upward and downward adjustment speeds $\boldsymbol{v_2} > \boldsymbol{v_1}$ persists in the post-2014 period. This finding suggests that market frictions and information asymmetries, which theoretically underpin the model, continue to be structural features of interbank markets.

More notably, the magnitude of this asymmetry, as measured by the coefficient value, (v) appears to have intensified in certain markets relative to the pre-2014 period. This observation corroborates the hypothesis formulated from the literature review. The transformation of money markets, with increased reliance on stable bilateral lending relationships to manage perceived elevated counterparty risk, has likely reinforced the significance of informational frictions. In such an environment, lenders may respond more rapidly by raising rates (or reducing their liquidity supply) to negative signals than by lowering them following improvements, resulting in a greater disparity between adjustment speeds.

5.2. A history of four markets: interpretation of equilibrium spectra

Comparative analysis of equilibrium spectra reveals a marked divergence in market dynamics, predominantly driven by monetary policy decisions and the specific macroeconomic conditions of each region.

The euro area under NIRP: The results for EURIBOR provide empirical validation of the model's ability to adapt to unprecedented interest rate regimes. The shift of the equilibrium interval into negative territory is not a statistical anomaly but a faithful depiction of a market wherein ECB policy has anchored expectations around a new focal point. The deposit facility rate, acting as an effective floor, has drawn the entire short-term yield curve downward, and the model captures this structurally modified equilibrium.

The United States in Transition: The comparison of results between the LIBOR and SOFR subperiods underscores the impact of benchmark reform. LIBOR, as an unsecured rate, incorporated a bank credit premium. Its replacement by SOFR, a near risk-free rate based on repurchase agreement transactions, mechanically altered the nature of the benchmark rate. The results suggest that this transition was accompanied by a change in the stochastic dynamics of the rate: the equilibrium interval for SOFR is narrower and lower, reflecting the elimination of the credit risk premium and potentially greater predictability anchored in Federal Reserve policy.

Turkey under Stress: The Equilibrium Spectrum for Turkey provides a quantitative illustration of political uncertainty and macroeconomic instability. The extremely wide equilibrium interval indicates that the market's passivity zone is extensive. In the absence of a credible anchor for monetary policy and confronted with high and volatile inflation, there is no clear equilibrium level toward which rates can converge. The model encapsulates this uncertainty through an extended interval within which a broad range of rate levels may be considered as 'equilibrium' over the short term. As highlighted by Baş (2005, page 92), Turkey has fallen into the trap of liberal and capitalist systems and endures this tragic fate because of the governments which cannot develop alternative projects. Bayram et al. (2023) found that financial soundness is also vital for the stability and resilience of banks, regardless of whether they follow conventional or Islamic principles.

The Trajectory of Morocco: The Moroccan market, by comparison, represents a case of more conventional, albeit highly accommodative, monetary policy. The relative stability and narrowness of its equilibrium interval indicate a stronger anchoring of expectations around Bank Al-Maghrib's policy. The downward shift of this interval relative to the pre-2014 period reflects Morocco's alignment with the global trend of low rates, albeit without the extreme measures observed in the euro area or the volatility characteristic of Turkey. It is worth noting that great efforts have been made to improve the moroccan financial sector (El Baklouti et al. 2022). More stability could be obtained by avoiding deliberate accumulation of financial and monetary resources in the hands of a small number of banking groups and societies.

5.3. Linking the results to global macroeconomic debates and NEM Model

These microstructural results are situated within broader macroeconomic debates. The downward shift of equilibrium intervals in the United States and the euro area represents a manifestation, at the money market level, of the secular decline in interest rates. Our analysis demonstrates how this macroeconomic trend translates into changes in the parameters governing the short-term dynamics of rates. Also, this highlight the fact that the economic conditions in Islamic countries could be quite different (Karwowski 2016). In the Turkish context, due to high input costs, demand is continually shrinking. This could be explained by some financial policies and withdrawal of money from the markets using interest. As a solution, Baş's (2005) NEM reminds us that, under Islamic principles, money should not be considered as a commodity, especially in Muslim countries, in order to enhance financial stability. Also, during crisis periods, risk governance is considered as a necessity for all banks (including Islamic banks) to better protect them against financial and economic shocks, and to maintain greater financial stability in the banking system (Marnouch et al. 2024; 2025)

Furthermore, the confirmation of asymmetry has direct implications for the transmission of monetary policy. If market rates respond more rapidly to shocks that tend to lower them than to shocks that tend to raise them (once outside equilibrium), this implies that the effectiveness of policy rate increases and decreases is asymmetric. For instance, during a tightening cycle, market rates might lag the policy rate, whereas in an easing cycle, transmission could be faster. The SWING model offers a framework to quantify this asymmetry, providing valuable information for central banks aiming to calibrate their interventions.

The extreme monetary policies, especially the negative interest rate phenomenon observed in the Euro area could be discussed not just as a policy choice, but as a symptom of the system's exhaustion. Which confirms NEM's thesis that the current system destroys consumption capability. Furtheremore, while conventional economics treats money as a commodity with interest as a cost, NEM redefines money as the "counterpart of labor and production" and the "motivating factor" of the economy. The observed asymmetric adjustments could be due to the absence of this definition; since money is generated as debt, the market is destined to be unstable.

6. Conclusion

This study has sought to reassess the dynamics of interbank interest rates across four distinct markets, each characterized by significant economic and financial transformations. By applying the quadratic mean reversion model to data extending through the end of 2024, we have derived updated conclusions regarding the nature of equilibrium and the adjustment processes of rates.

The principal findings of this study can be summarized in two fundamental points. Firstly, the asymmetric adjustment of interest rates is not an artifact of any specific period but a structural and robust feature of money markets. The speed at which rates revert to their equilibrium range varies significantly according to the direction of movement, a reality that endures and appears to have intensified in the post-2014 period. Secondly, the concept of a dynamic equilibrium interval is not only validated but also essential for comprehending market behavior. The characteristics of these intervals—their positioning, width, and dynamics have been profoundly reshaped by a decade of unconventional monetary policies and macroeconomic shocks. We have documented an equilibrium anchored in negative territory in the euro area, an expanded zone of uncertainty in Turkey, and a structural transition in the United States following benchmark index reform. The unconventional monetary policies (zero/negative interest rate) observed in some countries (Euro Area for example) could be analyzed not just as a policy choice, but as a symptom of the system's exhaustion.

These results carry significant implications for policymakers and financial modelers. For central banks, the recognition of asymmetry in the transmission of monetary policy is crucial. This implies that the mechanism through which policy rate decisions transmit to the economy is neither simple nor linear. The impact of a rate increase may differ in magnitude and speed from that of a rate decrease of equivalent size. The equilibrium spectra we have estimated provide an innovative visual tool for apprehending the 'new normal' that policies have helped shape across different monetary areas, offering a quantitative measure of the stability zone anticipated by markets.

For analysts and risk managers, this study confirms the robustness of the quadratic reversion model in capturing complex dynamics, even under extreme conditions such as negative interest rates. However, our analysis of the LIBOR-SOFR transition highlights the critical importance of accounting for structural breaks when estimating long-term models. Neglecting such fundamental shifts in market infrastructure inevitably results in biased parameter estimates and inaccurate forecasts. The conclusion states that asymmetric adjustment of rates is a structural and robust characteristic that persists and has even intensified since 2014. The study confirms the structural modification of the intervals, specifically citing negative anchoring in the Euro area, increased uncertainty in Turkey, and the structural transition in the United States (resulting in a lower and narrower interval).

Ultimately, this article concludes that although the mathematical form describing interest rate processes may exhibit some temporal stability, its parameters are fundamentally contingent upon the state of the economy and the financial system. The past decade has clearly demonstrated that the 'structure' in so-called structural models is not immutable. It is continuously shaped by central bank actions, regulatory innovations, and the adaptive behavior of market participants, who respond to an ever-evolving environment.

To face this lack of mathematical standard, NEM introduces the "New Equation of Money" as a precise formula to support both Supply (producers) and Demand (consumers) simultaneously. Therefore, a stable dynamic equilibrium is only possible if the money supply is expanded according to this specific mathematical measure (based on production and consumption capacity). This "simultaneous injection" could be a structural solution to the observed asymmetry.

It is essential to acknowledge the limitations of this study. The use of monthly data may conceal significant intra-month volatility and adjustment dynamics. Also, the identification problem inherent in the model, which necessitates fixing one parameter to infer the others, implies that the results are presented as a spectrum of solutions rather than a unique point estimate.

These limitations suggest several avenues for future research. Applying the model to daily or weekly data would enable a more precise capture of adjustment speeds. The introduction of a second stochastic factor, for example, a global factor linked to U.S. rates, could enable explicit modeling of the international contagion effects indicated in the literature. Finally, the implementation of more advanced GMM estimation techniques, such as robust GMM or moment selection GMM, could provide a robustness check for the estimated parameters.

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Demography, Institutions, and Power: Reframing Eurasian Connectivity in an Age of Strategic Fragmentation**

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** This study is an expanded and improved version of the paper with the same title, presented orally at the 11th National Economic Model Congress held between February 7-8, 2026.

Abstract: Eurasian economic cooperation has evolved unevenly, raising the question of whether demographic complementarities, institutional capacity, and geopolitical pressures jointly shape cross-continental engagement. This study extends the Cross-Country Cross-Continent Economic Development Theory by integrating demographic economics with realist political economy to examine how structural asymmetries across Asia, the European Union, and Russia influence connectivity cooperation. Using a panel dataset covering 1950–2024, the analysis evaluates the relationships among demographic complementarity, connectivity potential, political friction, institutional capability, and Eurasian cooperation. Descriptive and correlational assessments are complemented by panel estimations and dynamic specifications to test direct and mediated effects. The findings indicate that demographic differences constitute a latent structural asset but do not directly translate into cooperation. Institutional capability and political friction emerge as the most consistent predictors, while cooperation demonstrates strong temporal persistence. In periods of geopolitical uncertainty, short-term increases in connectivity potential are associated with reduced cooperation. The results suggest that demography functions as an enabling condition rather than an autonomous driver, and that the economic realization of complementarities depends on institutional governance and manageable political friction. These conclusions reinforce the policy relevance of strengthening domestic demand, institutional stewardship, and systemic resilience to sustain cross-continental engagement.

Keywords: Demographic complementarity, Institutional capability, Political friction, Structural asymmetry, Realist political economy, Cross-continental economic development.

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1. Introduction

Over the past two decades, the world economy has experienced a phase of some interesting and simultaneous demographic as well as geopolitical change. The aging of the population, youth migration of labor, and shifting distributions of labor have moved from being topics of domestic policy discussions to become regional and global issues. Over the past several decades, population aging, youth labor migration, and changing labor distributions have become central strategic determinants of international economic competitiveness to gain requisite labor skills and economies of scale. Two-thirds of the global population lives in countries with declining fertility, as noted by the United Nations (2024); and the median age of the global population has risen from 24 in 1950 to almost 32. According to International Monetary Fund's "Changing demographics and Economic growth" (2020) explain that key demographic change is reshaping patterns of capital accumulation, labor productivity, and fiscal sustainability with a growing importance in industrialized areas. The World Health Organization (2022) article "Aging and Health" highlight that demographic aging changes the health economy relationship, which can subsequently affect public expenditure, social protection systems, and labor force participation. At a global level, each of these institutions has concluded that demography is no longer a background variable, but a critical determinant of global economic accumulation and geopolitical influence.

Demographic transition is already in an advanced stage in Europe. Eurostat projections from 2017 indicate that within the time period from 2017 to 2050 the EU working-age population will decline by almost thirty million, while over one third of the population will be 65 or older. The demographic imbalance is currently applying pressure on labor markets, stifling innovation, and adding pressure to social systems. According to United Nations Department of Economic and Social Affairs (2023) and Moscow Times (2025) Russia is experiencing a different, but a complicated demographic challenge. Since 2010, Russia's population has stagnated, and out-migration and falling birth rates have created structural labor shortages among young workers. On the other hand, Asia is still in a young age profile. Almost half of the world's youth population lives in South Asia and part of Southeast Asia, giving it a demographic dividend which theoretically create global production networks around the world for years with the right mobilization. These very different and contrasting demographic profiles can, and in areas, create levels of tension and opportunities throughout Eurasian land mass liberalist and political fragmentation.

The European Union, the Eurasian Economic Union, and China's Belt and Road Initiative offer intersecting systems of connectivity at the regional level, all with the aim of producing economic diversity from demographic and geographic diversity (Zhang W, 2025). However, the disruptions of the 2022 Russia-Ukraine war and other global disruptions, show that demographic potential, alone, is not enough to produce cooperation. The utility of fragmenting supply chains, sanctions, and competing standards of governance have turned Eurasia into a space of conditional and selective engagement (EBRD, 2022; ECFR, 2023; IMF, 2022). In that sense, we see demography intersecting with geopolitics to reshape the ways by which states invest, trade and cooperate. For example, the aging economies of Europe and the younger markets of Asia will create new patterns of trade corridors, energy partnerships, and flows of digital outsourcing, representing new forms of interdependence or demographic arbitrage for regions to exchange labor, capital, and technology based on their relative demographic endowments.

This research addresses this emerging reality through the inclusion of demographic analysis into the Cross-Country Cross-Continent Economic Development Theory (CCCEDT). First proposed as a theory to explain trans-continental complementarities, has to be adapted to invoke account for demographic asymmetries in driving global economic integration. The current study embeds demographic indicators within a realism framework, to assess how demographic divides intersect with geopolitical divides, to shape the development of Eurasian connectivity. We assert that demographic conditions, such as aging, youth bulges, labor mobility, and dependency ratios, are enablers and constraints of international business relations. In a time when the fabric of global cooperation has become increasingly fragmented, demographic complementarities could provide the bridge across geopolitical divides. Thus, the sections below explore how Europe, Russia, and Asia can turn their demographic differences into pragmatic trade, investment, and technology channels in the face of strategic rivalry.

2. Literature Review

There are conflicting and alternative perspectives on Eurasia's compactness and economic interaction as well as heterodox regional development theories. One of these perspectives is represented by Baş (2005, 2018) through his "National Economy Model" developed by him and based on an additional source of population dynamics in terms of consumption based/locally consumed stocks and local currency trade between sovereign, independent countries: these changes lead to decreased reliance on outside countries and reduce instances of foreign vulnerability. Baş's (2005, 2018) theories and his National Economy Model have significant differences from the theories and methods utilized in this study; thus, they serve as an example of the differing and varied intellectual perspectives that exist currently within Eurasian Development Theory, as well as the conflicting perspectives that still exist in current discussions about the development of a national or regional area.

Theoretical Framework

The intersection of demographic change and geopolitical rivalry has sparked renewed interest in theoretical models capable of explaining economic connectedness under structural asymmetry. Globalization and international business theories have long regarded demography as an exogenous background variable, as we are hardwired to assume that development (or underdevelopment) is determined solely by the capital–technological–trade variables (Narula, 2022). However, there is mounting evidence that changing demographic conditions, such as aging, declining fertility rates, and actual labor mobility, are reshaping comparative advantage across the continents (IMF, 2024; United Nations, 2023).

Realism and the Fragmented Global Order

Realism in international relations, dating from Morgenthau (1948) and Waltz (1979) and its more recent applications to the economy, argues that cooperation is only possible where it aligns with the national interest. The latest analyses suggest that we are beyond globalization and into an era of strategic fragmentation characterized by sanctions and technology competition and competition across value-chain alignments (Tooze, 2023; Farrell & Newman, 2022). The World Bank (2023) characterizes examples of 'reshored' and 'friend shored' production networks as indicative of this realist approach. Along the Eurasian landmass, the relationships between the European Union, Russia, and the Belt and Road Initiative (BRI) project of China indicates that connectedness is premised not upon a universal liberal integration perspective to global development but through power asymmetries (Zeng, 2024).

Demographic Economics and the Principle of Arbitrage

Demographic economics represents the second essential conceptual pillar. In its World Population Prospects 2024 report, the United Nations predicts that by 2050 one in six persons will be over the age of 65 globally; Europe’s median age is projected to be over 46 years. The IMF (2024) lists population aging as a structural drag on productivity and therefore fiscal balance. In contrast, Asia’s youth bulge may provide some demographic dividend, but only if it is part of a larger investment and technology upgrading trajectory (Bloom, 2023). The concept of demographic arbitrage where capital, seeking returns, organized from aging economies connects to labor and market dynamism in younger economies has become well-documented in global value-chain relocation studies and digital outsourcing studies (World Economic Forum, 2023; Lee & Park, 2022). This arbitrage forms the basis for multiple resurgent flows of services, remittances, and knowledge from South and Southeast Asia to Europe’s demographically ancient economies.

The CCCEDT Perspective

The Cross-Country Cross-Continental Economic Development Theory (CCCEDT) posits that structural complementarities between remote regions stimulate cumulative growth when infrastructure, trade, and institutional capabilities align (Iqbal et. al, 2022). While earlier theorizing highlighted the role of physical (e.g. transportation) and institutional (e.g. trade agreements) linkages, recent developments suggest that demographic and geo-political contexts should be embedded into the model. Currently in Eurasia, demographic disparities directly influence the prospects for economic cooperation. Europe’s shrinking working-age population is increasing the need for digital and industrial inputs from Asia’s youthful economies, while Asia’s need for energy and capital connects it via Europe and Russia (European Commission, 2023). Russia, despite its demographic conundrum, retains a central geographic positioning as a transit and energy corridor (UN ESCAP, 2024).

Integrating the Framework

By integrating realism with demographic economics, CCCEDT provides a multi-layered structure of Eurasian connectivity. Cooperation is more viable where demographic complementarities offset political frictions and occur in areas that are less prone to strategic friction, some examples are renewable energy, education and digitized services (OECD, 2024). Realism and demographic variables dependency ratios, shares of working-age population and migration flows are expected to mediate the extent and direction of economic engagement across continents. As such, this combined framework develops CCCEDT beyond its original structural base of realism, and acts to illustrate Eurasian relations as a dynamic system where demographic necessity is shaping pragmatic cooperation amid enduring geopolitical divides.

