

Unlocking Artificial Intelligence Driven Perceived Business Growth Through Organizational Readiness and Employee Development in Saudi Enterprises

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Abstract

Artificial intelligence (AI) is transforming organizational capabilities and competitive advantage, yet limited research explains how AI adoption and organizational readiness translate into Perceived Business Growth (PBG) through sustainable employee development. Drawing on the Resource-Based View (RBV) and the Technology–Organization–Environment (TOE) framework, this study examines the relationships among AI Adoption, Organizational Readiness for AI, Employee Development, and PBG in Saudi organizations using survey data from public- and private-sector employees. The findings support the proposed direct and indirect relationships and identify Employee Development as a critical human-capital pathway linking AI Adoption and Organizational Readiness with PBG. By framing digital transformation within the context of Sustainable Development Goals, specifically SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure), the study extends the RBV–TOE perspective by integrating technological, organizational, and human-capability factors. The findings highlight the need to combine AI investment with organizational readiness and continuous workforce upskilling to support resilient, inclusive, and sustainable organizational growth in emerging digital economies.

1. Introduction

Artificial intelligence (AI) has evolved from an emerging technology into a strategic organizational asset, fundamentally transforming operational processes, workforce capabilities, and value creation [1, 2]. Technologies such as machine learning, predictive analytics, and automated decision-support systems enable organizations to optimize workflows, enhance operational efficiency, and drive innovation [3]. However, embedding AI into organizational structures does not automatically guarantee enduring competitive value. Emerging research indicates that realizing value from AI depends not only on acquiring technological assets but also on building supportive organizational contexts and strengthening the human capabilities needed to use them effectively [4]. This challenge is particularly evident in emerging digital economies like Saudi Arabia, where organizations are moving rapidly from technology acquisition to widespread implementation and value realization under the ambitious objectives of Saudi Vision 2030 [5].

From a human capital perspective, employee development serves as a primary mechanism through which AI investments generate organizational value [6]. The integration of AI alters job structures and task requirements, elevating the need for employees to acquire digital, analytical, and adaptive competencies [7, 8]. While advanced AI tools can automate routine tasks, organizational performance increasingly depends on effective human–AI collaboration, in which AI augments rather than replaces human capabilities [9]. Consequently, employee development is not merely an outcome of technological change, but a pivotal capability-building process that transforms technological potential into business outcomes. However, organizational context can constrain or enable an employee's capacity to build and deploy these competencies [10]. According to organizational readiness theory, successful digital transformation requires infrastructure, leadership commitment, governance, and a supportive learning

culture [11, 12]. While organizational readiness has traditionally been examined as a direct determinant of technology adoption, less is known about its simultaneous role in creating an environment that fosters workforce upskilling and, ultimately, business growth.

Despite growing interest in AI implementation, important theoretical and empirical gaps remain. First, existing literature often treats AI adoption, organizational readiness, employee development, and business performance as isolated relationships rather than examining them within an integrated framework [6]. Second, while previous studies acknowledge that human capital plays a role in technological outcomes, the mediating mechanism of employee development between AI adoption, organizational readiness, and Perceived Business Growth (PBG) remains insufficiently explicated, particularly within the Middle Eastern context [5].

In the broader context of sustainable development, it is essential to evaluate the benefits of AI in emerging digital economies such as Saudi Arabia. Digital transformation has evolved from a tool for immediate efficiency to a key driver of long-term economic resilience, sustainable innovation, and human capital sustainability, prompting stakeholders to align rapidly with Saudi Vision 2030. This approach is directly aligned with the United Nations Sustainable Development Goals (SDGs), especially SDG 8 (Decent Work and Economic Growth) – promoting productive employment and enhancing human capabilities in parallel with technological advances – and SDG 9 (Industry, Innovation and Infrastructure) – incorporating adaptive, sustainable digital infrastructure into business activity. Framing AI-enabled business growth as workforce augmentation ensures technological progress supports sustainable, inclusive economic growth rather than skill obsolescence.

