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RESEARCH ON THE RELATIONSHIP BETWEEN RISK PREVENTION AND ENTERPRISES PERFORMANCE IN SMALL AND MEDIUM ENTERPRISES IN THE CONTEXT OF BIG DATA IN HENAN, CHINA

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Abstract

This study aimed to examine the influence of big data management and risk prevention on small and medium enterprise performance and explain the mediating mechanism of management innovation underlying this effect. 582 enterprise senior and middle managers personnel covering different industries and regions in Henan Province participated in the study. Data was collected through an online survey questionnaire. Participants completed a survey to access big data management, risk prevention, management innovation, and enterprise performance. PLS-SEM was used to analyze the data to test the conceptual framework. Results showed big data management and risk prevention positively predicted management innovation and enterprise performance in SMEs in Henan province. Additionally, management innovation positively affected enterprise performance. Further analyses confirmed the mediating role of management innovation. The findings empirically validate big data management and risk prevention's role to influence enterprise performance both directly and indirectly by applying management innovation in SMEs. Practical and theoretical implications are discussed.

Keywords: Big Data Management, Risk Prevention, Management Innovation, Enterprise Performance.

1. INTRODUCTION

In the era of big data, small and medium-sized enterprises (SMEs) in Henan Province encounter both opportunities and challenges. Risk prevention has emerged as a crucial element in determining the performance and competitiveness of these enterprises. This study seeks to delve into the relationship between risk prevention and business performance among SMEs in Henan against the backdrop of big data. Henan is one of China's key economic regions, hosting a variety of cross-industry SMEs. Grasping the dynamic relationship between risk prevention and business performance in this scenario can offer essential insights for boosting the resilience and adaptability of SMEs in Henan during the big data era. These results could assist SMEs in Henan and other regions of China to develop more efficient risk management strategies, enhance overall competitiveness, optimize enterprise resource allocation strategies, and speed up continuous growth during this big data era.

1.1 Research Background

Big data technology has completely revolutionized risk prevention and control management among small and medium-sized enterprises (SMEs) in Henan Province of China (Wang & Wang 2020). Big data technology presents both opportunities and complications to small- and medium-sized enterprises (SMEs). How SMEs perceive and manage risks has evolved since

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adopting it (Singh & Singh 2019). Henan SMEs recognize the value in merging big data management and their risk prevention practices, offering opportunities to optimize risk management while decreasing control costs and increasing response agility of their business. This study seeks to analyze the role of management innovation in using big data technology for risk management and enterprise performance within Henan Province in China. SMEs play an integral part in Henan's economy and should reap benefits from taking innovative steps such as management innovation in terms of their technology use and risk mitigation measures. By drawing upon existing research areas and considering all relevant barriers faced by SMEs when adopting big data management practices such as risk prevention and management innovation (Chen et al. 2019), this research should yield fruitful understandings into their implementation as well as potential challenges they encounter during implementation (Chen et al. 2019).

1.2 Statement Problem

Johnson (2017) highlighted the importance of knowledge acquisition and development for SMEs to improve sustainability practices. Applying big data technology and effective risk management are becoming critical elements for the performance of SMEs, which contributes to regional economy development (Colaste, 2020). Integrating big data technologies and risk evaluation allows a change from traditional managerial methods into predictive patterns which could significantly boost corporate performance (Tran, 2020). Through predictive big data technology SMEs can implement strategies for recognizing threats while decreasing risks (Tran 2020; Khan et al 2021).However, the integration of big data technology management and SME risk management remains underexplored. This research aims to investigate the role of management innovation in influencing big data technology management, risk management and corporate performance within the context of SMEs in Henan Province, China.

1.3 Research Gap

There are some previous research emphasizing the significance of understanding the practice, capabilities and cooperation for SMEs to enhance their sustainability (Johnson, 2017). The practice of big data technology and risk management have been the essential variables influencing corporate performance and economic growth in Henan Province. Nonetheless, the literature on just how SMEs in Henan can properly take advantage of big data management and risk prevention to improve overall performance are limited (Ranjan & Foropon, 2021; Liu et al., 2021).

