

Artificial Intelligence and Uneven Development in GCC Economies: A Triadic System Model of Innovation, Inclusion, and Governance

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ABSTRACT: Artificial intelligence (AI) is increasingly reshaping economic development across the Gulf Cooperation Council (GCC), delivering significant productivity gains while simultaneously intensifying inequality, labour market polarization, and unequal access to digital resources. Although existing research explains these outcomes through either technological diffusion or institutional factors, it rarely examines how these dimensions interact. This paper addresses this gap by developing an integrated explanation of how AI-driven transformation generates uneven economic outcomes in GCC economies. The study adopts a conceptual, theory-building methodology based on analytical synthesis rather than empirical testing. It integrates insights from digital economy transformation, inclusive growth theory, socio-technical systems, and environmental, social, and governance (ESG) frameworks. Using mechanism-based reasoning, these perspectives are unified into the Triadic AI-Inclusive Growth Model (TAIGM), which is structured around three interdependent capacities: innovation, inclusion, and governance–sustainability. The findings conceptualize AI-driven inequality as an endogenous outcome of misalignment among these three capacities. When innovation advances faster than inclusion and governance adaptation, a dual-speed digital economy emerges, where high-productivity sectors rapidly capture AI benefits while other sectors remain structurally excluded or lag behind. In this view, economic outcomes are shaped less by technology diffusion itself and more by the degree of systemic alignment across institutional and socio-economic capacities. As a conceptual study, the TAIGM framework is not yet empirically validated. Future research should operationalize key constructs such as inclusion capacity and governance responsiveness and test their interaction effects using cross-country datasets, panel econometric techniques, or system dynamics modelling in AI-driven economies. Despite this limitation, the study contributes a mechanism-based framework that reconceptualizes inequality as a systemic consequence of AI transformation, advancing theoretical debates on inclusive and sustainable digital development in emerging economies.

KEYWORDS: Artificial intelligence; Gulf Cooperation Council (GCC); digital economy; inclusive growth; ESG; digital inequality.

1. INTRODUCTION

Artificial intelligence (AI) is rapidly reshaping economic development trajectories in the Gulf Cooperation Council (GCC), positioning the region as an emerging hub for digital innovation, smart infrastructure, and post-hydrocarbon economic diversification. GCC states have embedded AI within national development strategies to reduce dependence on resource-based revenues and transition toward knowledge-based economies (Haghighi & Alaamer, 2026; World Bank, 2025). This transformation is evident across sectors such as energy systems, financial services, logistics, and urban governance (Awashreh, 2026a), where data-driven and algorithmic decision-making increasingly underpin productivity, efficiency, and value creation (Albous et al., 2025; Bressane et al., 2026). From a sustainability perspective, AI contributes to multiple Sustainable Development Goals (SDGs), particularly SDG 8 (decent work and economic growth), SDG 9 (industry, innovation, and infrastructure), SDG 12 (responsible consumption and production), and SDG 13 (climate action). In this sense, AI operates not only as a technological tool but also as a foundational infrastructure for sustainability-oriented governance and economic coordination (Ametepey et al., 2024).

Despite these advantages, AI diffusion also generates significant socio-economic tensions. While it enhances productivity and competitiveness, it contributes to labour market polarization, unequal access to digital resources, and emerging forms of algorithmic inequality (Salhab et al., 2025). Its deployment in employment screening, credit allocation, and public service delivery further raises concerns regarding transparency, accountability, and fairness (Atef, 2026a). Many of these systems operate as opaque “black-box” mechanisms, limiting interpretability and weakening institutional oversight (Tripathi et al., 2025). These challenges are particularly pronounced in GCC economies due to structurally segmented labour markets and high dependence on migrant labour. Low- and medium-skilled workers face disproportionate exposure to automation risks and digital exclusion, whereas high-skilled groups capture a larger share of AI-driven productivity gains. Consequently, AI adoption interacts with pre-existing structural inequalities in ways that may reinforce rather than reduce socio-economic disparities (Di Muzio, 2024).

Existing literature provides important but partial explanations of these dynamics. Research on AI and digital transformation primarily emphasizes productivity gains and efficiency improvements, often treating distributional consequences as secondary effects. In contrast, inclusive growth literature focuses on inequality and access outcomes but tends to analyse these as end states rather than as processes generated through technological change (Awashreh & AlSaadi, 2026). Meanwhile, governance and socio-technical perspectives highlight institutional constraints, algorithmic bias, and regulatory challenges, yet often examine these factors independently from broader economic transformation processes (Awashreh, 2024).

This divergence reflects not only fragmentation but also differing analytical logics: productivity-oriented explanations in AI research, distribution-focused approaches in inclusive growth studies, and institution-centred perspectives in governance literature (Al Saadi & Atef, 2024). As a result, there remains limited understanding of how AI-driven systems interact with labour market structures and governance arrangements to produce uneven socio-economic outcomes. This raises a central question: how do AI-driven economic transformations interact with institutional and social structures to shape patterns of inequality in GCC economies? In particular, there is a lack of integrative frameworks that conceptualise these dynamics as system-level processes involving simultaneous interactions between technological change, inclusion mechanisms, and governance structures. Addressing this gap requires moving beyond technology-centric or single-dimension explanations toward an integrated analytical perspective. Accordingly, this study draws on digital economy transformation theory, inclusive growth theory, socio-technical systems theory, and ESG governance frameworks to examine AI-driven transformation as a co-evolutionary socio-technical-economic process. Within this context, the study develops a conceptual framework to explain how these structural dynamics unfold and how interactions between technological innovation, inclusion mechanisms, and governance systems shape economic outcomes in GCC economies.