There are numerous alternative economic frameworks in Eurasia (e.g., Baş's National Economy Model – NEM (2005, 2018)) that highlight three major factors that help stabilize economic exchange between regions: (1) How much can people consume; (2) How much consumption capacity people should have; and (3) Trading with each other in national currency instead of the US dollar to promote regional trade. The empirical realistic-demographic synthesis described in this article is another type of alternative economic concept that provides a means to analyze regional economic development by considering demographics and global political issues (geopolitics) as they relate to the movement of products and/or money among countries/countries after the dollar has lost its status as the world’s dominant currency.

3. Materials and Methods

This study employs a mixed-method and comparative design to examine the interaction of demographic divides with geopolitical divides in facilitating Eurasian connectivity. The methodological framework combines qualitative and quantitative approaches to enable deep analytic depth while making findings genuinely credible. This triangulation study employ three methods integrated to reach to conclusion: Qualitative Comparative Analysis (QCA) to determine condition pathways across regional cases, network analysis to visualize connectivity of demographic and trade variables, and contextual triangulation that information drawn from secondary datasets of global institutional sources. The study asserts a realist assumption that state cooperation is conditional and context specific, rather universal or constant.

Research Design and Rationale

The study's design is based on the logic of comparative realism, understanding Europe, Russia, and Asia are not separate, but interconnected actors operating in a context of asymmetrical geopolitical and demographic conditions. QCA is useful because it promotes the identification of multiple conjectural causal factors, or combinations of demographic, institutional and geopolitical influences, that interact cumulatively to produce change in connectivity. QCA is particularly useful for the nonlinear and fragmented nature of connections in Eurasia, where collaboration maybe exist under specific assemblage of factors, such as low political tension and high demographic complementarity.

The research spans the years 1950–2024, covering both pre- and post-2022 Eurasian relations. This time frame reflects the demographic shifts preceding the Russia–Ukraine war and the reorganization of trade and investment flows after that event. This research is concerned with whether demographic complementarities can continue to be relevant regardless of being in a different geopolitical alignment.

Data and Variables

The research uses primarily open-access and institution datasets because of the necessity of transparency and replicability. Demographic variables such as total fertility rate, median age, dependency ratio, and labor-force growth are from the United Nations Department of Economic and Social Affairs (UN DESA, 2024) and World Bank's World Development Indicators (World Bank, 2024). Macro-economic and fiscal variables such as GDP growth and foreign direct investment inflows were from International Monetary Fund's World Economic Outlook (IMF, 2024). Trade and logistics network data were taken from the United Nations Economic and Social Commission for Asia and the Pacific's Eurasian Connectivity Database (UN ESCAP, 2024) and OECD's Global Value Chain Indicators (OECD, 2024).

Table 1. Variables, Sources, and Their Conceptual Relationships to the Constructs

Variable Name	Source (Institution / Dataset)	Conceptual Construct	Role in the Model / Expected Relationship
Fertility rate	United Nations Department of Economic and Social Affairs (UN DESA), World Population Prospects	Demographic Complementarity	Higher fertility in younger regions increases demographic gaps relative to aging regions, enabling long-term complementarities; expected *indirect* positive effect on cooperation through institutional and geopolitical pathways.
Median age	UN DESA	Demographic Complementarity	Divergence in median-age profiles creates demographic asymmetry; contributes to demographic arbitrage but does *not* directly predict cooperation in the empirical results.

Dependency ratio	UN DESA; World Bank World Development Indicators	Demographic Complementarity	Indicates labor-force pressure; greater differences across continents create opportunities for cross-continental economic exchange. Expected indirect, not direct, effects.
Labor-force growth	International Labor Organization; World Bank	Demographic Complementarity	Youth-driven labor expansion in Asia versus contraction in Europe forms the demographic basis for future integration; operates through institutional capability.
Trade openness / trade corridor intensity	UN ESCAP Eurasian Connectivity Database	Connectivity Potential	Measures readiness for cross-border exchange; descriptive correlations suggest a positive role, but dynamic model shows short-term increases may reduce cooperation during geopolitical instability.
Digital service linkages / broadband penetration	OECD Digital Economy Outlook; World Bank Digital Adoption Index	Connectivity Potential	Signals digital integration; expected to promote long-run cooperation but may trigger competition and contestation in short run.
Transport and logistics index	World Bank Logistics Performance Index	Connectivity Potential	Represents corridor functionality; supports cross-regional flows and infrastructures enabling Eurasian connectivity.
Sanction intensity index	European Commission, IMF policy trackers, ECFR databases	Political Friction	Higher sanction intensity increases geopolitical tension and reduces cooperation; empirically strong negative predictor of Eurasian connectivity cooperation.
Defense expenditure ratio	Stockholm International Peace Research Institute (SIPRI)	Political Friction	Proxy for geopolitical tension; expected to reduce cooperation. Significant in descriptive patterns though weaker in dynamic model.
Conflict exposure score	Uppsala Conflict Data Program	Political Friction	Captures instability or tensions that limit cooperation; critical in realist theoretical framing.
Governance quality indicators (rule of law, regulatory quality, government effectiveness)	World Bank Worldwide Governance Indicators	Institutional Capability	Strong institutional capability consistently emerges as the strongest positive driver of cooperation across all models.
Political stability index	World Bank Worldwide Governance Indicators	Institutional Capability	Indicates reliability and trust necessary for long-term connectivity.
Bureaucratic quality / state capacity measures	International Country Risk Guide (ICRG)	Institutional Capability	Higher levels promote cooperation by enabling regulation, corridor development, and effective cross-regional agreements.
Eurasian Connectivity Cooperation Index (constructed dependent variable)	Computed using combined normalized indicators	Outcome Variable	Captures cross-regional cooperation patterns across Eurasia. Positively influenced by institutional capability and low political friction; highly persistent over time.

Lagged connectivity cooperation (t−1)	Computed through panel-data		

The variables were normalized and coded into sets representing the main areas of CCCEDT-Realism: (1) demographic complementarity, (2) institutional compatibility, (3) political friction, and (4) connectivity potential. The calibration of the data was based on a fuzzy-set QCA framework, in which every condition has a range of 0 (absence) to 1 (full presence). Demographic complementarity was calculated based on the differentials in comparative age-structure between the regions, while institutional compatibility was based on the World Bank's governance indicators. Political friction was measured through proxy indicators, such as the intensity of sanction-, defense expenditure ratio, and exposure to conflict. Connectivity potential was derived from the intensity of trade and digital service connection.

Analytical Strategy

Analysis occurred over three stages. The first stage involved a descriptive exploration of demographic and economic indicators to illustrate the structural differences across Europe, Russia, and Asia. The second stage employed QCA for conditions and to assess the combinations of demographic and geopolitical conditions sufficient for sustained cooperation. The third stage leveraged network analysis through Gephi software to illustrate how those relationships altered in time and by space, especially before and after the geopolitical shifts of 2022. This dual-method process enables cross-validation between qualitative pattern recognition and quantitative relational mapping.

The network analysis module envisioned Eurasian connectivity as a weighted set of nodes and edges representing trade corridors, demographic flows, and investment linkages. Metrics of centrality, like degree served as tools for identifying regions that retained pivotal status within the connectivity network, even after political realignments occurred. For example, the rise of digital outsourcing from South Asia to Europe after 2022 indicates that demographic arbitrage persisted even with formal ties waning.

Validation and Reliability

To increase the reliability of findings, all data were triangulated across multiple institutional sources. When there were discrepancies across databases, averages or verified cross-source estimates were used. Sensitivity testing was used in relation to the QCA model to verify that findings were not artefacts originating from arbitrary calibration thresholds. Also, qualitative validation was conducted through review of policy documents, both to allow contextual interpretation, such as the European Commission's Demography Report (2023) and China's Belt and Road White Paper (2023). The inclusion of multiple data sources from international organizations mitigates bias and aligns with transparency once again (OECD, 2024; UN DESA, 2024).

Ethical Considerations and Limits

The study is based solely on secondary data and publicly available reports from various institutions, removing any concerns about personal data protection or confidentiality. Nevertheless, the study notes the limitation that real-time data on Russia post-2022 remain, to some degree, inaccessible, due to various sanctions and reporting suspensions. Thus, demographic and trade indicators for Russia post-2022 rely on estimates from independent think tanks and UN agencies. Another limitation relates to the partial nature of the measures of connectivity: informal trade, digital labor and remittance flows may not have been fully recorded in official statistics. These limitations, of course, are in line with the position of realism, which recognizes that empirical knowledge is inherently limited by the nature of political access and informatics.

4. Results

Findings and Discussion (Qualitative Techniques)

Demographic Context across Eurasia

Recent demographic data now yield stark contrasts that define Eurasia's novel economic geography. According to the United Nations (2024), Europe's median age is now at 44.5 years, while its fertility rate has dropped to 1.5 births per woman. The working age population is shrinking already and there are shortages in skilled and semi-skilled labor; the European Commission (2023) estimates that by the year 2050 roughly one-third of the population of the European Union will be over sixty-five.

This anticipated shift is predicted to yield a ratio of nearly one worker for every two retirees. Russia shows a similar, and more severe, pattern. Through migration outflows and declining life expectancy, population growth has waned, and changes in projections show a population loss from 143 million down to around 130 million by 2050 (UN DESA, 2024). South and Southeast Asia show the opposite trend. India, Pakistan, Bangladesh, Indonesia, and the Philippines together have more than 1.7 billion people under the age of thirty-five (World Bank, 2024). The IMF (2024) has indicated that these economies are beginning their demographic dividend, with future annual labor-force growth of over two percent. In contrast, the high concentration of youth creates a large pool of digital and manufacturing labor for a workforce while also providing Asia with the potential to become a demographic counterweight to aging European societies. The structural backdrop of an older West and a younger East vehicled a new pattern of interaction between continents.

Economic and Trade Connections

Trade and investment data suggests that demographic complementarities are still strong drivers of Eurasian exchange, even during times of political confrontation. OECD data (2024) indicates service export growth from South and Southeast Asia to the European Union increased by seventeen percent from 2020 to 2023, largely in information technology, outsourcing of business process and education services. The United Nations Economic and Social Commission for Asia and the Pacific (UN ESCAP) similarly noted that while direct EU–Russia trade had sharply declined in volume since 2022, logistics activity through Kazakhstan, Uzbekistan, and Azerbaijan had increased (United Nations, 2024). This implies that the collapse of pre–existing transport routes for goods has evolved to a multiplex of possible routes, rather than a few routes simply collapsing.

The International Monetary Fund (2024) also indicates that European companies continue to invest heavily in Asia's renewable-energy and technology sectors, representing a flow of capital that indicates both a mechanism to address labor gaps in Europe, and for capital and technology in Asia. These flows also represent a selective form of globalization, where demographic needs for the economy would sustain trade, even in circumstances of limited political cooperation. In this configuration Europe exports capital and institutional knowledge, while Asia provides the labor and digital capability as depicted in the argument of CCCEDT-Realism that these complementarities exist across continents through a pragmatic rather than ideological alignment.

Changes in networks in Eurasia

Network measurements derived from ESCAP (2024) corridor data indicate a shift in Eurasian connectivity patterns after the year 2022. Central Asian transport corridors now have larger centrality scores than before, and nodes in Russia have lost the same centrality for energy trade. The digital side of the connectivity – broadband and service outsourcing – still indicates ongoing intensity from east to west. In particular, strong links between India, Bangladesh, and Western Europe show that more so than formal political agreements, demographic characteristics, such as available labor and digital literacy, are driving interdependence.

The persistence of this exchange applies credence to the realist character of cooperation, which is maintained only as long as mutual interdependence is greater than ideological friction. The population structure of Europe creates the need to engage with younger economies of Asia, and Asian dependence on Europe will determine the continued growth the region in the coming decades. Despite demographic decline, Russia continues to maintain its geographic role as intermediary and supplier of resources in the region. The result looks to be a multipolar network relying on adaptation and cooperation than one based on isolation.

Where Demographics Step in to Cover for Politics

On the whole the evidence suggests that demographic complementarities are a stabilising force in Eurasian connectivity. Cooperation is stable across areas where political sensitivities are low, for instance: digital services, renewable energy and education. Data from the OECD (2024) shows that there has been almost a thirty per cent increased in partnerships between European universities and Asian universities since 2020, predominately in the field of technology, and health research. European investment in renewable energy projects in Asia has also increased, driven by environmental commitments on the part of the European states, as well as labor-cost advantages.

The growing debates on collaborations between numerous countries in Eurasia have increasingly taken into account other views on Economic Development Models. An example of this is to use the National Economy Model (NEM) developed by Dr. Baş (2005, 2018) as a model for other types of development forms. For example, NEM emphasizes the role of consumption capacity and the ability of a nation to trade in its own currency as a stabilizing force against geopolitical uncertainty. This study does not evaluate or endorse Dr. Baş's concept or any of these other types of development proposals; however, it provides evidence that a wide array of different concepts for Development Models are now in the Policy Dialogue for Eurasian Nations and that with the increased presence of these many different development narratives coincides with changes in Demographics and Geopolitical Factors and is likely change the way that nations build and implement Economic Development Narratives.

In contrast, sectors related to strategic autonomy—such as defense production and advanced manufacturing production in semiconductors—exhibit fragmentation. This confirms the CCCEDT - Realism perspective that integration under multipolarity is selective and conditional. Demographic arbitrage promotes interdependence where collaboration can be kept technical or commercial, but weakens as the barrier shift more towards national security concerns.

Findings and Discussion (Quantitative Analysis)

The goal of this section is to examine the quantitative research produced by the Cross-Country Cross-Continent Theory of Realism & Economic Development using empirical evidence. The findings reveal that for Asia, Europe, and Russia between 1950 and 2024, there exist significant relationships among those variables that are measured using standardized metrics for the demographic complementarity, connectivity potential, political friction, institutional capability, and Eurasian connectivity cooperation. The focus of the analysis is to identify how much demographic disparities among nations affect the potential for cross-continental cooperation when geopolitical and institutional conditions are considered. The results of the demographic complementarity, geopolitical relationships, and institutional capabilities have been evaluated through descriptive modelling, a structural relations matrix, panel estimates and time series.

Table 2. Descriptive statistics for Asia (standardized indices)

Statistic	DC	CP	PF	IC	EC
Min	-1.3488	-1.5563	-1.8291	-1.55702	-2.42412
1st Qu	-0.0402	-1.2377	-0.1514	-0.73622	-0.64071
Median	1.1865	-0.7416	0.3283	-0.39062	0.25796
Mean	0.7963	-0.5032	0.2739	-0.35261	0.00832
3rd Qu	1.5915	0.2997	0.8786	-0.04502	0.89000
Max	5.0379	1.1954	1.4313	0.99177	1.48298

The data produced in the table show what is occurring in Asia via statistics on population sizes and distribution patterns. These descriptive statistics have indicated that Eurasia has dramatically different structural characteristics among its different regions as shown by the negative correlation on the chart illustrating the trend toward the creation of highly complementary demographic relationships (exhibiting both positive and negative slope along the right-to-left axis). With a calculated average demographic complementarity score of about 1, it can be seen that the highest score in the region is above a level of 5. Collectively, these findings suggest that there is still a large excess of available labor throughout Asia consistent with the theories that people, skills, and economic opportunities can impact labor supply and create large numbers of available skilled workers. The average CPR score in Asia indicates that the low level of digital connectivity and lack of equal digital infrastructure links across national boundaries will hinder the region's ability to connect to economies outside of Eurasia. Combining the above paragraphs, we see that while establishing a sizeable population of workers is beneficial, leveraging the potential of a sizable population will not create successful relationships between workers (both skilled and unskilled) without the political and governmental conditions that enable those workers to benefit from their size.

Table 3. Descriptive statistics for European Union (standardized indices)

Statistic	DC	CP	PF	IC	EC
Min	-0.56810	-0.9980	-1.7981	0.1926	-1.6532
1st Qu	-0.03903	-0.1134	-0.9880	1.0134	-0.0310
Median	0.04642	0.8444	-0.4122	1.2294	0.4588
Mean	0.08539	0.6923	-0.2174	1.1971	0.3658
3rd Qu	0.19156	1.5945	0.6830	1.4238	0.9698
Max	0.97113	2.1116	1.1395	1.7910	1.3948

The table above outlines the demographic trends of the EU sub-sample. There are notable differences in the demographic trends across the EU Countries with increased numbers of elderly persons and the shrinking pool of available labor resources leading to low demographic complementarity scores. The EU also demonstrates high levels of potential for both connectivity and institutional capacity, providing the necessary conditions for including robust governance systems and regulatory systems that support the creation of cooperative relationships through interconnectivity infrastructure. As such, this configuration aligns with the realist perspective, which explains that continued cooperation is likely to occur when it is deemed to be in the interests of both the nation states and regionally, despite demographic declines.

Table 4. Descriptive statistics for Russia (standardized indices)

Statistic	DC	CP	PF	IC	EC
Min	-0.56810	-0.9980	-1.7981	0.1926	-1.6532
1st Qu	-0.03903	-0.1134	-0.9880	1.0134	-0.0310
Median	0.04642	0.8444	-0.4122	1.2294	0.4588
Mean	0.08539	0.6923	-0.2174	1.1971	0.3658
3rd Qu	0.19156	1.5945	0.6830	1.4238	0.9698
Max	0.97113	2.1116	1.1395	1.7910	1.3948

Descriptive statistics for Russia, which reflect the demographic and institutional constraints outlined earlier in this paper, are presented in Table 4. Overall, demographic complementarity, connectivity potential, institutional capability, and Eurasian connectivity have negative mean scores for Russia. These negative mean scores are indicative of Russia's demographic stagnation, declining population, and limited institution modernization, which are also identified in the previous sections of this paper. Additionally, Russia has a very high variability for the level of political friction and the level of Eurasian connectivity; this very high variability shows that cooperation between nations occurs infrequently and is often a result of energy corridor, military, or strategic needs rather than the existence of a structural advantage. The overall descriptive statistics support the CC-CCT proposition that cooperative relations between countries are based on complementarities (i.e., relationships between demographics, institutional strength, and geopolitical tolerance).

