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Designing a Technology Transfer Model Based on the Implementation of the National Artificial Intelligence Development Program in the Petrochemical Industry

ABSTRACT

This study aimed to design and quantitatively validate a technology transfer model based on the implementation of the National Artificial Intelligence Development Program in the petrochemical industry. This applied, quantitative, cross-sectional study used a descriptive-correlational design. The statistical population consisted of managers, senior experts, technology specialists, digital transformation professionals, and other relevant personnel in the petrochemical industry in Tehran. Approximately 150 participants were selected through simple random sampling. Data were collected using a researcher-developed 26-item questionnaire covering six constructs: causal conditions, core phenomenon, strategies, contextual conditions, facilitating/intervening conditions, and consequences. Items were scored on a five-point Likert scale. Construct validity, convergent validity, discriminant validity, and composite reliability were examined. Because the Kolmogorov-Smirnov test indicated non-normal distributions for all variables, Partial Least Squares Structural Equation Modeling was performed using SmartPLS. All measurement indicators had significant loadings above the acceptable threshold, and composite reliability and average variance extracted values confirmed satisfactory reliability and convergent validity. All hypothesized structural relationships were statistically significant. Causal conditions had a strong positive effect on the core phenomenon ($\beta = 0.904$, $t = 14.185$), while the core phenomenon significantly affected strategies ($\beta = 0.579$, $t = 7.313$). Contextual conditions ($\beta = 0.756$, $t = 3.091$) and facilitating/intervening conditions ($\beta = 0.628$, $t = 4.157$) significantly influenced strategies. The strongest relationship was observed between strategies and consequences ($\beta = 0.913$, $t = 17.262$). Positive cross-validated communality values and Q^2 coefficients above 0.35 demonstrated satisfactory measurement quality and strong predictive relevance. The findings confirmed that AI technology transfer in the petrochemical industry is a multidimensional process in which operational and competitive pressures stimulate AI integration, contextual and intervening conditions shape strategic implementation, and appropriate strategies strongly determine technological, operational, environmental, and national outcomes.

Keywords: Artificial Intelligence; Technology Transfer; Petrochemical Industry; National AI Development Program; Digital Transformation; PLS-SEM; Technology Strategy

Introduction

Artificial intelligence (AI) has increasingly become a strategic technological capability with the potential to reshape industrial production, decision-making, process control, maintenance, innovation, and organizational competitiveness. In capital-intensive sectors such as the petrochemical industry, the strategic value of AI is particularly significant because production systems depend on highly complex chemical processes, continuous operations, extensive physical assets, large-scale data generation, strict safety requirements, and substantial energy consumption. The deployment of AI in such environments can support predictive maintenance, intelligent process control, anomaly detection, energy optimization,

quality improvement, demand forecasting, and more accurate operational decision-making. However, the acquisition of an advanced technology does not automatically result in effective utilization. What determines the success of technological adoption is the extent to which technological knowledge, capabilities, infrastructure, skills, and organizational routines are transferred, absorbed, adapted, institutionalized, and continuously developed within the receiving organization. Consequently, technology transfer should be understood not as a simple transaction involving the purchase of equipment, software, or technical licenses, but as a multidimensional process of capability building and organizational transformation [1, 2].

Technology transfer has traditionally been conceptualized as the movement of technological knowledge, know-how, expertise, processes, intellectual assets, and productive capabilities across organizations, sectors, regions, or countries. Contemporary research has expanded this understanding by emphasizing that effective transfer depends on interactive mechanisms through which technological knowledge is assimilated, reconstructed, and transformed into practical innovative capabilities. The transfer process may occur through formal contractual arrangements, licensing, foreign direct investment, research partnerships, university–industry collaboration, trade, joint ventures, specialist mobility, technical consulting, or informal knowledge spillovers. Barboza et al. emphasize the significance of knowledge spillovers and foreign direct investment in enabling technological capabilities to diffuse across organizational and geographical boundaries, highlighting that technology transfer outcomes depend on the recipient's ability to learn from external technological resources [3]. Similarly, Huegel et al. show that the initiation of knowledge and technology transfer depends on opportunity recognition and the selection of appropriate transfer channels, demonstrating that successful transfer is not merely a technical event but a deliberate strategic process shaped by institutional and organizational choices [4].

The strategic importance of technology transfer has become even more pronounced under conditions of accelerated digital transformation. Digital technologies differ from many traditional industrial technologies because their implementation requires continuous interaction among data, algorithms, infrastructure, people, governance mechanisms, and existing production systems. Zamani and Khamseh identify digital transformation as an important contemporary context for technology transfer and emphasize that successful transfer involves organizational, technological, managerial, and environmental dimensions rather than a narrow focus on technical acquisition alone [2]. In this context, AI represents an especially complex technology-transfer challenge because its effectiveness is highly dependent on data availability and quality, computing infrastructure, domain expertise, algorithmic competence, systems integration, organizational learning, and governance. The recipient organization must therefore develop the internal capacity to interpret AI outputs, maintain models, adapt algorithms to operational changes, secure digital infrastructures, and integrate AI-enabled decision systems with established workflows.

Recent research also indicates that AI is altering the institutional architecture of innovation and technology exchange. Orlando et al. argue that AI is contributing to the emergence of a new open-innovation paradigm in university–business research and development collaboration, where technological knowledge can be generated, exchanged, analyzed, and commercialized through increasingly data-intensive and digitally mediated relationships [5]. Chen et al. similarly demonstrate that technology transfer organizations are evolving from passive intermediaries into more active institutional actors that coordinate innovation networks and facilitate the commercialization and circulation of knowledge [6]. These developments are relevant beyond the university context because they illustrate a broader shift in technology transfer: organizations

increasingly require active coordination mechanisms, collaborative networks, specialized intermediaries, and governance arrangements capable of managing complex technological ecosystems. For the petrochemical industry, this implies that AI technology transfer may require cooperation among petrochemical companies, AI firms, universities, research centers, technology suppliers, regulatory bodies, and national innovation institutions.

Technology transfer is also closely connected to national technological development and industrial competitiveness. For countries seeking to strengthen domestic technological capabilities, dependence on imported technologies can provide short-term access to advanced systems while simultaneously creating long-term vulnerabilities if local absorptive, adaptive, and innovative capacities remain underdeveloped. Ponomarev and Gareev argue that catching-up countries need new approaches to international technology transfer that move beyond passive technological acquisition toward mechanisms capable of strengthening domestic technological learning and productive capabilities [7]. This perspective is particularly important in strategic industries such as petrochemicals, where technological dependence may affect productivity, competitiveness, resilience, and national economic security. A technology-transfer model associated with a national AI development program should therefore not merely facilitate access to AI systems; it should contribute to indigenous capability formation, knowledge internalization, technical workforce development, and reduced dependence on external suppliers.