To address these gaps, this study integrates the Resource-Based View (RBV) Barney [13] and the Technology–Organization–Environment (TOE) framework [14] to formulate a comprehensive explanatory model. The RBV posits that sustainable competitive advantage stems from combining technological assets with valuable, non-substitutable human capabilities. The TOE framework complements this by defining the contextual and organizational conditions required for effective innovation assimilation. Specifically, this study aims to answer the following central research question: Does Employee Development mediate the relationship between AI Adoption and Organizational Readiness for AI and Perceived Business Growth in Saudi enterprises? By addressing this question, the study contributes to the literature by showing how technological investments and organizational readiness interact synergistically with human capital enhancement to drive organizational growth.

2. Literature Review and Hypotheses Development

2.1 Theoretical Foundations and Conceptual Integration

This study integrates the Resource-Based View (RBV) and the Technology–Organization–Environment (TOE) framework to explicate how Artificial Intelligence (AI) Adoption and Organizational Readiness for AI enhance Perceived Business Growth (PBG) through the mediating mechanism of Employee

Development. According to the RBV, organizational performance differences arise from the effective utilization of valuable, rare, and inimitable resources and capabilities [13, 15]. While AI is a critical technological resource, standard AI technologies alone cannot sustain competitive advantage because they can be easily replicated [2]. RBV posits that technological assets require complementary human competencies to translate into organizational value [7]. The TOE framework extends this perspective by explaining the contextual factors that enable such resource integration. It suggests that technological, organizational, and environmental contexts dictate the successful assimilation of innovations [14]. In our model, Organizational Readiness acts as the critical TOE organizational antecedent that facilitates both AI implementation and the cultivation of an environment conducive to workforce upskilling [10, 11]. Thus, TOE explains the contextual capacity to absorb AI, while RBV explains how these integrated resources transform into business value through human capital (Employee Development). 2.2 Artificial Intelligence Adoption and Perceived Business Growth

AI adoption refers to the extent to which organizations incorporate AI-powered technologies—such as machine learning, predictive analytics, and intelligent decision-support systems—into their operational and managerial activities [1, 3]. The successful integration of these tools optimizes processes, improves decision-making quality, and enhances organizational agility. Empirical studies increasingly link AI capabilities to organizational effectiveness, innovation, and competitive outcomes [4]. Consequently, employees within organizations that actively adopt AI are more likely to perceive tangible progress in the organization's overall market position and growth trajectory.

H1: Artificial Intelligence Adoption has a positive effect on Perceived Business Growth. 2.3 Artificial Intelligence Adoption and Employee Development

The deployment of AI fundamentally alters task structures and operational workflows, shifting workforce demands from routine tasks toward activities requiring analytical reasoning, complex problem-solving, and technology integration [16, 17]. Consistent with the RBV, as organizations deploy AI assets, they simultaneously generate a compelling need to reskill and upskill their workforce to interact effectively with these intelligent systems [7]. AI integration, therefore, acts as a catalyst for continuous skill enhancement and technology-enabled professional development.

H2: Artificial Intelligence Adoption has a positive effect on Employee Development. 2.4 Employee Development and Perceived Business Growth

Employee Development serves as an organizational mechanism to elevate human competencies through targeted training, continuous education, and knowledge enhancement. When employees acquire advanced digital, analytical, and adaptive skills, they become better equipped to drive innovation, improve operational efficiency, and adapt to market changes [18]. From a capability-enhancement perspective, a highly developed workforce directly contributes to superior work practices and enhanced organizational value, thereby positively influencing the perceived trajectory of business growth.

H3: Employee Development has a positive effect on Perceived Business Growth.

2.5 Organizational Readiness for AI and Perceived Business Growth

Organizational Readiness encompasses the structural, financial, managerial, and cultural preparedness required to facilitate AI-enabled transformation [10, 11]. Based on the TOE framework, organizations with strong leadership commitment, adequate resources, and an adaptable culture are better positioned to embed AI seamlessly into their processes. This structural readiness reduces implementation barriers and enhances the organization's capacity to capitalize on emerging market opportunities, leading to improved perceptions of business growth and expansion.

H4: Organizational Readiness for AI has a positive effect on Perceived Business Growth.

2.6 Organizational Readiness for AI and Employee Development

Effective AI implementation requires an organizational context that actively supports learning and adaptation. Organizations with high readiness allocate the financial and technological resources needed to provide comprehensive training programs and access to AI tools. A flexible, readiness-oriented culture reduces resistance to change and fosters knowledge sharing [14]. Consequently, organizational readiness establishes the structural and cultural foundation necessary for robust employee development initiatives.