This research intends to bridge this gap by investigating the relationship between big data management, risk prevention, management innovation, and the performance of SMEs in Henan Province. By collecting empirical evidence from SMEs in this area, the study will certainly give profound understandings of the application of these ideas and the difficulties faced by SMEs in adopting big data technology administration practices (Chen et al., 2019). The development of risk management model based on big data technology might reinvent the means SMEs in Henan, enabling them to build more durable and competitive businesses efficient in maintaining development in the face of a progressively unstable economic situation (Khan et al., 2021).

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1.4 Research Question

The research questions proposed as follows:

- How to quantify the specific impact of big data management, and risk prevention on the performance of different industries and scales in small and medium-sized enterprises in Henan Province?
- What is the role of management innovation in connecting big data management, risk prevention and enterprise performance, especially whether it plays an intermediary role?

1.5 Research Objective

- To quantify the specific impact of big data management, and risk prevention on the performance of different industries and scales in small and medium-sized enterprises in Henan Province.
- To examine the mediating role of management innovation in the relationship between big data management, risk management, and corporate performance.

2. LITERATURE REVIEW

2.1 Underpinning Theories

There are primarily three theories supporting this research which are Resource-Based View, Dynamic capabilities and Risk Management theory.

The Resource-Based View (RBV) recommends that valuable, rare, inimitable, and non-substitutable (VRIN) resources can result in sustained competitive advantage and superior company efficiency (Barney, 1991; Peteraf & Barney, 2011). Intangible resources like business culture, administration capabilities, and details systems are VRIN strategic assets, while tangible resources like finance and plant only provide tempprary benefit (King, 2007). RBV logic has been used thoroughly to examine motorists of SME performance, consisting of innovation end results (Teece, 2019).

Dynamic capabilities describe a company's ability to purposefully adjust, integrate and reconfigure inner and exterior competences to deal with quickly altering environments (Teece et al., 1997). The dynamic capabilities viewpoint explains how companies sustain competitive advantages by deploying strategic sources to match evolving market possibilities (Eisenhardt & Martin, 2000). Prior studies show dynamic capabilities like company version innovation, tactical adaptability and alter leadership enhance enterprise durability and effectiveness (Birkinshaw et al., 2016).

Risk management theory highlights the requirement for companies to proactively recognize, analyze and alleviate various threats to ensure long-term sustainability and efficiency (Hopkin, 2018; Aven, 2019). Effective business risk management integrates risk factors to consider into critical preparation, decision making and operational implementation. Integrating these theoretical bases can offer beneficial understandings into the complex mechanisms underlying SME performance in the contemporary, volatile business world.

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2.2 Enterprise Performance

Present literature indicates that enterprise performance is a combination of strategic, operational, and financial outcomes (Brown, 2018). Moreover, key performance indicators (KPIs) have been acknowledged as an essential method for efficient enterprise performance management and evaluation (Operational metrics and data-driven assessments are necessary in accurately evaluating an enterprise's performance).

According to literature in this field, there are mainly four dimensions that reflects the enterprise performance: financial, learning & growth, customer, and internal process (Kaplan & Norton 2022; Thunnissen 2016; Reichheld & Sasser 1990). Financial metrics provide an effective measure to access performance, including measures like revenue growth, profitability, asset utilization and cash liquidity. Learning and growth dimensions offer insights into an organization's human capital resources and employee potentials. This dimension evaluates an enterprise's dedication to employee development through training, career progression opportunities and creating an environment to employees' continuous improvement (Garavan et al., 2021). Customer metrics such as after purchase satisfaction, customer loyalty, repurchase rates and market share occupation shows whether enterprise or brands meet customer expectations and maintaining repeat business (Reichheld & Sasser 1990). Internal process dimension measures the efficiency and effectiveness of an organization's operational activities. By implementing efficient workflows, enterprise digital systems, quality control practices and lean principles are some methods to improve process quality, which may in other way decreasing costs and be adaptive to market dynamics (McKinsey & Company 2021; Davenport 2018 and Womack Jones 1997).