Research Objectives

- To analyse how AI-driven transformation restructures economic systems in GCC economies
- To explain the emergence of uneven economic dynamics under AI adoption
- To develop the Triadic AI-Inclusive Growth Model (TAIGM)
- To examine how governance and ESG mechanisms can improve alignment between innovation and inclusion

Research Questions

- RQ1: How does AI restructure economic systems in GCC economies?
- RQ2: Why do uneven economic dynamics emerge under AI adoption?
- RQ3: How can governance mechanisms align innovation with inclusive outcomes?
- RQ4: What role do ESG frameworks play in moderating the distributive effects of AI?

The primary contribution of this study lies in developing an integrated conceptual framework that links AI-driven innovation, inclusion systems, and governance mechanisms within a unified analytical structure. By doing so, the study reframes inequality not as a direct outcome of technological adoption, but as a system-level phenomenon emerging from interactions between economic, social, and institutional processes. This provides a theoretically grounded and policy-relevant basis for understanding and governing AI-driven transformation in GCC economies and comparable contexts. The remainder of the paper is structured as follows: Section 2 reviews the literature; Section 3 presents the theoretical foundations; Section 4 develops the conceptual framework; Section 5 provides analytical discussion; Section 6 presents research propositions; Section 7 outlines the methodological positioning; Section 8 discusses policy implications; and Section 9 concludes.

2. LITERATURE REVIEW

Artificial intelligence (AI) is reshaping economic development trajectories in the Gulf Cooperation Council (GCC), positioning the region as an emerging hub for digital transformation, smart infrastructure, and post-hydrocarbon economic diversification.

2.1 Artificial Intelligence and Digital Economy Transformation

Artificial intelligence (AI) is widely conceptualised as a general-purpose technology (GPT) that transforms productivity systems, industrial organisation, and governance through automation, real-time analytics, and the optimisation of socio-economic processes, thereby generating system-wide effects across production systems and institutional structures (Leon, 2026). Within GCC economies, AI has become a central driver of economic diversification and post-hydrocarbon transformation, particularly through its application in smart cities, energy systems, logistics, and financial ecosystems. These developments reflect a transition toward data-intensive and algorithmically coordinated models of value creation (Mahmood et al., 2024).

Despite its strong emphasis on productivity enhancement and structural transformation, the AI literature generally treats distributional consequences as secondary. Even when issues such as skill-biased labour demand, employment displacement, or sectoral divergence are acknowledged, they are typically interpreted as unintended technological side effects rather than as structurally embedded outcomes shaped by institutional arrangements, labour market structures, and governance systems (Khogali & Mekid, 2023). This perspective limits understanding of how AI interacts with segmented labour markets and institutional frameworks to generate persistent socio-economic inequalities, particularly within GCC economies. Furthermore, much of the

existing literature implicitly assumes that productivity gains generated by AI will diffuse broadly across economic actors. However, emerging evidence indicates that these benefits are distributed unevenly, contributing to labour market polarisation, sectoral divergence, and unequal access to technological opportunities. This discrepancy highlights a fundamental tension between efficiency-driven theoretical assumptions and the distributive asymmetries observed in AI-driven economies (Awashreh & Ramachandran, 2024).

2.2 Inclusive Growth and Digital Inequality

The inclusive growth literature provides a normative framework for evaluating whether technological change promotes equitable participation, equal opportunities, and fair distribution of economic benefits (Saeed & Klugah, 2025; Awashreh, 2026b). Within digital economies, inequality is commonly associated with unequal access to digital technologies, disparities in digital skills, and differential exposure to algorithmic decision-making, all of which are reinforced by automation-induced labour market polarisation (Bircan & Özbilgin, 2025; Ananiades & Antunes, 2025). These dynamics are particularly pronounced in GCC economies, where segmented labour markets and a heavy reliance on migrant labour expose low- and medium-skilled workers to greater automation risks while simultaneously limiting opportunities for occupational mobility and digital inclusion (Mncube, 2027). Nevertheless, the inclusive growth literature generally conceptualises inequality as an outcome rather than as a systemic process generated through the interaction of technological change, labour market dynamics, and institutional structures. Although institutional capacity, education, and reskilling policies are recognised as important determinants of inclusive development, they are rarely integrated into a comprehensive framework that explains how inclusion systems co-evolve with technological transformation (Ernst, 2026). Consequently, the literature describes the manifestations of inequality without fully explaining the mechanisms through which it is systematically produced. Another limitation is the implicit assumption that policy interventions can effectively mitigate inequality after it has emerged. However, growing evidence suggests that inequality is endogenous to AI-driven transformation, arising from the continuous interaction between innovation systems, labour market institutions, and governance arrangements rather than existing solely as a policy failure requiring subsequent correction.

2.3 Socio-Technical Systems and Algorithmic Governance

Socio-technical systems theory conceptualises AI as an embedded system that is co-constructed through interactions among technological infrastructures, institutional arrangements, organisational practices, and broader socio-political contexts, thereby rejecting technologically deterministic explanations of innovation (Maas, 2025). Within the algorithmic governance literature, AI systems are shown to reproduce or amplify existing structural biases through feedback loops embedded in data collection, algorithmic design, and automated decision-making processes, particularly in employment, credit allocation, and public service delivery (Ahmad, 2026). One of the central mechanisms identified in this literature is governance lag, whereby the rapid deployment of AI technologies outpaces the capacity of regulatory and institutional systems to adapt, thereby weakening transparency, accountability, and public oversight (Ahmed et al., 2025). However, these perspectives remain only weakly connected to broader macroeconomic transformation processes. Although they explain how algorithmic bias emerges within socio-technical systems, they provide limited insight into how governance failures interact with technological innovation and labour market structures to generate wider socio-economic outcomes, including persistent inequality and structural divergence.