H5: Organizational Readiness for AI has a positive effect on Employee Development.

2.7 The Mediating Role of Employee Development

While AI Adoption and Organizational Readiness directly influence PBG, direct relationships alone provide an incomplete picture of how technological and organizational factors generate value. Integrating the RBV and TOE frameworks suggests that Employee Development functions as a critical complementary human-capital conduit. First, organizational readiness provides the supportive climate, leadership backing, and resources necessary for workforce upskilling. Once employees develop these competencies, the organization can leverage its technological assets to drive growth [11]. Thus, organizational readiness partially affects PBG through workforce development. Second, AI adoption fundamentally shifts skill requirements, compelling organizations to invest in human capital. The workforce's newly developed digital and analytical capabilities empower employees to optimize AI-integrated processes, make better decisions, and foster innovation [4]. Therefore, Employee Development serves as an alternative, human-centric pathway that translates AI adoption and the organization's foundational readiness into perceived organizational value.

H6: Employee Development mediates the positive relationship between Organizational Readiness for AI and Perceived Business Growth.

H7: Employee Development mediates the positive relationship between Artificial Intelligence Adoption and Perceived Business Growth.

In our model, Organizational Readiness acts as the critical TOE organizational antecedent that facilitates both AI implementation and the cultivation of an environment conducive to continuous workforce upskilling. Thus, TOE explains the contextual capacity to absorb AI, while RBV explains how these integrated resources transform into business value through human capital (Employee Development). Within a sustainable development framework, combining technological assets with human skill enhancement ensures that enterprise growth aligns with SDG 8 (decent work and sustainable growth) and SDG 9 (inclusive, resilient innovation).

3. Conceptual Model

The proposed model, based on the integrated RBV and TOE frameworks, investigates the direct and indirect effects of AI adoption and organizational readiness on perceived business growth. The framework allows the research to establish whether employee development is a significant pathway for technological adoption and organisational readiness in perceived business growth.

4. Methodology

This empirical research adopts a quantitative cross-sectional design to investigate the structural relationships among Artificial Intelligence (AI) adoption, Organisational Readiness for AI, Employee Development and Perceived Business Growth (PBG) in Saudi Arabian firms. The target population was the operational and managerial staff of the public and private sector organisations that operate in the Eastern Province of Saudi Arabia. Data were collected through a non-probability convenience sampling technique. The final analytical sample comprised 250 valid responses. In an effort to verify the statistical power, the sample size was assessed using the accepted empirical rules [19]. The sample size of $N = 250$ greatly exceeds the minimum requirement to achieve statistical power of 0.80 at $\alpha = 0.05$ with a medium effect size ($f^2 = 0.15$). The measuring instrument was developed by adapting multi-item scales from previous empirical research. We measured the adoption of artificial intelligence with five items adapted from [1]. These items are concerned with the operational adoption of machine learning, predictive analytics, and automated decision-support systems. Organisational Readiness for AI was operationalised with six items adapted from [1] to include executive leadership endorsement, technical infrastructure, financial resource allocation, and digital culture. Employee development was assessed with six items adapted from Gayathiri and Prabu [20], which focused on the enhancement of workplace and adaptive skills. Perceived Business Growth was measured with seven items adopted from [1, 21]. All survey metrics were based on a traditional five-point Likert scale, with 1 being “Strongly Disagree” and 5 being “Strongly Agree. Hypothesis testing and structural estimations were conducted with the use of Partial Least Squares Structural Equation Modelling (PLS-SEM).

5. Finding

The empirical model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM). Following the two-stage analytical strategy recommended by Hair et al. (2017), the measurement

model was first evaluated to establish construct reliability and validity, followed by an assessment of the structural model to test the hypothesized direct and indirect relationships.

5.1 Demographic Profile of Respondents

The final analytical sample comprised 250 operational and managerial personnel from public and private sector organizations in the Eastern Province of Saudi Arabia. Table 1 details the demographic distribution. Overall, 76.8% of participants were male, and 76.0% were Saudi nationals. The sample reflected a highly experienced cohort, with 58.0% possessing over 15 years of professional experience. Furthermore, 87.2% held a Bachelor's degree or higher (53.2% Bachelor's, 20.0% Master's, 14.0% Doctorate). Organizationally, 57.2% belonged to the private sector and 42.8% to the public sector, spanning major industrial sectors such as Education (32.0%), Oil & Gas (25.2%), and Government Services (23.2%).