2.3 Big Data Management

Big data management refers to the strategic organization and administration of massive, complex datasets, with the feature of high volume, variety, velocity, and veracity. The big data features present challenges to traditional data management. As organizations across industries are facing with digital economy's explosive data growth challenges, big data management capabilities have become critical in deriving insights, making strategic decisions, and creating sustainable competitive advantages (Mikalef et al. 2020).

Data collection, data processing, and data integration are the main dimensions to reflect big data management. Data Collection refers to the various sources, methods and approaches for massive and diverse datasets. Data processing is the process which raw data is transformed into usable formats for analysis. Organizations must develop sophisticated data processing capabilities to meet the increasing large amount of data. The process includes cleaning, transformation, and analysis of datasets (Thompson 2021; Williams 2019). Data integration involves gathering information from various sources into a complete view for more efficient analysis and decision-making. Companies facing data silos of heterogeneous big data sources must prioritize data integration (Ehrlinger & Woss 2019; Halevy et al 2018). These three dimensions form the core capabilities of organizations in today's big data context, which can effectively utilize big data for strategic forming and management goals.

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2.4 Risk Prevention

Risk prevention is the strategy of identifying, evaluating, and implementing strategies to eliminate potential risk to an organization (Aven, 2019). In the present dynamic business environment, risk prevention can provide vital protection to the small and medium enterprises. Risk prevention encompasses identifying risks, analyzing the likelihood and impact of the threats, planing avoidance or minimization measures (Bromiley et al. 2018). Conducting risk assessments allow prioritizing high-impact risks (Hopkin 2018). Establishing risk-aware culture within an organization is a crucial part of effective risk prevention (Craigen et al. 2019; Alles 2019).

Based on literature in risk management, there are mainly three dimensions reflecting this variable. The first aspect is identification and evaluation; this involves recognizing potential threats to organizational objectives as well as their likelihood and impact (Hopkin, 2018). Risk Monitoring and Control The second component is risk monitoring and control, which involves tracking identified risks, assessing residual risks, and implementing appropriate control measures to maintain effective and adaptable risk management strategies. This ongoing process ensures effective risk management strategies remain functional. Corporate compliance refers to adhering to applicable laws, regulations, and ethical standards (Park & Blenkinsopp 2017). Effective compliance helps organizations avoid penalties and build stakeholder trust, so it should be nurtured as a strategic capability through leadership, coordination and analytical tools (Gatzert & Martin 2015). Together these three components form a comprehensive approach to managing organizational risks and uncertainties.

2.5 Management Innovation

Management innovation refers to significant and novel changes made in an organization's operations, resources and people management in order to increase performance and create competitive advantages (Vaccaro et al., 2020). Such innovations may involve new practices, processes structures or techniques which differ substantially from industry or domain norms (Birkinshaw & Gupta 2018). Management innovation may also be driven by changing market conditions or technological advances or shifts in organizational strategy (Vaccaro et al. 2020).

Management innovation refers to any change that impacts how organizations manage operations, resources and people in order to enhance performance and gain a competitive advantage (Vaccaro et al., 2020). It comprises three essential dimensions. Planning and execution innovation refers to developing novel strategy formulation processes, planning systems and execution capabilities that allow a company to quickly adjust to changing market needs (Pisano, 2019).

Process innovation centers around increasing efficiencies, quality and flexibility through enhancements such as plant automation and digitalized supply chain execution. Service innovation involves making changes in offerings, delivery processes and business models enabled by digital technologies (Storey & Larbig 2018; Yip & Bocken 2018)

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2.6 Conceptual Framework

The previous studies provide a solid theoretical foundation for understanding the interrelationships between big data management, risk management, management innovation, and enterprise performance in the context of SMEs. However, there is a need for more empirical research that specifically examines these dynamics within the SME sector in Henan Province, China, which is the focus of the current study. This study intends to use a quantitative method, to investigate how big data management and risk prevention influence SME enterprise performance through the mediating variables of management innovation within the SME sector in Henan Province, China. The relationship between constructs and the proposed hypothesis based on the above discussion is represented in Figure 1.

