"LEVERAGING AI AND STRATEGIC MANAGEMENT FOR SUSTAINABLE DIGITAL TRANSFORMATION IN THE IRANIAN TELECOM INDUSTRY"

Research Paper

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"Abstract"

Iran's telecom industry is rapidly evolving as artificial intelligence (AI) becomes integrated into daily operations and service delivery. While many studies show that AI enhances performance, less is known about how AI capabilities and strategic management work together to drive sustainable digital transformation, particularly in emerging markets. This study addresses this gap by integrating four theoretical perspectives—the Technology Acceptance Model (TAM), Resource-Based View (RBV), Dynamic Capabilities (DC), and the Triple Bottom Line (TBL)—into a unified AI–Strategy–Sustainability framework.

A sequential explanatory mixed-methods design was adopted; however, this paper reports only the quantitative strand. Survey data were collected from 300 professionals at major Iranian operators (MCI, Irancell, Rightel) and analyzed using LISREL-based Structural Equation Modeling (SEM). The model demonstrated a good fit ($\chi^2/df = 2.41$, CFI = 0.94, RMSEA = 0.056). All hypotheses were supported: AI capabilities → digital transformation ($\beta = 0.61$, $p < .01$), strategic management → digital transformation ($\beta = 0.55$, $p < .01$), and AI capabilities → sustainability outcomes ($\beta = 0.48$, $p < .05$). The model explained a substantial proportion of variance (R^2_DT = 0.52; R^2_SUS = 0.23), indicating meaningful effect sizes.

Contribution: The findings demonstrate that AI capabilities and strategic management jointly explain R^2_DT = 0.52 and R^2_SUS = 0.23, extending the integration of TAM, RBV, and DC into a TBL outcome space. This shows that aligning AI adoption with strategic planning enhances both digital performance and sustainability outcomes in emerging-market telecom contexts.

Although the broader research explored additional analyses, including potential moderation and mediation effects, this paper focuses exclusively on the direct pathways tested in the conceptual model.

Keywords: AI, strategic management, sustainable digital transformation, Iranian telecom.

1 Introduction

The telecom sector is seeing one of the fastest transitions among all industries, driven by the integration of artificial intelligence (AI), digital platforms, and data-centric services. Telecom operators worldwide face pressure to provide quick, customized, and sustainable services while reviewing their business models to maintain competitiveness. Recent studies emphasize that AI techniques, like predictive analytics, automation, and natural language processing, can optimize network performance, enhance user experience, and accelerate service innovation. However, technology by itself does not ensure sustained transformation. Strategic management is essential to synchronize AI implementation with long-term competitiveness and sustainability objectives.

The telecom sector in Iran has had fast expansion over the last decade, marked by substantial increases in mobile and broadband adoption. Telecom firms like MCI, Irancell, and Rightel are crucial in delivering digital connectivity, fostering economic growth, and facilitating access to innovative services. In contrast to global leaders, Iranian operators encounter ongoing challenges: delayed adoption of AI technology, inconsistent digital strategies, poor incorporation of sustainability practices, and increasing environmental pressures associated with energy consumption and infrastructure utilization. Simultaneously, client expectations for better digital services are increasing, heightening the demand for more intelligent and sustainable transformation initiatives.

Despite an expanding body of international research on AI adoption and digital transformation, there is limited understanding of the connection between AI capabilities and strategic management in developing countries like Iran. Previous studies frequently addresses these topics separately, concentrating on either technological implementation or business strategy while neglecting their combined effect on long-term performance and sustainability. This shows a significant gap in both scholarly literature and professional practice.

This study investigates the interplay between AI capabilities and strategic management approaches in shaping digital transformation and sustainability outcomes within Iran's telecoms sector. The study utilizes four recognized theoretical frameworks: the Technology Acceptance Model (TAM), the Resource-Based View (RBV), Dynamic Capabilities Theory, and the Triple Bottom Line (TBL) (Davis, 1989; Elkington and Rowlands, 1999; Ferreira and Ferreira, 2024; Teece et al., 1997; Wang and Ahmed, 2007). The study integrates these viewpoints into a single framework, developing and evaluating a unified AI–Strategy–Sustainability model based on survey data from 300 professionals in the Iranian telecom sector. The results provide fresh perspectives on the synergistic functions of technology and strategy, illustrating that AI capabilities deliver optimal value when supported by competent strategic management and aligned with sustainability objectives.