Table 1
Demographic Profile of the Sample.

Factors	Frequency	Percentage
Gender	58	23.2
Female		
Male	192	76.8
Nationality		
Saudi	190	76.0
Non-Saudi	60	24.0
Years of experience		
Less than 5 years	32	12.2
5–10 years	38	15.2
11–15 years	35	14.0
More than 15 years	145	58.0
Education level		
High school or less	10	4.0
Diploma	22	8.8
Bachelor's degree	133	53.2
Master's degree	50	20.0
Higher than a master's degree	35	14.0
Organization sector		
Public	107	42.8
Private	143	57.2
Position level		
Entry – level employees	80	32.0
Line management (supervisory)	67	26.8
Middle management	70	28.0
Higher management	33	13.3
Industry Field		
Banking & Financial Services	5	2.0

Factors	Frequency	Percentage
Gender	58	23.2
Female		
Education	80	32.0
Government &Public	58	23.2
Health care	18	7.2
Manufacturing	5	2.0
Oil& Gas	63	25.2
Transportation & Logistics	21	8.4

Table 1 presents the demographic characteristics of the 250 participants in the study. The sample was predominantly male (76.8%) and female (23.2%). Participants were Saudi citizens (76.0%) or non-Saudis (24.0%). Regarding professional experience, most participants (58.0%) had more than 15 years of experience, indicating that the sample consisted mainly of experienced employees. In terms of educational qualifications, more than half of respondents (53.2%) had a bachelor's degree, while 20.0% had a master's degree. In terms of organisational sector, 57.2% of participants were in the private sector and 42.8% in the public sector. By hierarchical classification, entry-level personnel were the largest segment (32.0%), followed by middle management (28.0%) and line management/supervisory roles (26.8%). Overall, the most common industry sectors represented by participants were education (32.0%), oil and gas (25.2%), and government and public sector (23.2%).

Common Method Bias (CMB) and Collinearity Diagnostics

We assessed potential multicollinearity among the measurement indicators by examining Variance Inflation Factor (VIF) values. According to PLS-SEM standards [22], the outer VIF values must be less than the cautionary limit of 3.3 to exclude lateral collinearity and Common Method Bias (CMB). The VIF values range from 1.185 (AI5) to 2.935 (PBG6) and are all under the critical threshold of 3.3. These empirical findings indicate a lack of significant multicollinearity among the construct indicators, supporting the structural integrity and measurement validity of the proposed framework.

5.2 Measurement Model

The measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity (Hair et al., 2017). Lateral collinearity and Common Method Bias (CMB) were systematically assessed using full collinearity Variance Inflation Factors (VIFs). All indicator VIF values ranged between 1.185 and 2.935, remaining strictly below the conservative threshold of 3.3 [22], thereby confirming the absence of substantial multicollinearity and CMB. Construct reliability was confirmed as Cronbach's alpha (CA) values ranged from 0.737 to 0.892, and Composite Reliability (CR) values ranged from 0.835 to 0.918, all exceeding the recommended 0.70 benchmark. Convergent validity was

established, as the Average Variance Extracted (AVE) for all constructs surpassed the 0.50 threshold (ranging from 0.545 to 0.653). Minor indicator outer loadings below 0.707 (e.g., AI5 = 0.567, ED1 = 0.565, PBG4 = 0.559) were retained to maintain content validity, as the overall construct CR and AVE criteria met all statistical requirements [23].

