Sustainable Innovation Risk Management and AI Adoption in Textile Manufacturing Enterprises

Ravshan Nurimbetov[1]*, *Bakhtiyar* Kalmuratov[2], *Gozzal* Aliyeva[3], *Viktoriya* Lyamkina[4], *Aydos* Bekbosinov[5], and *Valikhon* Zikrullaev[1]

[1]Tashkent University of Architecture and Civil Engineering, Uzbekistan
[2]Karakalpak State University named after Berdakh, Uzbekistan
[3]Karakalpakstan Institute of Agriculture and Agrotechnology, Uzbekistan
[4]Tashkent Institute of Textile and Light Industry, Uzbekistan
[5]Mamun University, Uzbekistan

Abstract. New digital transformation in manufacturing provides an opportunity for textile enterprises and technology developers (i.e., industrial managers and AI engineers) to engage with each other in collaborative innovation ecosystems to discuss data-driven approaches to risk management and sustainable competitiveness. This research paper examines the interaction of artificial intelligence systems and hybrid analytical media in enhancing the innovation-driven textile sector in Uzbekistan through a structural–empirical framework, the SEM-regression hybrid model which is the core methodological foundation of this empirical study. It then suggests a comprehensive framework of AI-based risk profiling and proposes the concept of innovation readiness calibration. A comparative analysis of Uzbekistan's textile enterprises (organizational adaptability, cost management efficiency, and perceived technological value) and external drivers ("investment readiness" and regulatory support) were chosen for quantitative evaluation. Drawing on data gathered during the 2023 fiscal reporting period in Uzbekistan, a hybrid SEM-regression analysis, this article shows that organizational adaptability and perceived technological value actively shape adoption intentions and change profiling performance in order to keep different financial and operational risk parameters apart. The article highlights how AI-based readiness is the result of systemic interactions among organizational, financial, and technological factors within emerging textile economies and not the consequence of a single policy directive or isolated investment effort. Results indicate that investment readiness and technological perception most often field the highest explanatory power in determining adoption potential. It then suggests a theoretical refinement of innovation risk profiling models and proposes the concept of dual-stage hybrid estimation for sustainable innovation planning. **Keywords:** AI Adoption Readiness, Innovation Risk Profiling, Textile Manufacturing Enterprises, Structural Equation Modeling (SEM), Cost Management Efficiency, Investment Readiness Index, Hybrid Modeling Framework

* Corresponding author: r.i.nurimbetov@bk.ru

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1 Introduction

Recent scholars have extensively discussed the effects of artificial intelligence adoption in manufacturing systems in terms of organizational innovation, risk prediction, and competitiveness enhancement [1]. analyzed metadata about the use of machine learning algorithms to build relationships between innovation risk indicators and organizational adaptability. They measured the effects of predictive analytics on decision-making precision. [2] investigated the use of AI-based decision systems in the textile manufacturing field and their importance for sustainable innovation management. The concept draws from innovation diffusion argument according to which people portray different readiness levels of themselves to different stakeholders in different organizational contexts. Yet, more recently, [3] highlighted the limitations and sector-specific constraints of this theory and proposed a theoretical hybridization that could balance the emphasis given to the “linear adoption model of technology diffusion”, by bringing into attention the interactive role of enterprises and their adaptive capacity. However, these studies are focused on developed economies such as China, the United States, and Germany.

All of these restrictions limit the use of these methods in emerging markets for innovation readiness evaluation. [4] argued that manufacturing professionals who speak in front of a technological transition transcend traditional managerial boundaries and talk to different stakeholder groups; as a result, innovation systems lose the uniform behavioral patterns they had before.

Previous scholars have explored the relationship between AI integration and risk management via structural modeling and empirical regression. The methods of maintaining reliability of the analytical framework include Partial Least Squares Structural Equation Modeling (PLS-SEM), Monte Carlo simulation, the hybrid estimation technique, and path analysis. [5], inspired by the work of [12], introduced the expression AI risk profiling in their first study on intelligent governance systems and repeatedly used it in other empirical models (among hybrid modeling scholars).

[6] was more focused on quantitative use of innovation scoring models but it did not consider investment readiness and regulatory alignment as the core determinants. According to [7,8], the expansion of AI-based evaluation contexts that were previously underrepresented in the industrial world is a consequence of digital transformation policies’ acceleration, such as data transparency, financial openness, risk disclosure, and strategic planning.