This study offers three primary contributions. Initially, it presents a conceptual framework that integrates AI, strategic management, and sustainability into a singular model designed for the Iranian setting. Secondly, it offers empirical information regarding the interaction of these factors in shaping digital transformation outcomes. Third, it provides practical implications for business executives and politicians aiming to link AI deployment with broader sustainability and competitiveness objectives.

The research question for this article is:

RQ: How do AI capabilities and strategic management jointly influence digital transformation and sustainability outcomes in Iran’s telecom sector?

In this study, Strategic Management is modeled as an independent predictor rather than a moderator, reflecting its direct role in driving digital transformation alongside AI capabilities.

Three hypotheses are examined based on this inquiry:

H1: AI capabilities positively affect digital transformation, reflecting the Technology Acceptance Model (TAM), which links perceived usefulness to adoption and performance.

H2: Strategic management positively affects digital transformation, consistent with the Resource-Based View (RBV) and Dynamic Capabilities Theory (DC), which argue that managerial orchestration of resources enables technology-driven change.

H3: AI capabilities positively affect sustainability outcomes, aligned with the Triple Bottom Line (TBL) perspective, which emphasizes that efficiency and innovation can yield environmental and social value in addition to economic gains.

2 Theoretical Framework and Literature Review

2.1 Digital transformation and sustainability (global view)

Digital transformation (DT) has evolved beyond just adopting new technologies; it is now a crucial strategy that changes business models, how companies engage with customers, and improves operational efficiency. In the telecom field, DT facilitates advanced services like 5G, cloud computing, and Internet of Things (IoT) solutions. Researchers commonly describe digital transformation as the incorporation of digital technologies into essential business processes to generate new value and improve organizational effectiveness (Khan, 2023; Nadella, 2025).
Nonetheless, digital transformation brings up important questions regarding sustainability. The Triple Bottom Line (TBL) framework, introduced by Elkington in 1997, emphasizes the importance for organizations to achieve a balance between economic success, environmental responsibility, and social equity (Elkington and Rowlands, 1999).

Sustainability for telecom operators means lowering energy use, decreasing electronic waste, and providing fair access to digital services. Evidence from around the world indicates that both customers and regulators are placing greater importance on strategies focused on sustainability. These approaches help to build trust and enhance brand reputation (Zimmer and Järveläinen, 2022; Basile *et al.*, 2023).

2.2 Artificial intelligence capabilities in telecom

Artificial intelligence (AI) plays a central role in driving digital transformation in the telecom sector. Globally, telecom operators are using AI to enhance network optimization, predictive maintenance, customer personalization, and fraud detection. For example, AT&T, Vodafone, and China Mobile have successfully implemented AI solutions that boost efficiency, minimize downtime, and improve customer experience (Townsend, 2025).

AI capabilities can be categorized into five areas: (Khan, 2023; El-Hajj, 2025; WEF, 2025)

1. **Predictive analytics:** Anticipating service demand and avoiding network congestion.
2. **Process automation:** Reducing manual errors and accelerating service delivery.
3. **Natural language processing (NLP):** Powering chatbots, voice assistants, and digital helpdesks.
4. **Machine learning (ML):** Improving decision-making and detecting anomalies in network performance.
5. **Personalization tools:** Enabling tailored service bundles and data packages for users..

In Iran, telecom operators are still in the early stages of AI integration. Current initiatives are limited to pilot projects, such as customer churn prediction and automated billing systems. However, these projects tend to be isolated and lack strategic integration across the organization. This gap highlights the need to align AI adoption with broader business strategies to maximize value.