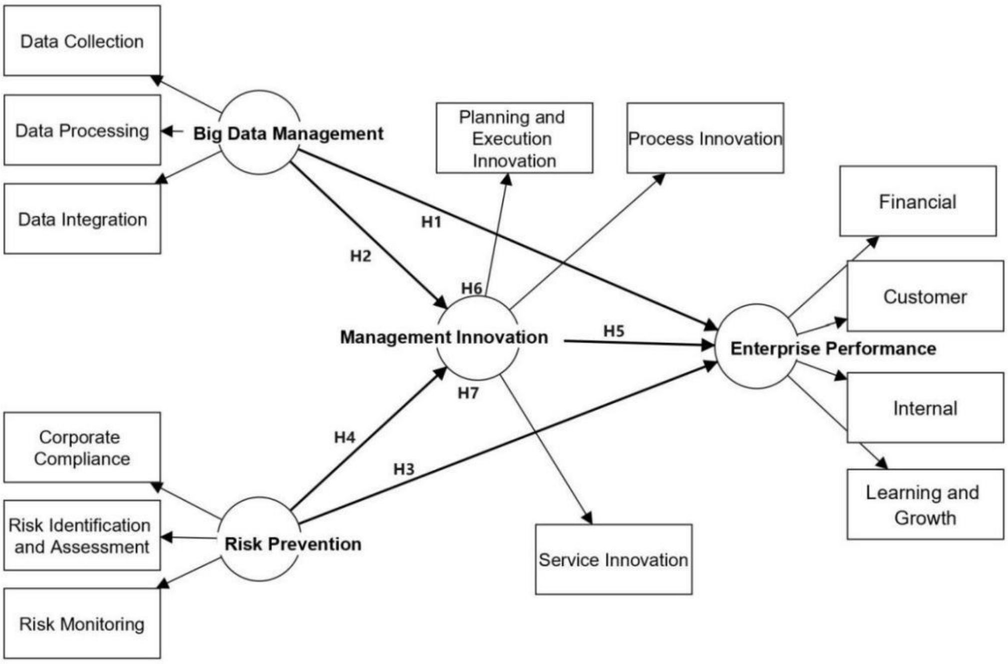

Figure 1: Conceptual Framework

2.7 Hypothesis

H1: There is a positive relationship between big data management and enterprise performance.

H2: There is a positive relationship between big data management and management innovation.

H3: There is a positive relationship between risk prevention and enterprise performance.

H4: There is a positive relationship between risk prevention and management innovation.

H5: There is a positive relationship between management innovation and enterprise performance.

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H6: Management Innovation plays a mediating role between big data management and enterprise performance.

H7: Management Innovation plays a mediating role between risk prevention and enterprise performance.

3. METHODOLOGY

In this research, cross-sectional research with quantitative study is employed to investigate the factors influencing enterprise performance. This type of observation design describes the general situation at one point in time among targeted population.

3.1. Research Instrument and Data

Data for this research were collected via an online survey platform that targeted senior and middle managers at small and medium-sized enterprises (SMEs) located in Henan Province. A questionnaire was distributed and collected through Wenjuanxing platform. After screening each questionnaire carefully, 18 with all maximum scores were identified as invalid and removed as part of our final sample of 582 valid responses used for data analysis. To analyze his data, the researcher used SmartPLS 4, an industry-leading statistical software for conducting structural equation modeling (SEM) analyses. Researchers used this comprehensive analytical approach to draw reliable and insightful conclusions from the survey data collected from SME managers in Henan Province. With this robust data collection and analysis methodology in place, the study provided valuable insight into the dynamic interaction among big data management, risk prevention, Management Innovation, enterprise performance in small and medium-sized businesses located within Henan province.