The relationship between technology transfer and industrial policy has also gained renewed scholarly attention. Bradlow and Kentikelenis emphasize that technology transfer represents an important mechanism through which industrial policies can be internationalized and connected to broader technological and environmental objectives [8]. Similarly, Jalilzadeh Tabrizi and Jalalpour discuss technology transfer within the framework of global sustainable development policies, drawing attention to the role of policy alignment in directing technology acquisition toward broader developmental goals [9]. These perspectives indicate that technology transfer is not institutionally neutral. Regulatory frameworks, national development priorities, innovation policies, financing mechanisms, intellectual property arrangements, and sectoral strategies can facilitate or constrain the movement and effective utilization of technology. Therefore, implementation of a national AI development program in the petrochemical sector requires an explicit understanding of how policy-level objectives are translated into organizational mechanisms and operational capabilities.

Policy effectiveness itself depends on the interactions among multiple components of the technology-transfer system. Zhenxu et al., using a system dynamics perspective, show that the implementation effects of technology-transfer policies emerge through complex interactions among policy instruments, innovation resources, organizations, and technological actors rather than through isolated interventions [10]. This systems perspective is directly relevant to AI development in petrochemicals because the effectiveness of a national program is likely to depend on coordinated development of digital infrastructure, financing, organizational capabilities, human resources, regulatory support, research and development, and industrial collaboration. An isolated investment in AI software, for example, may fail to produce meaningful operational benefits if industrial data remain fragmented, employees lack relevant competencies, organizational resistance is high, or technological systems cannot be integrated with existing operational technology environments.

The complexity of technology transfer becomes even greater when firms with unequal technological capabilities interact. Simms and Frishammar identify significant challenges in technology-transfer relationships between high-technology and low-technology firms, including asymmetries in knowledge, capabilities, expectations, and bargaining positions [11]. Such

asymmetries may also characterize relationships between specialized AI suppliers and conventional industrial enterprises. AI developers may possess sophisticated knowledge of machine learning and data science while lacking deep knowledge of petrochemical processes, whereas petrochemical specialists may possess extensive domain knowledge but limited expertise in AI model development, MLOps, algorithm validation, or advanced data engineering. Successful transfer therefore requires mechanisms capable of integrating heterogeneous forms of expertise. Without such integration, organizations may become dependent on external technology suppliers and remain unable to independently modify, maintain, or scale AI systems.

Knowledge transfer is consequently inseparable from human capability development. Although operating in a different sector, Stumbrienė et al. demonstrate that the transfer of technology-enabled innovation depends substantially on motivation, organizational support, perceived usefulness, and environmental conditions [12]. Twyman likewise emphasizes that technology transfer involves behavioral and organizational adaptation rather than simply the diffusion of technical artifacts [13]. These insights have substantial relevance for industrial AI because implementation frequently changes established routines, job roles, decision rights, and professional practices. Resistance to change can emerge when employees perceive AI as unreliable, threatening, difficult to understand, or incompatible with existing operating procedures. Accordingly, training programs, participation of domain experts, organizational communication, change management, and continuous technical learning should be treated as central components of AI technology transfer.

The transfer of AI technology also depends on the development of supporting digital ecosystems. Iftikhar et al. demonstrate the importance of integrating infrastructure, access, usage, knowledge transfer, and governance-by-technology within a multidimensional digital development framework [14]. Although developed in the context of financial technology, this multidimensional logic is highly relevant to industrial AI. Petrochemical firms require reliable data acquisition infrastructure, interoperable information systems, secure industrial networks, data governance procedures, analytical platforms, and technical capabilities for model development and deployment. The interaction between information technology and operational technology is especially important because AI applications frequently depend on real-time or historical data generated by industrial control systems, sensors, distributed control systems, supervisory systems, and equipment-monitoring platforms. The absence of integrated infrastructure can limit algorithmic performance even when advanced AI capabilities are externally available.

Furthermore, the adoption of AI introduces new risk dimensions that must be incorporated into technology-transfer models. Wang proposes a quantitative approach to assessing technology-transfer risks within collaborative innovation and demonstrates that transfer processes involve multidimensional uncertainties requiring systematic evaluation [15]. In petrochemical environments, such risks are amplified by the safety-critical nature of industrial operations. Errors in predictive models, unreliable sensor data, cybersecurity incidents, inappropriate automation, poor explainability, or insufficient human oversight may produce consequences extending far beyond ordinary information-system failure. Therefore, technology transfer must address not only technological performance but also risk governance, validation procedures, cybersecurity, data privacy, operational safety, accountability, and continuous monitoring of AI systems.

Environmental sustainability provides another major rationale for strengthening technology-transfer capabilities. Cobbold et al. demonstrate that the transfer and importation of low-carbon technologies can influence domestic green innovation and technological upgrading [16]. Tahmasbi Roshan and Arab Kalmeri similarly report that knowledge and technology transfer can contribute to green innovation, green supply-chain management, and improved environmental performance [17]. These

relationships are particularly salient in petrochemical production, where energy consumption, emissions, feedstock efficiency, process optimization, and environmental risks are central management concerns. AI-enabled technologies may contribute to improved energy efficiency, reduced raw-material consumption, optimized combustion, leak detection, emission monitoring, predictive maintenance, and more efficient resource allocation. Technology transfer in this context can therefore support not only productivity and competitiveness but also environmental performance and decarbonization objectives.

The relevance of technology transfer to circular and resource-efficient production has also been demonstrated by Ren et al., who identify technology-transfer adoption as an important mechanism for achieving circular-economy objectives in high-technology firms [18]. The resource-based perspective underlying this work is particularly useful because it conceptualizes technology not simply as an external artifact but as a resource whose strategic value depends on complementary internal capabilities. For petrochemical firms, AI can create competitive advantage only when it becomes embedded in organizational knowledge, data resources, technical infrastructure, and operational routines. Thus, the mere acquisition of advanced algorithms cannot guarantee superior performance; organizations require capabilities for absorption, integration, learning, adaptation, and continuous improvement.

The Iranian petro-refining context provides further evidence of the need for an integrated approach. Esmaeili et al. model the improvement of technology-transfer processes in Iran's petro-refining industry and emphasize the interconnected nature of variables affecting transfer effectiveness [19]. The petrochemical sector is characterized by large investments, technological complexity, dependence on specialized equipment and knowledge, and the need for sustained research and development. These characteristics make fragmented or ad hoc approaches to AI implementation particularly risky. A national AI development program can create strategic direction, but its effectiveness at the industrial level depends on the existence of mechanisms linking national priorities to company-level technological needs, organizational preparedness, financing arrangements, R&D capability, human-capital development, and operational implementation.

The literature also suggests that transfer outcomes are affected by the institutional environment surrounding knowledge production and commercialization. Chica highlights the importance of institutional and contextual conditions in knowledge and technology transfer, showing that the success of transfer activities is strongly influenced by the broader innovation environment in which organizations operate [20]. This observation reinforces the need to consider contextual conditions such as regulatory clarity, research infrastructure, cooperation networks, organizational support, and institutional incentives. In the petrochemical industry, these contextual factors may determine whether AI initiatives remain isolated pilot projects or develop into scalable industrial capabilities.