By comparison, India's leading operators—Jio and Airtel—report enterprise-level AI deployment across over 50% of major processes, ranging from network optimization to customer analytics. Similarly, the UAE's Etisalat and du have introduced AI-enabled carbon-tracking dashboards, integrating sustainability goals into operational strategies (jio, nd.; Toolify, 2023).

Relative to these peers, Iran's pilots remain modest in scale, presenting a significant opportunity to strengthen AI-driven transformation and integrate it into both operational efficiency and sustainability agendas.

The comparison underscores a critical insight: Iran's AI adoption challenge is not only technological but also strategic. Without embedding AI initiatives within long-term business models, operators risk missing opportunities to improve efficiency, customer experience, and environmental sustainability.

These gaps justify the study's focus on developing an AI–Strategy–Sustainability framework tailored to Iran's telecom sector.

2.3 Strategic management and dynamic capabilities

While AI offers technological possibilities, it is strategic management that decides if these possibilities result in lasting value. The Resource-Based View (RBV) proposed by Barney in 1991 suggests that companies can maintain a competitive edge over time if they have resources that are valuable, rare, and difficult to imitate (Ferreira and Ferreira, 2024). In the current context, AI capabilities can serve as valuable resources when they are supported by strategic alignment.

The Dynamic Capabilities Theory, proposed by Teece and colleagues in 1997, highlights the importance of a firm's ability to identify opportunities, take advantage of them, and adjust its resources in fast-changing environments. Telecom operators should integrate AI into their strategic planning, governance, and resource allocation to enhance adaptability (Wang and Ahmed, 2007).

Sustainability goals are increasingly influencing strategic management practices. Telecom companies are increasingly influenced by regulatory pressures, investor expectations, and customer demand to implement more environmentally friendly infrastructures, ensure transparent data governance, and provide inclusive digital access. Companies that integrate AI-driven innovation with strategies focused on sustainability are more likely to succeed in creating both competitive advantages and social benefits (Pigola *et al.*, 2021; Saxena *et al.*, 2021).

2.4 Integrating theories (TAM, RBV, DC, TBL)

This study draws on four complementary theoretical perspectives:

Technology Acceptance Model (TAM): Explains how perceived usefulness and ease of use influence adoption of AI tools within organizations. In the telecom context, TAM helps understand how professionals accept AI applications as part of their daily work (Davis, 1989).

Resource-Based View (RBV): Positions AI capabilities as potential strategic resources that deliver competitive advantage when effectively leveraged (Ferreira and Ferreira, 2024).

Dynamic Capabilities Theory (DC): Highlights how managers orchestrate and reconfigure resources to capture value from AI investments in a volatile market (Teece, Pisano and Shuen, 1997; Teece, 2007; Wang and Ahmed, 2007).

Triple Bottom Line (TBL): Extends the analysis to sustainability, emphasizing the balance of economic, environmental, and social outcomes in digital transformation (Elkington and Rowlands, 1999; Zimmer and Järveläinen, 2022).

By combining these frameworks, the study constructs an integrated AI–Strategy–Sustainability model that examines both technological adoption and strategic orchestration while explicitly linking them to sustainability outcomes.

2.5 Iran's emerging sustainability landscape in telecom

Iran's telecom operators are beginning to integrate digital transformation initiatives with sustainability goals, but several structural and operational challenges continue to slow this process.

Energy Inefficiencies and Infrastructure Gaps: Iran faces one of the highest energy intensities in the MENA region. Despite having abundant oil and gas reserves, outdated power generation systems operate at only ~33% efficiency, and approximately 13% of total electricity is lost during transmission annually. In 2024, the country faced a 14,000 MW power deficit, which triggered rolling blackouts and caused significant interruptions to telecom services. These inefficiencies raise operational costs and make the transition toward energy-efficient digital infrastructure far more complex (Minoukadeh, 2025).