3.2. Measures

This field survey allows for the capture of the breadth of current enterprise risk management (ERM) adoption levels across industries in Henan. The questionnaire data will be analyzed using partial least squares structural equation modeling, enabling the examination of the conceptual framework relationships. The survey instrument includes specific measures that have been validated in prior research. The ERM adoption construct uses items from Li, Wu, Ojiako, Johnson, and Chipulu (2018), assessing the firm's coordination capabilities for risk prevention. The IT infrastructure for risk management incorporates the scale assesses the technology support for data collection, monitoring, and response. The external collaboration network combines metrics from Zaefarian, Kadile, Henneberg, and Leischnig (2017), gauging the information sharing and joint capability development with partners. The entrepreneurial orientation, measuring risk-taking, innovativeness, and proactiveness tendencies, is adapted from the entrepreneurship scale developed by Covin and Wales (2012). Lastly, the firm performance indicators assess efficiency, quality, innovation, and profit outcomes based on management self-reports, as utilized in the study by Wang, Senaratne, and Rafiq (2015). By these validated scales and conceptually aligning them with the research objectives, the measurement approach ensures the reliability and validity of the data collection, allowing for robust analysis and interpretation of the results.

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4. DATA ANALYSIS AND RESULT

The data analysis is carried by SmartPLS 4.0 using PLS-SEM and blindfolding algorithm for hypothesis testing with measurement model assessment and structural model assessment. Predictive capabilities were also demonstrated using PLSpredict procedures.

4.1. Assessment of the Measurement Model

Tables 4.1 and 4.2 present results illustrating an assessment of internal consistency reliability and convergent validity for first-order and second-order constructs, respectively. Cronbach's alpha values ranged from 0.872 to 0.884 for first-order constructs and 0.757 to 0.808 for second-order constructs, respectively, while composite reliability (CR) values varied between 0.872 to 0.885 in both instances. All these values surpass the recommended threshold of 0.70, signifying satisfactory internal consistency reliability. The Average Variance Extracted (AVE) values ranged from 0.661 to 0.683 for first-order constructs and from 0.635 to 0.701 for second-order constructs; all were above the recommended 0.50 level to establish convergent validity of this measurement model (Nunnally & Bernstein 1994; Hair et al 2019). Furthermore, factor loadings on their respective constructs were all above 0.70, further showing its convergence validity (Nunnally & Bernstein 1994; Hair et al 2019).

Table 4.1: Reliability and Convergent Validity of First Order Variables

First Order Constructs	Items	Loadings	Cronbach's alpha	CR (rho_a)	AVE
FI	FI1	0.809	0.872	0.872	0.661
	FI2	0.815			
	FI3	0.821			
	FI4	0.816			
	FI5	0.804			
LG	LG1	0.831	0.882	0.884	0.680
	LG2	0.791			
	LG3	0.839			
	LG4	0.827			
	LG5	0.836			
CU	CU1	0.789	0.879	0.880	0.674
	CU2	0.826			
	CU3	0.847			
	CU4	0.816			
	CU5	0.827			
IN	IN1	0.825	0.881	0.881	0.677
	IN2	0.829			
	IN3	0.847			
	IN4	0.806			
	IN5	0.808			
DC	DC1	0.838	0.882	0.882	0.679
	DC2	0.815			
	DC3	0.810			
	DC4	0.819			
	DC5	0.837			

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First Order Constructs	Items	Loadings	Cronbach's alpha	CR (rho_a)	AVE
DP	DP1	0.831	0.884	0.884	0.682
	DP2	0.821			
	DP3	0.833			
	DP4	0.817			
	DP5	0.827			
DI	DI1	0.847	0.884	0.885	0.683
	DI2	0.831			
	DI3	0.828			
	DI4	0.800			
	DI5	0.825			
RI	RI1	0.819	0.875	0.876	0.667
	RI2	0.818			
	RI3	0.799			
	RI4	0.820			
	RI5	0.826			
RM	RM1	0.817	0.875	0.875	0.667
	RM2	0.810			
	RM3	0.830			
	RM4	0.814			
	RM5	0.812			
CC	CC1	0.833	0.883	0.884	0.681
	CC2	0.815			
	CC3	0.844			
	CC4	0.795			
	CC5	0.837			
PE	PE1	0.844	0.881	0.882	0.678
	PE2	0.813			
	PE3	0.812			
	PE4	0.823			
	PE5	0.826			
PI	PI1	0.812	0.876	0.876	0.668
	PI2	0.813			
	PI3	0.814			
	PI4	0.833			
	PI5	0.816			
SI	SI1	0.830	0.881	0.881	0.678
	SI2	0.826			
	SI3	0.835			
	SI4	0.823			
	SI5	0.802			

