Managing Technological and Market Risks in Engineering-Based Business Model Innovation: integrating digital decision support system

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Abstract. The extant literature regarding the effects of technological and market risks on business model innovation shows inconsistent findings, either positive or negative effects have been reported. The objective of this study is the integration of a digital decision support system for the management of technological and market risks in engineering-based business models in order to improve strategic decision quality and innovation outcomes. The objectives of the research are to identify the necessary decision criteria for correcting the assessment errors based on the priorities derived from the decision hierarchy. The two methods are applied to evaluate the relative importance of risk factors of engineering-based business model innovation over the period considered and analyze the structural relationships of the risk constructs in the technological and in the market domains. The method used is analytic hierarchy process, structural equation modeling, and regression analysis of the data taken from the observations of the engineering-based firms included in the empirical sample, collected for a period of five years (2019–2023). The results show that there is a strong relationship in the technological and market risk dimensions in the context of engineering-based business model innovation, and at the same time, digital decision support creates a more significant increase in long run business performance stability. Furthermore, the results suggest the complementarity of

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the two methodologies in the context of a digital decision support system for the analysis of the risk structure in engineering-based business models.
Keywords: Engineering-based business model innovation, technological risk complexity, market risk uncertainty, digital decision support systems, innovation performance, analytic hierarchy process (AHP), structural equation modeling (SEM)

1. Introduction

On the basis of the literature that business model innovation is an effective strategic approach for managing uncertainty, scholars consistently lobby for systematic analysis and support in either way through digital technologies and developments [1] and the creation of new value architectures [2]. The dominant research stream by Baden-Fuller in the field is often focused on the interaction of the business model, highlighting the strategic role of the business model logic of [3]. The productivity improvement from digital technology gain enables the firm to be less vulnerable and more adaptive in responding to changes in engineering products [3], [4].

Business models can be considered as indicators of the strategic orientation holding important implications for their competitiveness and survival of firms during periods of technological change and of market turbulence [5,6]. This inconsistency impedes on the advancement of theory and practice [7] as it is difficult for many managers of engineering-based firms to implement the appropriate risk management frameworks [8] [9]. Other studies have discussed the issue of the difficulty of creating sustainable business models, given the uncertainty of the ever-changing technological and market environments becoming increasingly complex [5] and [10],[15].

Studying how technological and market risk affects the firms' innovation performance in the context of engineering-based business model innovation provides useful insights for decision makers that undergo strategic transformation (where access to information was separated from ownership structures and decision rights were delegated from the top management to operational levels) [12,13]. These challenges are critical to decision making in the context of the engineering firm and therefore the role of digital decision support is to be the mediator of the evaluation and prioritization of risks meant for innovation success because a lack of structure in risk identification and risk assessment among managers and their willingness to rely on intuition [14] [8].

[11] argue that in engineering industries, business model innovation has become an important strategic domain owing to its positive effects on innovation performance and competitiveness, creating value creation mechanisms, revenue streams, and strategic flexibility, as well as its high added value and impact on other organizational functions. Other examples of studies providing evidence for causal relationships between innovation drivers include the relationship between technological capabilities and their market exploitation outcomes and the study of the dynamics of innovation across stages of the innovation process. There are two main approaches for the analysis of innovation-related risk: the qualitative methodologies and the quantitative methodologies.

Approaches to the evaluation of technological and market risks were addressed through a framework based on the analytic hierarchy process method [15] and [6] [2], through which it has been demonstrated (by studying a panel of firms) and realized over a period of five years 2019–2023, which explains the prioritization of risk factors and is a basis of strategic decision making. The regression analysis offers a static linear estimation of independent variables on innovation outcomes, but it cannot describe dynamic mechanisms by which risk-related variables interactively affect innovation performance [12,13,14]. The single-method methodologies fail to capture the multidimensional structure of the risk management process

[11,15]. The present study uses the three methods together in order to gain a better understanding of the risk structure, which is lacking in the limited empirical evidence about technological and market risk growth. Such approaches require the integration of complementary analytical perspectives of the studied phenomenon.

Therefore, the primary objective of this study is to examine the effects of the digital decision support system and its integration on the management of technological and market risks in the engineering-based business model innovation context. The paper aims to extend the potential for methodological triangulation of the understanding of the structural relationships between risk dimensions by using evidence both from prioritization analysis and from the econometric modeling framework. Studying how digital decision support affects the firms' decision quality in the context of engineering-based innovation provides reliable references for organizations that undergo digital transformation reforms (where access to information was separated from ownership structures and decision rights were delegated from the top management to operational levels).

