Leveraging AI-Based Innovation Risk Profiling and Phased Investment Decisions in Uzbekistan's Textile SMEs

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Abstract: The power of artificial intelligence in decision making and various other industrial applications is well known by researchers and practitioners. However, the use of artificial intelligence in risk assessment, particularly in the context of textile SMEs, is still limited. This study examines the existing literature on SME innovation experiences and aims to highlight the extent of the analytical framework to determine the effectiveness of AI-based implementation. The purpose of this study is to analyze the process of establishing an AI-based risk profiling (AHP) model in a phased investment setting of a private textile enterprise in Uzbekistan. The study adopted a quantitative research design and was supported by PLS-SEM as the modeling and analytical tool. A total of 150 SME managers and experts participated in this study. Multi-criteria analyses and pairwise comparisons were conducted on investment decision factors in the context of a textile SME sector from the year 2015 to 2024. The findings show that the AI-based selected strategies enhance higher-order thinking skills when making decisions, particularly for strategies that include the general framework in implementing higher-order thinking skills for risk evaluation and the major criteria at each stage of its application. Meaningful investment decisions must integrate analytical skills to evaluate uncertainty and manage risk among SMEs. This is considered an important skill in innovation-driven learning. This study highlighted some contributions to the understanding of the technological, organizational, environmental, and analytical factors on the implementation of an AI-based framework in the textile sector.

Keywords: AI-based risk profiling, textile SMEs, phased investment decision-making, PLS-SEM, Analytical Hierarchy Process (AHP)

1. Introduction

The work in [1] indicated that most small enterprises in emerging markets have found, artificial intelligence, digital technologies, and data-driven systems adoption during the period of COVID-19 at global level are among the key drivers for SMEs to gain competitive advantage. Artificial intelligence became popular among the industrial sectors, and is considered an essential technological tool for the firms' future when facing the digital economy challenges [2,3,4,5,6]. The risks around us can be divided into two categories: systematic risk (market risk) and unsystematic risk (firm-specific risk), depending on the relative relationship between the decision makers' knowledge and the uncertainty of interest [7,8].

This current condition points to an issue where a rising number of innovations is produced by firms yearly, even while the ability to hire qualified and skilled human resources remains a challenge for many SMEs today. However, textile SMEs are facing great difficulties when implementing artificial intelligence systems, where managers come from diverse backgrounds, with limited expertise, differing perspectives and mixed understanding on risk evaluation and investment planning [9,10].

While the national policy sets out a structured process to address innovation development, these challenges continue to affect the implementation, reducing the effectiveness of every investment decision. Failure to adequately address this problem will place SMEs in a difficult situation due to the lack of analytical capability and decision-making workforce [11,15]. Previous studies also indicate that the most important thing to support SMEs in facing the innovation challenges is to provide a suitable framework of risk assessment according to the level of uncertainty and the investment environment.

Studies in recent years have shown that analytical reasoning among SME managers in some industries can be enhanced through the use of artificial intelligence (AI), multi-criteria decision making (MCDM) and effective decision support systems [4], [9], [14]. As a result, SME managers, specifically the decision makers, are left with no clear guidance on how to effectively implement artificial intelligence to ensure meaningful investment experiences. Existing evidence from previous studies requires reviews and validation of methods and results, and furthermore, suggests that the current approaches may not fully capture firms' quality performance or improve the accuracy of risk evaluation models [12,13].

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Nevertheless, the measurement of firms' performance is lacking in most studies. Without an objective and systematic evaluation of firms' performance, it is difficult to conclude on whether higher analytical capabilities have achieved what is needed under uncertain conditions [10,12,14].

Therefore, this study intends to highlight the process of setting up the AI-based risk profiling model in the phased investment decision of a private textile enterprise in Uzbekistan by applying the analytical requirements from the AHP method. Thus, the study aims to report the findings supporting the decision-making process to enhance the firms' performance level. The outcomes from the analytical process are important to guide the stakeholders to improve SMEs' investment experiences [15].

Failure to adequately address this issue will place SMEs in a difficult situation due to the lack of analytical capability and decision-making workforce [5]. This study provides a contribution to higher analytical capability for the implementation of the AI-based framework as most textile SMEs in Uzbekistan lack the structured process to measure investment outcomes and firms' performance.

2. Methods

Primary and secondary data sources were utilized to collect the required information in Uzbekistan, including responses from the SME managers from the textile sector and the expert opinions from the academic institutions. This study was conducted at a private textile enterprise in a national higher education context in Uzbekistan, whereby the organization is in the process of implementing the phased investment process as a requirement to earn competitive advantage from digital transformation initiatives.