Comparative Context (Lessons from India and UAE): In contrast, several peer markets are progressing rapidly toward green telecom integration. India, for example, has rolled out solar-powered base stations at more than 10% of total telecom towers, while the UAE has committed to achieving net-zero emissions by 2030 through investments in smart grids and large-scale renewable integration. Relative to these benchmarks, Iran's low renewable energy share (<8%) and limited green telecom infrastructure highlight a widening sustainability gap. This underlines the strategic importance of adopting AI-driven solutions to accelerate Iran's transition toward sustainable telecom operations (Banzal and Thapar, 2024).

Limited Green Technology Adoption: Iran's share of clean energy remains below 8% of total electricity generation, compared to a global average of 41%. Renewable energy sources—primarily solar (0.4%) and wind (0.1%)—remain largely untapped, despite a combined technical potential of 60 GW solar and 30 GW wind capacity. While national energy plans aim to install 30 GW of renewable capacity by 2030, progress has been slow due to limited investment, outdated infrastructure, and fragmented regulatory policies (EMBER, 2025).

Digital Expansion as a Platform for Transformation: At the same time, Iran's telecom sector is undergoing significant digital expansion, creating a strong foundation for sustainable innovation. As of early 2025, there were 152 million active mobile connections—equivalent to 166% of the population—and 93% of these were broadband-enabled (3G, 4G, 5G). Additionally, 73 million Iranians (79.6% of the population) now have internet access (Kemp, 2025). This rapid digital growth opens up opportunities to integrate AI-driven energy optimization, predictive infrastructure maintenance, and sustainable network planning to reduce energy waste and improve operational efficiency.

In summary, Iran's telecom industry stands at a pivotal intersection. On one side, high energy intensity, low renewable integration, and outdated infrastructure present significant short-term sustainability challenges. On the other, rapid digitalization, expanding mobile broadband adoption, and the potential of AI-enabled technologies create a unique opportunity to transform Iran's telecom sector. Integrating AI-driven efficiency measures, green infrastructure planning, and strategic sustainability alignment will be critical to ensuring that the sector remains competitive, resilient, and environmentally responsible in the next phase of digital transformation.

2.6 Conceptual framework

The study presents a conceptual framework, illustrated in Figure 1, derived from the reviewed literature. In this framework, AI capabilities such as predictive analytics, automation, natural language processing, machine learning, and personalization are identified as key technological enablers of transformation.

Strategic management practices, such as planning, aligning resources, and fostering innovation, influence the ways in which these technologies generate value for organizations.

The results of sustainability—economic, environmental, and social—serve as the key indicators of successful change.

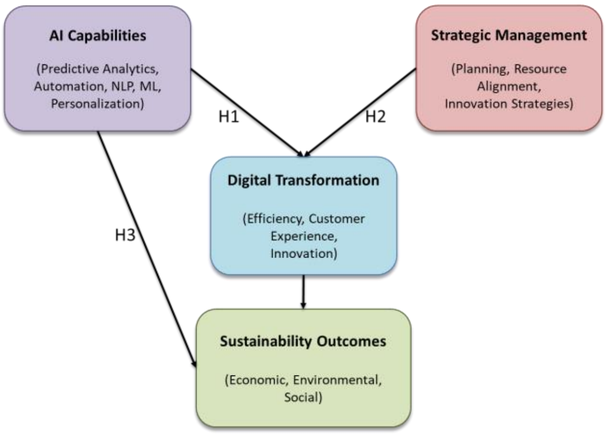

Figure 1. Conceptual Framework: AI–Strategy–Sustainability Model, (Designed by Author)

The model specifies direct effects only, where AI capabilities and strategic management independently contribute to digital transformation, and AI also influences sustainability outcomes. Although moderation and mediation were examined in the broader research, this paper reports only the direct relationships tested using SEM.

3 Methodology

3.1 Research design

This research uses a sequential explanatory mixed-methods approach. The design choice aims to achieve two main goals:

- To examine the proposed relationships among AI capabilities, strategic management, digital transformation, and sustainability outcomes through the use of quantitative data.
- To provide context and support for findings using qualitative insights from industry professionals.