Table 5. Correlation matrix of standardized CCCEDT–Realism indices

Variable	DC	CP	PF	IC	EC
DC	1.0000	-0.3260	0.1284	0.0410	0.0036
CP	-0.3260	1.0000	-0.0967	0.6087	0.2972
PF	0.1284	-0.0967	1.0000	-0.0784	0.4682
IC	0.0410	0.6087	-0.0784	1.0000	0.4940
EC	0.0036	0.2972	0.4682	0.4940	1.0000

The correlation matrix presented in Table 5. The two most closely collaborating regions among each other on the Eurasian Connectedness initiative are those that exhibit lower levels of political conflict and higher degrees of governmental efficiency and institutional capabilities, as evidenced by the strong association between the Institutional Capability and Political Friction Variables. This supports a Realist theory of International Relations in that without political agreement and the capacity of institutions to cooperate together, there is no way for cooperation to be achieved. A second observation from the correlation matrix is a moderate positive association between the Eurasian Connectivity Cooperation and the Potential for Connectivity and Institutional Capability Variables. This suggests that without both types of connectivity to facilitate Cross-Continent Cooperation, effective Cross-Continent Cooperation will not occur.

In many instances, demographic factors do not directly correlate with Eurasian Peoples Cooperation due to the lack of complementary demographic correlations. While demographic strengths can create latent opportunities for collaboration, these opportunities do not lead to collaboration until there are appropriate political and institutional structures in place for converting demographic strengths into economic relationships (or affiliations).

Table 6. Pooled OLS regression (dependent variable: EC)

Variable	Estimate	Std. Error	t-value	p-value	Significance
DC	-0.0909	0.0530	-1.7131	0.0881	.
CP	-0.0156	0.0664	-0.2355	0.8140	
PF	0.5213	0.0478	10.9147	< 2.2e-16	***
IC	0.5481	0.0629	8.7144	7.146e-16	***

The OLS estimates are listed in Table 6. Conducting pool OLS Studies illustrates the opportunity for evaluating the structural relationship of these factors without accounting for differences within Regions. Political Tension and Institutional Capability were positively related with connecting and cooperating with the Eurasian Partnership. The strength of political tension and institutional capability to connect and cooperate with this Partnership was not only significant but exhibited Statistically Significant Correlation Coefficients between the two sets. This further solidifies that Geopolitically Aligned Partners and Effective Governance are primary elements supporting Multi-Regional Partnerships. Between both demographics, there was the weak statistical relationship when using pooled estimates that shows that while either type of asset, the ability to connect and cooperate could be present, political readiness and Institutional Readiness were the only means of achieving a successful level of cooperation.

Table 7. Region fixed-effects regression (dependent variable: EC)

Variable	Estimate	Std. Error	t-value	p-value	Significance
DC	-0.0106	0.0709	-0.1496	0.8812	
CP	-0.0342	0.0633	-0.5395	0.5901	
PF	0.4833	0.0462	10.4673	< 2.2e-16	***
IC	0.9778	0.1103	8.8646	2.775e-16	***

Table 6 has additional controls to illustrate significant geographical variation within the variable (i.e., Europe, Asia, Russia) by adding the inclusion of geographic fixed effects; therefore, the addition of fixed effects provided additional evidence in the form of additional variables that show political tension and institutional capability are an important aspect across all three regions related to Eurasian Connectivity Cooperation. However, it should be noted that the significance and strong strength of these coefficients were shown to be stable, indicating they would likely be strong across all three regions. Similarly, there is no evidence of statistical significance for the possibility of Demographic Compatibility and Connectivity; however, the above-mentioned demographic/geo-political context will influence the potential for demographic and infrastructure influences to be felt through larger institutional/geo-political/infrastructural channels and will not operate in isolation from one another. This finding provides strong support not only for the earlier explanation of the conceptual framework but also for the empirical claim that the impacts of population dynamics on institutional and geo-political factors interact and provide a basis for determining the level of connectivity and cooperation that exists between the Eurasian nations.

Table 8. Region fixed-effects regression with robust clustered standard errors

Variable	Estimate	Std. Error	t-value	p-value	Significance
DC	-0.0106	0.0487	-0.2180	0.8276	
CP	-0.0342	0.1437	-0.2377	0.8123	
PF	0.4833	0.0949	5.0933	7.608e-07	***
IC	0.9778	0.2298	4.2542	3.114e-05	***

Table 8 indicates that the results of Model 2 are virtually identical to those obtained in Model 1 as presented in Table 7. While the same variables were utilized, the statistical methodology was modified to account for the presence of heteroskedasticity and serial correlation in the data, which was established through our diagnostic testing. Through controlling for regional influences and each year's influences, we see a substantial increase in variance explained through this model. Political conflict and institutional capability have remained the key drivers to promote working together on issues of connectivity in Eurasia. Conversely, when factoring the aforementioned drivers of cooperation using robust error variance clustering, it was shown that the potential for connectivity in Eurasia became increasingly negative. These findings confirm the contemporary Realist perspective, as the periods of rapid connectivity development and new trade routes coincide with instances of political instability and the introduction of sanctions or attempts to achieve dominance over neighboring regions.

Eurasia's cooperative response to connectivity opportunities grew progressively in a systematic way as time passed, and the analysis of the data using fixed year effects allows us to get a better sense for the development of that cooperative response. Prior to the collapse of the Soviet Union in 1991, cooperation among Eurasian countries was virtually non-existent. The inclusion of new trade routes available after the dissolution of the Soviet Union resulted in increased levels of cooperative activity among Eurasian countries. However, cooperative activity continued to be irregular, and that irregularity can be directly tied to various geopolitical and economic developments (e.g., the Financial Crisis of 2008 and the imposition of multiple sets of sanctions). While these changes have been a significant factor in influencing the cooperative behaviors of Eurasian countries regarding connectivity, long-run changes due to shifting population demographics and structure have been the primary drivers.

Table 9. Comparison of pooled, fixed-effects, and two-way fixed-effects models

Model	DC	CP	PF	IC	R-squared	Adj. R-squared
Pooled OLS	-0.091*	-0.016	0.521***	0.548***	0.510	0.501
Region FE	-0.011	-0.034	0.483***	0.978***	0.515	0.502
Region + Year FE	-0.095	-0.260	0.447***	0.367*	0.836	0.746

Table 9 presents a summary of the Pooled Model (Model 1), and the models with Region Fixed Effects (Model 2) and Two-Way Fixed Effects (Model 3). The Region fixed effects were an addition to the Base Pooled Model (PF). They statistically increased the number of significant coefficients for PF and IC compared to the other two models, which combined had around 84% R^2. The findings from the Two-Way Fixed Effects Model demonstrated a positive and significant coefficient for the Pooled Fixed Effects and an insignificant positive coefficient for the Intercountry fixed effects, using standard statistical significance. In comparison, the magnitude of the coefficient for Country (CP) was found to be negative. The periods of maximum CP connected the periods with maximum connectivity due to maximum competition and maximum sanctions, subsequently decreasing the total EC for Eurasia.

Table 10. Specification and diagnostic tests for panel regressions

Test	Statistic	df	p-value	Implication
F test for individual effects	F = 12.325	df1 = 2, df2 = 218	8.49e-06	Region fixed effects are jointly significant
LM (Breusch–Pagan) for RE vs pooled	$\chi^2 = 1.9017$	df = 1	0.1679	Weak evidence in favor of random effects over pooled OLS
LM for cross-sectional dependence	$\chi^2 = 48.05$	df = 3	2.078e-10	Strong cross-sectional dependence across regions
Pesaran CD test	z = 6.9102	-	4.839e-12	Confirms cross-sectional dependence in residuals
Breusch–Godfrey/Wooldridge serial correlation	$\chi^2 = 218.66$	df = 75	5.667e-16	Serial correlation present in idiosyncratic errors
Studentized Breusch–Pagan heteroskedasticity	BP = 38.295	df = 6	9.834e-07	Heteroskedasticity present; motivates robust SEs

The data presented in Table 10 show that the F test provides a strong case for the inclusion of fixed effects for each region. On the other hand, the Breusch-pagan LM statistic indicates that there is little support for random effects being used instead of OLS for the pooled sample. Another two tests, the LM and Pesaran CD test results, both provide strong evidence of cross-section dependence, as well as strong evidence of serial correlation in the residuals via the Breusch-Godfrey/Wooldridge test. The studentized Breusch-Pagan test results provide clear evidence of heteroskedasticity. Taken together, these test results allow for a sound justification for using fixed effect estimators along with robust, clustered standard errors, motivating the inclusion of time-fixed effects as well as dynamic specifications as robustness checks.

Table 11. Dynamic fixed-effects regression with lagged Eurasian cooperation

Variable	Estimate	Std. Error	t-value	p-value	Significance
Lagged EC	0.9898	0.0106	93.2862	< 2.2e-16	***
DC	0.0102	0.0131	0.7803	0.4361	
CP	-0.0743	0.0101	-7.3743	3.575e-12	***
PF	-0.0123	0.0092	-1.3490	0.1788	
IC	0.0104	0.0202	0.5167	0.6059	

The results of the modeling are shown in Table 11 and include the use of Dynamic Fixed Effects and a one period lag of EC. As such, these estimates show that Eurasian Connectivity will be significantly sustained throughout time, and once a specific channel of cooperation has been established (e.g., education, digital, logistics, energy, etc.), it is likely to exist indefinitely despite changes in the political and demographic environment that impact those channels from time to time. In the immediate future, there appears to be a significant negative effect of the potential for more connectivity on Eurasian Cooperation. This finding suggests that, as more digital corridors and/or infrastructure are developed, it creates an uncertain and competitive environment for the development of these types of projects; as demonstrated in earlier work on "weaponized interdependence". Demographic Complementarity, Political Friction, and Institutional Capability do not show any significant impact on Dynamic Modeling in the Short Term. Therefore, it is likely that these three

Structural Variables will have a long-term effect on the growth of Eurasian Cooperation, which will manifest over decades, rather than individual years.

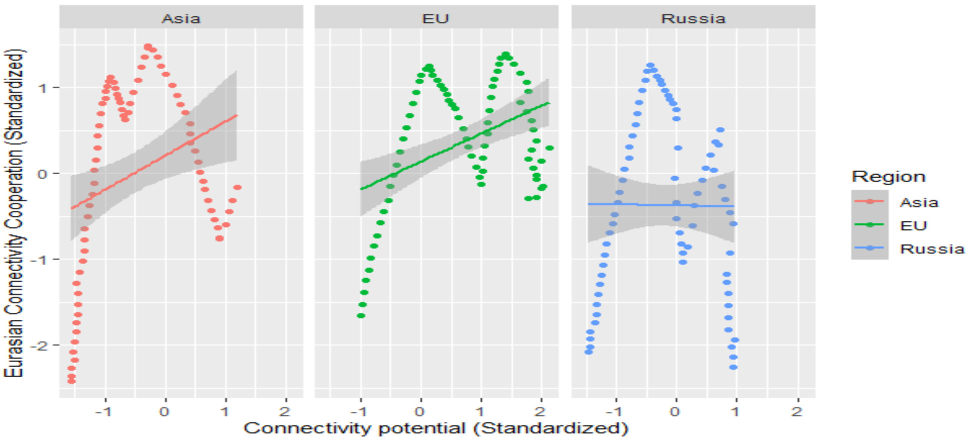

Figure 1. Scatterplots of EC versus Connectivity Potential (CP) by region

Figure 1 should show scatterplots of EC versus CP in regard to Asia, Europe, and Russia along with a fitted linear trend line for all regions. The scatterplot represents the correlation between CP (cost of capital) and EC (economic capital) in Europe as having a generally high positive correlation compared to scatterplots for Asia and Russia, which have weak to moderate correlations and are less concentrated geographically. Graphically demonstrating this correlation with the regression analysis indicates that CP has a moderate degree of correlation with EC and that once fixed effects and time dynamics are added, the correlation becomes even more complex.

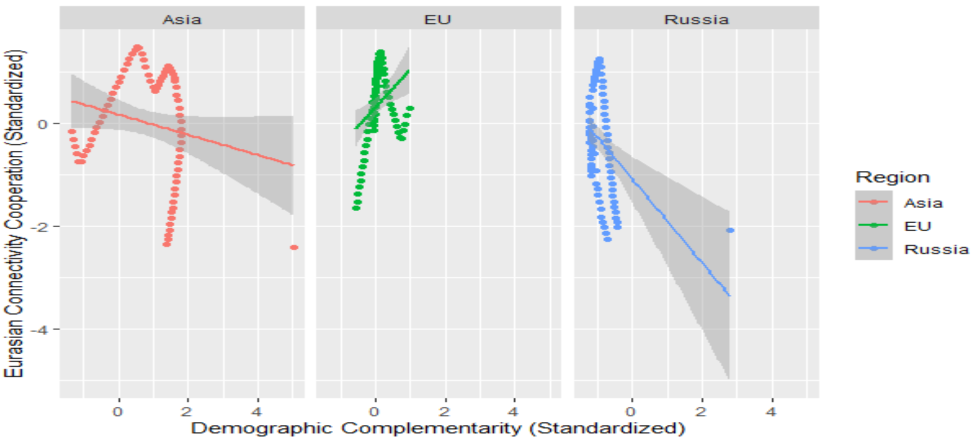

Figure 2. Scatterplots of EC versus Demographic Complementarity (DC) by region

Figure 2 shows the rankings of DC's and EC's for each region. Many of the points appear scattered on the chart with little relationship between the rankings of DC's and EC's. The Pearson coefficient in Table 4 illustrates that DC/EC pairings do not provide significant impact on each other. It would appear from this that demographic complementarity can help to enhance Eurasian cooperation but would also require increasing levels of connectivity and stronger institutions to achieve such an enhancement.

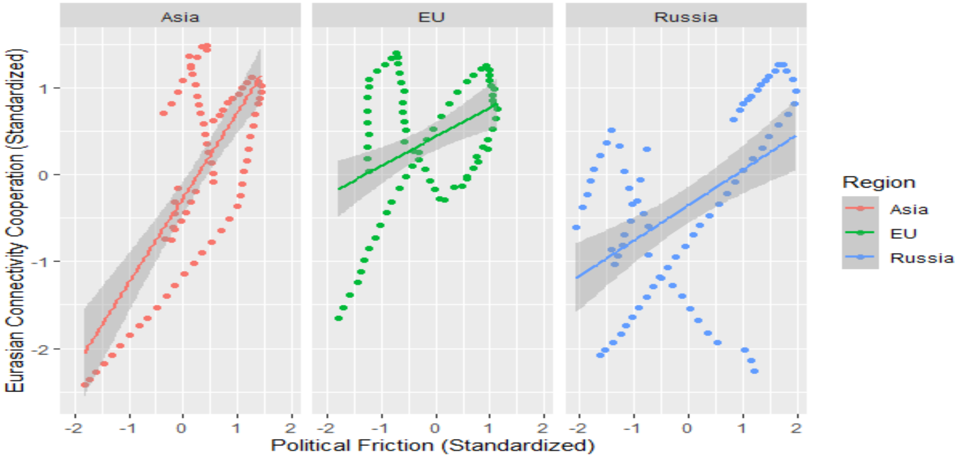

Figure 3. Scatterplots of EC versus Political Friction (PF) by region

In Graph 3, there seems to be a high correlation between PF (an indicator of less friction/slackness in relation to Politics) and EC (an indicator of how much a market supports Entrepreneurship), especially across the EU and some select Asian Economies. Additionally, not only does this scatterplot visually demonstrate this relationship, but the increasing arrows on the graphs suggest a statistically significant relationship as indicated by the PF coefficients in the Regression Analysis Tables.

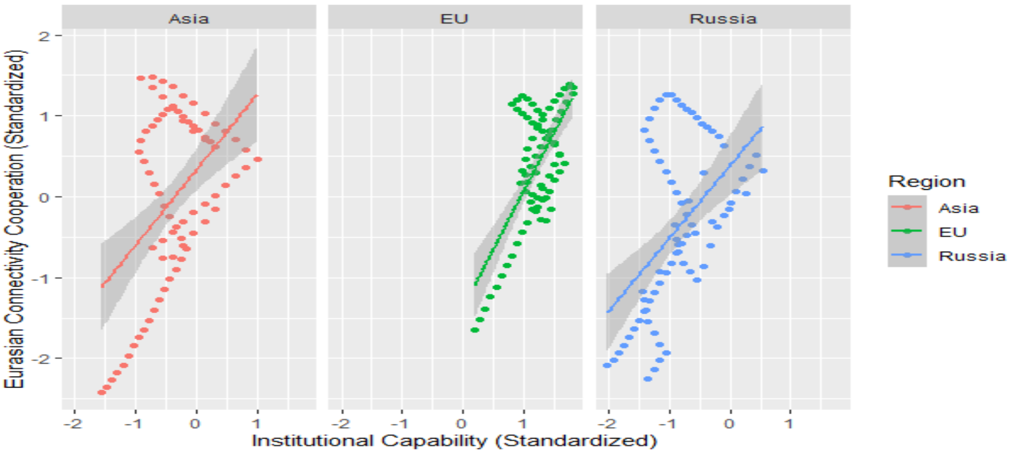

Figure 4. Scatterplots of EC versus Institutional Capability (IC) by region

Figure 4 will represent the correlation between the Economic Component (EC) and the Institutional Capacity (IC) ability. All of the country-specific regions represented on Figure 4 show that it is fairly common to see a correlation among countries in the EU region. Thus, an increase in IC should be associated with increased levels of cooperation between countries within the Eurasian continent. Similarly, Figure 4 provides evidence of this positive correlation that is consistent with the large IC coefficient seen in both the pooled and fixed effect models.

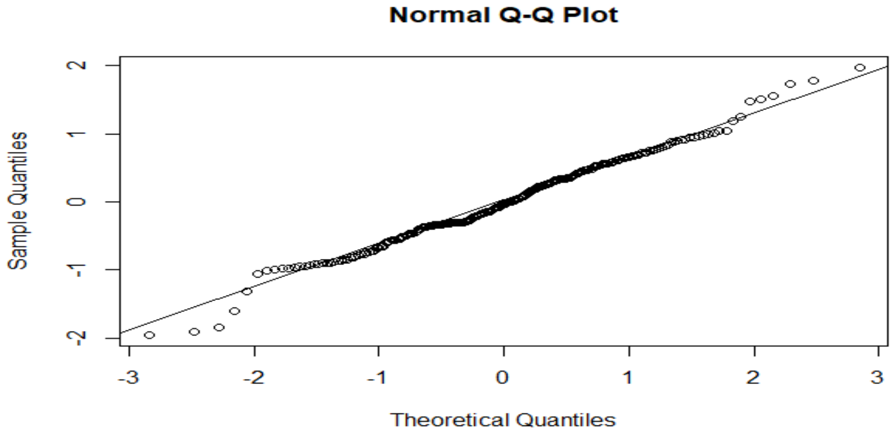

Figure 5. Residual diagnostics for the fixed-effects model

Residual diagnostics (e.g., time series plots of fixed effects residuals) will use both Figure 5 and Q-Q plots to assess whether time series plots of fixed effects residuals exhibit a certain degree of normality based upon the Q-Q plots. Typically, time series plots of fixed effects residuals will exhibit some form of serial correlation among the residuals while Q-Q plots will show that the residuals are approximately normally distributed as shown by the formal diagnostic statistics located in Table 9. The results of these visual assessments provide evidence in favor of using robust clustered standard error estimators but caution against making assumptions based on the traditional assumption of classical OLS.