This study contributes to the existing literature on the management of innovation-related risks by presenting the results of the joint application of the two methodologies on a common empirical sample and by providing evidence about their complementarity in the digital context, in the engineering sector as well as about the evolution of the risk structure over time. This research is conducted using the analytic hierarchy process, structural equation model, regression model, and longitudinal firm-level data to analyze the relationships between the technological risk and market risk growth in engineering-based firms for the period of 2019–2023. This study applies two different analytical concepts for the evaluation of innovation-related risks of engineering-based firms on the same empirical sample in order to compare the robustness of the methods and to provide insights on their potential integration. An integrated approach enables us to capture the simultaneous effects of technological and market risks on innovation performance concurrently. Due to the above-mentioned limitations of the single-method approaches, there has been recently a growing interest in hybrid modeling using the digital decision support framework.

2. Methods

The study uses longitudinal firm-level data of engineering-based firms operating in manufacturing and technology-intensive industries for the 2019–2023 period. Panel data are used from 2019 to 2023 within a single-country context focusing on engineering-based industries. Since technological risk exposure and market uncertainty conditions in manufacturing and engineering services areas are quite different, we focused our analysis on engineering-based firms with a valid sample size of 60. If y is a column vector of endogenous variables, i.e., $y = (y_1, \ldots, y_n)$ for a set of n variables, the structural equations and measurement equations define the latent vector η, such that η is a vector of unobserved variables.

N where T is the time dimension (i.e., the number of years), K is the number of parameters, β are the estimated coefficients, M is the number of equations in the model and L is the likelihood of the model. Out of the total firms that were considered, only engineering-based firms met the data availability conditions, with financial statements, survey responses received in advance and validated responses paid in advance at the time of the data collection (2019–2023).

Of the total sample of engineering-based firms analyzed, only observations were selected based on data completeness and consistency (balanced panel). The estimation period is limited because of the lack of consistent firm-level information for some engineering-based firms prior to this period. Because official statistics does not specify any particular classification criteria for the risk structure, this study used the definition of engineering-based firms (NACE Rev.2) (OECD) as a proxy for the industry classification and the definition of business model innovation (Teece) as a conceptual benchmark.

Out of the total firms that were considered, only engineering-based firms met the selection conditions, with complete data, responses received in digital format and fees paid in advance at the time of the survey administration (five-year panel). The reason for using the panel data in the balanced form is to avoid the problem of unobserved heterogeneity and make the estimation results more robust and reliable.

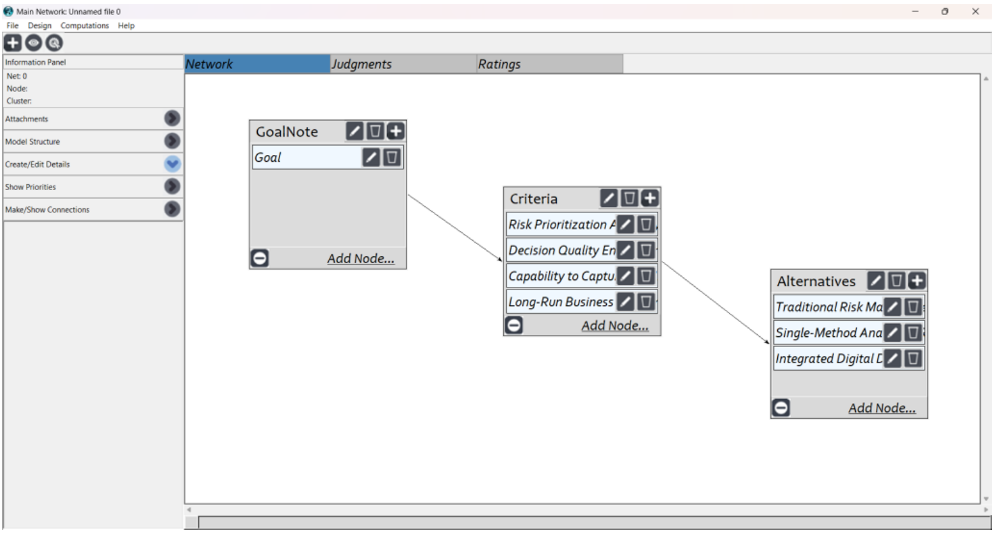

Fig. 1. Analytical Hierarchy Model by using SuperDecisions software.