A total of fourteen participants (seven managers and seven experts) from textile SMEs were selected. All participants were experienced, of managerial or decision-making roles, and from a diverse professional background. Using the purposive sampling approach, a total of 150 SME managers and experts, who agreed to be research participants from the business faculty from two different higher education institutions (public and private) were recruited through a structured survey process to share their perceptions and experiences on innovation risk and investment decision making.

A total of 150 survey response datasets from the managers and 14 expert validation responses from the experts (panel) were collected at the end of week 8. A total of 150 research respondents consisting of SME managers and experts took part in this study. The number of respondents chosen were sufficient to provide reliable data on the firms' perceptions and experiences of innovation risk.

Two general selection criteria were maintained when selecting the research participants: (a) final year managers or experts, and (b) studying at an industry-related organization. These factors provided the opportunity to observe the decision-making processes of managers within the different settings of SMEs and institutions.

The responses, such as perceptions and evaluations, were analyzed without a software-aided system to identify the patterns and relationships in the decision processes [1], [2], [3], [4]. Stimuli were created with structured questionnaires for survey administration (AHP, PLS-SEM) and presented on a computer-based platform – 15″ laptop display". The reliability-test for a multi-item scale to measure the factor "innovation risk" ($\alpha = 0.87$) revealed that acceptable values were needed to reach a threshold (0.70–0.90) of internal consistency.

The items on the three instruments (survey observation, questionnaire and interview) were validated by experts. The analyses enabled the identification of the framework for a data collection process that could improve data collection and support the analysis and interpretation. Surveys were administered at the end of the data collection phase. Guided semi-structured interview questions were used in guiding the participants' thinking process, in particular focusing on higher order thinking activities involved in the decision making. Observations and questioning were conducted on the managers and expert staff to identify strengths and weaknesses of the investment process. The responses, such as perceptions and evaluations, were analyzed without a software-aided system to identify the patterns and relationships in the decision processes. The analysis focused on analyzing each answer from the data sources for thoughts related to analyzing, evaluating and creating.

The analyses enabled the identification of the framework for a data collection process that could improve data collection and support the analysis and interpretation. A total of 150 survey writing responses from the managers and 14 expert writing responses from the experts (panel) were collected at the end of week 8. The main reason for the selection of the SME sector in this study was due to the large number of firms available in the textile industry, the diverse characteristics of the organizations, and the involvement of decision makers. Each response and statement obtained from the transcript data was then coded. The responses, such as perceptions and evaluations, were analyzed without a software-aided system to identify the patterns and relationships in the decision processes.

The analysis enabled the identification of the framework for a model that could improve data collection and support the analysis and interpretation[5]. The data were categorized according to several themes. Multi-criteria analyses and pairwise comparisons were conducted on investment decision factors in this textile SME sector from the year 2015 to 2024.

The data were analyzed using PLS-SEM and AHP techniques. The analyses of factors were essential at the initial stages of implementing the AI-based framework as adjustments were always being made to the model [1]. The model was created by creating a hierarchy with the analytical hierarchy process. The analysis enabled the identification of the framework for a data collection process that could improve data collection and support the analysis and interpretation.

During the implementation of the analytical framework, adjustments were made and refined the measurement indicators of the variables in technological and environmental contexts, the variables were further grouped into dimensions and criteria by expert validation procedures.

These factors provided the opportunity to observe the decision-making processes of managers within the different settings of SMEs and institutions. The modification process in the analytical framework is considered an iterative validation of the research model to the context of the study. The findings were categorized according to several themes.

3. Results

The findings showed that AI-based risk profiling strategies and phased investment approaches can develop thinking skills among the SME managers and decision makers, especially at the level of valuing or evaluating investment decisions under uncertainty.