4. Discussion

Empirical Results within the Theoretical Debate

According to the aforementioned arguments in this document, data derived from Validated Controlled Studies contributes to confirming the validity of the Demographics Complementarity Theory, by supporting its assumption about how Democratic Institutions Strengthen or Diminish the development of Demographic Complementarity Relationships between countries and their People. The association between the Variables of Institutional Strength and Manageable Political Friction enable the creation of Realistic opportunities for cooperation between Demographically Complementary Countries, as seen from the "Demographic Arbitrage" Theory and Realists' views of cooperation (as a means of attaining Strategic Goals). So, in summary the above reasons provide Evidence supporting the; 1.) Extended Cross-Country/Economic Development Theory. 2.) extended Cross-National Economic Development Theory. 3.) Conducting Empirical Research on Long-Run Demographic Complementary Relationships and the Potential Realization of Previously Held Written/Spoken Assumptions Regarding Demographic Complementarity.

The use of national currencies or domestic economic capacity as a single framework is also not supported by evidence; neither does the use of such currency or domestic economic capacity as a way of creating foreign cooperation between nations show how companies in these countries are able to create competitive advantages and how those same companies build inter-regional complementarities with one another using existing domestic economic systems. Instead, we argue that it is the emergence of inter-regional complementarities throughout Eurasia created by the interaction of the demographic, institutional, and geostrategic dimensions that enable companies to cooperate across international borders, rather than through the use of their domestic economic systems independently of one another as illustrated by the National Economic Model designed by Baş (2005, 2018). This is demonstrated in the National Economic Model developed by Baş (2005, 2018).

In this manner, demographic dimensions provide a potential framework for connecting across nations. Political and institutional dimensions are necessary to realize potential demographic connectors. We argue that demographic, institutional, and geostrategic dimensions have created the potential for companies to interact across international boundaries to the extent that they build inter-regional complementarities with one another; therefore, inter-regional demographic, institutional, and geostrategic dimensions can create opportunities for inter-regional economic cooperation.

Theoretical and Policy Implications

The results from this study empirically validate the original theoretical predictions made. The theory originally focused on North-South and South-South economic cooperation as a means to identify potential for cross-border complementarities through infrastructure, trade, and the establishment of institutions for the purpose of facilitating economic growth. The quantitative findings from this research support further evidence for that theory. The quantitative findings suggest that while demographic complementarities may not provide the basis for the initiation of cooperation between different continents, they can provide the foundations upon which such cooperation can happen if there are sufficient institutional capabilities and stable political systems to support it. This study further reinforces the conclusion that while demographic forces are often not the primary catalysts for intercontinental cooperation, they also cannot be regarded as merely inconsequential background circumstances that may influence potential for cooperation between continents.

Demographic factors affect how people use institutions and other means for development; conversely, demographic factors also influence how well institutions and other means will support the growth of demographic capabilities in an area. At the same time, research of the pooled and fixed effect models that provide evidence supporting a strong relationship between the ability of institutions to provide support to develop demographic capability indicates that the ability to create enduring forms of connectivity through demographic resources is based on effective institutions, or strong governance. Therefore, the regions that reliably possess strong institutional capacity are significantly more likely to develop their demographic advantages while the regions having weakly constructed governance will not have as high of a degree of success developing the demographic resources available in their areas.

A major determinant of the extent of connectivity between Eurasian regions is the actual occurrence of political friction. The quantitative analysis of empirical data collected from multiple regions and timeframes presents significant evidence for the theory that Regions with lower political friction have comparatively higher levels of inter-region connectivity as compared to Regions with greater political friction. It therefore follows, that there is substantial evidence to support the realist position that the ability to cooperate is primarily dependent upon political feasibility, rather than a result of ideological agreement such as normative integration of laws, etc. In addition, from the data analysis, it was concluded that to achieve demographic compatibility, both the connection potential to create connections is more complicated than is suggested by the descriptive and correlation analyses showing a positive correlation between cooperation and connectivity potential. While the descriptive and correlation analyses show the correlation between cooperation and connectivity, the dynamic model suggests that surges in connectivity potential in the short term often lead to decreased cooperation. The surge in connectivity potential often occurs as a result of the imposition of sanctions and the re-alignment of interests, and other circumstances producing the emergence of competition between a region's infrastructures. Thus, the increased connectivity potential creates an opportunity for competition between the two regions and inhibits the development of cooperative solutions. The findings concerning the potential to create connectivity align with the current literature concerning competitive strategies and weaponized interdependence as the governments and businesses of the different regions have begun to treat their various digital and physical infrastructures as contested (geopolitical) areas.

Using the Eurasian cross-regional model, as shown by the Dynamic Model for Eurasia, there was a very strong level of connectedness to one another. One of the most obvious examples of high connectivity in Eurasia would be through channels of cooperation that had already been developed, such as digital services, education, logistics routes, and energy partnerships, these channels offer the potential for long-term sustainability even with short-term volatility in the market. Thus, through the long-term viability potential, there is an indication that both demographic and institutional complementarity will be required in order to be able to define Long-Term Development paths for Eurasia. This also indicates that there should be continual evolving, high potential for either erosion or redirecting of institutions.

As such, this suggests that the Dynamic Model for Eurasia, should also contain additional modifications based on three principles identified in this study, in addition to augmenting the Cross-Country/Cross-Continental Economic Development Theory:

1. Demographic complementarity will indirectly influence an impact when there is political stability and institutional capability.

2. Institutional capability is the major catalyst for converting demographic and infrastructure resources into channels of Cooperation between the two economies.

3. Cooperation will always be durable because there is a constant cycle between the Long Term demographic and Institutional characteristics and vulnerability of economic structure to short-term shocks due to geopolitical tensions.

At present, demographic economics and political economy will eventually converge into one analytical model. What makes Eurasian cooperation different from other political economies is that in regards to Eurasia, the need to address demographic differences and geopolitical factors will serve to facilitate cooperation through both demographic and institutional means.

Development programs like the National Economy Model by Baş (2005, 2018) suggest that the economic performance of national economies that are based on domestic exchange rates and are guided by expectations or consumption-driven economic growth, cannot be attributed exclusively to patterns of economic cooperation between nations in different continents. Rather, inter-regional complementarity between countries, especially with regard to inter-regional demographic and institutional factors, is a major factor contributing to the overall degree of collaboration between neighboring countries. Evidence generated through analysis of this inter-regional complementarity demonstrates that inter-regional complementarity is the major driver influencing the extent to which countries in a given region cooperate with one another and that the national capacity of each individual country is a secondary factor. While heterodox development approaches do not contradict the National Economy Model's conclusions, the heterodox development models should be reviewed in the context of a much broader range of geopolitical and demographic dynamics.

These results imply from a domestic public policy perspective, that demographic change is now one of the biggest long-term structural influences on the international economic strategy of a nation.

The effect of demographic asymmetry will not only affect how countries interact with other countries from an evolutionary perspective; it is also one of the main drivers of how investment is transferred between nations; how the digital labor markets operate amongst differing nations; how countries interact through educational mobility; and how countries manage energy partnerships throughout East and West Eurasia. It is essential that policymakers have the awareness of demographic realities in order to establish and maintain successful institutional reforms (evolving governance frameworks); create digital infrastructure strategies that leverage on demographic realities and develop corridors of development in alignment with the demographic realities of the respective nations. Where appropriate, demographic realities are linked all together and can be the source of conflict if not effectively managed and governed. Therefore, it is imperative that policymakers must coordinate their governance and political will around assisting nations to maximize their respective demographic potentials and enhance their connectivity amongst themselves and through the regional and global economy.

5. Conclusions

In this project, we aimed to understand how demographic complementarity serves as an instrument to stabilize Eurasia by providing mechanisms for cooperation in times of geographic division and fragmentation. We have discovered that demographic factors do significantly influence cooperative abilities; however, the role of demographic complements is not directly correlated to the formation of cooperative relationships as previously believed. It is through the establishment of the foundation for cooperative relationships that demographic complements enable the development and establishment of cooperation, using institutional capabilities and political systems to facilitate long-term economic interconnections formed by the transformation of demographic and infrastructural differences.

Three overarching conclusions arise from the evidence

Europe, Russia, and Asia create a geo-economic triangle that has an unequal balance of power and resources within the three regions; yet, each of these three regions has not only an economic complementarity with the other two regions, but also represent different types of economic and infrastructure limitations based on different demographic, institutional, and geopolitical factors. Demographically, Europe is declining in population, while younger Asian economies are increasingly in need of European products and services and European technology. Economically, Asia is growing in population and a significant portion of this growth consists of new digital workers; thus, Asia requires investment, technology and access to the European market. According to Asia's geography and energy matrix (the physical movement of energy through Eurasia), Russia continues to control most of the energy routes and the transport of energy from Russia to Europe. Thus, the political environments in each of these regions and how they change or develop will play an integral role in developing the overall geopolitical relationship among Europe, Russia, and Asia.

Secondly, the political realities involved would determine the potential to convert the current complementary relationship among Europe, Asia and Russia, to a cooperative one, however, this conversion would most likely depend on the level of political friction currently existing between these regions along with the ability of the political system of each region to support cooperation.

As indicated by the data compiled on political friction and institutional capabilities for all three systems, there is a significant amount of political friction that exists and that economic logic is insufficient basis for cooperation. In order for cooperation to take place political tensions must be at levels to allow for cooperation, but in addition institutions must have institutional capacity for a long-term relationship to continue. Thus, demographic and infrastructural advantages do not offset the impact of weak governance or unresolved geopolitical differences.

The analysis of the evolution/resilience of Eurasian synergy reflects the historical influence of synergy on future cooperation through its long-established path-dependent nature as evidenced by the Dynamic Panel Model (50% or greater coefficient for lagged cooperation). That is, once a channel exists for cooperation, it will tend to perpetuate its existence by being influenced in a positive way by subsequent geopolitical shocks. As a result, it is possible for channels for cooperation to exist through multiple geopolitical disruptions; thus, the impact of any disruption cannot be negated quickly but will take a long time to reverse. Therefore, in the medium-to-long term demographic institutional compatibility is one of the strongest factors influencing the direction of cooperative relationships in Eurasia, while the intensity with which those relationships are being conducted correspond to the short-to-mid-term impacts of geopolitical disruption, but will not necessarily be negated over the long term.

In light of these findings, the policy implications are clear.

1. Policy strategies must explicitly align with demographic realities:

Europe's demographic decline requires policies that facilitate educational partnerships, managed migration, digital outsourcing, and collaborative innovation with younger regions. Asia must invest in human capital and technological upgrading to convert its demographic advantage into sustained productivity.

2. Institutional capability must be strengthened as a precondition for cooperation:

Without credible regulatory systems, national planning capacity, and rule-based coordination, demographic and infrastructural advantages cannot lead to meaningful cooperation.

3. Geopolitical management is essential.

Reducing political friction through diplomatic agreements, transparency initiatives, and conflict-minimizing institutions is a necessary condition to allow interregional complementarities to operate.

4. Connectivity corridors should be designed with political and demographic sensitivity.

Infrastructure and digital networks must reflect both demographic needs and geopolitical realities. Competitive corridor expansion without political coordination can trigger instability rather than cooperation.

5. Regional institutions must adopt demographic complementarity as a guiding framework.

Mechanisms such as the European Union's Global Gateway, China's Belt and Road Initiative, and the Eurasian Economic Union should incorporate demographic criteria into planning, focusing on education, skill mobility, and digital service exchange.

In conclusion, this study demonstrates that Eurasian connectivity is shaped by an interaction between demographic asymmetries, institutional capability, and geopolitical feasibility, rather than by demographic forces operating in isolation. While the Cross-Country Cross-Continent Economic Development Theory explains the structural conditions under which cooperation becomes viable, the empirical results indicate that the translation of demographic complementarities into durable economic cooperation requires supportive national-level policy instruments. In this regard, the National Economy Model offers a complementary policy perspective by emphasizing consumption capacity, social stabilization, and reduced external vulnerability as mechanisms for sustaining cooperation once it emerges. The findings therefore suggest that demographic complementarities gain practical relevance only when supported by institutional strength and domestic economic policies that enhance purchasing power and resilience. This integrated perspective underscores that long-term Eurasian cooperation is neither purely demographic nor purely geopolitical, but the outcome of coordinated demographic realities, institutional governance, and policy choices operating across national and cross-continental levels.

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The Relationship Between Energy Consumption and Human Development Index: The Role of Electricity, Natural Gas and Oil Consumption

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Abstract: The objective of this study is to empirically analyze the effects of electricity, natural gas, and oil consumption on the Human Development Index (HDI) in Turkey and to offer policy recommendations within the scope of sustainable development. To this end, unit root tests were applied to the time series data for electricity, natural gas, oil consumption, and HDI covering the 1990–2022 period, followed by the ARDL cointegration test to reveal the model's long- and short-run effects. According to the cointegration test results, a statistically significant relationship was observed in the short run between the one-period lagged value of oil consumption and the current period value of electricity consumption. While the one-period lagged value of oil consumption negatively affected the HDI in the short run, the current period value of electricity consumption affected it positively. In the long run, a significant relationship was found only between HDI and electricity consumption, with electricity consumption having a positive effect on the HDI. The impact of oil consumption on the HDI is transitory and becomes evident in the subsequent period. Electricity consumption, on the other hand, creates a stronger positive effect on the HDI in the long run rather than the short run.

Keywords: Human Development Index, Energy Consumption, Sustainability, ARDL Cointegration Test

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1. Introduction

Since the dawn of human history, energy needs have been regarded as an indispensable element for the survival of the human race, the procurement of sustenance, and the facilitation of physical and biological development [1]. However, over the years, these rudimentary perspectives on the concept of energy have been supplanted by more complex considerations. The concept of energy gained a broad field of application, particularly with the Industrial Revolution. The energy demand, which became increasingly intricate following the Industrial Revolution, led to an intensified human dependence on energy in daily life. Factors such as rapid technological advancement, the growth trajectories of economies, population growth, and the subsequent rise in housing needs, transportation requirements, and industrialization have caused a precipitous increase in energy demand. Today, energy consumption is utilized as an indicator of the social and economic development of nations. Nevertheless, the chaotic environment following the Industrial Revolution caused countries to undergo a difficult economic period. During this era, nations entered a process of rapid growth and development, evaluating economic and social progress solely through the lens of economic growth [2-3].

Until the 1970s, the concept of development was largely conceptualized and evaluated solely through per capita national income. The reliance on per capita income alone to explain national welfare drew significant criticism. Foremost among these criticisms was the notion that the level of per capita national income remains insufficient in explaining development on its own. Consequently, after the 1980s, the concepts of development and advancement were integrated, transforming "development" into a concept that encompasses not only economic progress but also human development [4]. Following this shift, in the 1990s, the concept of human development began to be utilized as a welfare indicator for countries, transcending per capita national income. The concept of human development first emerged as data in 1990 under the title of the Human Development Index (HDI), introduced by the Pakistani economist Mahbub ul Haq. The Human Development Index (HDI) was first introduced in the 1990 Human Development Report published by the United Nations Development Programme (UNDP). The index is constructed based on three core dimensions: life expectancy, education, and income. Specifically, it combines indicators of life expectancy at birth, educational attainment, and gross national income per capita. The HDI is calculated as the geometric mean of these three dimensions and is published annually at the country level, providing a broader measure of development that incorporates education and health alongside national income [5-6-7-8].

The objective of this study is to empirically analyze the effects of electricity, natural gas, and oil consumption on the Human Development Index in Türkiye and to offer policy recommendations within the scope of sustainable development. The primary motivation for selecting Türkiye as the sample of this study lies in the parallel trajectory observed over the past three decades between the country’s rising HDI performance and the structural transformation of its energy consumption patterns. As an emerging economy striving to achieve sustainable development goals, Türkiye’s demand for and dependence on energy resources have steadily increased. In this context, Türkiye provides a relevant case for examining how major energy sources, namely electricity, natural gas, and oil, influence welfare, access to healthcare, and educational outcomes. A review of the existing literature indicates that most studies focus on the relationship between aggregate energy consumption and the HDI. To provide greater analytical depth and address this gap in the literature, the present study disaggregates total energy consumption and concentrates specifically on electricity, natural gas, and oil consumption.

In Türkiye, electricity, natural gas, and oil consumption constitute approximately 82% of total energy consumption. The gradual substitution of fossil fuels by electricity and the increasing share of renewable energy sources in electricity generation are of critical importance for energy independence [9-10]. Beyond energy independence, this situation positively affects the HDI through the dimension of a long and healthy life by minimizing the environmental impacts caused by fossil fuels [11]. Furthermore, the role of electricity in healthcare services, education, and economic activities is gaining increasing importance. It is evident that electricity plays a critical role in the HDI, as it enhances the living comfort and welfare levels of individuals in all areas of daily life [12-13]. The type of resources used in electricity generation in Türkiye is significant for the HDI. In a scenario where fossil fuels are heavily utilized in electricity production, environmental problems may arise.

Moreover, disruptions in energy supply or fluctuations in energy prices would adversely affect economic stability, thereby negatively impacting the HDI. In a scenario where the share of renewable energy sources in electricity generation is high, a positive effect on the HDI is expected by minimizing the negative impacts of environmental issues and energy dependency.