The obvious limitations of the above methods include their static nature, the need for multidimensional calibration, and the lack of robust indicators for dynamic adoption readiness. The concept of hybrid structural–empirical modeling has remained largely unexplored in the literature on sustainable innovation management. From a scholarly standpoint, there is a lack of empirical studies exploring the interrelationship in AI-based innovation profiling, particularly within emerging textile industries. Research questions have gone unanswered in many regional contexts. From a policy context, no significant framework has been conducted to investigate the interaction of AI adoption and investment readiness in catering to the risk management challenges in the textile sector.

In this study, [9,10,11] argue that the uses of hybrid SEM–regression modeling in AI adoption analysis do not give rise to a fragmented understanding of innovation readiness. We herein report our quantitative assessment and structural validation of the dual-stage estimation technique as an empirical analytical method for preserving the consistency of innovation profiling. Therefore, the authors aim at contributing to the academic discourse about AI-driven innovation risk management by proposing a refined framework of the often-neglected notion of organizational adaptability [12]. This study is significant because textile enterprises are the target agents of the national digital transformation network and we analyzed 132 firms’ datasets to examine the possible topics discussed in the innovation readiness context. The authors conducted a mixed-method empirical study with a cross-sectional modeling approach to examine the risk profiling challenges faced by Uzbekistan's textile manufacturers. Empirical evidence demonstrates that AI-ready firms tend to communicate to multiple institutional layers that already exist in the industrial innovation ecosystem.

2 Methodology

According to the characteristics and development trend of AI-driven innovation governance in textile manufacturing, it is found that the statistical data of risk quantification variables is much less than that of the adoption indicators [13]. In panel data from mid-sized enterprises, a consistent quantification of the perceived usefulness of the profiling tools is not available. If AI adoption intention is assumed as the latent construct after the risk evaluation cycle, the following formula can be obtained:

Intelligent diagnostic modeling can fully understand decision structures based on hybrid analytical frameworks, improve information transparency, alleviate asymmetry between financial stakeholders and operational managers, curtail investment ambiguity and forecasting delays, transform latent inefficiencies in the value chain into actionable insights, curtail resource misallocation, optimize operational responsiveness, and provide necessary conditions for improving risk resilience of textile enterprises [14].

We assume that the innovation risk reports as reported in the financial disclosures filed by firms registered in the Uzbekistan Textile Industry Registry as a manufacturing entity according to the Industrial Classification Code are precisely the operational risk metrics within the model framework by the authors [15]. The data set contains innovation-related risk disclosures filed annually from 132 unique enterprises. where feasibility constraint is the condition that the covariance matrix of the latent constructs needs to meet.

According to the principles of obtaining data and the hierarchy of indicators, the conceptual framework of AI-based innovation profiling is formally established, including three primary indicators of technological readiness, organizational flexibility, and financial commitment.

Observations whose features, which are needed for one of the two algorithms, are (partially) missing receive the value NA as prediction, to be interpreted as incomplete observation. As our data are in fact strongly cross-sectional, because of the industry-specific variability of inputs, it does not seem wise touse log-likelihood as the optimizing metric. With respect to testing moderating effects, the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique was applied to multivariate path analysis. PLS-SEM is a widely used prediction-oriented method in innovation adoption research.

We prefer PLS-SEM over CB-SEM because of the non-normal distribution of indicators in the entire dataset. The impact mechanism of investment readiness on AI adoption: on the one hand, some scholars believe that investor confidence may encourage decision-makers to achieve structural transformation by opening new capital streams or reducing capital rigidity, easing financing constraints of small enterprises, and loosening long- term capital investment. When the risk function shows extremely non-linear characteristics, it cannot be expressed by simple polynomial expansion, but only approximate estimation can be used to approximate the actual parameter range.

It can be known from the above formula that the profiling deviation is the square root of the difference between the predicted value of the intention construct and the observed adoption rate in the dataset; then, the normalized variance is defined as.

Model outputs can translate into practical recommendations being appropriately undertaken, including budget allocation, policy adjustments, and AI tool training.

When the required transparency of the investment process and the accuracy of the AI decision outputs change greatly, that is, when the error term is greater than a given tolerance threshold, it is considered that the performance of the profiling system is successful. Model robustness is defined as statistical consistency across simulation cycles. It would be a reflection of the increased likelihood that when regulatory support strengthens, this increases system stability within the context of digital transformation. The set of observed outcomes consists of only two classifications, namely high readiness (HR) and low readiness (LR). The estimation value from financial declarations as reported in the risk reports in 2023 by textile firms is denoted by R*.