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Table 4.2: Reliability and Convergent Validity of Second Order Variables

Second Order Constructs	Items	Loadings	Cronbach's alpha	CR (rho_a)	AVE
Enterprise Performance （ENPE）	FI	0.771	0.808	0.809	0.635
	LG	0.825			
	CU	0.802			
	IN	0.789			
Big Data Management (BDMA)	DC	0.844	0.787	0.787	0.701
	DP	0.822			
	DI	0.845			
Risk Prevention (RIPR)	RI	0.826	0.762	0.762	0.677
	RM	0.827			
	CC	0.816			
Management Innovation (MAIN)	PE	0.810	0.757	0.758	0.673
	PI	0.827			
	SI	0.826			

The Fornell-Larcker criterion requires that the square root of average variance extracted (AVE) for each construct should exceed its highest correlation with any other construct in the model (Fornell & Larcker, 1981).

Table 4.3 displays this as bolded diagonal elements representing square roots of average variance extracted for each construct while off-diagonal elements represent correlations among them; results showed that every construct in Table 4.3 had greater square root of average variance extracted than highest correlation in its model, suggesting adequate discriminant validity within its measurement model.

Table 4.3: Discriminant Validity - Fornell-Larcker Criterion

	CC	CU	DC	DI	DP	FI	IN	LG	PE	PI	RI	RM	SI
CC	**0.825**												
CU	0.346	**0.821**											
DC	0.271	0.331	**0.824**										
DI	0.263	0.241	0.580	**0.826**									
DP	0.285	0.270	0.537	0.538	**0.826**								
FI	0.295	0.479	0.300	0.268	0.254	**0.813**							
IN	0.320	0.519	0.265	0.264	0.248	0.471	**0.823**						
LG	0.319	0.554	0.291	0.294	0.311	0.526	0.534	**0.825**					
PE	0.312	0.291	0.260	0.338	0.325	0.294	0.235	0.348	**0.824**				
PI	0.249	0.319	0.271	0.312	0.258	0.279	0.240	0.326	0.499	**0.817**			
RI	0.507	0.252	0.264	0.270	0.272	0.305	0.331	0.316	0.314	0.270	**0.817**		
RM	0.510	0.308	0.270	0.295	0.253	0.281	0.290	0.309	0.293	0.286	0.532	**0.817**	
SI	0.289	0.286	0.273	0.306	0.268	0.272	0.284	0.327	0.498	0.536	0.267	0.248	**0.823**

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4.2. Assessment of Structural Model