While the share of natural gas and oil resources in Türkiye's total energy consumption was 50% in 2000, this figure has risen to 62% today. This situation can negatively affect the HDI through health and quality of life by causing environmental issues [14]. The production of such intensely consumed resources also becomes vital. The limited production of natural gas and oil in Türkiye leads to nearly all of these İtwo resources being supplied through imports. The fact that Türkiye is a resource-poor country in terms of natural gas and oil reserves, combined with the intensive consumption of these two sources, poses a challenge for energy security. This situation could hinder the achievement of sustainable development goals by negatively affecting Türkiye's economic stability in the event of even the slightest problem in energy flow. While natural gas and oil consumption can have such negative effects on the HDI, positive effects can also be observed. Natural gas and oil are fundamental energy sources used in the manufacturing sector [15]. The growth of these sectors increases the income levels of individuals, leading to a rise in living standards and a positive impact on the HDI. Natural gas, on the other hand, meets heating needs, particularly in residential areas and health facilities. This situation is thought to positively affect the HDI by improving the quality of healthcare services and ensuring healthy living conditions [16].

In the subsequent sections of the study, a literature review related to the subject will be presented. Following the literature review, the effects of electricity, natural gas, and oil consumption on the Human Development Index will be examined in line with the study's objective. Subsequently, the dataset and the model will be introduced, followed by the methodology and econometric findings. In the conclusion section, the empirical findings will be discussed, and energy-specific policy recommendations will be made, taking into account the effects of electricity, natural gas, and oil resources on the Human Development Index.

2. Literature Review

Access to energy resources constitutes a critical issue for emerging economies such as Türkiye. Energy functions not only as a production input but also as a fundamental determinant of human development, as reflected in the Human Development Index (HDI), which incorporates education, healthcare, and living standards. In this regard, examining how the composition of energy consumption influences the HDI is essential for designing effective energy policies and translating them into broader social welfare gains.

Niu et al. (2013) analyze the causal relationship between electricity consumption and the HDI for 50 countries classified by income groups over the period 1990–2009, employing panel data techniques. Their empirical framework includes variables such as the HDI, GDP per capita, consumption expenditures, urbanization rate, life expectancy at birth, and adult literacy rate. The findings indicate that electricity consumption exerts a positive and statistically significant effect on the HDI in high-income countries [9].

Ouedraogo (2013) investigate the relationship between energy consumption, electricity consumption, and the human development index for 15 developing countries between 1988 and 2008 using panel data analysis. In this framework, the HDI was designated as the dependent variable, while total energy consumption, electricity consumption, and Brent crude oil prices were used as independent variables. It was observed that total energy consumption and electricity consumption had little effect on the HDI in the short run. In the long run, however, it was concluded that while there is a negative cointegration relationship between total energy consumption and the HDI, a positive cointegration relationship exists between electricity consumption and the HDI [14].

Wang et al. (2018) investigate the relationship between renewable energy consumption, economic growth, and the Human Development Index in Pakistan for the period 1990–2014. Their empirical model includes carbon emissions, renewable energy consumption, economic growth, trade openness, and urbanization as explanatory variables. The results suggest that renewable energy consumption and carbon emissions positively contribute to the HDI, while trade openness, economic growth, and urbanization have a negative effect on human development [17].

Adekoya et al. (2021) examine the effect of renewable energy consumption and carbon emissions on the human development index by dividing 126 countries into 8 regions for the period 2000–2014 through panel data analysis. It was observed that renewable energy consumption affects the human development index in most regions, though results vary by region. Specifically, it was concluded that renewable energy consumption negatively affects the HDI in the MENA, Central America, and Caribbean regions, while having a positive impact on the European region. Furthermore, carbon emissions were found to have a positive effect on the human development index across all regions [18].

Türkmen & Naimoğlu (2021) aimed to test the hypothesis of the necessity of energy use for poverty reduction and the improvement of life quality in Türkiye, considering the period 1990–2019 and utilizing variables such as energy consumption, energy prices, and the human development index. The findings indicate that energy consumption is a significant variable for increasing the human development index in the long run, whereas the index shows minimal response to energy price changes. In the short run, it was concluded that energy consumption affects the HDI positively in the current period but negatively in its lagged value, while energy prices remained ineffective [19].

Kaewnern et al. (2023) employ panel data analysis for a group of countries ranked among the top ten in the Human Development Index, namely Norway, Switzerland, Ireland, Germany, the People's Republic of China, Australia, Iceland, Sweden, Singapore, and the Netherlands, over the period 1996–2007. The study investigates the impact of economic growth, renewable energy consumption, research and development (R&D) expenditures, and total natural resource rents on the HDI. The empirical findings indicate that all independent variables exert a positive effect on human development. In addition, the results reveal a unidirectional causality running from the HDI to renewable energy consumption and R&D expenditures, as well as a bidirectional causal relationship between the HDI and economic growth [20].

Durgun (2023) observed the relationship between total energy consumption and the human development index in Türkiye using time series analysis, considering data from 1990 to 2021. According to the cointegration test results, a cointegration relationship was found between the variables. In the long run, the effect of energy consumption on the human development index is positive and significant. According to causality test results, there is a unidirectional causal relationship from energy consumption to the human development index in the long run [21].

Akpolat, A. G. and Bakırtaş, T. (2024) studied the BRICS countries together with Egypt, Iran, and Türkiye for the period 1990–2021. Using panel data analysis, they examined the relationship between renewable energy consumption, fossil fuel consumption, carbon emissions, and the Human Development Index (HDI). Their results show a U-shaped relationship between renewable energy consumption and the HDI. This means that renewable energy may have a negative or weak effect on human development at low levels, but its effect becomes positive after a certain point. They also found an inverted U-shaped relationship between fossil fuel consumption, carbon emissions, and the HDI. In other words, fossil fuels and carbon emissions may support human development at first, but after reaching a certain level, they start to harm it [22].

Akyazı, S. and Korkmaz, İ. (2024) examined the relationship between the green economy and the Human Development Index in Türkiye between 1990 and 2018. They used variables such as HDI, energy consumption, green patents, and carbon emissions. According to the Granger causality test results, the HDI is a Granger cause of energy consumption, green patents, and carbon emissions. This means that changes in human development help predict changes in these variables [23].

Kutlu, Ş. Ş. (2024) examined the effects of human development and renewable energy consumption on environmental sustainability in Türkiye for the period 1990–2020. The study used variables such as ecological footprint, the Human Development Index (HDI), renewable energy consumption, and industrial sector value-added. The findings show that, in the long run, human development improves environmental sustainability by reducing the ecological footprint [24].

Akın, F. and Dinçer, S. (2025) conducted a panel data analysis for newly industrialized countries, including Brazil, China, India, Indonesia, Malaysia, Mexico, the Philippines, South Africa, Thailand, and Türkiye, covering the period 1990-2022. The study analyzed the effects of renewable energy consumption and the Human Development Index on economic growth. The results show that both renewable energy consumption and the HDI have a positive and significant effect on economic growth. At the country level, renewable energy consumption positively affects growth in China, India, Indonesia, and Türkiye. The study also found a two-way (bidirectional) causality between the HDI and economic growth, and between the HDI and renewable energy consumption [25].

3. Econometric Analysis

In this section, information regarding the dataset and the model to be utilized in the analysis will be provided first. Subsequently, the econometric methodology will be discussed, followed by the econometric analysis phase in accordance with the objective of the study.

3.1. Dataset and Model

An econometric model has been established to test the relationship between the HDI and energy consumption. In the constructed model, the variables of the Human Development Index, electricity consumption, natural gas consumption, and oil consumption were employed to examine the impact of energy consumption on the HDI. The Human Development Index serves as the dependent variable, while electricity consumption, natural gas consumption, and oil consumption variables are utilized as independent variables. To reduce the risk of heteroscedasticity caused by the large scale and high variation in energy consumption data, the natural logarithms of these variables were taken. This transformation also helps the data become more stable. In contrast, since the Human Development Index (HDI) is already a normalized index ranging from 0 to 1, it was included in the model in its original level form. The econometric model of the study was tested using the following equation:

$$HDI_t = \beta_0 + \beta_1 LNELEC_t + \beta_2 LNNAT_t + \beta_3 LNOIL_t + \varepsilon_t \quad (1)$$

In the model, β_0 represents the constant term, β_1, β_2 and β_3 denote the partial regression coefficients of the model, and ε_t refers to the error term. Detailed information regarding the other variables is presented in Table 1.

Table 1. Information on Variables

Name	Description	Type	Period	Source
HDI	Human Development Index	-	1990-2022	UNDP
LNELEC	Electricity Consumption	Bin TEP	1990-2022	EİGM
LNNAT	Natural Gas Consumption	Bin TEP	1990-2022	EİGM
LNOIL	Oil Consumption	Bin TEP	1990-2022	EİGM

Reference: [26-27].

Data on electricity consumption, natural gas consumption, and oil consumption were obtained from the General Energy Balance tables of the General Directorate of Energy Affairs (EİGM), while the Human Development Index was sourced from the United Nations Development Programme (UNDP) statistical databases. The variables utilized in the study consist of annual data covering the period 1990–2022, each comprising 33 observations.

Table 2. Descriptive Statistics of Variables

	HDI	LNELEC	LNNAT	LNOIL
Mean	0.7217	4.0443	3.9045	4.4615
Median	0.7110	4.0874	4.0430	4.4410
Maximum	0.8550	4.3882	4.4752	4.6457
Minimum	0.5980	3.5941	2.8520	4.2950
Standard Deviation	0.0856	0.2463	0.4449	0.1024
Skewness	0.1486	-0.2847	-0.5766	0.5002
Kurtosis	1.6225	1.8504	2.3866	2.2641
Jarque- Bera	2.7306	2.2629	2.3462	2.1210
Prabability	0.2553	0.3226	0.3094	0.3463
Observations	33	33	33	33

Table 2 presents the descriptive statistics for the variables. Between 1990 and 2022, the average Human Development Index value for Türkiye was 0.7217. Considering this multi-year average, it is possible to state that Türkiye is among the countries exhibiting high human development. The standard deviations of the series are notably low, indicating that the majority of the data points are clustered around the mean. Among the energy sources, natural gas exhibits the highest standard deviation at 0.4449, whereas the series with the lowest standard deviation is oil, at 0.1024.

3.2. Econometric Methodology

The unit root tests developed by Dickey and Fuller (1979) are applied not only to first order autoregressive processes but also to higher order autoregressive processes. A first order autoregressive model is constructed as follows [28].

$$Y_t = \Phi_1 Y_{t-1} + \varepsilon_t \tag{2}$$

Here, the error term (ε_t) is expected to be a clean sequence. However, if the variables do not fit the first order autoregressive model, then contrary to what is expected, there will be autocorrelation in the error term. Therefore, this problem of autocorrelation in the error terms should be eliminated. Dickey and Fuller (1981) developed the Dickey and Fuller (1979) unit root test to eliminate the autocorrelation problem in the error term, and lagged values of the dependent variable were added to the model. This was an attempt to eliminate the autocorrelation problem in the error term. This model is called the Augmented Dickey-Fuller unit root test [28-29-30].

Augmented Dickey-Fuller equations are written as follows to test for the presence of a unit root in the series:

$$\triangle Y_t = \delta Y_{t-1} + \textstyle\sum_{j=1}^{p} \delta_i \triangle Y_{t-j} + \varepsilon_t \tag{3}$$

$$\triangle Y_t = \mu + \delta Y_{t-1} + \textstyle\sum_{j=1}^{p} \delta_i \triangle Y_{t-j} + \varepsilon_t \tag{4}$$

$$\triangle Y_t = \mu + \beta t + \delta Y_{t-1} + \textstyle\sum_{j=1}^{p} \delta_i \triangle Y_{t-j} + \varepsilon_t \tag{5}$$

When we look at these three equations, equation (3) refers to the test equations without constant term and trend, equation (4) includes constant term, and equation (5) includes both constant and trend. In this case, these tests are called Augmented Dickey-Fuller unit root tests [31-32].

In the Dickey-Fuller unit root test, it is assumed that the distribution of shocks is statistically independent and their variance is constant. In other words, it is assumed that there is no autocorrelation between shocks. Phillips-Perron (1988) developed a nonparametric unit root test in their study. In this study, Phillips-Perron improves these assumptions developed by Dickey-Fuller and Augmented Dickey-Fuller and makes a new assumption about the distribution of randomly occurring shocks. Three different equations can be developed for the Phillips-Perron unit root test. However, a simple equation for the Phillips-Perron test can be given as follows [33].

$$Y_t = \mu + \Phi_1 Y_{t-1} + \varepsilon_t \tag{6}$$

$$(1 - \Phi_1 L) Y_t = \mu + \varepsilon_t$$

In this equation, the unit root for the model is found with $1/\Phi_1$. When $\Phi_1 = 1$, the series contains unit root, which means that the series is non-stationary. In the Dickey-Fuller unit root test, the τ (tau) test will be used, while in the Phillips-Perron unit root test it will be expressed as Z_a. The formula used for the PP unit root test is given below.

$$Z_a = T(\Phi_1 - 1) - CF \tag{7}$$

Here CF is used as correction factor. In this context, if the test statistic calculated in equation (7) is greater than the critical value, it is concluded that the series contains unit root, that is, it is non-stationary [34].

Zivot Andrews (1992) constructed the test with the assumption that the break time is unknown. While Perron (1989) estimates the break time as an exogenous variable in the model, in Zivot Andrews approach, the break time is estimated as an endogenous variable in the model. According to Zivot Andrews, estimating the break time as an exogenous variable in the model will change the test results in the direction of no unit root. In the Zivot Andrews approach, the break time is assumed to be at any point. Zivot Andrews unit root test Model A (Intercept) allows for a break in level, Model B (Trend) allows for a break in trend and Model C (Intercept and Trend) allows for a break in both level and trend [35-36].

Model A $$Y_t = \mu + \beta t + \Phi_1 Y_{t-1} + \gamma_2 DU_t(\lambda) + \sum_{j=1}^{p} \delta_j \triangle Y_{t-j} + \varepsilon_t \quad (8)$$

Model B $$Y_t = \mu + \beta t + \Phi_1 Y_{t-1} + \gamma_3 DUM_t(\lambda) + \sum_{j=1}^{p} \delta_j \triangle Y_{t-j} + \varepsilon_t \quad (9)$$

Model C $$Y_t = \mu + \beta t + \Phi_1 Y_{t-1} + \gamma_2 DU_t(\lambda) + \gamma_3 DUM_t(\lambda) + \sum_{j=1}^{p} \delta_j \triangle Y_{t-j} + \varepsilon_t \quad (10)$$

Here, $\mathrm{DU_t}$ denotes a dummy variable at the level, while $\mathrm{DUM_t}$ denotes a break in slope. μ is the intercept and ε_t is the error term.

In Johansen and Engle-Granger cointegration tests, variables are expected to be stationary at the same degree. In addition, ignoring lagged values of variables in Johansen and Engle-Granger cointegration tests leads to specification errors. Pesaran and Shin (1995) and Pesaran et al. (2001) proposed an autoregressive distributed lag (ARDL) model instead of using equations for cointegration relationship. Thus, the ARDL model has started to be used as a model that allows us to examine the cointegration relationship between variables that are stationary of different degrees. The ARDL model has advantages such as allowing us to perform cointegration tests on variables that are stationary at different degrees and providing statistically more reliable results by using the unconstrained error correction model [37-38]. The following process is followed to explain the ARDL model.

$$Y_t = a + \sum_{j=1}^{k} a_i Y_{t-j} + \sum_{j=0}^{k} \beta_i X_{t-j} + \varepsilon_t \quad (11)$$

After determining the lag length of the model, the bounds test is applied to determine whether there is a cointegration relationship between the variables. As a result of the bounds test, the F-statistic value is obtained. When this value is compared with the lower and upper critical values, it is concluded whether there is a cointegration relationship between the series. If the F-statistic value obtained here is greater than the upper critical value, there is a cointegration relationship between the variables, if it is less than the lower critical value, there is no cointegration relationship between the series, and if it is between the lower and upper critical values, no comment can be made on whether there is a cointegration relationship between the series.

3.3. Econometric Findings

To reveal the long-term and short-term relationships between the series, stationarity tests will be conducted first. The integration levels of the series will be determined through stationarity testing, and the appropriate cointegration method will be selected based on these results to perform the long-term and short-term analysis of the model.

3.4. Unit Root Test Results

In econometric analysis, non-stationary series lead to various issues, most notably the problem of spurious regression. In a model suffering from spurious regression, the R^2 value appears higher than its actual value, which calls the reliability of the study into question. Therefore, unit root tests are a prerequisite for the model to yield statistically more reliable results. This prerequisite also plays a decisive role in selecting the specific analytical methods to be applied to the model. In addition to traditional unit root tests, this study also utilizes unit root tests that account for structural breaks. The hypotheses for the unit root tests are formulated as follows:

H_0: The series contains a unit root (the series is non-stationary).

H_1: The series does not contain a unit root (the series is stationary).

Table 3. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Test Results

	ADF				**PP**			
	Level		**First Difference**		**Level**		**First Difference**	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend	Intercept	Intercept and Trend	Intercept	Intercept and Trend
HDI	0.2200	-1.9134	-4.5384[a]	-4.4714[a]	0.1126	-2.1734	-4.5378[a]	-4.4735[a]
LNELEC	-2.4826	-0.9552	-4.5574[a]	-5.2453[a]	-7.3937[a]	-0.1016	-4.5746[a]	-11.7205[a]
LNNAT	-3.5520[b]	-3.7102[b]	-4.4006[a]	-4.6965[a]	-4.2885[a]	-4.1301	-4.4994[a]	-8.2757[a]
LNOIL	-0.5180	-1.9898	-6.0602[a]	-5.9399[a]	-0.4703	-1.9963	-6.0559[a]	-5.9368[a]
Critical Values								
1%	-3.6537	-4.2733	-3.6617	-4.2846	-3.6537	-4.2733	-3.6617	-4.2846
5%	-2.9571	-3.5578	-2.9604	-3.5629	-2.9571	-3.5578	-2.9604	-3.5629

Note: The optimum lag length in the ADF Unit Root Test is determined according to the Schwarz Information Criterion and the optimum bandwidth in the Phillips-Peron Unit Root Test is determined according to the Newey-West Bandwidth method. The letters a and b indicate that the series is statistically significant at the 1% and 5% significance level, respectively.