Table 2
Construct Reliability and Convergent Validity Results

Constructs	Items	Loadings	CA	CR	AVE
Artificial Intelligence	AI1	0.865	0.737	0.835	0.563
	AI2	0.789			
	AI4	0.748			
	AI5	0.567			
Employee Development	ED1	0.565	0.860	0.897	0.597
	ED2	0.815			
	ED3	0.788			
	ED4	0.856			
	ED5	0.786			
	ED6	0.791			
Organizational Readiness AI	RAI1	0.773	0.892	0.918	0.653
	RAI2	0.684			
	RAI3	0.870			
	RAI4	0.860			
	RAI5	0.805			
	RAI6	0.841			
Perceived Business Growth	PBG1	0.828	0.855	0.890	0.545
	PBG2	0.828			
	PBG3	0.719			
	PBG4	0.559			
	PBG5	0.579			
	PBG6	0.842			
	PBG7	0.818			

Discriminant validity was assessed using the Heterotrait-Monotrait ratio of correlations (HTMT). As shown in Table 3, all HTMT ratios were below the conservative threshold of 0.85 (ranging from 0.468 to 0.845), confirming distinct empirical boundaries among all theoretical constructs [24].

Table 3
Discriminant Validity via HTMT Ratios

Constructs	1	2	3	4
Artificial Intelligence				
Business Growth	0.834			
Employee Development	0.841	0.845		
Organizational Readiness for AI	0.468	0.587	0.496	

5.3 Structural Model and Hypotheses Testing

The structural model was evaluated using a bootstrapping procedure with 5,000 resamples to determine path coefficients (β), t-statistics, p-values, coefficients of determination (R^2), and Cohen's f^2 effect sizes [19]. The structural framework demonstrated strong explanatory power. The predictors collectively accounted for 81.9% of the variance in Perceived Business Growth ($R^2 = 0.819$), while AI Adoption and Organizational Readiness explained 51.0% of the variance in Employee Development ($R^2 = 0.510$). Cohen's f^2 effect size analysis revealed that AI Adoption exerted a very large effect on PBG ($f^2 = 1.459$) and a large effect on Employee Development ($f^2 = 0.666$). Organizational Readiness showed small effect sizes on both Employee Development ($f^2 = 0.074$) and PBG ($f^2 = 0.083$). Direct hypothesis testing supported all five proposed direct paths (H1–H5) at $p < 0.05$. AI Adoption positively influenced PBG ($\beta = 0.712$, $t = 13.433$, $p < 0.001$; H1 supported) and Employee Development ($\beta = 0.613$, $t = 10.476$, $p < 0.001$; H2 supported). Employee Development positively affected PBG ($\beta = 0.175$, $t = 3.225$, $p = 0.001$; H3 supported). Furthermore, Organizational Readiness exerted positive direct effects on PBG ($\beta = 0.136$, $t = 2.966$, $p = 0.003$; H4 supported) and Employee Development ($\beta = 0.205$, $t = 3.334$, $p = 0.001$; H5 supported). Mediation analysis evaluated the indirect effects via bootstrapping. The indirect path from Organizational Readiness to PBG through Employee Development was statistically significant ($\beta = 0.036$, $t = 2.143$, $p = 0.032$; H6 supported). Similarly, AI Adoption indirectly affected PBG through Employee Development ($\beta = 0.107$, $t = 3.163$, $p = 0.002$; H7 supported). Because both direct and indirect pathways remained significant and exhibited identical positive directions, Employee Development is categorized as a complementary partial mediator in both relationships [23].

Table 4
Structural Model Path Coefficients and Hypothesis Testing

Paths		Beta	SE	T-value	p value	Finding
H1	Artificial Intelligence -> Business Growth	0.712	0.053	13.433	0.000	YES
H2	Artificial Intelligence -> Employee Development	0.613	0.059	10.476	0.000	YES
H3	Employee Development -> Business Growth	0.175	0.054	3.225	0.001	YES
H4	Organizational Readiness AI -> Business Growth	0.136	0.046	2.966	0.003	YES
H5	Organizational Readiness AI -> Employee Development	0.205	0.061	3.334	0.001	YES
H6	Organizational Readiness AI -> Employee Development -> Business Growth	0.036	0.017	2.143	0.032	YES
H7	Artificial Intelligence -> Employee Development -> Business Growth	0.107	0.034	3.163	0.002	YES

6. Discussion and Conclusion

This study empirically validates the integrated Resource-Based View (RBV) and Technology–Organization–Environment (TOE) framework in the Saudi organizational context. The structural findings demonstrate that achieving AI-enabled growth requires more than capital investment in technology. Instead, value realization relies on combining technological assets, organizational readiness, and human capital capabilities.