Despite the growing literature on technology transfer, AI, digital transformation, sustainability, innovation policy, and industrial development, important conceptual gaps remain. Much of the technology-transfer literature examines universities, international trade, foreign direct investment, high-technology alliances, or generalized innovation ecosystems, whereas the specific requirements of transferring AI technologies into safety-critical, capital-intensive petrochemical environments remain insufficiently modeled. In addition, existing studies frequently examine individual determinants of technology transfer separately, while successful implementation of national AI policy requires an integrated understanding of causal drivers, the central technological phenomenon, contextual conditions, facilitating and intervening factors, strategic actions, and resulting consequences. The petrochemical context therefore requires a model capable of simultaneously incorporating production-

related motivations, intelligent process integration, organizational and technological infrastructure, regulatory conditions, partnership mechanisms, financing, training, knowledge exchange, cybersecurity, operational complexity, and expected performance outcomes.

Such an integrated model is also necessary because AI technology transfer should be understood as an evolutionary capability-building process rather than a one-time implementation event. Effective transfer requires organizations to continuously learn from operational data, update technological systems, develop internal expertise, collaborate with external technology providers, and institutionalize new decision-making mechanisms. When these elements are aligned with national policy, technology transfer can potentially generate multiple levels of outcomes, including greater production reliability, improved product quality, lower energy and raw-material consumption, stronger preventive management, enhanced technological competitiveness, and reduced external dependence. Conversely, without an integrated implementation framework, national AI development ambitions may remain disconnected from the operational realities of industrial enterprises.

Accordingly, the aim of the present study was to design and quantitatively validate a technology transfer model based on the implementation of the National Artificial Intelligence Development Program in the petrochemical industry.

Methodology

The present study employed a quantitative, applied, and cross-sectional research design with a descriptive-correlational approach. The primary purpose of the study was to design and empirically validate a technology transfer model based on the implementation requirements of the National Artificial Intelligence Development Program in the petrochemical industry. The study focused on identifying the structural relationships among the major organizational, technological, managerial, infrastructural, policy-related, and implementation-related factors involved in transferring artificial intelligence technologies into the petrochemical sector. Because the proposed model consisted of several latent constructs and hypothesized relationships among them, the quantitative design was considered appropriate for estimating the relative contribution of each construct, evaluating the relationships among variables, and assessing the overall explanatory and predictive performance of the proposed model. The study was conducted within the petrochemical industry, with the field data collection concentrated among managers and senior specialists working in Tehran. The target population consisted of managers, senior experts, technology specialists, digital transformation professionals, information technology personnel, process and operations specialists, innovation and research and development personnel, and other professionals whose organizational responsibilities were directly or indirectly related to technology management, artificial intelligence implementation, digital transformation, technology transfer, industrial automation, data management, or strategic planning in the petrochemical industry. Individuals were considered eligible for participation when they possessed sufficient professional experience in the petrochemical sector and adequate familiarity with technological development, artificial intelligence, digital transformation, or technology-transfer processes. The inclusion of respondents with managerial and specialist responsibilities was intended to ensure that the collected data reflected informed judgments regarding both the strategic and operational requirements of artificial intelligence technology transfer.

The quantitative sample consisted of approximately 150 respondents. This sample size was selected with consideration of the requirements of structural equation modeling using the partial least squares approach, the number of latent variables

and indicators included in the proposed model, and the need to achieve adequate statistical power for estimating structural relationships. Because the study aimed to examine a relatively complex explanatory model involving several interconnected constructs, a sample of approximately 150 participants was considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM), particularly given the predictive and model-development orientation of the research. Participants were selected using a simple random sampling procedure from accessible members of the target population. This sampling strategy was adopted to provide eligible members of the population with an approximately equal probability of participation and to reduce systematic selection bias. Data collection for the quantitative phase was conducted during February 2026. Participation was voluntary, and respondents were informed that their responses would be used exclusively for scientific purposes. Confidentiality of individual responses was maintained throughout data collection and analysis, and the questionnaire did not require the disclosure of personally identifying information beyond general demographic characteristics necessary for describing the sample.

Data were collected using a researcher-developed questionnaire specifically designed to measure the dimensions and indicators of technology transfer associated with implementation of the National Artificial Intelligence Development Program in the petrochemical industry. The questionnaire was developed according to the conceptual foundations of technology transfer, artificial intelligence adoption, digital transformation, industrial innovation, technological infrastructure, organizational readiness, and the requirements of artificial intelligence deployment in complex industrial environments. Particular attention was given to the specific characteristics of the petrochemical industry, including the interaction of information technology and operational technology infrastructures, industrial data availability, process automation, reliability and maintenance requirements, process safety, technology governance, intellectual property considerations, technological capability development, and the organizational conditions required for transferring artificial intelligence from technological development environments into operational industrial settings. Accordingly, the questionnaire was designed not merely to measure attitudes toward artificial intelligence but to evaluate the broader organizational and technological ecosystem necessary for successful AI-oriented technology transfer.

The questionnaire contained two general sections. The first section collected demographic and professional information concerning the respondents, such as gender, age, educational level, professional experience, occupational position, and relevant area of specialization. These variables were used primarily to describe the characteristics of the statistical sample and were not considered the principal explanatory constructs of the structural model. The second section contained the main measurement items corresponding to the constructs included in the proposed technology transfer model. The items were formulated as declarative statements and measured using a five-point Likert scale ranging from 1, representing “strongly disagree,” to 5, representing “strongly agree.” Higher scores therefore indicated a greater perceived presence, importance, or effectiveness of the corresponding factor in facilitating artificial intelligence technology transfer within the petrochemical industry. Although individual Likert items are ordinal in nature, composite scores derived from multiple items were treated as approximately continuous measures for multivariate statistical analysis and structural equation modeling.

The measurement instrument was subjected to quantitative validity and reliability assessment before interpretation of the structural relationships. Construct validity was examined through confirmatory measurement-model assessment. Indicator reliability was evaluated by examining the standardized outer loadings of individual items on their corresponding latent constructs. Factor loadings of 0.70 or higher were considered desirable, while items with loadings between 0.50 and

0.70 were retained when their removal did not substantially improve composite reliability or convergent validity and when they were theoretically important to the construct. The statistical significance of indicator loadings was also evaluated through bootstrapping. Convergent validity was assessed using the Average Variance Extracted (AVE), with values of at least 0.50 considered indicative of adequate convergent validity, demonstrating that each latent variable explained at least half of the variance of its indicators. Discriminant validity was evaluated to ensure that conceptually distinct constructs represented empirically distinguishable dimensions. The Fornell–Larcker criterion was examined by comparing the square root of the AVE for each construct with its correlations with the other constructs. In addition, the Heterotrait–Monotrait ratio of correlations was considered as a complementary criterion for evaluating discriminant validity.

Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability. Values of 0.70 or higher were regarded as evidence of acceptable reliability, whereas very high values were examined for potential item redundancy. Composite reliability was given particular attention because it does not assume equal indicator loadings and is therefore suitable for PLS-SEM measurement models. The overall measurement assessment consequently ensured that the questionnaire demonstrated satisfactory indicator reliability, internal consistency, convergent validity, and discriminant validity before the structural relationships among the study constructs were interpreted.