Consequently, a tension emerges between governance optimism—which assumes that improved regulation can resolve AI-related risks—and the persistence of structural inequalities. This suggests that regulatory interventions alone may reduce algorithmic bias but are unlikely to eliminate systemic inequalities without broader alignment among technological innovation, institutional governance, and labour market structures (Awashreh, 2025).

2.4 ESG and Sustainable Digital Transformation

Environmental, Social, and Governance (ESG) frameworks provide an important perspective for evaluating the sustainability implications of digital transformation across environmental efficiency, social equity, and governance transparency dimensions (Alhazemi, 2025). Within AI-driven contexts, ESG frameworks address issues including energy consumption, labour displacement, algorithmic fairness, and governance accountability (Ramachandran & Atef, 2026a; Mansour et al., 2026; Liu et al., 2025). Common ESG instruments include algorithmic audits, sustainability reporting, regulatory compliance mechanisms, and governance standards designed to guide the responsible deployment of AI technologies.

Despite these contributions, ESG frameworks remain predominantly reactive, focusing on evaluating and mitigating the impacts of AI after deployment rather than shaping technological development during earlier stages of innovation. Their effectiveness also depends heavily on institutional capacity, regulatory enforcement, organisational commitment, and transparency mechanisms (Awashreh et al., 2026). Furthermore, ESG principles remain only weakly integrated into models of AI-driven economic transformation and are generally treated as external governance mechanisms rather than as embedded components of socio-economic systems. As a result, their explanatory capacity remains limited with respect to understanding how sustainability, technological innovation, and socio-economic inequality interact within AI-driven economies (Atef & Ramachandran, 2025).

2.5 Research Gap and Integration Logic

The existing literature reveals fragmentation across four distinct analytical perspectives. First, the AI literature primarily adopts an efficiency-oriented logic, emphasising productivity growth, technological innovation, and economic transformation. Second, the inclusive growth literature adopts a distributional logic, focusing on inequality, social inclusion, and equitable access to economic opportunities. Third, socio-technical systems and algorithmic governance research employ an institutional logic, examining governance constraints, regulatory capacity, and algorithmic bias. Finally, ESG research follows a normative-regulatory logic, emphasising sustainability, accountability, and responsible governance mechanisms.

Although each perspective offers valuable insights, none provides a comprehensive explanation of how AI-driven transformation generates persistent socio-economic inequality. In particular, the literature does not adequately explain how innovation systems, labour market structures, governance arrangements, and sustainability mechanisms interact and co-evolve within contexts such as GCC economies, where rapid AI adoption coincides with segmented labour markets, state-led development strategies, and ambitious digital transformation agendas (Awashreh & Hassiba, 2026).

This limitation reflects a broader theoretical gap: the absence of a system-level framework that integrates technological innovation, inclusive growth, institutional governance, and sustainability into a unified analytical model. Addressing this gap motivates the development of the Triadic AI-Inclusive Growth Model (TAIGM), which conceptualises these dimensions as interconnected and co-evolving subsystems that collectively shape the economic and social outcomes of AI-driven transformation.

3. THEORETICAL Foundations

Digital Economy Transformation Theory conceptualises artificial intelligence (AI) as a general-purpose technology (GPT) that restructures production, distribution, and governance through automation, digitalisation, and large-scale optimisation (Ajuzieogu, 2025). In GCC economies, this transformation is reflected in the expansion of smart cities, AI-enabled energy systems, intelligent logistics, and digital financial platforms. While the theory provides a robust explanation of productivity enhancement and structural economic transformation, it is primarily efficiency-oriented and gives limited attention to how institutional arrangements and labour market structures shape the distribution of technological benefits. Consequently, it explains economic transformation but provides only limited insight into the persistence of socio-economic inequality. Within the Triadic AI-Inclusive Growth Model (TAIGM), this perspective forms the theoretical foundation of Innovation Capacity (IC).

Inclusive Growth Theory examines whether economic and technological progress generates equitable access to opportunities and a fair distribution of development benefits (Krysovaty et al., 2024). In AI-driven economies, this perspective extends to issues of digital access, skills development, labour market participation, and institutional inclusion. However, empirical evidence indicates that AI frequently reinforces existing inequalities through labour displacement, skill-biased technological change, and increasing demand for high-skilled workers (Dawadi et al., 2026). These dynamics are particularly evident in GCC economies, where migrant-dependent and segmented labour markets amplify disparities in employment opportunities and access to digital capabilities (Chedrawi et al., 2026). Although Inclusive Growth Theory highlights distributive outcomes, it generally conceptualises inequality as an outcome rather than as a dynamic process generated through interactions between technological innovation, labour market institutions, and governance systems. Consequently, it does not fully explain how inclusion systems co-evolve alongside technological transformation. Within TAIGM, this perspective underpins Inclusion Capacity (INC).

Socio-Technical Systems Theory conceptualises AI as a socio-technical system that is co-constructed through continuous interactions among technological infrastructures, institutional arrangements, organisational practices, and broader social contexts (Mesenhöller, 2025). The theory explains how algorithmic bias emerges within AI systems used in recruitment, credit scoring, and public governance through interactions between data, institutional practices, and automated decision-making (Lartey & Law, 2025). A central concept is asynchronous co-evolution, whereby technological innovation and institutional adaptation evolve at different rates, creating governance gaps, regulatory lag, and reduced institutional oversight (Okolo, 2025). Nevertheless, the theory primarily operates at the meso level and provides limited explanation of macroeconomic outcomes such as persistent inequality, structural divergence, or labour market polarisation. Within TAIGM, this perspective informs Governance–Sustainability Capacity (GSC).