6.1 Discussion of Direct Relationships

The empirical results confirm that AI Adoption is the strongest direct driver of Perceived Business Growth (PBG) in the structural model. From an RBV perspective, this indicates that when organizations deploy machine learning, predictive analytics, and automated decision systems in core operations, employees perceive substantial operational progress, improved decision-making efficiency, and greater market competitiveness [2, 13]. This relationship aligns closely with Saudi Arabia's Vision 2030 initiatives, where digital transformation is directly linked to enhanced enterprise capability. Furthermore, AI adoption exhibits a robust positive impact on Employee Development. As AI reshapes work processes and automates routine operational tasks, it forces a structural shift in skill requirements. Employees must acquire analytical, technical, and collaborative competencies to work alongside intelligent systems [7, 16]. This reinforces the RBV premise that technological deployment inherently stimulates upgrades in complementary human capabilities. Employee Development, in turn, positively influences PBG. While its direct effect size is smaller than that of direct AI adoption, it highlights human capital as an indispensable auxiliary resource. Continuous upskilling improves problem-solving capacities and

operational adaptability, enabling the workforce to convert technological tools into sustained organizational performance [18]. Regarding Organizational Readiness for AI, the findings confirm its positive contribution to both PBG and Employee Development. In line with the TOE framework, organizational contexts characterized by strong executive leadership, technical infrastructure, financial allocation, and a flexible digital culture lower adoption barrier [14] [11]. Readiness establishes the structural foundation that enables employees to access training, experiment with new technologies, and contribute to enterprise expansion.

This relationship aligns with Saudi Arabia's Vision 2030 initiatives and global sustainability objectives (SDG 9), where digital transformation and resilient infrastructure are directly linked to enhancing sustainable enterprise capability. Furthermore, prioritizing employee development alongside AI deployment ensures that technological progress advances decent work and human resource longevity (SDG 8), preventing job displacement through active skill augmentation.

6.2 Discussion of Mediating Pathways

A key contribution of this study is testing Employee Development as a mediating mechanism [19]). The indirect pathways from both AI Adoption and Organizational Readiness to PBG through Employee Development were statistically supported, confirming a complementary partial mediation model. First, the significant indirect link between Organizational Readiness and PBG demonstrates that structural readiness achieves part of its impact by creating a supportive environment for workforce learning [10, 11]. Readiness provides resources and culture, which in turn elevate employee capabilities and ultimately lead to perceived growth [12]. Second, the indirect path between AI Adoption and PBG indicates that human capital enhancement serves as a key conduit through which technological investments generate business value [6]. While AI technology directly optimizes operational efficiency, its value is fully realized only when employees have the digital and analytical skills needed to manage, interpret, and leverage AI outputs. This complementary mediation emphasizes that technology adoption and human capability development must proceed in tandem [7].

7. Implications

7.1 Theoretical and Practical Implications

Theoretically, this study contributes to the digital transformation and sustainability literature by combining the organizational-context focus of the Technology-Organization-Environment (TOE) framework and the internal-capability perspective of the Resource-Based View (RBV) within the framework of the UN Sustainable Development Goals. Saudi business leaders and policymakers must align investments in advanced artificial intelligence (AI) technology with targeted workforce retraining programs to create strong, future-ready companies. Investing in AI infrastructure without investing in digital culture and employee skills will not only prevent enterprises from developing optimally, but also undermine sustainable workplace transformations.

8. Limitations and Future Research

Several limitations warrant consideration. First, the study employed a cross-sectional convenience sampling design in the Eastern Province of Saudi Arabia, which limits causal inference and broad generalizability. Future research should utilize longitudinal designs and probability sampling across diverse geographic regions. Second, relying on self-reported survey data for Perceived Business Growth introduces potential subjective bias; future studies could integrate objective key performance indicators (KPIs) or financial metrics. Finally, exploring moderating variables such as organizational agility, AI maturity, or leadership style could provide deeper insights.

9. Conclusion

This study confirms that AI Adoption, Organizational Readiness, and Employee Development are synergistically bound in driving Perceived Business Growth in Saudi organizations. The empirical evidence proves that while direct AI integration is the primary driver of growth perceptions, developing human capital and ensuring organizational readiness provide the essential baseline and mediating mechanisms for sustainable enterprise transformation.