The study combines both quantitative and qualitative approaches, ensuring that it is statistically sound while also being relevant to the practical needs of the Iranian telecom sector, however, this paper focuses exclusively on the quantitative strand. Qualitative findings, such as interviews with industry experts and thematic analysis, were conducted in the broader study but are not reported here.

3.2 Population and sampling

The participants in the study were professionals employed at leading telecom companies in Iran, such as MCI, Irancell, Rightel, and a few regional providers. A stratified random sampling method was employed to guarantee representation from both managerial and technical positions.

Using the Krejcie and Morgan (1970) formula (Krejcie and Morgan, 1970), we established a target sample size of 300 respondents. This size ensures a 95% confidence level with a margin of error of ±5%. A total of 356 questionnaires were distributed, and 300 valid responses were received, leading to a response rate of 84.3%. Within the qualitative strand of the broader study, 12 semi-structured interviews were conducted with senior managers to provide contextual insights into the SEM results. These details are excluded from this paper for brevity.

The distribution of roles among the respondents is summarized in Table 1.

Respondent Role	Frequency	Percentage
Senior Managers	54	18%
Middle Managers	72	24%
Engineers	114	38%
Analysts/Planners	60	20%
Total	**300**	**100%**

Table 1. Distribution of Respondents by Job Role

3.3 Measurement instruments

A structured questionnaire was designed using validated scales from prior research, adapted to the Iranian telecom context. Each construct was measured using items rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The measurement items were adapted from prior studies: AI Capabilities (El-Hajj, 2025), Strategic Management (Ferreira and Ferreira, 2024), Sustainability Outcomes (Zimmer and Järveläinen, 2022), and Digital Transformation (Khan, 2023). The questionnaire was reviewed by three academic and industry experts to ensure contextual validity.

Table 2 presents the constructs, dimensions, and example indicators.

Construct	Dimensions	Example Indicators	Items
AI Capabilities	Predictive analytics, automation, NLP, ML	Use of AI for process optimization, predictive decision-making	7
Strategic Management	Planning, resource alignment, innovation strategies	Integration of AI into organizational strategy	7
Sustainability Outcomes	Environmental, social, economic	Energy efficiency, e-waste reduction, inclusive access	6
Digital Transformation	Efficiency, customer experience, innovation	Service speed, quality improvements, innovation rates	6

Table 2. Constructs, Dimensions, and Example Indicators

This instrument ensures coverage of all latent constructs identified in the conceptual model.

3.4 Data collection and ethics

Data collection was conducted between January and March 2025, combining online distribution with in-person surveys at telecom offices and industry conferences. To ensure reliability and ethical compliance:

- Participants provided informed consent.
- Responses were kept anonymous and confidential.
- Data were used exclusively for academic purposes.

The high response rate and balance of managerial/technical roles strengthen the credibility and representativeness of the dataset.

3.5 Data analysis procedures

Data analysis followed a four-stage process using SPSS and LISREL:

1. **Descriptive Statistics:** Summarized demographic characteristics, AI adoption levels, and organizational readiness.

2. **Measurement Model Validation (CFA):** Tested reliability, convergent validity, and discriminant validity of constructs. Items with weak loadings ($\lambda < 0.30$) were removed, while those above the recommended thresholds ($\lambda \geq 0.50$, $p < .05$) were retained.
3. **Structural Model Testing (SEM):** Estimated hypothesized relationships (H1–H3) among constructs.
4. **Model Fit Assessment:** Evaluated indices including χ^2/df, CFI, GFI, RMSEA, and SRMR to confirm adequacy of the proposed framework.

Prior to SEM estimation, we tested the dataset for multivariate normality, multicollinearity, and missing data. All assumptions were met (VIF < 3.0, skewness < ±1.5, missingness < 2%), ensuring robustness of SEM estimates. This approach provided both statistical rigor and theoretical alignment, ensuring that results could be meaningfully interpreted in the context of AI-driven transformation and sustainability.

4 Results and Analysis

This section presents the findings based on descriptive statistics, measurement model validation (CFA), structural model testing (SEM), and model fit assessment. Results are structured into four subsections for clarity and supported with figures, tables, and interpretive insights.