Environmental, Social, and Governance (ESG) Theory integrates environmental, social, and governance dimensions into the assessment of technological systems and their broader societal impacts (Mu et al., 2026). Within AI-driven contexts, ESG frameworks address issues including energy efficiency, labour market impacts, algorithmic fairness, governance transparency, and organisational accountability (Lal & You, 2025). However, ESG is generally applied as an external governance framework rather than being embedded within innovation systems themselves. Consequently, its effectiveness depends heavily on institutional capacity, regulatory quality, enforcement mechanisms, and governance consistency, limiting its ability to explain the systemic co-evolution of innovation, inclusion, and governance. Within TAIGM, ESG contributes to Governance–Sustainability Capacity (GSC). GCC economies are characterised by rentier-state structures, migrant-dependent and segmented labour markets, and state-led models of digital transformation. These structural characteristics concentrate technological control, reinforce labour market stratification, and accelerate AI adoption while simultaneously contributing to uneven distributional outcomes. Collectively, the four theoretical perspectives provide complementary yet incomplete explanations of AI-driven economic transformation. The AI literature adopts

an efficiency-oriented perspective, Inclusive Growth Theory emphasises distributional outcomes, Socio-Technical Systems Theory focuses on institutional dynamics, and ESG Theory advances a normative-regulatory perspective. However, these perspectives are based on distinct analytical assumptions and do not provide an integrated explanation of how AI-driven transformation generates persistent socio-economic inequality. TAIGM addresses this theoretical limitation by integrating Innovation Capacity (IC), Inclusion Capacity (INC), and Governance–Sustainability Capacity (GSC) as interdependent and co-evolving subsystems that jointly shape the outcomes of AI-driven transformation.

4. CONCEPTUAL FRAMEWORK: THE TRIADIC AI-INCLUSIVE GROWTH MODEL (TAIGM)

To address the theoretical gaps identified in the preceding literature and reconcile competing perspectives on AI-driven development, this study proposes the Triadic AI-Inclusive Growth Model (TAIGM) as a system-level conceptual framework for explaining economic transformation in GCC economies. The model integrates innovation, inclusion, and governance into a unified analytical structure, providing a comprehensive explanation of how AI-driven technological change interacts with institutional arrangements and labour market dynamics to generate both economic growth and distributional outcomes. Rather than treating productivity, inclusion, and governance as independent phenomena, TAIGM conceptualises them as mutually dependent subsystems whose interactions determine the sustainability and inclusiveness of digital transformation. All citations have been retained exactly as provided.

4.1 Definition of the Core Components

To ensure conceptual clarity and terminological consistency, the three core components of TAIGM are defined as follows.

- Innovation Capacity (IC): The ability of an economic system to generate productivity gains through AI-driven technological and organisational transformation.
- Inclusion Capacity (INC): The ability of an economic system to absorb, diffuse, and distribute productivity gains across individuals, sectors, and social groups.
- Governance–Sustainability Capacity (GSC): The ability of an economic system to regulate, constrain, and stabilise AI-driven transformation through institutional, regulatory, and environmental, social, and governance (ESG) mechanisms.

These definitions are fixed and are applied consistently throughout the conceptual framework.

4.2 Theoretical Justification of the Triadic Structure

TAIGM is a mechanism-based framework that explains how artificial intelligence (AI) restructures economic systems in emerging digital economies, particularly within the GCC. The model conceptualises AI-driven transformation as the interaction of three interdependent subsystems: Innovation Capacity (IC), Inclusion Capacity (INC), and Governance–Sustainability Capacity (GSC). The triadic structure is derived from the principle of structural completeness in socio-technical economic systems, whereby stable and sustainable system outcomes require the simultaneous presence of three complementary mechanisms:

- value creation mechanisms;
- value distribution mechanisms; and
- system-level constraint mechanisms.

Existing theoretical perspectives explain these mechanisms only partially. Digital Economy Transformation Theory explains productivity growth and structural change but generally treats distributional outcomes as exogenous (Rahman, 2025). Inclusive Growth Theory focuses on the distribution of economic gains but does not explicitly explain how these gains emerge from technological innovation. Meanwhile, Socio-Technical Systems Theory and ESG frameworks emphasise governance, institutional adaptation, and sustainability but do not fully integrate these elements into broader macroeconomic transformation processes (Vărzaru, 2025; Ayoub, 2026).

TAIGM addresses these limitations by integrating these fragmented theoretical perspectives into a single, minimally sufficient system structure. Within this framework, each subsystem performs a distinct and indispensable function. The absence of any subsystem results in structural incompleteness:

- without IC, productivity gains cannot be generated;
- without INC, productivity gains cannot be effectively distributed; and
- without GSC, innovation lacks institutional regulation and long-term stability.

Accordingly, AI-driven transformation is conceptualised as a constrained socio-technical economic system in which economic outcomes emerge from structured interactions among innovation, inclusion, and governance capacities (Rahman, 2025; Ayoub, 2026).

4.3 Structural Components of TAIGM

(1) Innovation Capacity (IC)

Innovation Capacity represents the principal engine of economic transformation. It encompasses AI-enabled automation, predictive analytics, platform coordination, and algorithmic optimisation, all of which enhance productivity and improve the allocation of economic resources.

Its causal sequence is represented as:

AI deployment → productivity gains → reallocation of labour and capital

IC generates economic value by increasing productivity; however, it does not determine how these gains are distributed across society.

(2) Inclusion Capacity (INC)

Inclusion Capacity determines how productivity gains are absorbed and distributed throughout the economy. It functions as the transmission and absorption mechanism that links innovation outcomes with employment opportunities, income distribution, and broader socio-economic participation.