Declarations

Ethics approval and consent to participate:

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of King Faisal University (KFU-REC-2026-MAY– ETHICS4273 - date of approval: 06/05/2026). Informed consent to participate informed consent to participate was obtained from all the participants.

Competing interests:

The authors declare no competing interests.

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Author Contribution

H.M., A.M., and A.A. contributed equally to the conceptualization, methodology, data collection, formal analysis, and writing—original draft preparation and review and editing. All authors reviewed and approved the final manuscript.

Data Availability

Data will be provided upon request.

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Figures

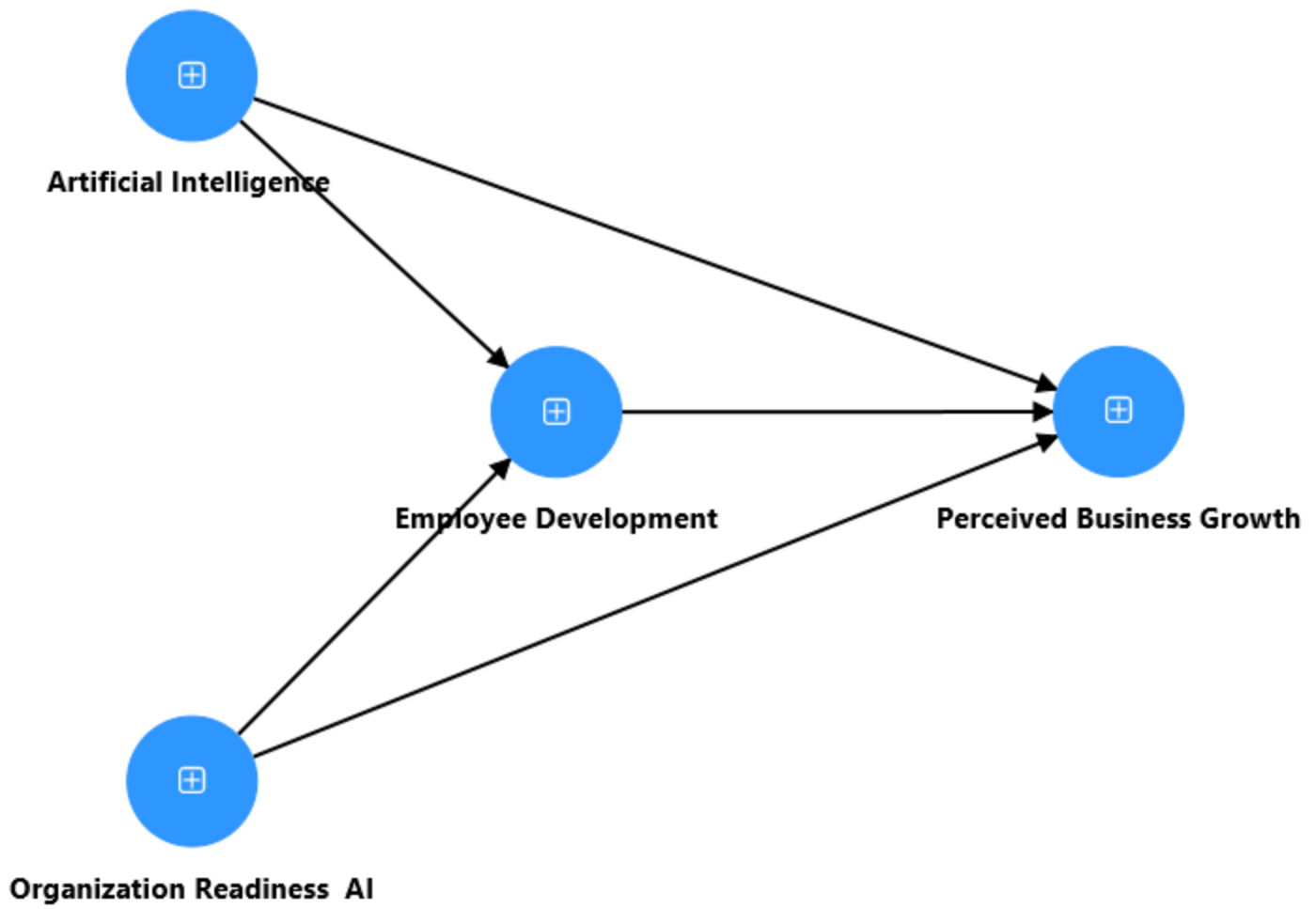


Figure 1

Research Framework

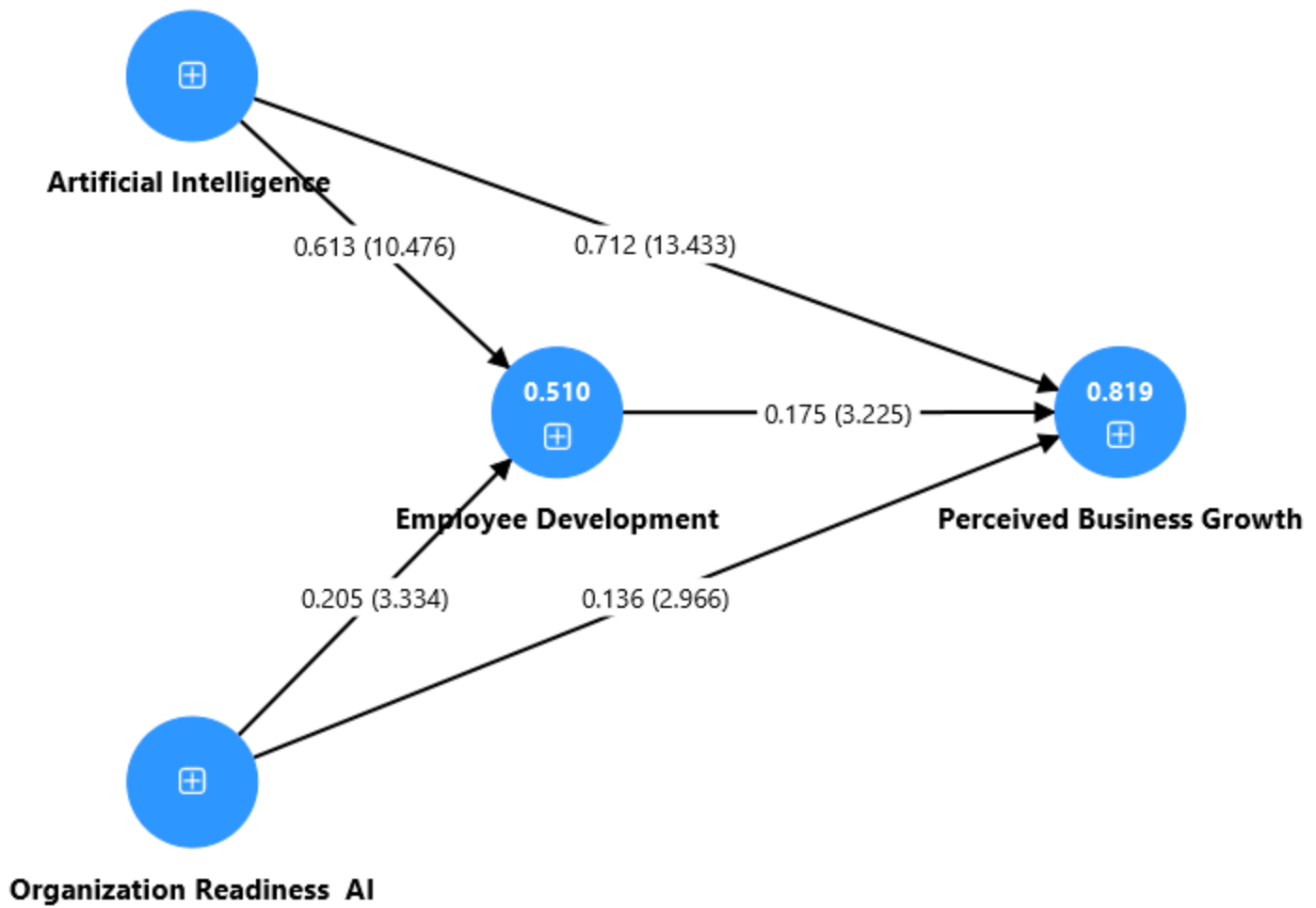


Figure 2

Research Framework with findings