The collected data were initially screened and prepared for statistical analysis. Descriptive statistics were used to summarize the demographic and professional characteristics of the respondents and to describe the distribution of the principal study variables. Frequencies and percentages were calculated for categorical demographic variables, while means and standard deviations were calculated for the questionnaire constructs and indicators. The dataset was examined for incomplete questionnaires, missing values, response patterns, and potential data-entry errors before conducting inferential analyses. The distributional characteristics of the variables were also investigated through measures such as skewness and kurtosis. Because Partial Least Squares Structural Equation Modeling is comparatively robust to deviations from multivariate normality, strict multivariate normality was not treated as a prerequisite for model estimation; nevertheless, examination of distributional properties was conducted to identify potentially problematic indicators and to provide an accurate statistical description of the data.

The proposed technology transfer model was evaluated using Partial Least Squares Structural Equation Modeling with SmartPLS software. PLS-SEM was selected because the study was primarily oriented toward model development, prediction, and explanation of the factors affecting technology transfer associated with implementation of the National Artificial Intelligence Development Program in the petrochemical industry. This method is particularly appropriate for models containing multiple latent variables, complex structural relationships, and several observed indicators and is suitable when the primary objective is to maximize the explained variance of endogenous constructs. The statistical analysis was conducted in two sequential stages consisting of assessment of the measurement model and assessment of the structural model.

In the measurement-model assessment, the psychometric properties of the constructs were examined through indicator loadings, Cronbach's alpha, composite reliability, Average Variance Extracted, convergent validity, and discriminant validity. Indicators exhibiting inadequate loading values were examined carefully with consideration of both statistical performance and conceptual relevance. Multicollinearity among indicators and predictor constructs was assessed using the Variance Inflation Factor (VIF), with values within accepted thresholds indicating the absence of problematic collinearity. Following confirmation of the adequacy of the measurement model, the structural model was assessed to determine the magnitude,

direction, and statistical significance of relationships among the latent variables included in the proposed technology transfer framework.

Structural relationships were evaluated using standardized path coefficients. The statistical significance of the estimated coefficients was examined through a nonparametric bootstrapping procedure in SmartPLS, which generated standard errors, t statistics, and confidence intervals for the model parameters. Relationships were considered statistically significant when their corresponding probability values were below the predefined significance level of 0.05 and the bootstrapped confidence intervals did not include zero. The explanatory power of the model was evaluated using the coefficient of determination (R^2) for endogenous constructs, indicating the proportion of variance in each dependent construct explained by its predictor variables. Effect size statistics (f^2) were also examined to determine the relative contribution of individual exogenous constructs to the explained variance of the corresponding endogenous variables. Predictive relevance was evaluated through appropriate PLS-based predictive indices, including Q^2 where applicable, with values greater than zero interpreted as evidence that the model possessed predictive relevance for the endogenous constructs.

The overall adequacy of the proposed model was further evaluated using appropriate PLS-SEM model-quality criteria. The Standardized Root Mean Square Residual (SRMR) was examined as an approximate indicator of model fit, together with measurement and structural quality indices. The final importance of the model components was determined by considering a combination of standardized factor loadings, structural path coefficients, explained variance, effect sizes, and the statistical significance of estimated relationships. Components with stronger standardized effects and greater explanatory contributions were interpreted as having greater importance in the implementation of technology transfer based on the National Artificial Intelligence Development Program within the petrochemical industry. This analytical procedure made it possible not only to validate the measurement structure of the proposed model but also to determine the relative importance of its components and assess the extent to which the model could explain the mechanisms underlying artificial intelligence technology transfer in the petrochemical industry.

Findings and Results

The quantitative analysis was conducted to evaluate the measurement properties of the proposed constructs and to test the structural relationships underlying the technology transfer model based on the implementation of the National Artificial Intelligence Development Program in the petrochemical industry. The questionnaire included 26 items distributed across six major constructs: causal conditions, core phenomenon, strategies, contextual conditions, facilitating/intervening conditions, and consequences. The distribution of the questionnaire items across these constructs is presented in Table 1.

Table 1

Structure and Items of the Research Questionnaire

Construct	Item	Questionnaire Item
Causal Conditions	Q1	Importance of reducing unplanned shutdowns in production lines
Causal Conditions	Q2	Need for intelligent optimization of thermal and chemical processes
Causal Conditions	Q3	Necessity of producing new product grades with precise formulations
Causal Conditions	Q4	Intelligent monitoring of leaks and environmental hazards
Causal Conditions	Q5	Maintaining market share against regional competitors
Causal Conditions	Q6	Need for early detection systems for technical failures
Core Phenomenon	Q7	Integration of artificial intelligence from feedstock to final product
Core Phenomenon	Q8	Use of intelligent control systems
Core Phenomenon	Q9	Use of artificial intelligence predictions for continuous learning

Strategies	Q10	Collaboration with specialized artificial intelligence companies across different operational areas
Strategies	Q11	Financing innovative projects that may involve relatively high levels of risk
Strategies	Q12	Establishment of capable research and development teams for developing new technologies and products
Strategies	Q13	Provision of specialized training courses for petrochemical experts
Strategies	Q14	Transfer of technical knowledge through interorganizational collaboration
Contextual Conditions	Q15	Availability of data-collection infrastructure at industrial sites
Contextual Conditions	Q16	Development of clear and facilitating regulations
Contextual Conditions	Q17	Establishment and development of research and development centers
Facilitating/Intervening Conditions	Q18	Complexity associated with designing sophisticated chemical processes
Facilitating/Intervening Conditions	Q19	Organizational resistance to change
Facilitating/Intervening Conditions	Q20	Importance of data security and privacy, particularly against cyberattacks
Consequences	Q21	Increased reliability and stability of production
Consequences	Q22	Improved product quality and reduced consumption of raw materials
Consequences	Q23	Reduced fuel and electricity costs and lower carbon impacts
Consequences	Q24	Implementation of a preventive management approach
Consequences	Q25	Improvement of the country's position in the application of artificial intelligence in the petrochemical industry
Consequences	Q26	Substantial reduction in technological dependence on other countries

Before estimating the structural model, the distributional characteristics of the study variables were examined using the Kolmogorov–Smirnov test. The null assumption of normality was rejected for all six constructs. The significance level was 0.000 for causal conditions, the core phenomenon, contextual conditions, facilitating/intervening conditions, strategies, and consequences. Therefore, the distributions of all principal variables differed significantly from a normal distribution. This finding supported the use of Partial Least Squares Structural Equation Modeling, which does not require multivariate normality to the same extent as covariance-based structural equation modeling. Accordingly, SmartPLS and the partial least squares estimation procedure were used to evaluate the measurement and structural models.

Construct validity was subsequently investigated by examining the standardized outer loadings and their corresponding significance statistics. A measurement item was considered acceptable when its standardized loading exceeded 0.40 and its significance statistic exceeded the critical value of 1.96. As shown in Table 2, all 26 indicators satisfied both criteria. Standardized loadings ranged from 0.521 to 0.887, while significance statistics ranged from 2.892 to 43.062. Therefore, none of the measurement items required exclusion on the basis of inadequate construct validity.