INC operates through several institutional mechanisms, including:

- reskilling system elasticity;
- labour mobility structures;
- digital access parity; and
- fairness in allocation systems.

Its causal sequence is represented as:

Productivity gains → inclusion filtering → distribution outcomes

Although INC does not generate innovation, it determines the extent to which innovation translates into inclusive economic development.

(3) Governance–Sustainability Capacity (GSC)

Governance–Sustainability Capacity regulates and constrains AI-driven innovation through institutional, regulatory, and ESG-related mechanisms that promote accountability and long-term sustainability.

Its principal components include:

- regulatory enforcement;
- algorithmic transparency;
- ESG integration; and
- data governance systems.

Its causal sequence is represented as:

Governance constraints → innovation trajectories → systemic risk regulation

GSC primarily shapes innovation by defining institutional boundaries within which technological change occurs. Although it does not directly determine distributional outcomes, it influences them indirectly through its effects on innovation pathways.

4.4 Core System Mechanisms

To maintain structural consistency and avoid uncontrolled circularity, TAIGM adopts a bounded interaction structure in which causal relationships are directional rather than fully recursive.

The primary directional relationships are:

- IC influences INC through productivity restructuring.
- GSC constrains IC through regulatory and governance mechanisms.
- INC determines the distribution of productivity gains.

The framework does not assume direct feedback loops between INC and GSC or from INC back to IC.

(i) Innovation–Inclusion Transmission Mechanism

The relationship between innovation and inclusion determines the extent to which productivity gains become socially inclusive.

- High IC combined with weak INC produces limited diffusion of productivity gains.
- High IC combined with strong INC produces broad and equitable distribution of productivity gains.

Accordingly, INC determines whether technological progress translates into inclusive socio-economic outcomes.

(ii) Governance Constraint Mechanism

Governance determines the institutional boundaries within which innovation operates.

- Weak GSC permits relatively unregulated innovation expansion.
- Strong GSC channels innovation through regulated and sustainable pathways.

Thus, GSC constrains innovation while reducing systemic risks associated with AI deployment.

(iii) Asynchronous Evolution Mechanism

The three subsystems evolve at different temporal rates:

- IC evolves rapidly because it is technology-driven.

- INC evolves at a moderate pace through institutional and labour market adjustment.
- GSC evolves more slowly because regulatory adaptation typically lags technological change.

These differences in adjustment speed create persistent structural tensions during AI-driven economic transformation (Chen et al., 2025).

4.5 Emergent Outcome: Dual-Speed Digital Economy

TAIGM proposes that a dual-speed digital economy emerges when Innovation Capacity, Inclusion Capacity, and Governance–Sustainability Capacity evolve at different rates over time.

Formally,

AI-driven productivity expansion + uneven inclusion capacity + delayed governance adaptation → cumulative divergence

This divergence produces two distinct development trajectories. The first consists of high-speed sectors, characterised by extensive AI adoption, rapid productivity growth, capital-intensive production, and accelerated innovation diffusion. The second consists of low-speed sectors, characterised by limited absorptive capacity, weaker transmission of productivity gains, slower institutional adaptation, and persistent structural constraints. Because these differences reinforce themselves over time, the resulting divergence is cumulative and path-dependent, reflecting sectoral differences in the ability to absorb and distribute AI-generated productivity gains (Gafsi et al., 2026).

4.6 Core Proposition of TAIGM

TAIGM proposes that AI-driven transformation generates inclusive and sustainable economic outcomes only when Innovation Capacity, Inclusion Capacity, and Governance–Sustainability Capacity evolve in coordinated alignment. Conversely, persistent misalignment among these three subsystems produces uneven distribution of productivity gains, reinforcing structural inequality and limiting the long-term benefits of AI-enabled economic transformation.

4.7 Model Logic

TAIGM conceptualises AI-driven transformation as a constrained, non-linear system characterised by directional causality.

Within this framework:

- Innovation Capacity drives productivity expansion.
- Inclusion Capacity determines the distribution of productivity gains.
- Governance–Sustainability Capacity constrains innovation pathways through institutional regulation.

Rather than assuming unrestricted recursive feedback among all subsystems, the model is built around bounded interactions that generate path-dependent outcomes when subsystem development becomes imbalanced.

4.8 Theoretical Contribution

TAIGM makes several theoretical contributions to the literature on AI-driven economic transformation. First, it establishes a structurally complete triadic framework that integrates innovation, inclusion, and governance within a single analytical model. Second, it assigns distinct and non-overlapping causal functions to each subsystem, thereby reducing conceptual ambiguity regarding their respective roles. Third, the model reconceptualises inequality as an endogenous outcome of system dynamics rather than as an external consequence of technological change. Finally, TAIGM embeds governance as an internal structural constraint on economic transformation, thereby providing a coherent conceptual framework that is theoretically grounded and empirically testable.

4.9 Empirical Operationalisation

TAIGM is operationalised through measurable constructs corresponding to its three core subsystems. Innovation Capacity (IC) is measured using indicators such as AI adoption rates, automation intensity, digital infrastructure, and technological readiness. Inclusion Capacity (INC) is operationalised through measures of workforce skill distribution, labour mobility, reskilling and upskilling capacity, digital access, and workforce participation. Governance–Sustainability Capacity (GSC) is captured using indicators of ESG performance, regulatory quality, institutional effectiveness, data governance, algorithmic transparency, and accountability mechanisms.