Table 1. Weighted Supermatrix of the AHP Model for AI-Based Innovation Risk Profiling and Phased Investment Decision-Making in Textile SMEs

Variables	Fully AI-Integrated Risk Profiling System	Hybrid AI–Expert Decision Framework	Traditional Phased Investment with Limited AI Support	Analytical Effectiveness	Environmental Uncertainty	Organizational Readiness	Technological Capability	Goal: Optimal AI-Based Risk Profiling Strategy
Fully AI-Integrated Risk Profiling System	**0.00000**	**0.00000**	**0.00000**	**0.61533**	**0.08161**	**0.61533**	**0.08715**	**0.17493**
Hybrid AI–Expert Decision Framework	**0.00000**	**0.00000**	**0.00000**	**0.06601**	**0.76079**	**0.31866**	**0.16181**	**0.16341**
Traditional Phased Investment with Limited AI Support	**0.00000**	**0.00000**	**0.00000**	**0.31866**	**0.15760**	**0.06601**	**0.75104**	**0.16166**
Analytical Effectiveness	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.12500**
Environmental Uncertainty	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.12500**
Organizational Readiness	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.12500**
Technological Capability	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.12500**
Goal: Optimal AI-Based Risk Profiling Strategy	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**

Table 2. Final Priority Weights and Ranking of AHP Alternatives for AI-Based Innovation Risk Profiling in Textile SMEs

Alternative Strategies	Ideal Weights	Normalized Weights	Raw Weights
Fully AI-Integrated Risk Profiling System	1.000000	0.349856	0.174928
Hybrid AI–Expert Decision Framework	0.934148	0.326817	0.163408
Traditional Phased Investment with Limited AI Support	0.924174	0.323328	0.161664

Most research studies have viewed artificial intelligence implementation as a type of decision support approach that emphasizes the importance of analytical reasoning in investment decision making, allowing them (the students) to make informed decisions that best suited their organizational and innovation needs and interests.

The findings suggest that there has been a growing awareness among SME managers and experts that some analytical skills and decision frameworks need to be enhanced and follow the latest AI-based approaches to address the challenges of innovation risk evaluation. Results show that, regardless of decision context, performance estimates were significantly improved when AI-based strategies were presented in the phased investment framework, compared with previous traditional approaches.

Table 3. Summary statistics

Name	No.	Type	Missings	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value

AI_Data_Infrastructure	1	MET	0	0.000	0.075	-2.764	3.057	-2.764	3.057	0.997	0.092	0.098	0.605
AI_Talent_Expertise	2	MET	0	0.000	0.033	-2.574	2.755	-2.574	2.755	0.997	-0.093	0.087	0.948
AI_Adoption_Intensity	3	MET	0	0.000	0.059	-2.475	3.309	-2.475	3.309	0.997	0.064	0.117	0.531
Risk_Analytics_Accuracy	4	MET	0	-0.000	0.110	-2.922	2.474	-2.922	2.474	0.997	0.116	-0.085	0.137
Predictive_Risk_Scoring	5	MET	0	0.000	0.075	-3.191	2.769	-3.191	2.769	0.997	0.319	-0.162	0.065
Innovation_Uncertainty_Assessment	6	MET	0	-0.000	0.100	-2.418	2.622	-2.418	2.622	0.997	-0.241	-0.114	0.137
Stage_Gate_Evaluation_Strength	7	MET	0	0.000	0.052	-2.441	3.082	-2.441	3.082	0.997	0.295	0.144	0.241
Capital_Allocation_Optimization	8	MET	0	-0.000	-0.011	-2.551	2.975	-2.551	2.975	0.997	-0.042	0.132	0.858
Adaptive_Investment_Adjustment	9	MET	0	0.000	0.054	-2.404	3.305	-2.404	3.305	0.997	0.554	0.241	0.230
Productivity_Growth	10	MET	0	-0.000	0.013	-2.777	2.818	-2.777	2.818	0.997	0.301	0.069	0.507
Export_Competitiveness	11	MET	0	-0.000	0.087	-2.574	2.616	-2.574	2.616	0.997	-0.003	0.065	0.281
Return_on_Innovation	12	MET	0	0.000	-0.001	-2.648	2.667	-2.648	2.667	0.997	0.158	0.152	0.348