In contrast to single-method approaches, we adopted the integrated approach to analyze the mechanisms by which technological and market risk affects engineering-based business model innovation. The first-difference regression (Δ) is performed on the original firm-level variables and on the transformed variables where Δ is the first difference operator. The structural equation modeling method was selected by the research design because it could estimate the direct and indirect effects in a single analysis (measurement and structural).

In fact, the SEM framework assumes that the system follows an endogenous process where n is the number of latent constructs of the measurement model in the analysis. The effects of risk-related variables on innovation performance and the interdependencies among variables were evaluated through the procedures below; For every pair of criteria and sub-criteria included in the hierarchy, the following analytical steps are applied: We also re-estimated the regression models with robust standard errors, the results were consistent. Innovation performance was firstly measured with firm-level indicators, which represents the innovation output. The coefficients in this way are compared with the critical threshold according to the rule: $\Delta\beta - \beta > 0$, where β represents baseline level for one risk dimension; $\Delta\beta$ represents changed level for another dimension. Another key variable, decision quality, measures the degree of risk assessment accuracy. The result of the stationarity test is important as it determines latter the choice of the appropriate econometric analysis model to be used; either a static model or a dynamic model. The dependent variable is innovation performance (measured by output indicators). The indicators analyzed in the model are those presented in Table 1.

Firm performance is the economic outcome, measured by current total revenues over net assets. We classified three groups of variables from the panel data. Regarding technological risk (also known as technology-related uncertainty), there are the following dimensions: The second group variables are related to market risk measures, such as market volatility, the demand uncertainty, and competitive intensity. The third group variables contain organizational information about management and innovation heads, including age, gender, education level and experience of the innovation head, the firm size, firm age, and ownership structure, R&D intensity, and the region in which the firm is located. The proposed framework used AHP, SEM, regression analysis, and the digital decision support system to analyze the role of risk management in the performance of engineering-based firms. “The model used is one of the dynamic regression models, compared by their information criteria (AIC/BIC − 1) based on the indicators mentioned in Table 2, from which the following indicators set out in Table 3 were selected…”

The structural equation modeling analysis was executed using statistical software packages (AMOS and STATA) for ruling out estimation bias and multicollinearity issues [1,2]. Specifically, the SEM framework played a central role in estimating latent constructs at different stages in the analytical model. This approach is employed to estimate relationships that are more or less unobservable or totally latent [1]. Formalizing the measurement and structural relationships of latent variables used to capture risk interactions, we apply a PLS-SEM model [3]. Through the estimation of the model, additional parameters were derived that were statistically significant and consistent of the structure of the risk constructs.

Most of the observed variables in the model are not normally distributed; therefore, the estimation of the SEM model, robust maximum likelihood (MLR), is applied. The third criterion is the model fit, which includes the goodness-of-fit measures for both measurement and structural components on the right-hand side.

Firms’ innovation performance and the strength of their technological risk and market risk relationships capture the ability to generate risk-adjusted innovation effects. This approach further strengthens validity in the empirical analysis. In the attempt to gain insights into how the different constructs enabled the evaluation of risk, the variables were operationalized using indicators gained from previous studies, as the empirical proxies of latent constructs.

The model – where the latent variables reflect the four dimensions above – is specified as follows: (1) This enabled us to classify variables as technological or market, and as direct or indirect in relation to the structure of the model.

The respondents were requested to evaluate each indicator on a five-point Likert-scale ranging from strongly disagree to strongly agree. The group variables for each dimension are the corresponding indicators. In line with the previous empirical findings, instead of estimating the full model itself we have estimated first a measurement model consisting of four main constructs:

Next, the different variables were grouped in terms of whether they referred to technological risk, market uncertainty, or organizational characteristics, and what dimension they described. To define the balanced group, we selected observations falling in the complete panel-data range of the time period 2019–2023.