The proposed framework is designed for empirical validation using multiple complementary analytical approaches. Structural Equation Modelling (SEM) provides the primary methodology for testing the hypothesised causal relationships among the three latent constructs, including the direct, indirect (mediation), and conditional (moderation) effects specified by TAIGM. System Dynamics Modelling may be employed to examine the temporal evolution of the three subsystems and the cumulative effects of their interactions over time, whereas Agent-Based Simulation can be used to analyse heterogeneous behavioural responses across sectors, organisations, and labour groups, thereby capturing emergent macro-level outcomes arising from micro-level interactions. Figure 1 presents the proposed Structural Equation Model (SEM) corresponding to the conceptual architecture of TAIGM and illustrates the hypothesised relationships among Innovation Capacity, Inclusion Capacity, Governance–Sustainability Capacity, and AI-driven inclusive growth outcomes. The SEM operationalises the theoretical framework by translating its conceptual pathways

into empirically testable relationships, thereby providing a foundation for future quantitative validation across GCC economies and other comparable digital contexts.

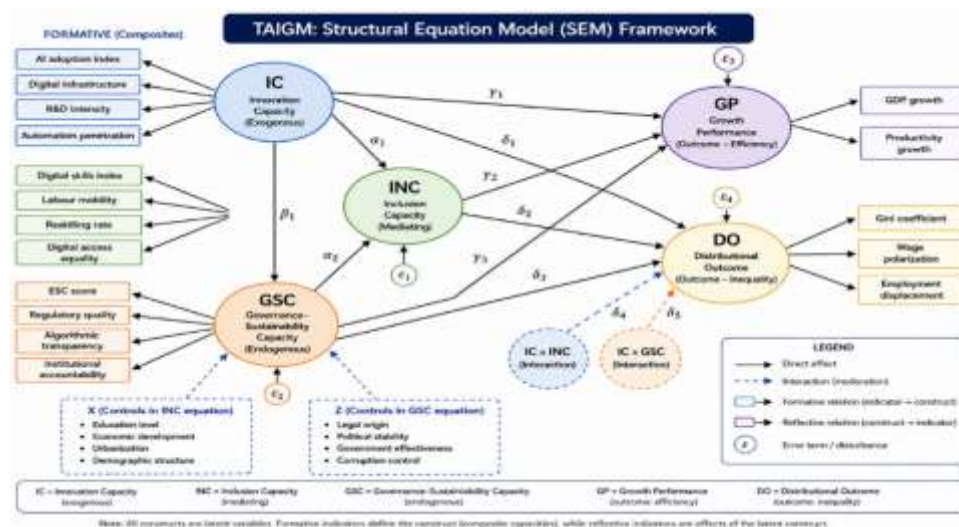


Figure 1. structure equation model

source: Authors own work

5. DISCUSSION

Building on the TAIGM framework, AI-driven transformation in GCC economies generates uneven economic and social outcomes through sectoral restructuring, institutional asymmetries, governance challenges, and uneven ESG implementation. Rather than diffusing uniformly across the economy, AI adoption varies considerably across sectors according to differences in capital intensity, digital readiness, and institutional capacity. High-adoption sectors, including finance, energy, and logistics, have integrated AI into core operational systems such as algorithmic credit scoring, predictive maintenance, fraud detection, and supply chain optimisation, resulting in substantial productivity gains (Albous et al., 2025; Mahmood et al., 2024). By contrast, labour-intensive sectors such as construction, retail, and low-skilled services exhibit slower and more fragmented adoption because of weaker digital infrastructure, lower workforce skill levels, and continued dependence on migrant labour. In these sectors, AI is more commonly deployed to reduce labour costs or substitute routine tasks than to drive productivity-enhancing innovation (Ranabahu et al., 2025).

The public sector presents a hybrid pattern of AI adoption. While AI is increasingly incorporated into smart governance initiatives and public service delivery, its effectiveness varies according to institutional capability and the maturity of data governance systems. Consequently, concerns regarding transparency, accountability, and the oversight of algorithmic decision-making remain significant (Alrawahna et al., 2025; Atef, 2026b). These variations demonstrate that AI diffusion is inherently uneven, highlighting the need for sector-specific rather than aggregate analyses of digital transformation. Sectoral differences are further amplified by cross-country variation within the GCC. The UAE and Saudi Arabia have emerged as regional leaders in AI adoption through comprehensive national AI strategies, substantial public investment, and state-led digital transformation programmes, achieving advanced implementation across finance, smart cities, and energy systems (Chattha et al., 2025). In contrast, other GCC states have experienced slower rates of AI diffusion because of smaller market size and comparatively weaker institutional and technological capacity. Within individual economies, cumulative advantage further reinforces these disparities, as sectors with high AI adoption reinvest productivity gains into continued technological upgrading, whereas sectors with limited adoption remain constrained by shortages of capital, digital infrastructure, and skilled labour, restricting their participation in AI-driven value creation (AIDossary, 2026).

These structural asymmetries extend to labour markets, where AI-driven transformation produces unequal employment outcomes. High-skilled workers benefit from rising demand, wage premiums, and expanded career opportunities, whereas low- and medium-skilled workers, particularly migrant labour, face greater risks of job displacement, wage stagnation, and labour market exclusion (Mncube, 2027; Chedrawi et al., 2026). Consequently, inequality emerges as a structural consequence of sectoral specialisation and labour market segmentation rather than as a temporary adjustment associated with technological change.