Table 2

Construct Validity of the Measurement Model

Construct	Item	Significance Statistic	Standardized Loading
Causal Conditions	Q1	7.037	0.797
	Q2	13.758	0.816
	Q3	23.814	0.747
	Q4	15.022	0.793
	Q5	16.459	0.820
	Q6	10.620	0.674
Core Phenomenon	Q7	32.527	0.811
	Q8	15.189	0.887
	Q9	10.620	0.549
Strategies	Q10	18.330	0.742
	Q11	25.929	0.774
	Q12	13.140	0.626
	Q13	5.816	0.531
	Q14	10.926	0.709
Contextual Conditions	Q15	19.712	0.756
	Q16	14.294	0.699
	Q17	43.062	0.839
Facilitating/Intervening Conditions	Q18	15.893	0.696
	Q19	14.479	0.661

	Q20	7.037	0.705
Consequences	Q21	15.693	0.713
	Q22	11.880	0.682
	Q23	2.892	0.521
	Q24	19.354	0.762
	Q25	6.575	0.852
	Q26	4.604	0.747

The strongest indicator of the causal conditions construct was Q5, concerning the maintenance of market share against regional competitors, with a standardized loading of 0.820, followed closely by Q2, representing the need for intelligent optimization of thermal and chemical processes, with a loading of 0.816. Within the core phenomenon, Q8, representing the use of intelligent control systems, showed the strongest loading at 0.887. For the strategy construct, the strongest indicator was Q11, relating to financing high-risk innovative projects, with a loading of 0.774. Within contextual conditions, Q17, representing the establishment of research and development centers, had the strongest loading at 0.839. The facilitating/intervening indicators were relatively homogeneous, ranging from 0.661 to 0.705, with data security and privacy receiving the highest loading. Finally, Q25, representing improvement in the country's position in the application of AI in the petrochemical industry, was the strongest indicator of consequences, with a loading of 0.852.

Convergent validity was evaluated using Average Variance Extracted, whereas discriminant validity was assessed through the Fornell–Larcker criterion. According to the Fornell–Larcker criterion, the square root of the AVE for each latent construct should exceed its correlations with the other constructs. The results are presented in Table 3.

Table 3

Discriminant Validity Based on the Fornell–Larcker Criterion

Construct	Causal Conditions	Contextual Conditions	Core Phenomenon	Facilitating/Intervening Conditions	Strategies	Consequences
Causal Conditions	0.711					
Contextual Conditions	0.732	0.847				
Core Phenomenon	0.542	0.351	0.855			
Facilitating/Intervening Conditions	0.551	0.465	0.258	0.792		
Strategies	0.367	0.487	0.540	0.464	0.754	
Consequences	0.159	0.239	0.637	0.256	0.613	0.801

The diagonal values represented the square roots of the AVE values as reported in the Fornell–Larcker matrix. These values were generally greater than the corresponding interconstruct correlations, indicating that the latent constructs were sufficiently distinguishable from one another. Thus, the model demonstrated an acceptable level of discriminant validity, suggesting that the indicators associated with each construct shared stronger relationships with their intended construct than with other constructs in the model.

Composite reliability and convergent validity were also examined for all six constructs. Composite reliability values greater than 0.70 were regarded as indicative of satisfactory internal consistency, while AVE values greater than 0.50 indicated adequate convergent validity. The results are shown in Table 4.

Table 4

Composite Reliability and Convergent Validity

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)
Causal Conditions	0.721	0.674
Core Phenomenon	0.736	0.691

Contextual Conditions	0.715	0.622
Facilitating/Intervening Conditions	0.769	0.654
Strategies	0.759	0.632
Consequences	0.811	0.661

All composite reliability coefficients exceeded the recommended threshold of 0.70, ranging from 0.715 for contextual conditions to 0.811 for consequences. These values demonstrated satisfactory internal consistency across all constructs. Similarly, all AVE values exceeded the threshold of 0.50 and ranged from 0.622 to 0.691. The core phenomenon had the highest AVE value at 0.691, followed by causal conditions at 0.674, consequences at 0.661, facilitating/intervening conditions at 0.654, strategies at 0.632, and contextual conditions at 0.622. Therefore, the indicators explained more than half of the variance in their corresponding latent constructs, confirming satisfactory convergent validity.

Following confirmation of the measurement model, the PLS-SEM structural model was assessed in both significance-statistic and standardized-coefficient forms. The significance model illustrates the bootstrapped significance statistics associated with the estimated relationships, whereas the standardized model presents the magnitude and direction of the structural path coefficients.