Table 3 presents the results of the traditional unit root tests. According to the ADF and PP unit root tests, the null hypothesis was rejected for the HDI and LNOIL variables after taking their first differences, indicating that these series are stationary. For the LNNAT series, both tests concluded that the variable is stationary at its level value. Regarding the LNELEC series, while the ADF test indicated stationarity at the first difference, the PP test suggested that the series is stationary at levels. Consequently, based on the ADF and PP unit root test results, it was concluded that the HDI and LNOIL series are integrated of order one I(1), whereas the LNNAT and LNELEC series are integrated of order zero I(0).

Another reason for the non-stationarity of series containing a unit root is that shocks to the series leave a permanent effect. Put differently, in the presence of structural breaks, traditional unit root tests like ADF and PP, which do not account for such breaks, tend to yield results favoring the acceptance of the null hypothesis (i.e., that the series is non-stationary). Therefore, in addition to traditional unit root tests, Zivot-Andrews and Lee-Strazicich unit root tests, which incorporate structural breaks, were applied to the series.

Table 4. Results of Zivot-Andrews and Lee-Strazitch Unit Root Test with Breaks

	Zivot-Andrews				**Lee-Strazitch**			
	Level		**First Difference**		**Level**		**First Difference**	
	Model A	Model C	Model A	Model C	Model A	Model C	Model A	Model C
HDI	-3.66	-4.55	-5.61[a]	-6.22[a]	-2.412	-10.045[a]	-4.518[a]	-7.305[a]
Structural Break	2010	2013	2016	2019	2002 2015	2006 2011	2006 2017	2008 2011
LNELEC	-2.99	-3.20	-5.64[a]	-5.54[b]	-2.193	-5.215	-5.533[a]	-6.359[b]
Structural Break	1999	2006	2004	2004	2013 2018	1999 2004	1997 2005	1997 2000
LNNAT	-4.99[b]	-4.26	-5.34[a]	-6.21[a]	-1.471	-6.253[b]	-4.00[b]	-7.727[a]
Structural Break	2003	2005	1998	2003	2011 2017	1998 2003	1996 2001	2001 2008
LNOIL	-5.46[a]	-4.64	-3.65	-5.38[b]	-3.075	-9.410[a]	-6.482[a]	-7.145[a]
Structural Break	2015	2015	2011	2015	2000 2014	1999 2013	1996 2011	1998 2012
Critical Values								
1%	-5.34	-5.57	-5.34	-5.57	-4.073	-6.821	-4.073	-6.821
5%	-4.93	-5.08	-4.93	-5.08	-3.563	-6.166	-3.563	-6.166

Note: The letters a and b indicate that the series is statistically significant at 1% and 5% significance level, respectively.

According to the results of both unit root tests that account for structural breaks presented in Table 4, the null hypotheses for the LNNAT and LNOIL series were rejected, concluding that they are stationary at their level values. While the ADF and PP tests suggested that the LNOIL series was non-stationary at levels, the Zivot-Andrews (ZA) and Lee-Strazicich (LS) tests—which incorporate structural breaks—asserted that the series is stationary at levels. In fact, while the LNOIL series is stationary at its level value, it was observed that a "spurious non-stationarity" existed due to the structural breaks within the series. According to the ZA test, the LNELEC and HDI series became stationary after their first differences were taken. Regarding the LS test, which accounts for two breaks, the LNELEC series became stationary at the first difference, whereas the HDI series was found to be trend-stationary at its level value. Consequently, the ZA and LS break-incorporating unit root tests yielded results consistent with the ADF and PP tests, with the exception of the LNOIL series.

The ZA and LS unit root test results in Table 4 indicate that the variables experienced structural breaks in similar years. The most striking structural break date in the table is 2011. This year represents a period when the Turkish economy grew by approximately 9%, and industrial production along with household welfare reached peak levels. This high growth performance created a break in the LNELEC, LNNAT, LNOIL, and HDI series. For the LNELEC and LNNAT series, break dates are clustered around 2003, 2004, and 2005. The implementation of the Energy Market Law in 2003 led to the liberalization of the energy sector and its rapid expansion. Particularly after 2003, the expansion of natural gas infrastructure for the purpose of resource diversification led to a rapid increase in the share of natural gas in energy consumption. This process, which began with the liberalization of the energy sector, structurally influenced the electricity and natural gas consumption series.

The ZA unit root test identifies 2015 as the break date for the LNOIL series. In 2015, there was a surge in US shale oil production. Meanwhile, OPEC did not reduce oil production as part of its strategy to protect market share. The simultaneous occurrence of these two situations caused an unprecedented supply glut in global energy markets. Concurrently, developments such as the decline in growth rates in Asian and European countries and the subsequent decrease in energy demand led to a drop in oil prices of approximately 80 dollars/barrel. The fall in oil prices resulted in lower production and logistics costs, creating a structural break for the LNOIL series in 2015.

3.5. ARDL Cointegration Bound Test Results

Based on the unit root test results, the ARDL (Autoregressive Distributed Lag) Cointegration Bound Test was employed to examine the long-term and short-term relationships between the variables. In the ARDL bound test, the primary requirement is to determine the optimal lag length of the model. Prior to identifying the optimal lag, the maximum lag length to be utilized in the model must be established. The accurate specification of the lag length is of vital importance for the reliability of the model. The determination of the maximum lag length varies depending on the data type and the sample size used in the study. Due to data constraints and the use of annual data, the maximum lag length in this study was set to 2, and the Schwarz Information Criterion (SIC) was utilized for model estimation. After determining the maximum lag length and the information criterion, the most appropriate model for the ARDL cointegration bound test was identified as the ARDL(1, 0, 0, 1) model. The hypotheses for the cointegration test are formulated as follows:

H_0: There is no cointegration relationship between the series

H_1: There is a cointegration relationship between the series.

Once the appropriate model is determined in the ARDL cointegration test, a Bound Test is applied to establish whether a cointegration relationship exists between the variables. In the bound test, if the F-statistic value is greater than any of the upper bound critical values, the null hypothesis is rejected, and it is concluded that a long-term cointegration relationship exists between the variables.

Table 5. ARDL (1,0,0,1) Model Bound Test Results

			Critical Values	
k	**F-Statistic**	**Significance Level**	*Lower Bound (I0)*	*Upper Bound (1)*
3	10.0420[a]	%1	3.65	4.66
		%5	2.79	3.67

Note: *k* denotes the number of independent variables. The letters *a* and *b* indicate statistical significance at the 1% and 5% levels, respectively. The lower and upper bound critical values were obtained from Table CI(ii) Case II in the study by Pesaran et al. (2001), [38].

Table 5 presents the results of the ARDL (1,0,0,1) model bound test. Since the calculated F-statistic value exceeds the upper bound critical value at the 1% significance level, the null hypothesis is rejected. Consequently, it is concluded that a cointegration relationship exists between electricity consumption, natural gas consumption, oil consumption, and the Human Development Index during the period under study.

Table 6. ARDL (1,0,0,1) Model Long-Run and Short-Run Estimation Results

Long-Run Coefficients				
Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Probability*
LNELEC	0.7925[a]	0.2219	3.5719	0.0013
LNNAT	-0.1627	0.1124	-1.4478	0.1588
LNOIL(-1)	-0.3635	0.2698	-1.3473	0.1887
C	-0.1911	0.8415	-0.2271	0.8220
Short-Run Coefficients				
Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Probability*
HDI(-1)	-0.2090[b]	0.0910	-2.2960	0.0303
LNELEC	0.1656[b]	0.0639	2.5919	0.0157
LNNAT	-0.0340	0.0267	-1.2720	0.2151
LNOIL(-1)	-0.0760[b]	0.0358	-2.1207	0.0440
C	-0.0399	0.1883	-0.2122	0.8337
D(LNOIL)	0.0034	0.0525	0.0650	0.9487
DUMMY	-0.0076[b]	0.0036	-2.1139	0.0447
ECT (-1)	-0.2090[a]	0.0274	-7.6318	0.0000
Diagnostic Test Results				
R^2			0.9966	
Adjusted R^2			0.9958	
Breusch-Godfrey Serial Correlation Test			3.1678 (0.2052)	
Jarque-Bera Normality Test			2.2517 (0.3243)	
F-statistic			1216.6 (0.0000)	
Breusch-Pagan-Godfrey Heteroscedasticity Test			8.2465 (0.2206)	
Ramsey RESET Test			0.5187 (0.4787)	

Note: The letters *a* and *b* denote that the series is statistically significant at the 1% and 5% levels, respectively. The values in parentheses represent the probability (p-values).

The long-run and short-run coefficient estimations of the ARDL (1,0,0,1) model are presented in Table 6. Upon examining the long-run coefficients, a cointegration relationship was previously identified between electricity, natural gas, and oil consumption and the HDI. When evaluating the long-run coefficients in the model, the one-period lagged value of oil consumption and the current-period value of natural gas consumption were found to be statistically insignificant. This indicates that a reliable and distinct relationship could not be established between oil and natural gas consumption and the HDI. Instead, this relationship manifests through indirect effects rather than direct ones. In essence, this suggests that the long-term impact of oil and natural gas on welfare is transmitted through electricity generation and their roles as intermediate inputs.

Conversely, the long-run relationship between electricity consumption and the HDI was found to be statistically significant at the 1% level. In other words, while other variables are held constant (ceteris paribus), a 1% increase in electricity consumption results in a 0.7925% increase in the HDI in the long run. This finding demonstrates that electricity is not merely a technical energy input; it functions as a fundamental leverage for the HDI, directly facilitating everything from healthcare services and the digitalization of education to high-value-added production.

In the short run, a positive cointegration relationship was identified between electricity consumption and the HDI, consistent with the long-run findings. While other variables are held constant, a 1% increase in electricity consumption results in a 0.1656% increase in the HDI. This indicates that while increases in electricity consumption are immediately reflected in the HDI, the impact remains more limited compared to the long-run effect. Furthermore, while only electricity consumption showed a statistically significant relationship with the HDI in the long run, the one-period lagged value of oil consumption was found to be statistically significant at the 5% significance level in the short run. However, the relationship between the lagged value of oil consumption and the HDI is negative. Specifically, ceteris paribus, a 1% increase in the one-period lagged value of oil consumption leads to a 0.0760% decrease in the HDI. It is considered that as the consumption of import-dependent resources like oil increases, although short-term economic growth may be achieved, this situation negatively affects purchasing power (the income component of the HDI) in the subsequent period through the channels of current account deficits and inflation.

Furthermore, the coefficient of the dummy variable, included exogenously to represent the identified structural break, was found to be negative and statistically significant at the 5% level. This result indicates that the period of structural break identified in the model (the shocks between 2005-2012) exerted downward pressure on the HDI. The Error Correction Term (ECT) was found to be negative and statistically significant at the 1% level, as expected. This confirms that the error correction mechanism is operational and that short-term deviations occurring in the model converge back to equilibrium in the long run. The error correction parameter was estimated at -0.2090. In other words, it is observed that 20.90% of a short-term deviation will be corrected in the following year, returning to long-run equilibrium. This implies that the effect of a deviation will completely dissipate after approximately five years.

According to the diagnostic test results, it was determined that the model does not suffer from issues such as serial correlation, heteroscedasticity, or functional form specification errors. Furthermore, the results indicate that the model's residuals exhibit a normal distribution and that the model possesses high explanatory power.

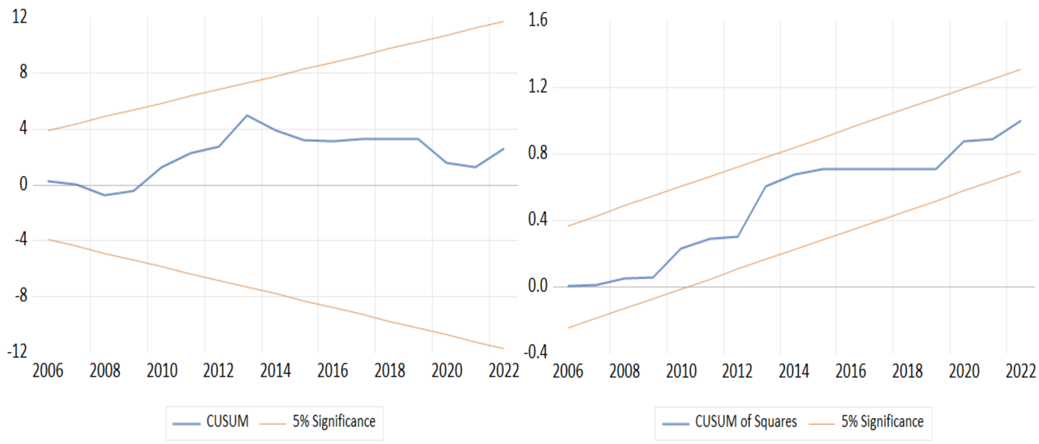

Figure 1. CUSUM and CUSUM-SQ Test Results (Status Prior to the Dummy Variable)

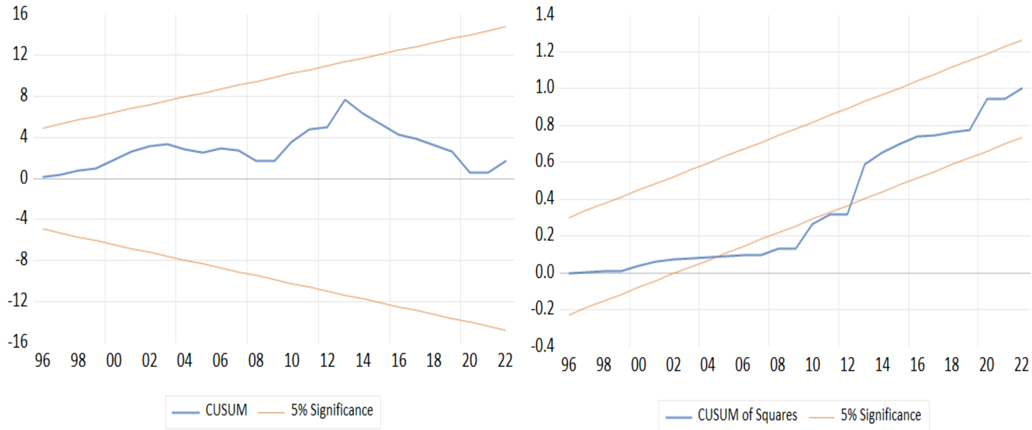

Figure 2. CUSUM and CUSUM-SQ Test Results (Status Post-Dummy Variable)

CUSUM-SQ tests were employed. The CUSUM-SQ test indicated a structural break between 2005 and 2012, as the statistics moved outside the critical boundaries (reference lines). To mitigate the effects of this structural break, a dummy variable was added to the model as an exogenous regressor. Following the inclusion of the dummy variable, both CUSUM and CUSUM-SQ tests demonstrated that the model's residuals remained within the reference lines, indicating that the model exhibits a stable structure. The CUSUM and CUSUM-SQ graphs before and after the inclusion of the dummy variable for the period in question are presented in Figure 1 and Figure 2.

4. Conclusion

When examining the literature on energy consumption and development, it is observed that studies predominantly focus on the economic dimension of development. Evaluating the concept of development solely through its economic aspect overlooks the dimension of human welfare, leading to an incomplete assessment of development. Consequently, studies focusing on energy consumption in relation to the Human Development Index (HDI), which considers all dimensions of development, have begun to contribute significantly to the literature. In this study, the relationship between electricity, natural gas, and oil consumption and the HDI in Türkiye over the 1990–2022 period was tested using ADF, PP, ZA, and LS unit root tests and the ARDL cointegration methodology.

According to the ARDL cointegration test results, a cointegration relationship was identified in the short run between the one-period lagged value of oil consumption, the current-period value of electricity consumption, and the HDI. In the long run, it was concluded that a cointegration relationship exists only between electricity consumption and the HDI. No cointegration relationship was detected between natural gas consumption and the HDI. In the short run, the effects of changes in oil consumption on the HDI manifest in the subsequent period. Although this effect negatively impacts the HDI in the short run, it is observed that this influence disappears in the long run. In this context, an increase in oil consumption creates a temporary negative effect on the HDI, affecting the index with a lag. There may be several reasons why oil consumption lacks a significant impact on the HDI in the long run or loses its influence over time. While the effects of oil consumption are felt in the short term, factors such as technological advancements and the transition to renewable energy sources in the long run may offset the impact of oil on the HDI. Alternatively, increasing societal awareness regarding environmental issues over time may lead to the elimination of the short-term negative effects of oil consumption on the HDI in the long-term equilibrium.

A robust cointegration relationship was identified between electricity consumption and the HDI. While the positive impact of electricity consumption on the HDI is limited in the short run, this effect becomes significantly more pronounced in the long run. In the short run, electricity consumption creates a positive—albeit limited—impact on the HDI by meeting instantaneous energy needs in healthcare, education, and daily life. Investments in electrical infrastructure and the successful integration of renewable energy sources into electricity generation enable electricity consumption to exert a more permanent and substantial positive influence on the HDI in the long run compared to the short run. The fact that improvements in electrical infrastructure, integration of renewable energy sources, and the associated economic transformations require time limits the short-run impact of electricity consumption on the HDI. However, the realization of these systemic changes over the long term causes the positive impact of electricity consumption on the HDI to become stronger and more significant.

This study demonstrates that the consumption of resources such as oil and natural gas, which have high import dependency in Türkiye, poses a challenge not only to energy security but also to the achievement of Türkiye's sustainable development goals. To attain these targets, policy-makers in Türkiye should prioritize focusing on electricity resources rather than oil and natural gas. In this context, prioritizing policies such as improving energy efficiency, transitioning to renewable energy sources, expanding access to electricity, shifting energy consumption habits, and reducing carbon emissions will play a crucial role in enhancing both the HDI and energy security. To promote energy efficiency, it is essential to raise public awareness and implement regulations aimed at increasing efficiency in sectors such as housing, industry, and transportation. Furthermore, technologies with high energy efficiency should be supported through tax incentives, favorable credit facilities, and subsidies. Incentive mechanisms must be developed to increase investments in renewable energy and to facilitate technological advancement. Simultaneously, Türkiye needs to set ambitious targets to increase the share of renewable energy sources in its electricity generation mix. Strengthening and expanding the electrical infrastructure, particularly by facilitating access in underserved areas, will also improve access to vital services such as education and healthcare in those regions. This situation will create a positive impact on the HDI. One of the most critical policies to be prioritized is the transformation of individual energy consumption habits. Raising public awareness is a task that must be carried out in tandem with energy conservation and environmental sustainability. Through education provided at homes, schools, and workplaces, society should be sensitized to environmental pollution and energy efficiency to foster long-term sustainable habits. Regarding the reduction of oil and natural gas consumption, the progressive taxation system—where higher consumption levels incur higher costs—should be maintained to encourage a shift in energy consumption patterns. The industrial sector also plays a pivotal role in the reduction of carbon emissions. While necessary awareness-raising activities must be conducted at the societal level, it is essential to develop and rigorously implement an Emissions Trading System (ETS) for the industrial sector.