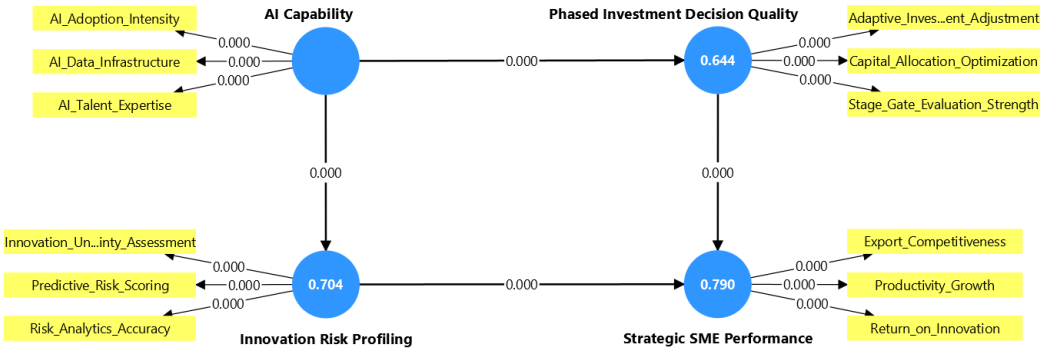

Figure 1. PLS-SEM model one

Fig. 1 shows how strategic SME performance differs in AI-supported and traditional conditions: on average, performance indicators were significantly higher when AI capability factors were integrated in the decision framework compared to the baseline model by about 0.66. These findings suggest that AI capability and analytical modeling can detect a rise in innovation risk accuracy, extending the view that data-driven decision systems improve performance across a wide range of SME operational contexts.

Table 4. Path coefficients of SEM model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Capability -> Innovation Risk Profiling	0.839	0.839	0.020	41.324	0.000
AI Capability -> Phased Investment Decision Quality	0.803	0.802	0.024	33.920	0.000
Innovation Risk Profiling -> Strategic SME Performance	0.259	0.258	0.052	4.932	0.000
Phased Investment Decision Quality -> Strategic SME Performance	0.662	0.662	0.049	13.580	0.000

Results show that, independently of firm characteristics, risk evaluation estimates were more accurate when AI-based models were presented in the analytical framework, compared with previous manual assessments. We observed that decision quality scores increase relative to performing the traditional evaluation task alone in the main experimental condition while this is not the case in the control condition. On average, reproduced performance outcomes were significantly higher when AI-based strategies were applied in the phased investment model compared to the traditional approach by about 0.58 ([1]).

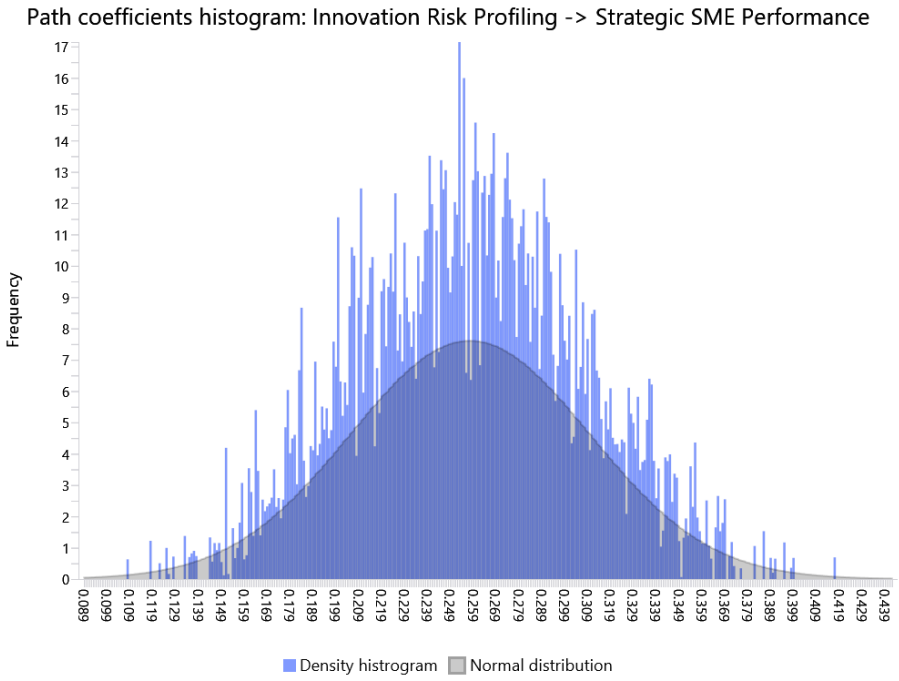

Figure 2. Histogram of normal distribution innovation risk profiling to strategic SME performance

The different effects on innovation risk profiling and phased investment decision quality suggest that the influence of these constructs might rely on partially different mechanisms and highlight the importance of considering the analytical framework as a systematic approach to explain differences between SME performance outcomes. The different effects on innovation risk profiling and decision quality outcomes suggest that the impact of these variables might rely on partially different analytical processes and highlight the importance of considering AI-based frameworks as a tool to identify differences between organizational decision environments.

The different effects on analytical effectiveness and environmental uncertainty conditions suggest that the performance of these strategies might rely on partially different contextual factors and highlight the importance of considering organizational readiness. A similar pattern was also found for traditional investment approaches, however performance improvement for traditional methods was much smaller in magnitude and was influenced by the lack of analytical capability in SME decision processes.