Figure 1

Significance Model of the Proposed Technology Transfer Framework

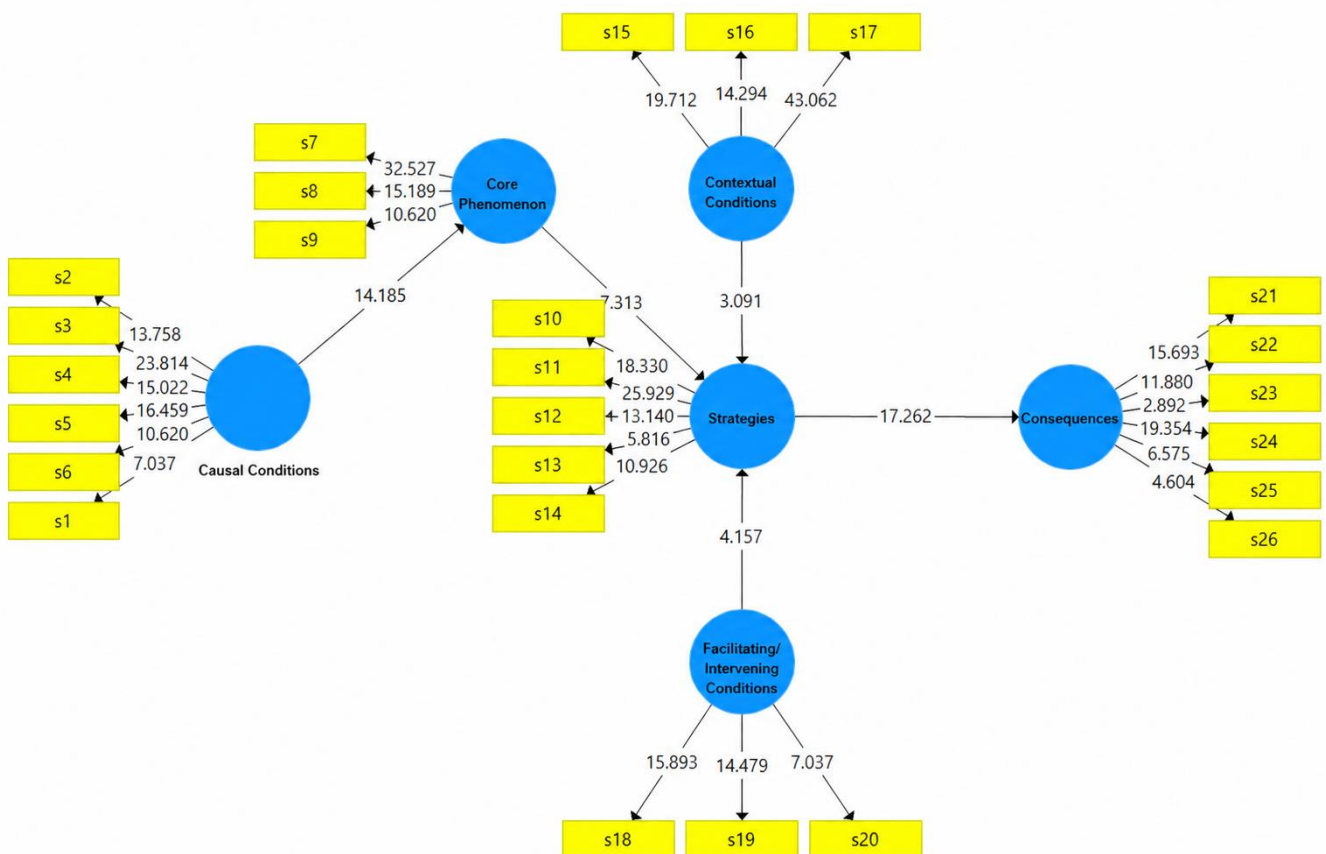
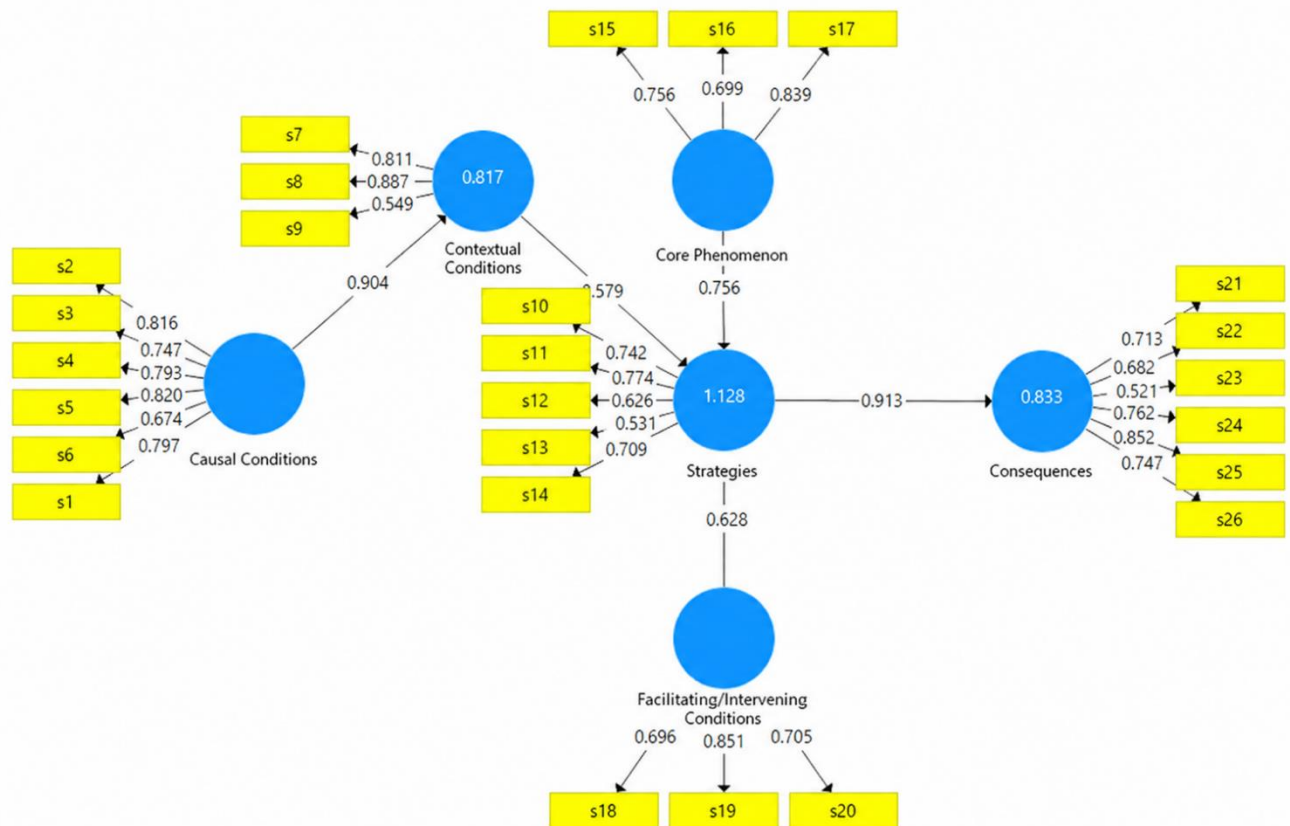


Figure 2*Standardized Path Coefficient Model of the Proposed Technology Transfer Framework*

The results of the structural-model analysis are summarized in Table 5. All five hypothesized structural relationships were statistically significant because the significance statistics were greater than 1.96. In addition, all standardized path coefficients substantially exceeded the minimum acceptable value of 0.40.

Table 5*Structural Model Results*

Structural Relationship	Significance Statistic	Standardized Path Coefficient	Result
Causal Conditions → Core Phenomenon	14.185	0.904	Supported
Core Phenomenon → Strategies	7.313	0.579	Supported
Contextual Conditions → Strategies	3.091	0.756	Supported
Facilitating/Intervening Conditions → Strategies	4.157	0.628	Supported
Strategies → Consequences	17.262	0.913	Supported

The strongest structural relationship was observed between strategies and consequences, with a standardized path coefficient of 0.913 and a significance statistic of 17.262. This finding indicated that the implementation of appropriate technology-transfer strategies had a very strong positive relationship with the expected technological, operational, economic, and national outcomes. The second strongest relationship was found between causal conditions and the core phenomenon, with a standardized coefficient of 0.904 and a significance statistic of 14.185, showing that the underlying technological, competitive, operational, and safety-related drivers strongly shaped the integration of artificial intelligence within the petrochemical technology-transfer system.

Contextual conditions also exerted a substantial positive effect on strategies, with a standardized coefficient of 0.756 and a significance statistic of 3.091. This result suggested that the availability of industrial data infrastructure, supportive regulations, and research and development capacity strongly influenced the extent to which appropriate technology-transfer strategies could be implemented. Facilitating/intervening conditions had a significant positive relationship with strategies, with a coefficient of 0.628 and a significance statistic of 4.157. Thus, factors related to process complexity, organizational readiness for change, cybersecurity, and data protection were materially associated with strategic implementation. Finally, the core phenomenon had a significant positive relationship with strategies, with a standardized coefficient of 0.579 and a significance statistic of 7.313. Accordingly, greater integration of AI throughout petrochemical processes, use of intelligent control systems, and application of predictive AI capabilities were associated with stronger strategic responses concerning collaboration, financing, capability development, training, and technical knowledge transfer. Overall, all proposed structural relationships were supported, providing empirical confirmation of the principal relationships incorporated into the technology transfer model.