After we have quantified the latent constructs, in the second step we employed a regression analysis model in order to exclude those variables which do not collect sufficient information from the panel dataset and those which do not contribute significantly at all. More specifically, we used structural equation modeling (SEM) estimation model for modelling measurement and structural relationships. The chosen method to estimate the relationships was a structural equation approach based on the maximum likelihood estimation [1]. For both models, the same variables and indicators is applied using panel data and they are jointly analyzed in terms of their effects and their overall contribution to the model [3].

Most of the observed variables in the model are not normally distributed; therefore, the estimation of the SEM model, robust maximum likelihood (MLR), is applied. Through the estimation of the model, additional parameters were derived that were statistically significant and consistent of the structure of the risk constructs. The indirect effect through latent variables (or mediating variables) is verified using the SEM framework. This approach further improves robustness in the empirical analysis.

These were first classified in relation to single-method approaches so as to determine whether different analytical methods had different ways to refer to such risk structures. Both approaches include technological and market risks as possible determinants of innovation performance, which reflect a distinction in different analytical perspectives (i.e., single-method estimation and integrated approach, regression for direct effects, prioritization of criteria and structural modeling). The criteria were chosen based on how they cover different dimensions in risk evaluation frameworks and further based on an integrated approach in the design of the methodology to cover as many as possible interactions to describe technology-to-market relationships (literature was carefully searched for possible indicators and constructs). Extensive validation and robustness testing procedures to verify the reliability and consistency of the integrated framework before implementing it within different analytical stages (AHP & SEM, regression).

The SEM method was selected by the research design because it could estimate the measurement and structural relationships in a single analysis (latent and observed). The rest of the empirical sections continues under the assumption both technological and market risks are interdependent and dynamic as this is the case of the core hypothesis of the paper's model based on the results of AHP and SEM estimations. It is worth noting that a dynamic model can be converted to a static model in levels with restrictions. Relative to the current mean value of performance, the average growth rate was positive per year, indicating that, on average, about one-third of current performance value resulted from innovation activities in our sample. The error-correction model allows the short-run dynamics of the endogenous variables to converge to their long-run equilibrium while allowing for adjustment processes.

3. Results

The lower variance in residuals shows the regression analysis, as technological risk and the market risk variables are systematically associated with innovation performance, while decision support intensity, its coefficient and direction are strongly related to decision quality (Table 1). The results indicate that the relationship in all risk dimensions is not constant over time but is structurally dependent on the technological risk complexity and on the market signal noise. The combined AHP–SEM evidence implies that the global priority of integrated digital decision support significantly increased when a firm's decision support intensity level increased by one standard deviation.

Table 1. Linear regression.

Technological Risk Complexity Index	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Market Signal Noise Index	.587	.146	4.01	0	.294	.881	***
Decision Support Intensity	-.708	.152	-4.65	0	-1.013	-.403	***
Innovation Coordination Load	-.049	.134	-0.37	.716	-.319	.22	

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Strategic Decision Quality	.295	.216	1.37	.178	-.138	.729	
Innovation Performance	-.355	.186	-1.91	.062	-.729	.018	*
Constant	-.01	.067	-0.15	.878	-.145	.125	

Mean dependent var	-0.155	SD dependent var	0.909
R-squared	0.713	Number of obs	60
F-test	26.866	Prob > F	0.000
Akaike crit. (AIC)	94.798	Bayesian crit. (BIC)	107.364
*** p<.01, ** p<.05, * p<.1			

The consistency of the results to the findings of four different models reveals several important empirical regularities. It also indicates that the mean average innovation performance and its dispersion were stable and positive during the period.

Table 2. Variance Inflation Factor (VIF) Diagnostics for the Regression Model.

Variable	VIF	1 / VIF
Strategic Decision Quality	5.55	0.180
Innovation Performance Load	4.66	0.215
Market Signal Noise Index	3.24	0.309
Innovation Coordination Load	2.82	0.355
Decision Support Intensity	2.14	0.468
Mean VIF	3.68	—

In the context of structural equation modeling, the existence of a statistically significant effect of the technological risk complexity indicates the existence of a direct relationship between technological risk and market signal noise.

Table 3. Shapiro–Wilk Test for Normality of Regression Residuals.

Variable	Observations	W Statistic	V Statistic	z Value	Prob > z
Residuals	60	0.9867	0.721	−0.704	0.7593

Table 4. Skewness–Kurtosis Test for Normality of Regression Residuals.