The expansion of AI into governance systems also introduces differentiated institutional risks, particularly in employment, finance, and public service delivery. Algorithmic recruitment and screening systems may reproduce biases against migrant and low-skilled workers because they rely on historically biased datasets and opaque decision-making processes (Awashreh, 2025). Similarly, AI-based credit scoring can disadvantage individuals lacking formal financial histories, while automated public service systems may improve administrative efficiency but simultaneously produce rigid and less transparent allocation decisions (Alrawahna et al., 2025). These risks stem from structural factors, including fragmented data systems, algorithmic opacity, and uneven regulatory and

technical capacity. They are further intensified by governance lag within GCC economies, where regulatory frameworks often evolve more slowly than technological innovation (Kenzie, 2024). Although AI governance frameworks are becoming more widespread, their implementation remains uneven, suggesting that algorithmic risks primarily reflect institutional weaknesses rather than purely technical limitations.

Comparable patterns are evident in the implementation of environmental, social, and governance (ESG) frameworks. Although ESG principles are increasingly incorporated into AI governance, their effectiveness differs substantially across GCC countries because enforcement ranges from comprehensive regulatory systems to predominantly voluntary reporting regimes, resulting in inconsistent oversight and monitoring (Oehmichen et al., 2025). Adoption also varies across organisations. Large corporations and state-linked enterprises generally possess greater financial and organisational capacity to comply with ESG requirements than small and medium-sized enterprises (SMEs), which often face significant resource constraints. Furthermore, ESG mechanisms remain largely *ex post*, focusing on evaluating AI outcomes rather than proactively shaping innovation pathways, while inconsistencies in ESG measurement frameworks limit comparability across sectors and countries. Consequently, ESG functions as a conditional governance mechanism whose effectiveness depends on regulatory enforcement, institutional maturity, and its integration within broader governance systems.

Taken together, AI-driven transformation across GCC economies is characterised by structural unevenness, institutional differentiation, and social stratification. High-productivity sectors and highly skilled workers capture a disproportionate share of AI-generated benefits, whereas structurally constrained sectors and vulnerable labour groups experience greater risks of exclusion, displacement, and limited participation in digital value creation. Within the TAIGM framework, these outcomes are understood as endogenous consequences of the interaction among Innovation Capacity, Inclusion Capacity, and Governance–Sustainability Capacity, reinforcing inequality and sectoral divergence through differences in sectoral composition, labour market segmentation, and institutional capability.

6. RESEARCH PROPOSITIONS

This section translates the TAIGM framework into testable propositions capturing the interaction between Innovation Capacity (IC), Inclusion Capacity (INC), and Governance–Sustainability Capacity (GSC). The propositions specify moderation, mediation, and system-level alignment effects underlying AI-driven inequality in GCC economies (see table 1).

Table 1. Research Propositions

ID	Research Proposition	Hypothesis Statement	Theoretical Basis	Expected Effect
P1	Innovation Capacity (IC) × Inclusion Capacity (INC) (<i>Moderation</i>)	AI adoption increases inequality; however, this effect becomes significantly weaker when Inclusion Capacity (INC) is high. Conversely, under weak INC conditions, AI adoption amplifies inequality.	Digital Economy Transformation Theory; Inclusive Growth Theory	INC negatively moderates the relationship between AI adoption and inequality.
P2	Innovation Capacity (IC) → Inclusion Capacity (INC) → Inequality (<i>Mediation</i>)	The effect of AI adoption on inequality is mediated by Inclusion Capacity (INC), such that AI increases inequality primarily through weak inclusion mechanisms, including limited workforce reskilling, restricted labor mobility, and unequal digital access.	Inclusive Growth Theory; TAIGM Structural Logic	INC partially or fully mediates the relationship between AI adoption and inequality.
P3	Innovation Capacity (IC) × Governance–Sustainability Capacity (GSC) (<i>Moderation</i>)	The positive relationship between AI adoption and inequality is significantly reduced under strong Governance–Sustainability Capacity (GSC), supported by effective ESG integration, transparent algorithmic governance, and responsible regulatory institutions.	ESG Governance Theory; Socio-Technical Systems Theory	GSC negatively moderates the relationship between AI adoption and inequality.
P4	System Alignment (Integrated Effect)	Inclusive and sustainable AI-driven outcomes emerge only when Innovation Capacity (IC), Inclusion Capacity (INC), and Governance–Sustainability Capacity (GSC) are jointly aligned. Misalignment among these capacities generates structural inequality, uneven AI diffusion, and sectoral divergence.	TAIGM Framework (Integrative Synthesis)	Joint alignment of IC, INC, and GSC produces inclusive AI development and minimizes inequality.

source: Author own works

7. METHODOLOGICAL POSITIONING

This study adopts a conceptual and model-oriented research design to develop the Triadic AI-Inclusive Growth Model (TAIGM) as a system-level explanatory framework. Rather than relying on single-method empirical testing, it focuses on modelling interaction effects and system structures linking artificial intelligence (AI), inequality, and governance within GCC economies (Dündar, 2025). The aim is to explain how AI-driven transformation produces differentiated outcomes through the interaction of innovation, inclusion, and governance systems, while also establishing a foundation for future empirical validation (Al-Maadid et al., 2026).

7.1 Methodological Design

The study follows a structured three-stage theory-building process:

- (i) Conceptual synthesis: Integration of interdisciplinary literature on AI and digital transformation, inclusive growth, socio-technical systems, and ESG governance to identify key constructs and theoretical gaps.
- (ii) Analytical abstraction: Derivation of three core system components—innovation, inclusion, and governance—sustainability—and identification of recurring structural patterns, including governance lag, diffusion asymmetry, and inclusion constraints.
- (iii) Model construction: Specification of TAIGM as a structured system of directional relationships among subsystems, enabling both simulation and empirical testing of AI-driven transformation processes (Yang et al., 2026).