4.1 Descriptive statistics and respondent profile

The survey achieved 300 valid responses from professionals in the Iranian telecom sector. As shown in Table 3, 64% of respondents were male and 36% female. Educational attainment was relatively high, with 57% holding postgraduate degrees. Work experience was also substantial: 74% had more than six years of industry experience. The sample therefore reflects a highly knowledgeable respondent base, strengthening the credibility of findings.

Additionally, since the majority of respondents have extensive experience, the dataset reflects informed perspectives and reduces potential response bias, which enhances the credibility of subsequent SEM interpretations.

Characteristic	**Category**
Gender	Male (64%), Female (36%)
Education	Diploma (11%), Bachelor (32%), Master/PhD (57%)
Experience	0–5 years (26%), 6–10 years (34%), 11+ years (40%)

Table 3. Demographic Profile of Respondents

4.2 AI adoption and organizational readiness

Respondents reported moderate-to-strong adoption of AI capabilities.

Tables 4 and 5 present the results for AI adoption and organizational readiness levels across telecom companies.

AI Capability Area	**Low Adoption**	**Moderate Adoption**	**High Adoption**	**Mean (1–5)**	**Interpretation**
Predictive Analytics	14%	41%	45%	**3.94**	Widely adopted
Process Automation	18%	43%	39%	3.76	Moderately strong
NLP / Chatbots	33%	47%	20%	**3.08**	Still emerging
Machine Learning (ML)	26%	49%	25%	3.31	Early integration

Customer Personalization	22%	45%	33%	3.52	Growing adoption

Table 4. AI Adoption Levels Across Telecom Companies

Respondents reported moderate-to-strong adoption of AI capabilities. Predictive analytics achieved the highest adoption (Mean = 3.94 on a 5-point scale), while NLP/chatbots were less developed (Mean = 3.08). This suggests that Iranian telecom operators are progressing in data-driven optimization but have yet to invest fully in customer-facing AI applications.

Readiness Dimension	**Low Readiness**	**Moderate Readiness**	**High Readiness**	**Mean (1–5)**	**Interpretation**
Strategic Alignment	12%	38%	50%	**3.97**	Well-established
Innovation Culture	18%	42%	40%	**3.78**	Strong
Sustainability Orientation	31%	47%	22%	**3.12**	Needs improvement

Table 5. Organizational Readiness Indicators

Organizational readiness indicators revealed strong strategic alignment with AI (Mean = 3.97) and a solid innovation culture (Mean = 3.78). By contrast, sustainability orientation lagged behind (Mean = 3.12), highlighting an opportunity to better connect digital transformation with environmental and social goals.

This aligns with the SEM findings, where strategic management significantly predicts digital transformation ($\beta = 0.55$, $p < .01$), but low sustainability orientation confirms that AI-driven initiatives are not yet fully integrated with environmental and social priorities.

4.3 Measurement model validation (CFA)

Confirmatory Factor Analysis (CFA) was conducted to validate the four latent constructs: “AI Capabilities,” “Strategic Management,” “Digital Transformation,” and “Sustainability Outcomes”. Items with loadings below 0.30 were removed, while retained indicators showed loadings above 0.50 and were statistically significant ($p < .05$).

Removed ($\lambda < 0.30$): Customer Support (SCM), Developing a Strategy (IND), Empowering Staff (COP), Strategic Leadership (RES), Environmental Analysis (JSEC), Innovation & Technology (SSUP).

Retained ($\lambda \geq 0.30$, majority ≥ 0.50): R&D (ECO), Data Analysis (POL), Automation (GEO), Security & Information Protection (ORG), Cooperation & Communication (SER), Skills in Risk Management (COM), Financial Stability (REW), Risk Management (SOC).

Following item refinement, we assessed internal consistency (Cronbach’s α), composite reliability (CR), and average variance extracted (AVE) at the construct level.