Variable	Observations	Pr(Skewness)	Pr(Kurtosis)	Adj. χ^2 (2)	Prob > χ^2
Residuals	60	0.7390	0.7639	0.20	0.9043

The coefficient of the market signal noise index in the linear regression model has a statistically significant and positive value indicating that innovation performance declines from lower to higher levels of market uncertainty (Table 1). The diagnostic tests showed that the model estimates are robust for the empirical analysis through the standard statistical tests (values obtained by the Shapiro–Wilk test) as well as the variance inflation value for the regression models, it is within the acceptable range of 2019–2023 (balanced panel), which demonstrates that all the assumptions have been satisfied and the proposed model is statistically valid and internally consistent of the studied relationships (Table 2-4).

Table 5. Structural Equation Model (OIM) Estimates for Technological and Market Risk Relationships.

			OIM			
	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
Structural						
market_signal_noise_index						
tech_risk_complexity_index	0.308	0.086	3.590	0.000	0.140	0.477
innovation_coordination_load	0.514	0.086	6.000	0.000	0.346	0.682
strategic_decision_quality	-0.125	0.108	-1.160	0.246	-0.336	0.086
_cons	-0.016	0.055	-0.290	0.769	-0.125	0.092
decision_support_intensity_index						
tech_risk_complexity_index	-0.299	0.079	-3.770	0.000	-0.455	-0.144
strategic_decision_quality	0.776	0.131	5.920	0.000	0.519	1.033
innovation_performance	-0.471	0.126	-3.740	0.000	-0.718	-0.224
_cons	0.046	0.051	0.890	0.371	-0.054	0.146
var(e.market_signal_noise_index)			0.177	0.032	0.124	0.254
var(e.decision_support_intensity_index)			0.152	0.028	0.106	0.217

Table 6. Model Fit Statistics Based on Likelihood Ratio Tests.

Fit Statistic	Value	Description
χ^2_{MS} (3)	10.066	Model vs. saturated
p > χ^2 (MS)	0.018	Significance level
χ^2_{BS} (9)	146.010	Baseline vs. saturated
p > χ^2 (BS)	0.000	Significance level

This suggests that the impact of technological risk on innovation performance varies with the level of the decision support intensity, the higher the level of decision support, the lower the impact of technological risk on performance (Table 5-6).