When we compare our results with previous studies, our findings are similar to those of Niu, Shuai et al. (2013) and Ouedraogo, Nadia S. (2013), especially in showing that electricity consumption has a strong and positive effect on the Human Development Index (HDI). However, while Akpolat, A. G. and Bakırtaş, T. (2024) find an inverted U-shaped relationship between fossil fuels and the HDI, our results differ from theirs regarding natural gas consumption. In our study, natural gas and oil consumption do not have a direct long-term effect on human development in Türkiye. Instead, their impact appears to be indirect.

Although this study provides important findings on the relationship between energy consumption and the HDI in Türkiye, it has some limitations. First, the analysis covers only the period 1990–2022 and focuses on three main energy sources. Due to data limitations, renewable energy could not be included as a main variable in the econometric model. Future research could expand this study by using panel data analysis at the regional level within Türkiye or by comparing different groups of countries.

5. Patents

This research did not result in any patents.

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The Use of Artificial Intelligence in Businesses: A Comparison of the Private and Public Sectors

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Abstract: Technology is an indispensable factor for private sector and public enterprises operating in today's world. The most effective aspects of technology for businesses are digitalization and artificial intelligence. Private sector businesses operating in a changing and evolving world are struggling in a highly competitive environment. The primary goal of these businesses is to retain their existing customers and gain new customers by staying ahead of their competitors. The way for businesses to gain a competitive advantage over their rivals and ensure customer satisfaction at this point is through technology and artificial intelligence, one of its derivatives. Just as private sector businesses operate with the aim of ensuring customer satisfaction, public sector businesses also continue their activities with the aim of satisfying citizens. In today's world, where technology plays an active role in every aspect of our lives, not only private sector businesses but also public sector businesses benefit from technology in many ways. These businesses, whose primary goal is to meet the needs of citizens, actively use technology and artificial intelligence applications to meet those needs more quickly, efficiently, and effectively. It is anticipated that artificial intelligence applications will be used more actively and in more areas in both private sector businesses and public enterprises in the coming period. This study examines the areas of application of artificial intelligence in private sector businesses and public enterprises by comparing them.

Keywords: Artificial Intelligence, Artificial Intelligence Applications, Artificial Intelligence in the Public Sector, Artificial Intelligence in Businesses

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1. Introduction

Artificial intelligence, which we use in almost every area of our lives today, is the most current version of technological developments that began with the Industrial Revolution and continue to this day. Artificial intelligence, which is the most powerful key to survival and competitiveness, is widely used in many areas in both the public and private sectors (Chibunna et al., 2024).

Rapid changes and developments in technology have brought about a process of change and transformation not only in private sector businesses but also in public administration. The aim of the public sector (Fountain, 2001) is to be fair and equal to citizens, providing them with fast, accurate and efficient services. At this point, technology, along with the accompanying digitalisation and its latest derivative, artificial intelligence, provides public institutions with significant benefits in achieving these aims. Although processes in the public sector are less dynamic than those in the private sector, they tend to be uniform and static due to the requirements of measurability and accountability. In particular, the governance approach, which is the dominant paradigm of the new public administration, can be facilitated by intelligent automation through artificial intelligence in terms of stakeholder communication, transparency, and participation, thereby promoting its success, widespread adoption, and ownership (Efe & Özdemir, 2021). The ability to make rational decisions in public administration is crucial in terms of providing equal and fair services to citizens. Artificial intelligence is actively used in the collection, classification and conversion (Khan & Al-Badi, 2020) of data into usable information for decision-making. When correct and rational decisions are made, citizens' trust in public institutions will increase and satisfaction will be ensured. Another benefit of using artificial intelligence in public institutions is that it eliminates time and space constraints. In the days when public services were provided manually and physically, citizens could only access these services during office hours by going to the relevant institutions. However, with digitalisation, many services have begun to be provided through artificial intelligence-supported applications. Citizens can now benefit from these services without any time or location constraints. This situation has saved time by reducing bureaucratic tasks and has also provided institutions with cost advantages in terms of resources such as paper and electricity consumption.

Private sector businesses must closely follow technological developments and adapt their operations accordingly to survive (Andries & Debackere, 2006). With the advent of technology and digitalisation into our lives, the survival of businesses has become dependent on these factors. It is expected that artificial intelligence will become a vital competitive tool for businesses in the future, causing disruptive changes in job roles and content, management style, organisational structure, and culture (Ünal and Kılınç, 2020: 51). The primary objective of business is to ensure customer satisfaction. The path to achieving customer satisfaction lies in the effective use of artificial intelligence. Businesses must, above all, be accessible. With AI-powered applications, customers can reach businesses anytime, anywhere. Furthermore, with AI support, customer information is stored in databases and can be utilised to provide more effective services to customers. When artificial intelligence is used correctly and effectively to ensure customer satisfaction, a competitive advantage for businesses is inevitable. Artificial intelligence is used in businesses not only in terms of providing customer service but also in many areas within business. Artificial intelligence technologies are utilised in the collection and processing of information and in determining alternative options in decision-making processes at the management level. Artificial intelligence is widely used in the manufacturing sector in the development and use of machines and in quality management activities (Gültaş, 2026). Artificial intelligence is utilised in human resources for personnel selection and placement, performance evaluation processes, and training. Accounting operations, which were previously performed manually, are now also carried out with artificial intelligence supported technologies. As can be seen, the use of artificial intelligence in businesses saves time, eliminates unnecessary tasks, provides cost advantages, and ultimately increases productivity. This results in customer loyalty and competitive advantage, which keep the business afloat and drives it forward.

2. Artificial Intelligence Applications in Public Enterprises

In today's world, dominated by globalisation and technology, we continue our lives within a system that is evolving almost daily. Adapting to these developments has become a necessity not only for private sector businesses but also for public enterprises. Governments (as indicated in Table 1) have begun to develop new policies for the use of technology and its derivatives in the management of public enterprises. From the second half of the 20th century onwards, economic crises in Western countries (Tsiflikidou & Metaxas, 2023) accelerated the search for reforms in public administration and paved the way for the emergence of the 'New Public Management' (Lane, 2002) paradigm. The goal of reducing bureaucracy, one of the fundamental approaches of new public management, is supported today by the intensive use of information and communication technologies. Digitalisation in public administration both enables the state to achieve a more minimalist structure and allows public services to be delivered quickly and easily (Boyalı, 2025: 208-209). Countries are realising how important national artificial intelligence strategies are, and the number of states developing artificial intelligence strategies (Demaidi, 2025) is increasing every day. National objectives can generally be summarised as reducing costs and adding value. Specifically, each state developing an artificial intelligence strategy seeks to integrate artificial intelligence and its technology into its system in a manner appropriate to its own state structure and character (Ulaşan, 2020: 120).

Table 1. Use of Artificial Intelligence in Governments

AI Tasks	Government Activity	Opportunity Area
Recognition, Event detectio, Forecasting, Personalisation, Interaction support, Goal-driven optimisation, Content generation, Reasoning with knowledge structures	- Internal operations - Policymaking - Service delivery - Internal and external oversight	- Productivity (efficiency and effectiveness) - Responsiveness - Accountability

Source: OECD, 2024

The table highlights the four core functions of artificial intelligence. These are (OECD, 2024); efficiency (widely used to ensure internal operations in the public sector), effectiveness (used particularly to improve decision-making processes), responsiveness (used to improve service delivery), and accountability (used in risk detection).

The integration of technological developments into corporate processes is important for the purpose of carrying out work and operations more quickly within organisations. With the development of organisations' software and data storage infrastructure, there has been a significant increase in the amount of data they hold. Artificial intelligence technologies and business intelligence solutions (Bulusu, 2020), which are among the most widely used applications in this field, are intensively used to extract meaningful information and insights from raw data (Şimşek et al., 2019: 397). Making equal, fair and rational decisions in public institutions is crucial for public administration. Modelling the information gathering stage of decision-making with artificial intelligence (Leyer et al., 2020), which is an important example of rational decision-making in public administration, and developing expert systems based on artificial intelligence to gather as much accurate information as possible for public decision-makers to make rational and high-quality decisions in possible situations is a crucial step for public administration. (Önder and Saygılı, 2018: 647). In the domains of medicine and criminal justice, where stakes are high, the utilization of AI algorithms is currently most effectively constrained to aid humans in making informed decisions (Zax, 2026). Today, artificial intelligence is not yet at a level where it can replace human intelligence in decision-making. However, it can assist managers in making decisions that are fairer, faster and more accurate.

The fundamental purpose of the public sector is to effectively deliver the services it creates for its citizens (Obsborne, 2020). Many services, such as obtaining a criminal record, graduation certificate, identity card sample, paying taxes, voting, establishing a company, writing petitions to institutions, submitting applications, registering, and obtaining information from public institutions, are now carried out using artificial intelligence applications. These services are carried out quickly via computers, smartphones, and smartwatches, without any time or location constraints (Tanrıverdi, 2021: 298-299).

Artificial intelligence and artificial intelligence applications are emerging in many areas within public enterprises. They are used in general public services) such as healthcare, education, disaster management, public administration and policy implementation, urbanisation (Gesk & Layer, 2022, public relations, and employment processes; in defence services in areas such as intelligence, strategic planning, and threat detection; in public order and security services (Henman, 2020); in economic services such as development and growth, decision-making processes, identification of public investments, and elimination of cyclical imbalances; environmental protection services such as sustainability, externalities, biodiversity, climate change, waste management, marine clean-up, and environmental taxes (Konya & Nematzadeh, 2024); housing and social welfare services such as urbanisation, social welfare, safe housing, and urban transformation; public health services such as patient profiles, healthcare workers, and public health (Panahi, 2025); in leisure, culture and religion services such as librarianship, Islamic Finance applications, and culture; in public education services (Achanta, 2025) such as curriculum, learning processes, assessment, and distance learning; and in social security and social assistance services (Aydın, 2024: 175-176).

Another area where artificial intelligence is widely used in public enterprises is accessibility (Susar &Aquaro, 2019). Public enterprises have made communication and accessibility more active through AI-powered chatbots (Nze, 2024), which they use in many areas to enable customers to communicate their needs and find quick solutions to those needs.

Artificial intelligence applications in public enterprises are highly significant in terms of both time and paper savings. In this regard, public enterprises actively utilise artificial intelligence, particularly in archiving (Svärd et al, 2024). Article h-3/3 of the 2020-2024 Strategic Plan published by the Presidency of the State Archives, the regulatory body for archiving in Turkey, states that ‘the necessary information systems will be established and maintained at both the institutional level and the level of archiving objectives.’ The British National Archives' 2017-2019 Digital Strategy document emphasises the need to develop new e-discovery tools to assist with selection and evaluation in archives and mentions the exploration of machine learning applications. The New Zealand National Archives 2057 Strategy document mentions that the increasing use of computational analytics and machine learning for decision-making based on large data sets may be seen (Öztürk, 2022: 57).

There are numerous examples of artificial intelligence applications in the public sector around the world. Önder and Saygılı (2018) list these as follows: In 2015, the US Department of Homeland Security's Citizenship and Immigration Services created the 'EMMA' application (Villa-Nicholas &Sweenay, 2020), a virtual assistant designed to answer questions from large numbers of citizens. In the cities of Jacksonville in the US state of Florida and San Diego in the US state of California, 'smart street lamps,' an LED lighting technology product, are used to help collect a range of important data, from identifying free parking spaces for drivers to increasing traffic control and efficiency and alerting the public about hurricanes. The US Army website uses Sergeant STAR (SGT STAR), an interactive virtual assistant described as the army's virtual guide, to help visitors understand everything they want to know about the army when new recruits are about to start their service. It uses artificial intelligence to answer questions, check users' qualifications, and connect them with the authorities who hire them. After the US healthcare law came into effect in 2010, the US government created a programme called EnrollAmerica (Orzol & Hula, 2018) to identify Americans without health insurance and enrol them in the new healthcare plan. In 2007, the Hong Kong Immigration Department developed an algorithmic system to categorise passport applications into three main categories, due to the large number of customers each year and the large number of forms issued to these customers. In addition, the E-Government Applications used in Turkey and the Presidency's Digital Transformation Office are examples of the use of artificial intelligence. In addition, Ulaşan (2020) has outlined the areas in which governments use artificial intelligence as follows: South Korea has one of its main objectives as leading global artificial intelligence R&D investments. India aims to use artificial intelligence for inclusive growth, archive data related to artificial intelligence and make it accessible. The United States prioritises the use of artificial intelligence in the military and training the workforce of the next generation. The European Union wishes to use artificial intelligence for socio-economic change. China (Robeerts et al., 2021) attaches importance to information sharing and wishes to establish global technical standards related to artificial intelligence. The United Kingdom attaches importance to the diagnosis of diseases and the ethical dimension of artificial intelligence. The United Arab Emirates aims to reduce government costs and improve government performance through artificial intelligence. Singapore is in favour of creating artificial intelligence innovations that benefit people. Japan's goals (Dirksen & Talahashi, 2020) are to achieve success in robotics and revitalise efficiency with artificial intelligence. France aims to protect its own strategies through artificial intelligence investments. In addition, environmentally friendly artificial intelligence studies are being developed. Canada aims to attract global entrepreneurs and talented engineers to its country by leading artificial intelligence research. Germany (Sharbaf, 2021) is in favour of redesigning work in the age of artificial intelligence and enriching work-life balance. Denmark (Holm & Lorenz, 2022) evaluates artificial intelligence on an ethical and human-centred basis. Finland aims to be one of the best countries in the world in the application of artificial intelligence technologies.

Artificial intelligence has not yet developed as much in public administration as it has in the private sector. The reason for this is that public sector employees resist or oppose these innovations for fear of losing their jobs. Artificial intelligence in public administration can certainly simplify many tasks and increase reliability (Mishra et al., 2024). It may even lighten the decision-making burden on public administrators and prevent some managers from making decisions based on their own interests. However, a public administration system that does not require human involvement could also give rise to an entirely different debate (Avaner and Çelik, 2021: 5). Artificial intelligence applications have become an important tool in developing a faster, more efficient, effective and sustainable approach in public administration. However, this application can also lead to numerous problems, primarily concerning ethics, security, data security, infrastructure, and access issues. Therefore, while artificial intelligence applications offer many advantages in public administration, they also bring concerns (Erol, 2024: 23).

Artificial intelligence is widely used in both the private and public sectors in almost every country in the world (Susar & Aquaro, 2019). Examples (Turkish Informatics Association, 2024) of the use of artificial intelligence in the public sector are summarized in Table 2.

Table 2. Examples of Artificial Intelligence Used in the Public Sector

Project	Country	Description
CitizenLab- Youth for Climate	Belgium	Through the CitizenLab platform, the "Youth for Climate" project used data analysis tools to collect thousands of ideas from citizens and turn them into meaningful actions. Natural Language Processing (NLP) technology was used to analyze contributions written in multiple languages and process the results more effectively. This made it possible to analyze contributions more quickly and turn them into action.
Flemish Infoline- Automatic classification of incoming phone calls	Belgium	In this project run by the Flanders Information Service, incoming phone calls are automatically classified using Natural Language Processing (NLP) technology. This system ensures that incoming questions are categorized more quickly and directed to the correct answer provider. Additionally, response suggestions are automatically provided.
Verontrustingen- Enabling accurate predictions to detect day-care services inspectioni	Belgium	This project is an artificial intelligence system that aims to make more accurate predictions to improve the quality of childcare services in Flanders. The system uses machine learning algorithms to determine which childcare centers should be inspected, thereby optimizing limited inspection capacity.
Mobile phone usage on vehicles	Belgium	This project, conducted by the Vias Traffic Institute, is testing AI-powered camera systems to detect drivers using cell phones while driving. The system identifies instances where drivers are distracted by their phones through photographs, and police can initiate legal action based on these images.
VDI- Protection of digital infrastructure	Norwegian	In this project conducted by the Norwegian National Security Authority, new AI-powered sensor technologies are being developed to protect digital infrastructure. Artificial intelligence automatically analyzes detected malware and shares the results.
EPISA- Entity and property inference for semantic archives	Portuguese	EPISA automatically analyzes documents and related assets in archives using natural language processing and machine learning methods. This creates a richer and more automatically manageable model than existing archiving processes.
CCM-SNS-Verification of medical prescriptions	Portuguese	This project, run by the Portuguese Public Health Service, uses artificial intelligence to detect fraud in prescriptions and improve the electronic prescription system. Artificial intelligence analyzes databases to detect fraud and irregularities.
REDOC- Digital Tutor to make easier learning the STEM subject	Italy	REDOC is a digital education platform designed to facilitate students' learning in STEM subjects. The platform offers students a gamified learning experience through interactive lessons and video tutorials.