Construct	**Cronbach’s α**	**CR**	**AVE**	**Interpretation**
AI Capabilities	0.89	0.91	0.63	Strong reliability & convergent validity
Strategic Management	0.87	0.90	0.61	Strong reliability & convergent validity
Sustainability Outcomes	0.84	0.88	0.58	Acceptable–strong
Digital Transformation	0.90	0.92	0.66	Excellent reliability & validity

Table 6. Construct Reliability and Convergent Validity (CFA)

As results in Table 6 indicates, all constructs meet recommended thresholds ($\alpha \geq 0.70$, CR ≥ 0.70, AVE ≥ 0.50), confirming internal consistency and convergent validity.

Furthermore, factor loadings for retained items ranged between 0.52 and 0.86, and cross-loadings were examined to confirm discriminant validity

Discriminant validity was evaluated using the Fornell–Larcker criterion, which requires each construct's √AVE to exceed its correlations with other constructs. The diagonal entries below report √AVE; inter-construct correlations (from the LISREL latent correlation matrix) were lower than the corresponding diagonals, indicating the constructs are empirically distinct.

Construct	AI Capabilities	Strategic Management	Sustainability Outcomes	Digital Transformation
AI Capabilities	0.79			
Strategic Management		0.78		
Sustainability Outcomes			0.76	
Digital Transformation				0.81

Table 7. Fornell–Larcker Matrix (√AVE on the Diagonal)

Overally, a small set of low-loading indicators was removed; all retained indicators are significant ($p < .05$) and predominantly $\lambda \geq 0.50$. Construct-level α/CR/AVE confirm strong reliability and convergent validity, and Fornell–Larcker indicates discriminant validity. The measurement model is therefore fit for purpose, and the analysis proceeds to the SEM stage for hypothesis testing.

4.4 Structural model (SEM) and hypotheses tests

Structural relations among AI Capabilities, Strategic Management, Digital Transformation, and Sustainability Outcomes were estimated in LISREL. All hypothesized effects were positive and statistically significant.

Table 8 summarizes the LISREL SEM results, standardized path coefficients (β), t-values, p-values, and decisions for hypotheses H1–H3.

H	Structural Path (From → To)	β (std.)	t-value	p-value	Decision
H1	AI Capabilities → Digital Transformation	0.61	7.92	< .01	Supported
H2	Strategic Management → Digital Transformation	0.55	6.87	< .01	Supported
H3	AI Capabilities → Sustainability Outcomes	0.48	5.23	< .05	Supported

Table 8. SEM Results, Standardized Path Estimates and Significance

The strongest effect was observed for AI Capabilities on Digital Transformation ($\beta = 0.61$). Strategic Management also had a substantial positive effect on Digital Transformation ($\beta = 0.55$), while AI Capabilities significantly influenced Sustainability Outcomes ($\beta = 0.48$). These findings suggest that technology and strategy operate as complementary levers in driving transformation.

Additionally, the structural model explained 52% of the variance in Digital Transformation ($R^2\_DT = 0.52$) and 23% in Sustainability Outcomes ($R^2\_SUS = 0.23$), indicating strong explanatory power.

4.5 Model fit assessment

Model adequacy was evaluated using multiple indices (Table 9). The ratio $\chi^2/df = 2.41$ is below the <3.00 guideline, indicating acceptable parsimony; the incremental fit CFI = 0.94 exceeds the ≥0.90 threshold; and the absolute fit GFI = 0.91 also meets the ≥0.90 criterion. Error-based indices are within recommended bounds (RMSEA = 0.056 ≤ 0.06, SRMR = 0.052 ≤ 0.08).

Index	**Recommended Threshold**	**Result**	**Interpretation**
χ^2/df	< 3.00	2.41	Acceptable
CFI	≥ 0.90	0.94	Good fit
GFI	≥ 0.90	0.91	Good fit
RMSEA	≤ 0.06	0.056	Acceptable
SRMR	≤ 0.08	0.052	Good fit

Table 9. Structural Model Fit Indices

Taken together, these statistics indicate an adequate-to-good overall fit, supporting the suitability of the AI–Strategy–Sustainability model for substantive interpretation.