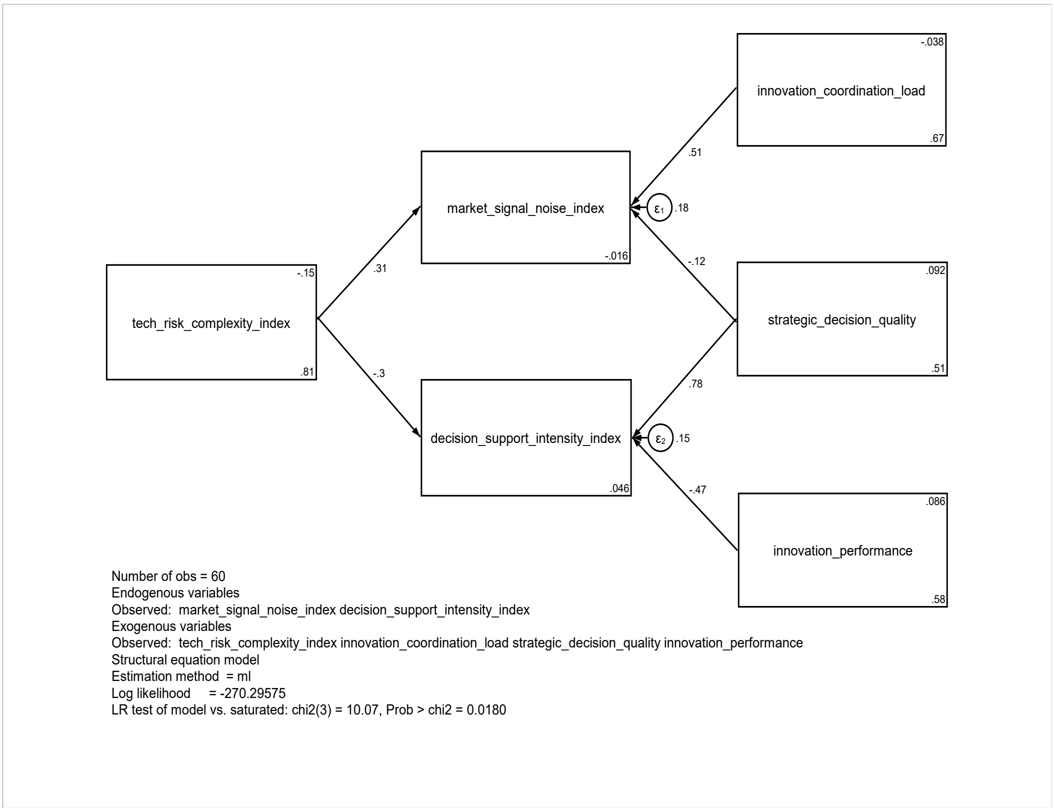

Fig. 2. Structural Equation Model.

Thus, we conclude that the integration of information regarding the prioritization of the risk structure and the use of both a quantitative and a hierarchical approach provides a more comprehensive understanding in the management of innovation-related risks. This is necessary because changes in the risk structure could have effect on various dimensions of the innovation process, one of which is the decision quality.

Table 7. Global Priority Weights of Alternatives and Criteria in the AHP Model for Engineering-Based Business Model Innovation.

Elements	Integrated Digital Decision Support	Single-Method Analytical Approach	Traditional Risk Management	Capability to Capture Risk Interdependencies	Decision Quality Enhancement	Long-Run Business Performance Stability	Risk Prioritization Accuracy	Global Priority
Integrated Digital Decision Support	0.00000	0.00000	0.00000	0.72669	0.10615	0.66667	0.60263	0.26277
Single-Method Analytical Approach	0.00000	0.00000	0.00000	0.19995	0.19288	0.22222	0.08234	0.08718
Traditional Risk Management	0.00000	0.00000	0.00000	0.07336	0.70097	0.11111	0.31503	0.15006

Capability to Capture Risk Interdependencies	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Decision Quality Enhancement	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Long-Run Business Performance Stability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Risk Prioritization Accuracy	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.12500
Overall Goal	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

It started because of the finding that because of the increase in the decision support intensity of firms, the effect of technological risk growth on the innovation performance is higher compared with the effect of the market risk increase on performance growth (Table 7). The magnitude of the direct effect of strategic decision quality on innovation performance (SEM) (Figure 2) and the coefficient representing the effects of decision support intensity on innovation performance (regression) are statistically insignificant (Table 8).

Table 8. Final Priority Weights of Risk Management Alternatives in the AHP Model

Risk Management Alternative	Ideal Weights	Normalized Weights	Global Priority (Raw)
Integrated Digital Decision Support System	1.000000	0.525532	0.262766
Single-Method Analytical Risk Management	0.331759	0.174350	0.087175
Traditional Risk Management	0.571076	0.300118	0.150059

The evidence indicates that the relationship in all models is not linear over time and it is conditional depending on the risk dimension and on the analytical method. Thirdly, in order to control for structural instability in the panel, we conduct a structural break test using the procedure developed by Bai and Perron, and found significant breaks in some sub-periods. The robustness in relation to the results was also tested by re-estimation using the first-difference method, with consistent data on the effects of the risk dimensions on the innovation performance values (robust standard errors).

4. Discussions

Our findings of complementary, interactive, and dynamic effects contribute to the current business model innovation and risk management literature by providing empirical evidence of the structural interdependence between technological risk and market risk under a digital decision support framework. The results of the paper confirm that the integration of the two studied analytical methodologies results in a more comprehensive understanding of the dynamic interactions of innovation-related risks over time [1,2].

The results of the empirical analysis are shown in Tables 1–8; the results demonstrate that both of the risk dimensions are statistically relevant. The estimates indicate that both the technological risk and the market risk are significant at a conventional confidence level, and there is a systematic association between risk structure and innovation performance [3,4,5].