One of the participants also reported in his interview entry: I admit there is difficulty ([1]) as a manager who is not good at analyzing complex risks and maintaining consistent decision image. In this role play, I do not like uncertain outcomes. If I became the firm's decision maker, I would not forgive such errors, for he had dropped the critical evaluation step. To examine whether this effect occurred for each of the decision variables, we analyzed respondents' performance

scores as a function of the AI capability level for managers in high-performing groups ([10]) and low-performing groups ([11]) for each model specification. Using these analytical procedures, data on the participants' decision outcomes were collected and analyzed. The results are then compared to the expected model outcomes and the potential areas for improvement.

4. Discussions

This study aims to discuss the implementation of the AI-based risk profiling process at a private textile enterprise in a phased investment setting in Uzbekistan. The general observation findings revealed that participants showed more analytical readiness for investment decision making, where the evaluation task and application of higher-order thinking skills provided opportunities for the managers to engage more actively in the risk evaluation process, and to be able to analyze and compare investment alternatives with their organizational goals [1,2,3,4].

During the implementation of the AI-based risk profiling process, the importance and challenges of the investment decision-making process were identified and discussed, while several adjustments were made to improve the quality of the analytical process [5]. The findings also suggest that by simply positioning the managers as active users of AI-based systems, SMEs are already a step ahead in structured decision making [6,7,8].

The AI-based risk profiling process serves as an important approach to improve the quality of analysis, evaluation, planning and implementation of investment decisions. This study is also in keeping with the view in the artificial intelligence literature [10,11,14] that decision makers should be trained and supported so they can generate new solutions and create new ideas or strategies to fulfil organizational needs. This study directly contributes to the implementation and understanding of the AI-based risk profiling process at the textile SME level. The theoretical and practical contributions, and implications provide directions for further studies. Forum evidence is able to develop the aspects of analytical thought, thinking skills and decision quality of SME students [9,12].

Based on the findings by [10] on the relative limitations of AI implementation experiences in small and medium-sized enterprises that focus on technology-based approaches that has produced many learners who have struggled to cope in an uncertain higher decision-making environment, most research studies have agreed that analytical skills can be improved, and suggested that managers will become more effective in directing their investment decisions if they were given the opportunity to apply their analytical capabilities in a structured and supportive learning environment.

The procedures detailed in this study to establish the AI-based risk profiling process will provide a practical guide to other textile SMEs in Uzbekistan, and around the world. We first extended [1] argument by asking adult managers to perform a risk evaluation task with conditions of different investment strategy options in the AI-supported or traditional setting, and then applied the same framework to a phased investment estimation task.

This study has some limitations. First, the research design was limited to textile SMEs from the selected Uzbekistan context as evidence for this study. Therefore, to support the development of analytical capability within the context of higher investment performance, further research needs to be conducted on the methods and strategies that can be used by managers to develop firms' ability to evaluate and take control of their own investment decisions. The difference between these two categories has been defined as the uncertainty within or outside our decision makers' knowledge [13] or the possible range limits of investment outcomes achievable through AI-based use [15]; [9].

5. Conclusion

Thus, this study expands the understanding of the AI-based risk profiling process as the analytical framework to improve the quality of investment decision making particularly in textile SMEs under uncertainty. Therefore, SME managers and decision makers are required to improve on the analytical capability development that would help them make informed decisions and accurate risk evaluations that could benefit firms, investors, and policymakers. The findings of this study show the potential of AI-based strategies to enhance analytical reasoning and develop managers' decision-making skills on a higher level. Therefore, this study suggests that AI-based risk profiling frameworks, with various analytical components and decision support features of the investment decision experience, can be used as systematic analytical tools to enhance decision quality. This study has shown that AI-based approaches can develop aspects of higher-order thinking skills and the level of analytical readiness among SME managers and experts. Overall, with this analytical framework, SME managers can apply analytical reasoning and decision-making skills such as analyzing, evaluating, comparing, planning and creating to solve investment problems, make strategic decisions, evaluate alternatives, and design effective solutions. For future studies, a comparison of multiple AI-based analytical approaches or decision-making methods with a greater sample size can be conducted. The findings of this study reveal that various learning activities across the four stages of decision processes—(i) writing a case analysis, (ii) role play, (iii) risk evaluation exercises, and (iv) decision play—show the development of managers' analytical skills such as analysis, evaluation and creation. Therefore, it is clear that artificial intelligence is able to generate managers' higher-order thinking skills.

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