These fit indices also meet Hu & Bentler's (1999) recommended cut-offs, (Hu and Bentler, 1999) providing further evidence of the robustness of the SEM model.

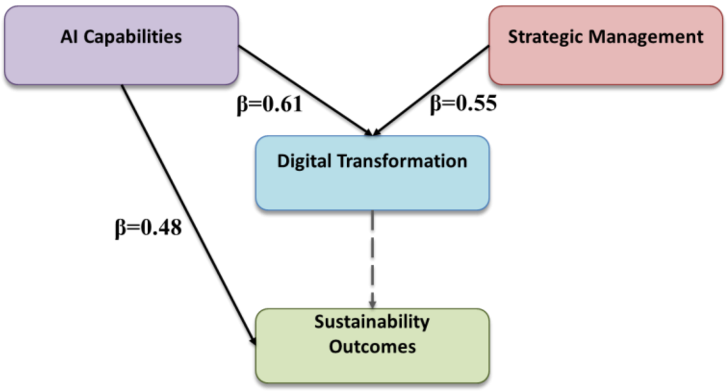

Figure 2. Structural Model Results (SEM) (Designed by Author)

In Figure 2, the arrow from Digital Transformation to Sustainability Outcomes is included as a supportive linkage rather than a tested hypothesis. This path is theoretically grounded in TBL literature but was not tested in the current SEM; future studies may examine potential indirect effects through Digital Transformation.

5 Discussion

This study emphasizes how AI capabilities and strategic management work together to facilitate digital transformation and sustainability in Iran's telecom sector. SEM results confirm that AI capabilities had the strongest effect on digital transformation ($\beta = 0.61$, $p < .01$), while strategic management also contributed significantly ($\beta = 0.55$, $p < .01$), jointly explaining 52% of its variance ($R^2\_DT = 0.52$).

This highlights that digital transformation is not just a technical process; it results from a mix of resources, management coordination, and the overall direction of the organization. These findings integrate TAM, which explains AI adoption; RBV and DC, which emphasize leveraging unique resources through adaptive capabilities; and TBL, which connects transformation efforts to sustainability goals.

The findings highlight the importance of viewing AI adoption and sustainability as related priorities in management. Focusing on predictive analytics and automation, along with effective planning and governance, can accelerate transformation and lead to additional environmental and social benefits. For policymakers, this suggests designing national strategies that integrate AI adoption with energy efficiency, renewable investments, and sustainability-driven regulations.

A supportive, although not hypothesized, connection was also noted between digital transformation and sustainability outcomes. This suggests a potential indirect pathway where efficiency gains from digitalization contribute to sustainability, consistent with TBL perspectives and motivating future mediation analyses.

6 Conclusion

This research examined the digital transformation and sustainability outcomes of the Iranian telecom industry via the perspective of AI capabilities and strategic management. The study validated three significant relationships by integrating survey responses from 300 experts with structural equation modeling: first, strategic management positively influences digital transformation; second, AI capabilities directly enhance sustainability outcomes; and third, AI capabilities positively impact digital transformation. Together, these variables explain 52% of the variance in digital transformation (R^2_DT) and 23% in sustainability outcomes (R^2_SUS), indicating strong predictive validity.

The research makes three contributions. First, it proposes an integrated AI–Strategy–Sustainability model grounded in TAM, RBV, DC, and TBL, advancing theoretical understanding. Second, it demonstrates empirically that technology and strategy act as complementary levers, rather than independent drivers, of transformation. Third, it highlights how AI-enabled efficiency can extend to environmental and social dimensions, reinforcing the relevance of sustainability in digital agendas.

Limitations include the cross-sectional design, reliance on self-reported measures, and focus on a single industry in one country. Future research should employ longitudinal data, cross-sectoral comparisons, and objective performance metrics to strengthen generalizability. Extending the model to peer markets like UAE and India would further test its robustness and external validity.

Overall, the study provides strong evidence that aligning AI adoption with strategic management and sustainability goals is essential for telecom operators seeking to remain competitive, innovative, and environmentally responsible in an increasingly digital economy.

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