Similarly, this study shows that decision support intensity has a moderating effect on the impact of technological risk on innovation performance in the engineering-based firm context. In our regression and SEM results analyses, the negative effect of technological risk complexity was attenuated by the presence of digital decision support, which is consistent for both linear regression and structural equation modeling [6,7]. Apart from its direct adverse effect on innovation performance, this study also reveals that decision support intensity weakens the impact of market uncertainty on performance outcomes in the longitudinal panel. More specifically, the results of the study indicate that the main empirical findings of the two methods in terms of risk prioritization are aligned; technological risk complexity leads market signal noise, that market signal noise leads both coordination inefficiencies and performance decline, and that decision support intensity leads improvements in decision quality and performance stability [8]. Digital decision support has a substantial influence on firms' strategic decision-making, which means that the accuracy in risk assessment will directly affect firms' innovation outcomes [9,10]. The results also indicate that technological risk's structural complexity affects innovation growth in the technology–market interface, while market risk growth also strongly conditions the innovation trajectory. The level of the decision support intensity has the capacity to reduce both assessment errors and uncertainty, thereby weakening the channel through which risk exposure enhances performance volatility.

In addition, the study demonstrates that each analytical method focuses on different aspects of the risk structure and suggests the complementarity of the results of the methods in the digital context. In other words, besides their direct effects, digital decision support and its intensity have indirect effects on innovation performance through the risk management process [11,12]. Understanding the interaction between technological risk and market risk growth in the context of engineering-based firms (a firm population that experienced both digital transformation reform and the increase in market turbulence in the past five years), could provide useful insights for other technology-intensive industries [13]. The results indicate that both the coefficients are significant at a 5% level, and there is a robust relationship between risk dimensions and innovation performance. The F-statistic is also significant, while the diagnostic tests of normality and multicollinearity are satisfactory, which suggests that the model is generally well specified [14,15]. Overall, the combination of the two methods provides a more reliable explanation on the nature of the relationship between two risk dimensions compared to the results obtained only by each one of the two approaches.

The digital decision support system is of real interest to managers due to the complexity of the processing of risk-related information and its ability to support decisions based on the integrated data taken from the firm level. Hence, a higher level or stronger presence in the decision support intensity is necessary for engineering-based firms to enhance decision quality in innovation activities. Therefore, a pure increase alone does not necessarily accelerate the development of the innovation performance. Thus, it is confirmed that technological risk affects innovation performance in the case of engineering-based firms, supporting the technology-led innovation view. Thus, it is also confirmed that market risk's uncertainty also affects the innovation outcome, extending the market-led innovation view and even the dynamic perspective (interaction effect). Unlike previous studies, this present study shows that the impact of technological risk on innovation performance varies with the level of the decision support intensity and its integration [7,8]. Unlike earlier studies which assumed a single effect (either positive or negative) of risk on innovation with the use of a single method, our analysis captures the simultaneous direct and indirect effects of risk on performance and explains the inconsistent findings among the previous studies [9,10,11].

This study extends a dynamic idea by showing the conditional effects of risk on innovation performance at various levels of the decision support intensity (or its absence), an issue that was not explicitly addressed in previous empirical studies. Even though, the research question of innovation-related risk has been examined in a large number of studies using either a qualitative approach or a quantitative approach, this study extends the existing literature by presenting a joint analysis of risk dimensions on a common sample and by providing a detailed comparison of methods [12,13].

This suggests that the existing approaches on risk management have not been able to reduce the uncertainty to the level that it would have fully observable effects on the technology–market interface. Due to the limited time horizon of our panel dataset, we are unable to illustrate the detailed long-term evolution of this dynamic effect. Hence, future research needs to re-evaluate the risk structure as well as incorporate the necessary institutional and organizational factors that would ensure generalizability in the analysis. [11] point out that the business model logic (or potential value creation) is more important than technology (or potential innovation) alone.

5. Conclusion

The implication of this study is that technological risk complexity and market signal noise affect the innovation performance in the engineering-based business model innovation context. The results are consistent with the existing evidence in the literature of innovation-related risk, where technological risk and market risk are interdependent for one another in the digital decision support framework. This study also used a hybrid analytical model at the same time to gain more comprehensive information and robust results for innovation risk management research. This study provides empirical evidence about the complementarity of the two methodologies in the digital context, in the engineering sector as well as about the evolution of the risk structure over time. Although the study has important implications and an original contribution to the existing literature in the context of technological and market growth, still it is not beyond the limitations. The results show a conditional effect on innovation performance and risk growth in engineering-based firms, but this does not mean that the performance change in innovation outcomes is the result of the technological risk as a single driver. Apart from the scope and time horizon of the panel, future research could also examine the role of the institutional environment, organizational capabilities (governance structures) or external shocks on the risk–innovation relationship. The study used data only for one country, so future research can use comparative data from more countries in different institutional settings to see heterogeneous results.

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