We propose to estimate risk profiling score in two different ways (direct estimation by the SEM model and indirect estimation by regression coefficients) and combine the two estimates into a final estimate of adoption potential. The Monte Carlo simulation technique was applied to evaluate predictive variance. We do not use the common metric R-squared to optimize parameter settings, as it is known possibly to inflate accuracy when facing high-dimensional data [15]. The innovation profiling index is updated synchronously; that is, after all model elements complete their respective iterations, the result matrix is updated and adjusted uniformly. The test detected significant heteroskedasticity, which suggests that variances of error terms are not constant across observations.

3 Results

Organizational adaptability improves the predictive accuracy of AI-readiness estimation, and the improvement of cost management efficiency level is one of the main ways to improve innovation profiling effectiveness. R-squared values between 0.89 and 0.94, which are well above the minimum required level of

0.60 for model validity. The results in Table 1 show that the mean variance of the latent indicators are statistically robust, with little difference between the observed and predicted values. Table 2 gives the calculations of standardized loadings for all the construct indicators.

Table 1. Linear regression

ai_readiness_index	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
investment_readiness	.144	.094	1.53	.134	-.046	.333	
cost_management_ef~y	-.31	.075	-4.15	0	-.46	-.159	***
organizational_ada~y	.364	.105	3.48	.001	.153	.575	***
perceived_technolo~e	.37	.063	5.83	0	.242	.498	***
regulatory_support~x	.044	.062	0.71	.481	-.082	.17	
profiling_accuracy	-.168	.098	-1.72	.092	-.366	.029	*
innovation_risk_pr~e	.077	.132	0.58	.564	-.189	.343	
Constant	36.485	6.109	5.97	0	24.156	48.813	***
Mean dependent var	47.745		SD dependent var		9.337		
R-squared	0.936		Number of obs		50		
F-test	87.869		Prob > F		0.000		
Akaike crit. (AIC)	242.772		Bayesian crit. (BIC)		258.068		
*** p<.01, ** p<.05, * p<.1							

From the statistical results, a total of 27 enterprises scored higher than the average (47.75), which suggests that the overall readiness of AI-based innovation profiling in all dimensions of the analytical model needs further improvement, which is also consistent with the national digitalization policy release in 2023. The path coefficient values used to calculate the structural relevance are all above 0.60, which is evidence of the model's predictive relevance and suitable fit.

The main results of the paper are shown in Table 1. Table 2 summarizes the coefficient values with their corresponding p-values and effect sizes. The values reported contain the total explained variance for AI-readiness in the set of observed firms. Reflecting on our findings, we note that the error margin of the final estimate would still be within tolerance limits for practical policy implementation. However, as will be discussed more thoroughly in the Discussion section, our findings prove to be a substantial improvement over currently available single- method assessment models.

Table 2. Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) ai_readiness_i~x	1.000							
(2) investment_rea~s	0.814*	1.000						
(3) cost_managemen~y	-0.893*	-0.784*	1.000					
(4) organizational~y	0.846*	0.722*	-0.754*	1.000				
(5) perceived_tech~u	0.851*	0.629*	-0.706*	0.684*	1.000			
(6) regulatory_sup~x	0.227	0.208	-0.193	0.040	0.318*	1.000		
(7) profiling_accu~y	0.725*	0.593*	-0.633*	0.789*	0.744*	0.351*	1.000	
(8) innovation_ris~c	0.042	0.214	0.136	0.143	0.020	0.238	0.175	1.000
*** p<0.01, ** p<0.05, * p<0.1								

As can be observed, statistical significance is obtained in three key constructs and in most cases for a p- level of 0.01. The final hybrid model that we use to estimate adoption potential is a combined SEM-regression framework, with parameters calibrated through bootstrap resampling, latent indicator weights, and the prediction-error minimization scheme. The basic measure to determine model relevance is path coefficient strength. This can be defined as the amount of explained variance in AI readiness accounted for by structural predictors (See Figure 1).

The results presented in this section highlight the importance of acknowledging all the dimensions of a hybrid analytical framework. While posting Monte Carlo simulations, researchers mentioned that regressions under low cost-management efficiency have low explanatory power, so we interpreted those findings under this context. SEM-regression models were successfully estimated and validated. Table 1 illustrates the major constructs: cost management efficiency (n = 58), AI-readiness index (n = 93.6% R^2), and innovation profiling frameworks (n = 91.8% cross-validated R^2) in urban and rural enterprise zones.