7.2 Modelling Strategy

The study adopts a dual-modelling strategy that combines system dynamics modelling and structural equation modelling (SEM) to capture both system evolution and causal relationships. System dynamics modelling represents TAIGM as a dynamic system in which Innovation Capacity (IC), Inclusion Capacity (INC), and Governance–Sustainability Capacity (GSC) evolve over time through interacting feedback structures. This approach captures time delays, non-linearities, and interdependencies, enabling simulation of long-term trajectories and policy scenarios. Structural equation modelling (SEM) is used to empirically test the hypothesised relationships outlined in Section 6, including mediation effects (INC) and moderation effects (GSC), as well as to estimate latent constructs such as inclusion capacity and governance quality (Bužinskienė et al., 2026).

7.3 Measurement and Calibration Strategy

TAIGM is operationalised using the following indicators:

- Innovation Capacity (IC): AI adoption rates, digital infrastructure indices, automation intensity, R&D investment
- Inclusion Capacity (INC): skill distribution metrics, labour mobility rates, digital access indicators, reskilling participation
- Governance–Sustainability Capacity (GSC): ESG scores, regulatory quality indices, algorithmic transparency measures, data governance frameworks

In system dynamics modelling, these indicators are used to initialise system conditions, parameterise relationships among subsystems, and simulate alternative development pathways.

Key data constraints in the GCC context include limited availability of AI-specific sectoral data, inconsistent ESG reporting standards, and insufficient measurement of algorithmic governance and migrant labour dynamics. As a result, proxy indicators are required, and findings must be interpreted with appropriate methodological caution.

7.4 Analytical Focus

The methodological focus is on interaction effects, system structure, and non-linear dynamics rather than isolated correlations. The analysis examines how different configurations of innovation, inclusion, and governance capacities generate divergent inequality and inclusion outcomes across GCC economies.

7.5 Validity and Empirical Transferability

Although conceptual in design, TAIGM is structured for empirical operationalisation. System dynamics modelling enables simulation of long-term structural behaviour, while SEM provides statistical testing of theoretical propositions using real-world data. This dual approach enhances internal validity through explicit causal structure and external validity through applicability to GCC and comparable digital economies.

7.6 Positioning of the Study This study is positioned within conceptual and policy-oriented model development, aiming to explain AI-driven economic transformation in structurally complex economies. By integrating system modelling with empirical validation pathways, it bridges the gap between theoretical abstraction and policy-relevant analytical frameworks.

8. POLICY IMPLICATIONS

The governance of AI-driven transformation in GCC economies requires sequenced and system level interventions across structural, institutional, and operational dimensions rather than fragmented policy tools. The primary priority is aligning innovation expansion with inclusion systems and governance capacity, as current GCC strategies remain largely innovation-led and focused on AI adoption, infrastructure, and competitiveness. While these strategies enhance productivity and diversification, they may also intensify structural inequality when inclusion and governance systems evolve more slowly. Policy design therefore needs to integrate

inclusion mechanisms directly into national AI strategies, synchronise labour market transformation with technological deployment, and embed governance considerations at the design stage rather than treating them as post-deployment corrections. A second priority is strengthening institutional capacity for AI governance through enforceable oversight in high-impact domains such as employment, credit, and public services, supported by mechanisms such as audits, explainability standards, and traceability systems to reduce opacity and bias.

In this context, ESG frameworks should shift from voluntary reporting toward enforceable regulatory instruments embedded within governance systems so that fairness and sustainability considerations shape system design rather than being assessed after implementation, although their effectiveness still depends on regulatory capacity and consistency. At the operational level, policy should focus on inclusive participation through reskilling, AI literacy, and labour transition programmes, particularly for low- and medium-skilled workers, alongside improved labour mobility and expanded digital infrastructure for SMEs, peripheral regions, and migrant workers, since infrastructure quality strongly determines whether AI benefits are widely distributed or concentrated. Overall, effective AI governance depends on coordinated alignment across structural, institutional, and operational levels, because persistent fragmentation across these layers, combined with labour segmentation and uneven regulatory enforcement, risks reinforcing rather than reducing structural inequality in AI-driven economic transformation.

9. CONCLUSION

This study identifies three central findings regarding AI-driven economic transformation in GCC economies. First, AI operates as a structural driver of economic reconfiguration, reshaping production systems, factor allocation, and coordination mechanisms. However, productivity gains do not automatically translate into inclusive outcomes, as their distribution is conditioned by labour market structures and institutional capacities. Second, inequality in AI-driven economies emerges as a conditional and endogenous system outcome rather than a direct consequence of technological adoption. Uneven development of inclusion mechanisms and governance capacity leads to asymmetric distribution of AI-generated benefits and reinforces existing socio-economic hierarchies. Third, the interaction between technological acceleration, institutional adaptation, and labour market dynamics generates persistent structural divergence across sectors. This divergence reflects cumulative effects of uneven co-evolution rather than short-term adjustment processes. A key limitation of this study is its conceptual nature. While the framework specifies causal mechanisms and interaction effects, it does not provide empirical estimation or calibration. It therefore requires validation through quantitative and computational approaches.

Future research should empirically test interactions between innovation, inclusion, and governance capacities using system dynamics modelling and structural equation modelling, particularly in GCC and other rapidly digitising economies. This would strengthen the empirical grounding of the TAIGM framework and enable scenario-based policy analysis. The applicability of the framework is context-dependent, as it is primarily designed for structurally segmented digital economies such as the GCC, where rapid technological adoption coexists with labour market segmentation, state-led development models, and evolving governance systems. Its explanatory power may therefore be more limited in highly diversified or institutionally mature economies with different structural configurations. Overall, the study provides a system-level perspective on AI-driven transformation, highlighting that economic outcomes depend not only on technological advancement but on the alignment between innovation systems, inclusion mechanisms, and governance capacity.

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