MPAI Community-Moving Picture, Audio and Data Coding by Artificial Intelligence	Switzerland	MPAI is an international, non-profit organization that develops data, audio, and video coding standards using artificial intelligence. This project facilitates the integration of these technologies by creating AI-supported data coding standards.
AI to Process Veteran Feedback	USA	Veterans Affairs (VA) uses artificial intelligence to analyze feedback from veterans. Artificial intelligence categorizes free-text feedback, identifies key trends, and helps provide faster service based on this feedback.
AI for Patent Search	USA	The United States Patent and Trademark Office uses artificial intelligence to evaluate patent applications. AI technology speeds up the examination process by helping to find similar patents and prior art.
AI to Analyze Weather Hazards	USA	The National Oceanic and Atmospheric Administration (NOAA) uses artificial intelligence to analyze heat waves in cities and protect the public. This system analyzes high temperatures in advance and informs communities about extreme weather conditions.
AI-Powered Predictive Policing	USA	Some police departments in the US are using artificial intelligence systems to predict crime. AI analyzes crime trends and historical crime data to enable more effective planning of police patrols.
AI for Fraud Detection in Welfare Programs	USA	Various social service agencies in the United States use artificial intelligence to detect fraud in welfare programs. AI systems play an effective role in identifying fraudulent claims by detecting anomalies.
AI to Monitor Air Quality	USA	The Environmental Protection Agency (EPA) uses artificial intelligence to monitor and analyze air quality. AI systems help develop healthier environmental policies by predicting air pollution levels.
AI for Urban Planning	USA	Urban planners in the U.S. are using artificial intelligence for the planning and development of urban areas. AI enables the creation of more efficient city plans by analyzing population density and infrastructure needs.
AI for Personalized Learning	USA	Schools in the U.S. are using artificial intelligence to create customized education programs tailored to students' needs. AI analyzes students' performance and recommends personalized learning paths.
AI for Museum Curation	USA	Museums are using artificial intelligence systems to make the curation and exhibition of works more efficient. AI assists in categorizing artworks and planning exhibitions.
AI for Cybersecurity in Defense	USA	The U.S. Department of Defense uses artificial intelligence to protect against cybersecurity threats. AI automatically detects and analyzes threats, enabling rapid response.

Source: Turkish Informatics Association, 2024

When examining the projects in the table, it is seen that governments utilize artificial intelligence in public services, economy, health, environmental protection, community contribution, education, culture, religion, defense, and social areas. These studies demonstrate the diversity of artificial intelligence applications in the public sector.

Although the use of artificial intelligence applications in the public sector is becoming increasingly widespread, citizens may resist these applications for security reasons. This is where the concept of artificial intelligence governance comes into play. AI governance refers to systems that help ensure AI systems, tools, and applications are more secure and ethical (https://www.ibm.com, 2026). AI governance specifically addresses security-related risks and works to mitigate them. By eliminating existing risks, it ensures that AI services provided in the public sector meet citizens' expectations.

3. Artificial Intelligence Applications in Private Sector Businesses

Competition in today's job market has reached very serious levels. Businesses are struggling to survive by adapting to constantly changing environmental conditions. Undoubtedly, the environmental factor (Andires & Debackere, 2006) that has undergone the most change in this competitive environment is technology. As it is in every area of our lives, technology plays an important role in the continuity of business activities. Artificial intelligence, one of the most current forces of technology and digitalisation, is used in many areas within businesses. In their study, Sarnıç & Acar (2024) found that businesses use artificial intelligence to increase customer satisfaction, enable them to respond to rapidly changing demands, allow them to continuously monitor consumer preferences, contributing to time management, offering a human-centred approach, increasing productivity, improving decision-making processes, providing a competitive advantage, contributing to environmental sustainability, helping to control resource usage, and reducing costs (Sarnıç & Acar, 2024: 174).

The use of artificial intelligence in businesses (as indicated in Table 3) aims to make operations more efficient and effective. Costs (Butcher & Robert, 2004) are also an important factor that businesses need to focus on in terms of efficiency and effectiveness. With the widespread design and implementation of AI-supported quality management systems in industries, quality costs can be reduced by improving quality-related activities and detecting and eliminating errors early on (Ever & Demircioğlu, 2022: 59). In addition (Ojika et al., 2022), the use of AI technologies will eliminate unnecessary activities in businesses, providing a cost advantage to the business. Although investments in artificial intelligence may scare shareholders, the cost advantages they provide to the business far outweigh the costs incurred.

Table 3. Areas of Application for Artificial Intelligence in the Business World

Area of Use	Explanation
IT operations	AIOps (Artificial Intelligence for IT Operations) is an application that involves the use of artificial intelligence, machine learning, and natural language processing models to simplify IT operations and service management.
Marketing and sales	Customer data helps marketing teams develop marketing strategies by identifying trends and spending patterns.
Customer service	Artificial intelligence helps improve the customer experience by enabling businesses to provide 24/7 customer service and deliver faster response times.
Content creation	Generative Artificial Intelligence (GenAI) is a rapidly growing field that helps organizations optimize content creation.
Cybersecurity	Artificial intelligence tools can be used to improve network security, detect anomalies, identify fraud, and help prevent data breaches.
Supply chain management	The application of artificial intelligence in supply chain management takes the form of predictive analytics, which helps price future shipping and material costs. Predictive analytics also helps organizations maintain appropriate inventory levels.

Source: https://www.ibm.com, 2026

As shown in the table, artificial intelligence has a wide variety of uses in the business world. If the private sector aims for efficiency and success, artificial intelligence technology must be integrated with the workforce. Using artificial intelligence will minimize errors in IT systems, which will increase performance.

The journey of artificial intelligence, which began with a question posed at the 1956 "Dartmouth College Workshop (McCarthy et al., 1955)" , started with processing data provided initially. Later, with its artificial neural networks, it reached the point of being able to learn by itself, either using specific variables or through its own algorithms. (İnce et al., 2021:52). Artificial intelligence has recently emerged as a method used in management levels of businesses, particularly in deci

sion-making processes. However, the use of artificial intelligence in management levels brings with it a number of problems. Some of these issues include (Voronin & Savchenko, 2024) how to manage artificial intelligence, the potential downsides of being controlled by artificial intelligence, the possibility that artificial intelligence may be more ruthless when not complying with management regulations, the difficulty of finding people with the appropriate skills to manage artificial intelligence, how to develop and update artificial intelligence systems and how to solve problems, as well as ethical and security issues (Berberoğlugil, 2023: 94). Another issue encountered is the concern that artificial intelligence will replace humans, particularly in decision making processes. However, Jarrahi (2018) states that artificial intelligence will not be used to replace humans, but rather to offer a holistic and intuitive approach that will enhance human cognitive abilities and help them cope with uncertainty through higher computational power, greater information processing capacity, and a more analytical approach (Jarrahi, 2018:1).

The area where artificial intelligence technologies are most widely used in business is production systems. Artificial intelligence technologies in production are effectively used in many areas, such as (Chryssolouris, 2023) improving the quality management process, facilitating quality control activities, ensuring efficiency in the production process, increasing competitiveness, and ensuring sustainable development (Ever and Demircioğlu, 2022: 67-68). Robots and artificial intelligence used in production will be much more disruptive than anything we have seen before. The most effective artificial intelligence systems will be designed around the concept of intelligent augmentation. By handling mathematics and fundamental analyses, they will lighten the tedious load of skilled operators, absorb data, classify and prioritise information, perform simulations, and ultimately leave the decision on the action plan to the human operator (Buchmeister et al., 2019).

With customer satisfaction becoming a fundamental goal, the retail sector, which interacts directly with customers, has also begun to gain increasing importance. Gülşen (2019), stating that artificial intelligence will contribute significantly to the transformational change in retail, has indicated that the use of artificial intelligence in the retail sector will provide the following benefits to businesses: it can automate processes, increase efficiency and reduce costs, increase sales, provide a competitive advantage, improve customer satisfaction, loyalty and shopping experience, enable supply chain and logistics optimisation, enable improved sales and inventory management, enable faster and more effective decisions based on collected big data, enable digital marketing optimisation, create an integrated channel experience, enables realistic retailing in the virtual environment, identifies customers entering physical stores through facial recognition and mobile technologies, enables personalised marketing activities in physical and electronic store environments, provides faster service and reduces customer waiting times in stores, and enables more efficient and improved workforce allocation (Gülşen, 2019: 425). Today, e-commerce websites and mobile applications have taken the place of the retail sector. Artificial intelligence technology provides significant advantages to mobile applications in areas such as (Rouky, 2025) personalising the user experience, data analysis, demand forecasting and inventory management. Thanks to personalised recommendations, users can easily find the products they want and receive services tailored to their needs. Data analysis assists businesses in reaching the right target audience with the right product. As a result of this analysis, customer demand can be predicted in advance and inventory management can be carried out more effectively (Karakulle and Aktepe: 2023:44-45).

With digitalisation, many accounting activities that were previously performed manually have begun to be carried out using computer-supported systems. In his study, Varol (2023) designed a model of how accounting, auditing and tax practices will be fully automated in the near future using artificial intelligence-based systems. In this model: The Tax Administration, KGK, banks, the Internet of Things, big data and all information systems (Huerta & Jensen, 2017) within the company will be able to exchange data in real time; Accounting transactions and internal control activities will be automatically performed by the system, and identified issues will be forwarded to predefined individuals and units; The KGK's system will automatically access all data necessary for independent auditing, and the audit and reporting of financial statements will be performed automatically; As the company's accounting records will be transferred to the Tax Administration's system in real time, e-ledgers and declarations will not be sent, and the system will be able to perform tax audits automatically and alert the relevant units when irregularities are detected; It is assumed that the accounting and auditing professions will inevitably disappear in their current form and be replaced by IT specialists knowledgeable in the fields of accounting and auditing. The job descriptions of these specialists could include financial consultancy and system auditing. The damage that attacks on information systems will cause to software and hardware will also occur in the envisaged system. However, it is expected that cybersecurity measures will develop in parallel with this (Varol, 2023: 179).

Another function where artificial intelligence applications are used is human resources (Afzal et al, 2023). With the increasing importance given to employees, who are the internal customers of businesses, the human resources function, which previously operated within different departments, now operates independently in many businesses. As with every function in the business, digitalisation has brought about changes in the human resources function. Thanks to artificial intelligence applications, many processes (Madanchian et al., 2023) that were previously done manually are now easier and faster. In the human resources function, artificial intelligence is increasingly influencing many areas, from job design and analysis to recruitment and placement, performance and training. The information of employees working with artificial intelligence tools can be displayed and updated. Artificial intelligence and machine language can be used in human resources function components that have an integrated function in terms of recruitment, personnel selection, performance analysis, personnel data collection, real-time information provision, and accurate information provision. On the other hand, conversational artificial intelligence can also provide analytical and key performance indicator information, such as identifying the best-performing employees and pending task requests (Tiftik, 2021: 386-387).

Global studies confirm the rapid increase in the corporate adoption of artificial intelligence. According to McKinsey & Company (2025) data, 92% of executives plan to increase their investment in artificial intelligence over the next three years, while the Stanford AI Index (2025) report shows that 78% of companies are actively using artificial intelligence applications as of 2024. These figures clearly demonstrate that artificial intelligence is at the heart of digital transformation strategies on a global scale (Şahinbaş, 2025: 186). Studies predict that artificial intelligence will remain a central factor in corporate life in the coming years.

Looking at the world's leading companies, it is evident that artificial intelligence is actively used in many sectors. In the financial sector, which is undergoing a digital transformation in its activities (Bredt, 2019), companies such as In-Data Laboratories, Mastercard, Morgan Stanley, Goldman Sachs, and Klarna actively use artificial intelligence. In the software and technology sector, perhaps the sector where artificial intelligence is most active (Mohammad, 2020), companies such as Microsoft, Adobe, Salesforce, ClickUp, Intel, IBM, and Apple are successfully utilizing artificial intelligence. In addition, BMW and Toyota in the automotive sector, Under Armour and Zara in the clothing sector, Bentley in the construction sector, and EasyJet in the airline industry are effectively utilizing artificial intelligence. As a result of digitalization and globalization, the effects of artificial intelligence are also seen in e-commerce, which is becoming widespread around the world (Fedorko et al., 2022; Bawack et al., 2022) Companies such as Amazon, Wayfair, Alibaba, and Shopify are successfully using artificial intelligence.

4. Comparison of the Private Sector and the Public Sector

Technology, which is present in every aspect of our lives, is changing, renewing and developing every day. This change, innovation and development are quite important in terms of making life easier for both people and organisations. Technology, digitalisation and its most powerful key today, artificial intelligence (Newman et al, 2022), are used in many areas in both the private and public sectors.

The aim of public institutions is to find solutions to citizens' problems and meet their needs. In the private sector, the aim is to ensure customer satisfaction. Both sectors have a specific target audience, which they serve, utilising artificial intelligence applications at this service point (Black et al,2001). Today, artificial intelligence related applications are used extensively in education, healthcare and public services (Wirtz et al, 2019). This eliminates problems such as waiting times and congestion in public institutions and saves citizens time. Furthermore, these applications make it possible to carry out work and transactions not only during office hours but also at any desired time. In the private sector, there are also applications that meet customer needs in a short time. Thanks to these applications, customers can reach businesses more quickly and easily, wherever and whenever they want. This ensures customer satisfaction and, consequently, a competitive advantage. Today, technology is the key to competition. Technology, digitalisation and its derivatives (Boikova et al., 2021) are crucial in competition between private sector businesses and between countries. For this reason, technology and its most recent derivative, artificial intelligence, are used intensively in both the private and public sectors.

Artificial intelligence applications are used in both the private and public sectors, particularly at the management level in decision-making (Wirtz et al., 2019). Artificial intelligence applications are used in public and business management to make rational decisions. Artificial intelligence is utilised in the collection and classification of data and the creation of options prior to managerial decisions. However, the use of artificial intelligence in management activities also brings with it debates about artificial intelligence replacing human intelligence. Although this is not currently the case, people working in these institutions may show resistance to artificial intelligence for this reason. Furthermore, the issue of how artificial intelligence should be managed is also an uncertain topic in business and public administration (Almada,2023). Advances in technology and, consequently, in artificial intelligence will provide answers to these questions over time.

Sustainability and streamlining are concepts that are becoming increasingly important and widespread today. Issues such as causing less harm to nature and using resources more efficiently are among the objectives of both public institutions and the private sector. With technology and artificial intelligence applications, paper usage and waste have been significantly reduced, particularly in businesses (Yaşar, 2025).. Significant developments have occurred in this area, especially with the use of technology instead of paper for archiving. Reducing paper usage has both minimised the damage to the environment and reduced costs. With many processes being carried out using artificial intelligence-supported applications, public institutions and private sector businesses no longer require as much space as before. This has also resulted in savings in many energy sources (Göde et al., 2023). The reduced use of resources such as electricity, water and natural gas has had a positive impact on both the environment and costs.

In terms of artificial intelligence, it is crucial for the public and private sectors to act to-gether and collaborate in order to ensure the efficiency of the applications that will be used. The US government's 'Manhattan Project (https://www.reuters.com, 2026)' in this regard has facili-tated co-operation between the private and public sectors (https://www.ibm.com, 2026).

Artificial intelligence is a technological innovation that is widely used by both public institutions and private sector businesses, and its use is anticipated to continue in the future. Alongside all the benefits announced in both public institutions and the private sector, there are also a number of drawbacks. The perception that artificial intelligence will replace human intelligence causes employees to resist this innovation. Although this is not yet the case, organisations can eliminate this perception by providing training to their employees and involving them in the process. Another problem encountered with artificial intelligence is security concerns. Fears about potential security breaches may make citizens or customers hesitant to use these applications. Similarly, access issues that may occur in the system can also reduce the usage rates of the applications. As artificial intelligence is a new concept in our lives, these drawbacks will be resolved in the coming period with developments in this field.

5. Conclusions and Recommendations

In recent years, technology has been the fastest and most rapidly developing environmental factor worldwide. Keeping up with technological changes and adapting to them has become not just a necessity but an imperative for individuals, businesses operating in the private sector, and governments alike. Over the years, numerous derivatives of technology and, consequently, digitalisation have entered our lives. The most recent and up-to-date of these is artificial intelligence and its applications. Artificial intelligence is widely used in both the private and public sectors in today's world and is developing further every day.

The aim of public institutions is to provide services to citizens in line with their needs and problems. Countries such as South Korea, India, America, China, the United Kingdom, the United Arab Emirates, Singapore, Japan, France, Turkey, Canada, Germany and Denmark actively use artificial intelligence in public services and public affairs. Governments benefit from artificial intelligence in many areas, from healthcare to education, security to military services. The fundamental purpose of using artificial intelligence in the public sector is rationality and fairness. Artificial intelligence is particularly useful in the collection and processing stages of decision-making in public administration. Another purpose of using artificial intelligence is to ensure efficiency. Thanks to artificial intelligence, many activities that were previously carried out manually in physical environments within organisations are now performed using AI-supported applications. This results in both cost and time savings. The archiving process, which previously involved storing files in a specific area, is now carried out in AI-supported virtual environments. This also provides cost advantages to organisations and minimises the damage caused to the environment. Artificial intelligence has also increased accessibility to public institutions. Activities that were previously only possible during working hours can now be carried out at any time of the day, without any location or time constraints. This has solved problems such as work backlogs in institutions and citizens having to wait.

Digitalisation and its latest derivative, artificial intelligence, have taken centre stage in the business world. In the competitive environment where businesses compete in international markets, artificial intelligence applications have become the key to competitive advantage and customer satisfaction. Artificial intelligence applications are encountered in almost every function, from management to production, marketing to human resources, quality to accounting. Today is the age of speed, and it is highly unlikely for businesses to keep up with this pace without technology. Customers want their needs to be met as quickly as possible and expect businesses to be accessible whenever needed. As these demands cannot be met physically or manually, artificial intelligence applications come to the rescue of businesses at this point. Of course, artificial intelligence is not only used for customer satisfaction in businesses. Artificial intelligence and AI-supported applications are utilised in virtually every aspect of business operations, including determining the right options in management decision-making processes, mechanisation in production, recruitment in human resources, training, performance evaluation, keeping records more accurately and easily in accounting, quality control processes, marketing processes, and R&D activities. By using artificial intelligence, businesses eliminate unnecessary tasks and costs, resulting in leaner operations and increased efficiency. It is clear that artificial intelligence will continue to be a concept that guides all business activities in the future. Businesses that can keep up with the changes in artificial intelligence and adapt to them will gain a competitive advantage, while those that cannot adapt will fall behind in this competition.

Artificial intelligence is a concept that continues to renew and develop itself every day, and it will become essential for institutions to continue their operations in the coming periods. This study addresses the fundamental aspects of artificial intelligence usage in public administration and the private sector. Future studies should focus on examining the use of artificial intelligence in the private sector in greater detail, either on a sectoral or functional basis. Research conducted on a functional basis, in particular, will be able to explain more clearly which artificial intelligence applications are more commonly used in the relevant functions of a business. In addition, research examining the impact of artificial intelligence applications used in the public sector on citizens will enable the observation of the advantages and disadvantages of such applications.

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