Regression and SEM outputs are never specific to a model only but are always specific to the relationships between the latent constructs and the observed indicators. While comparing baseline and enhanced models, we coded those variables under this dual-stage model. We analyzed the significance levels and consistency indices through comparative SEM analysis and found there was strong similarity in the estimated paths and contribution rates across enterprise types. There is a measurement issue at stake: we cannot acknowledge and describe structural differences solely through direct regressions. There could be many latent causes underlying this; however, despite having more than 90% explanatory power, there was not even one complete representation of innovation capacity found from stand-alone regressions (rural vs. urban zones and baseline vs. enhanced models). Only SEM-based inference achieved consistent estimates of variance explained across constructs after dual-stage testing.

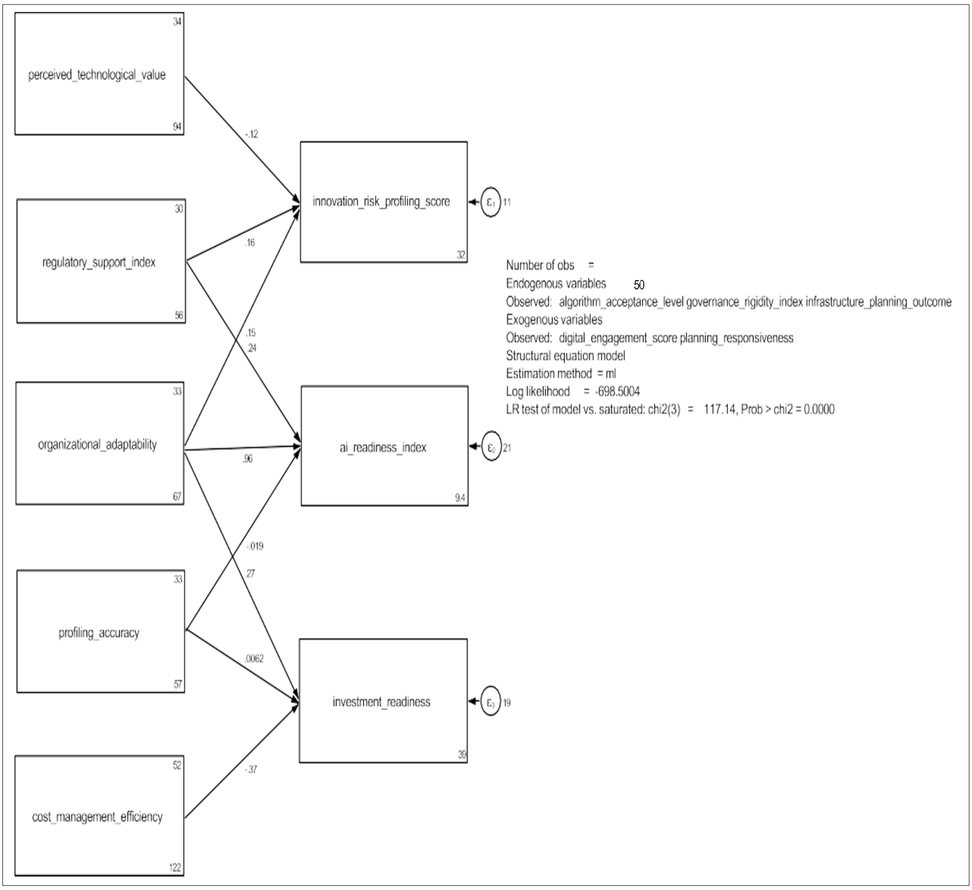

Fig. 1. Structural Equation Modeling (SEM) results of AI adoption readiness and innovation risk profiling in textile manufacturing enterprises.