The quality of the measurement model was further assessed through the cross-validated communality index (Cv Com). Positive values of this index indicate that the measurement model possesses adequate capability to reproduce or predict the observed indicators through their respective latent constructs. The Cv Com values were 0.421 for causal conditions, 0.665 for the core phenomenon, 0.237 for contextual conditions, 0.326 for facilitating/intervening conditions, 0.267 for strategies, and 0.157 for consequences. All values were positive. The core phenomenon demonstrated the highest measurement-model quality, with a value of 0.665, whereas the consequences construct had the lowest value at 0.157. Nevertheless, because all values were above zero, the measurement models for all constructs demonstrated acceptable predictive quality.

The predictive quality of the structural model was additionally evaluated using the Stone–Geisser Q^2 criterion. In PLS-SEM, Q^2 values greater than zero indicate predictive relevance, while values around 0.02, 0.15, and 0.35 are commonly interpreted as reflecting small, medium, and large predictive relevance, respectively. The Q^2 values obtained for the study constructs were 0.421 for causal conditions, 0.553 for the core phenomenon, 0.628 for contextual conditions, 0.377 for facilitating/intervening conditions, 0.516 for strategies, and 0.528 for consequences. All reported values exceeded 0.35, indicating strong predictive relevance. Contextual conditions showed the highest Q^2 value at 0.628, followed by the core phenomenon at 0.553, consequences at 0.528, strategies at 0.516, causal conditions at 0.421, and facilitating/intervening conditions at 0.377. These results demonstrated that the proposed structural framework possessed substantial predictive capability for the principal constructs examined in the study.

Discussion and Conclusion

The present study was conducted to design and quantitatively validate a technology transfer model based on the implementation of the National Artificial Intelligence Development Program in the petrochemical industry. The findings confirmed the adequacy of both the measurement and structural models and showed that all proposed structural relationships were statistically significant. In particular, causal conditions exerted a strong positive effect on the core phenomenon, the core phenomenon significantly affected strategies, contextual conditions significantly influenced strategies, facilitating/intervening conditions significantly affected strategies, and strategies had a very strong positive effect on consequences. The strongest structural coefficient was observed for the relationship between strategies and

consequences, followed closely by the relationship between causal conditions and the core phenomenon. These results indicate that successful technology transfer in the context of AI implementation in the petrochemical industry depends on a coherent sequence in which operational and competitive pressures stimulate the integration of AI, this integration is translated into strategic actions under appropriate contextual and facilitating conditions, and these strategies subsequently generate operational, technological, and national-level outcomes.

The significant and strong effect of causal conditions on the core phenomenon suggests that the need to reduce unplanned shutdowns, improve thermal and chemical processes, produce more precise product grades, monitor environmental hazards, maintain market competitiveness, and detect technical failures at an early stage provides a powerful foundation for AI technology integration. This finding is consistent with the broader technology-transfer literature, which emphasizes that technology adoption is usually stimulated by concrete organizational needs and perceived performance gaps rather than by technological novelty alone. Khamseh et al. conceptualize technology transfer as a managed process that must be connected to organizational needs and strategic objectives rather than being treated simply as the acquisition of external technology [1]. Similarly, Zamani and Khamseh identify technological, organizational, and environmental pressures as influential dimensions of technology transfer in the context of digital transformation [2]. The present results therefore suggest that the adoption of AI in the petrochemical sector is most likely to become meaningful when it addresses clearly recognized operational problems and strategic priorities.

This interpretation is also compatible with the findings of Esmaeili et al., who showed that technology transfer in Iran's petro-refining industry is shaped by an interconnected system of technological, managerial, and organizational factors [19]. The strong causal path identified in the present study reinforces the view that AI technology transfer cannot be separated from the operational realities of the industry. In a petrochemical environment, where downtime, process instability, equipment failure, product inconsistency, and environmental incidents may generate substantial economic and safety consequences, technologies that directly respond to these risks are more likely to receive managerial support and organizational investment. Wang's risk-oriented perspective on technology transfer is also relevant here, because technology-transfer decisions are influenced by the expected balance between technological opportunity and implementation risk [15]. Thus, the strong effect of causal conditions can be interpreted as evidence that organizational urgency and risk exposure create the necessary momentum for AI integration.

The findings further indicated that the core phenomenon had a significant positive effect on strategies. In other words, greater integration of AI across production processes, increased use of intelligent controls, and stronger reliance on AI-based prediction and continuous learning were associated with greater emphasis on strategic actions such as collaboration with specialized AI firms, financing innovative projects, building research and development teams, training petrochemical experts, and transferring technical knowledge through interorganizational cooperation. This result corresponds closely to the emerging literature on AI-based open innovation. Orlando et al. argue that AI is reshaping research and development collaboration by creating new forms of open innovation in which organizations increasingly depend on partnerships, knowledge exchange, and distributed technological capabilities [5]. The present findings extend this logic into the petrochemical setting by showing that the more deeply AI is embedded in operational processes, the greater the need for strategic collaboration and structured capability development.

The importance of collaboration is also supported by Chen et al., who describe the evolving role of technology-transfer institutions as increasingly active coordinators rather than passive intermediaries [6]. Although their study focuses on the university environment, the broader implication is relevant: technology transfer becomes more effective when specialized actors actively coordinate relationships among technology developers, users, knowledge institutions, and commercial partners. Huegel et al. similarly emphasize that transfer begins with opportunity recognition and the deliberate selection of suitable transfer channels [4]. In the context of this study, cooperation with specialized AI firms, structured financing of high-risk innovation, and interorganizational knowledge transfer can be understood as mechanisms that operationalize the transition from technological opportunity to industrial implementation.

The significant positive effect of contextual conditions on strategies also represents an important finding. The availability of data-collection infrastructure, the development of clear and facilitating regulations, and the establishment of research and development centers were all shown to support strategic implementation. This result is highly consistent with the view that technology transfer is embedded within institutional and infrastructural environments. Chica emphasizes that knowledge and technology transfer is shaped by contextual and institutional conditions that can either enable or constrain the movement and application of knowledge [20]. Similarly, Zhenxu et al. demonstrate that the effectiveness of technology-transfer policy depends on systemic interactions among policy instruments, institutions, resources, and innovation actors [10]. The present findings therefore suggest that AI-related technology transfer cannot be successfully implemented through organizational strategies alone; the surrounding technological and regulatory infrastructure must also support those strategies.

The importance of digital infrastructure is further reinforced by Iftikhar et al., who show that technology-enabled development depends on the combined presence of infrastructure, access, usage, knowledge transfer, and technology-based governance [14]. In the petrochemical industry, this is particularly relevant because AI applications depend heavily on reliable industrial data, interoperable systems, and integrated IT/OT environments. Without sufficient data infrastructure, AI models cannot be trained, validated, or continuously improved. Likewise, unclear regulatory frameworks can inhibit experimentation, increase perceived risk, and reduce organizational willingness to invest in AI-enabled transformation. Consequently, the strong contextual effect observed in the present study supports the argument that national AI policies need to be translated into concrete infrastructural and regulatory mechanisms at the industrial level.