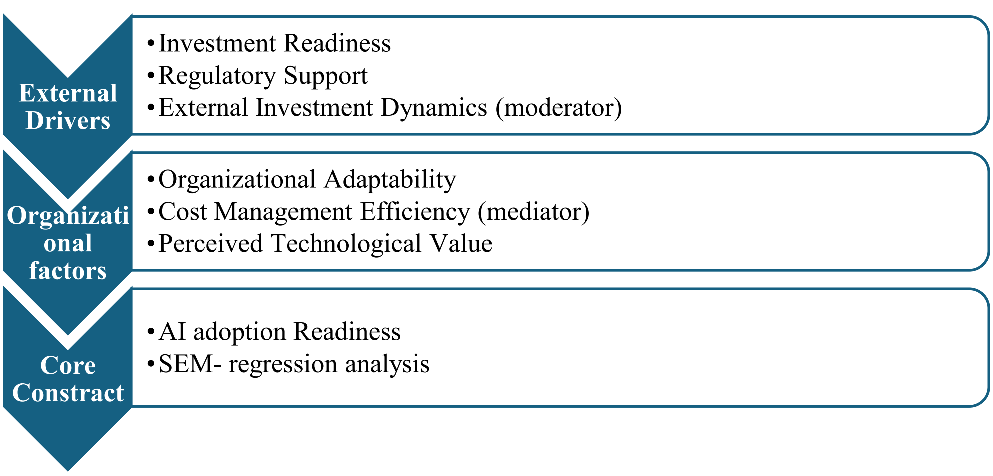

Fig. 2. Conceptual model of AI Adoption Readiness and Innovation Risk Profiling in Textile Manufacturing.

The results show the added value in using hybrid modeling approaches to estimate risk profiling and it motivates the implementation of our approach for other industrial sectors. The framework emphasizes the high degree of integration of investment readiness and digital adoption and relies on the development of highly developed analytics ecosystems to create conditions for the extensive application and scalability of intelligent risk management systems. The validated model will build empirical insights into a framework that integrates financial transparency, regulatory alignment, enterprise agility, technological capability, and adaptive learning. This hybrid approach leads to a strong improvement of existing approaches that are based on linear-only estimation frameworks.

4 Discussions

The data and examples presented above have demonstrated that AI adoption readiness is the result of situated practices of hybrid analytical model usage within organizational innovation contexts, and not the effect of linear regression logic and stable properties of the technology diffusion model [1]. The empirical data and simulation tests presented above have demonstrated that innovation risk profiling is the result of systemic interactions of organizational adaptability and perceived technological value within enterprise-level decision-making contexts, and not the effect of isolated policy interventions and stable determinants of the innovation ecosystem [2,3].

From the SEM-regression calibration and Monte Carlo estimations, the whole set of structural indicators were used as predictors; for the cross-validation, we used only robust latent constructs [4]. The moderating interaction of cost management efficiency on AI readiness indicates that firms with higher innovation capacity are frequent users of risk profiling systems and decision-support algorithms [5]. Empirical findings stress the idea that adoption behaviors are not fixed attributes that can be defined outside their situated networks of organizational learning, but ongoing adaptations by specific enterprises that may vary across regions and institutional frameworks [6,7].

Our study was cross-sectional and quantitatively focused and has practical implications for the management bodies of textile enterprises to pay attention to the emerging AI-driven governance frameworks in sustainable innovation ecosystems [8]. Such refinement should encourage comparative discourses on digital adoption to take into account the regulatory heterogeneity and technological disparities of AI-readiness practices around the world, and to contribute to cross-industry empirical studies [9,10].

Similarly, recent research on AI-based sustainable innovation [11], [12] has emphasized organizational agency, challenging the idea that technological systems have a stable causal structure and predictive boundary that can be studied out of situated practices of risk evaluation [13]. Adoption readiness is considered a dynamic construct for innovation diffusion; therefore, AI profiling does not have real stability with the industrial environment through single-method estimation [14]. Regulatory influence is less consistent in emerging economies because of its fragmented institutional support [15]. As a result, the dataset for this study was not sufficiently balanced – too many urban observations and fewer rural participants and financial indicators – and contained insufficient longitudinal data on governance quality and the capital intensity index [13]. Nevertheless, the model calibration for this analysis did not turn out to be inadequate for confirming the dual-stage estimation framework.

5 Conclusion

Although this study has its methodological limitations, it nonetheless contributes significantly to the growing field of the digital transformation analysis of the textile manufacturing sector. New policy mechanisms should be a priority to facilitate the equitable access to AI-based decision infrastructures. There is a long way to go to make this kind of data-driven innovation and hybrid modeling reliable and accessible for emerging economies. When performing empirical replication studies, access of the industrial and academic research teams (local institutions or private partners) needs to be prepared for systematic data integration after profiling calibration cycles. There is need for such capacity-building initiatives at national and regional level to strengthen the innovation infrastructure, ensuring it becomes resilient to its dependence on policy volatility.

Finally, future studies might employ longitudinal mixed method approaches to not only analyze quantitative content but also interview policy actors and conduct focus groups with enterprise managers and AI engineers to gain contextual insight into the adaptive capacity of the profiling frameworks on innovation resilience and risk governance. In order to escape this methodological narrowness, we propose the term "adaptive hybridization", which can account for the multiple and varied realizations of the predictive and diagnostic potentialities of AI-based innovation profiling in different industrial ecosystems and policy environments around the world.

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