The facilitating/intervening conditions also demonstrated a significant effect on strategies. These conditions included the complexity of chemical-process design, organizational resistance to change, and the importance of data security and privacy, particularly in relation to cyberattacks. This result indicates that strategic implementation is influenced not only by supportive factors but also by constraints and risks that organizations must actively manage. Simms and Frishammar show that technology transfer is especially challenging when collaborating organizations differ in technological capabilities and knowledge intensity [11]. In such relationships, capability asymmetries may generate communication problems, knowledge dependence, and implementation difficulties. These challenges are highly relevant to petrochemical firms collaborating with specialized AI vendors because one party may possess advanced algorithmic capabilities while the other has deeper process expertise. Effective strategy therefore requires mechanisms for integrating these different knowledge domains.

The role of organizational resistance is also supported by Stumbrienė et al., who demonstrate that technology-enabled innovation depends significantly on motivation, perceived usefulness, and organizational conditions [12]. Twyman likewise emphasizes that technology transfer involves behavioral adaptation and institutional change rather than merely the diffusion

of a technical solution [13]. These findings help explain why employee training, capability development, and participation are necessary strategic responses in the present model. AI implementation may alter professional roles, decision structures, and established routines, which can generate resistance if employees do not understand the technology or perceive it as a threat. The current findings therefore support the view that human and organizational dimensions should be treated as integral components of AI technology transfer.

The strong path from strategies to consequences was the most notable structural result. The standardized coefficient of 0.913 indicates that the implementation of appropriate strategies was strongly associated with increased production reliability, improved product quality, reduced material and energy consumption, preventive management, improved national standing in AI utilization, and decreased dependence on external countries. This finding is consistent with the resource-based perspective presented by Ren et al., who show that technology-transfer adoption can create strategic and operational benefits when it is integrated into organizational capabilities [18]. The present study similarly indicates that AI technologies generate value not simply through acquisition, but through coordinated strategic actions that embed the technology in organizational processes.

The environmental and efficiency-related consequences are also consistent with the findings of Tahmasbi Roshan and Arab Kalmeri, who link knowledge and technology transfer to green innovation, green supply-chain management, and improved green performance [17]. Cobbold et al. likewise show that the transfer of low-carbon technologies can stimulate domestic green innovation [16]. In the petrochemical industry, AI can support more efficient energy use, improved feedstock utilization, emission monitoring, process optimization, and predictive maintenance. Therefore, the strong strategy-to-consequence path suggests that well-designed technology-transfer strategies may generate both economic and environmental benefits.

The findings also have implications for national technological development. Bradlow and Kentikelenis argue that technology transfer can play a major role in advancing industrial policy and supporting wider technological upgrading [8]. Jalilzadeh Tabrizi and Jalalpour similarly connect technology transfer with sustainable development and national innovation policy [9]. The current findings suggest that effective AI technology transfer in the petrochemical sector can contribute to broader national objectives such as reducing technological dependence and improving the country's competitive position in the use of advanced industrial AI. Ponomarev and Gareev's emphasis on the need for catching-up countries to move beyond passive acquisition toward domestic capability development is especially relevant [7]. Thus, the consequences identified in this study should be viewed not merely as firm-level outcomes but as potential components of national technological resilience.

The role of knowledge spillovers also helps explain the importance of collaborative strategies. Barboza et al. show that technology transfer is influenced by knowledge spillovers and foreign direct investment, emphasizing the importance of absorptive capacity in transforming external knowledge into domestic capability [3]. The present findings are compatible with this interpretation because partnerships with AI companies, R&D capability, and technical training can all enhance absorptive capacity. Rather than remaining dependent on external vendors, petrochemical firms can use collaboration as a pathway to internalize knowledge, build technical expertise, and gradually develop greater autonomy in managing AI technologies.

Taken together, the results support an integrated interpretation of AI technology transfer in the petrochemical sector. Causal pressures create the demand for AI integration; the core phenomenon reflects the degree to which AI becomes

embedded in industrial operations; contextual and facilitating/intervening conditions shape the feasibility of implementation; strategies translate technological potential into organizational action; and consequences represent the operational, environmental, competitive, and national outcomes of successful transfer. The study therefore reinforces the idea that technology transfer is a systems-level process rather than a linear transaction. This interpretation is consistent with research emphasizing the systemic, collaborative, institutional, and capability-based nature of modern technology transfer [5, 6, 10].

The present study had several limitations. First, the quantitative data were collected from a relatively limited sample of managers and senior specialists in the petrochemical industry, which may restrict the generalizability of the results to all organizations and occupational levels within the sector. Second, the study relied on self-reported questionnaire data, and the responses may therefore have been influenced by perceptual bias, social desirability, or differences in respondents' familiarity with artificial intelligence and technology-transfer processes. Third, the study used a cross-sectional design, which limits the ability to infer temporal or causal changes in technology-transfer processes over time. Fourth, the model focused on a defined set of organizational, technological, contextual, strategic, and outcome variables and may not capture every relevant factor, such as international sanctions, detailed financing structures, vendor-specific dependencies, regional infrastructure differences, or organization-specific digital maturity. Finally, the empirical validation was conducted within the petrochemical context, and the extent to which the model can be transferred to other industrial sectors remains uncertain.

Future studies should test the proposed model using larger and more diverse samples from multiple petrochemical companies and geographic regions. Longitudinal designs are recommended to investigate how the relationships among AI integration, organizational strategies, and technology-transfer outcomes change across different stages of implementation. Researchers may also examine moderating variables such as organizational size, digital maturity, ownership structure, technological absorptive capacity, cybersecurity maturity, and previous experience with AI projects. Comparative studies between petrochemical firms and other capital-intensive industries could further assess the external validity of the model. Future research may also develop more detailed models of individual dimensions, including AI governance, intellectual property arrangements, financing mechanisms, IT/OT integration, workforce reskilling, and vendor dependence. In addition, multi-group analysis could be used to compare the perspectives of managers, engineers, IT specialists, operations personnel, and AI professionals.

Petrochemical organizations should treat AI technology transfer as a coordinated transformation program rather than a set of isolated technology projects. Managers should prioritize AI applications that directly address measurable operational problems such as unplanned shutdowns, equipment failures, energy consumption, product-quality variation, and environmental risks. Companies should establish dedicated cross-functional teams combining process engineering, IT, operational technology, data science, cybersecurity, and technology-management expertise. Investment should also be directed toward industrial data infrastructure, interoperable systems, R&D centers, staff training, and structured collaboration with specialized AI firms. Clear governance mechanisms should be established for data ownership, cybersecurity, model validation, intellectual property, and accountability. At the policy level, supportive regulations, funding mechanisms, and incentives for joint industrial R&D can accelerate implementation. Organizations should also design collaborations in a way that promotes genuine knowledge transfer and internal capability building rather than long-term dependence on external technology suppliers.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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