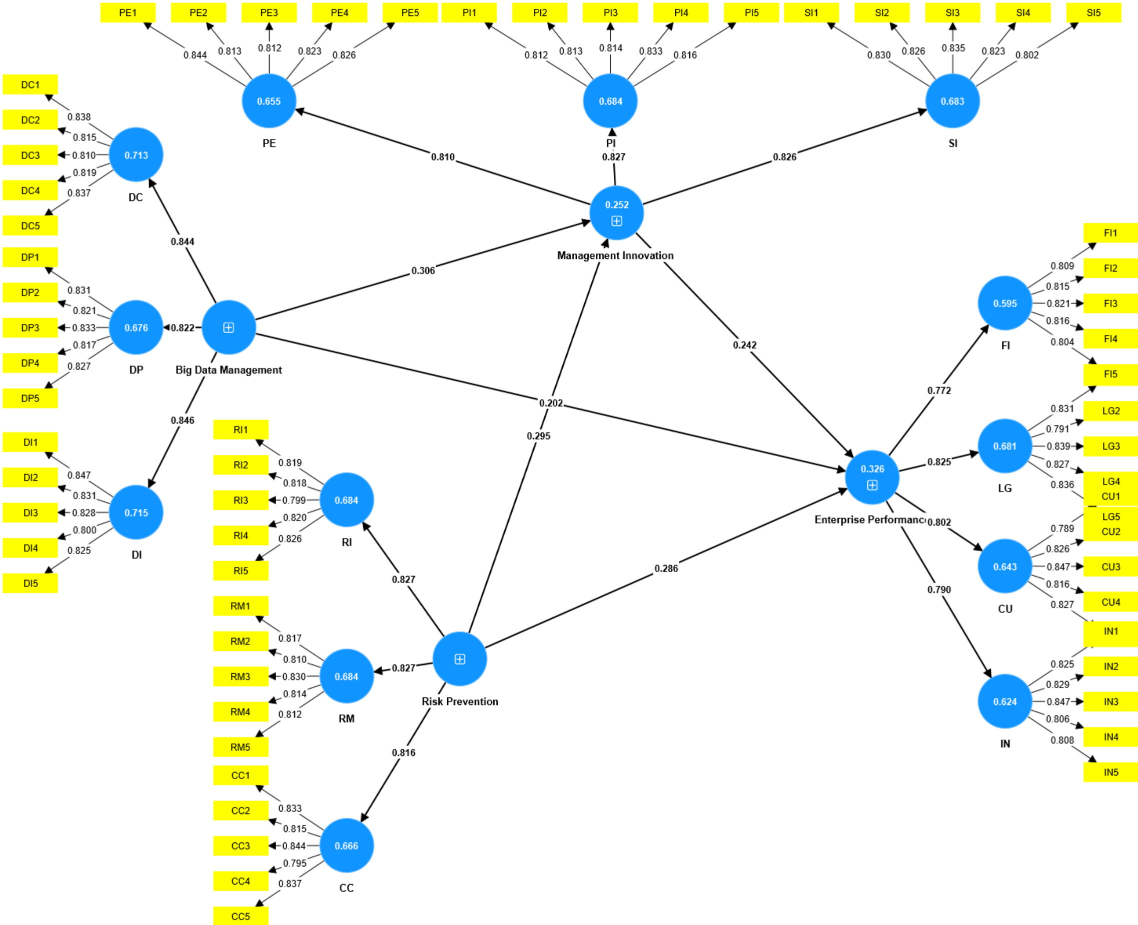

Figure 2: Structural Model Results

As illustrated in Tables 4.7 and 4.8, the results of hypothesis testing show several significant direct and indirect effects. Regarding direct effects, Big Data Management had a positive and significant effect on Enterprise Performance (β=0.202, $p<0.001$) and Management Innovation (β=0.306, $p<0.001$), supporting H1 and H2. Risk Prevention also has a positive and significant effect on Management Innovation (β=0.295, $p<0.001$) and Enterprise Performance (β=0.286, $p<0.001$), supporting H3 and H4. Furthermore, Management Innovation has a positive and significant effect on Enterprise Performance (β=0.242, $p<0.001$), supporting H5.

The mediating effects were also supported. Big Data Management has an indirect positive effect on Enterprise Performance through Management Innovation (β=0.074, $p<0.001$), supporting H6. Similarly, Risk Prevention has an indirect positive effect on Enterprise Performance through Management Innovation (β=0.071, $p<0.001$), supporting H7. These findings suggest that the integration of big data management and risk prevention strategies can enhance enterprise performance through the facilitation of management innovation within SMEs.

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Table 4.7: Hypothesis Test - Direct Effects

	Hypothesis	Original sample (O)	T statistics (|O/STDEV|)	P values	Decision
H1	Big Data Management -> Enterprise Performance	0.202	5.076	0.000	Accepted
H2	Big Data Management -> Management Innovation	0.306	7.526	0.000	Accepted
H3	Risk Prevention ->Management Innovation	0.295	7.282	0.000	Accepted
H4	Risk Prevention -> Enterprise Performance	0.286	7.090	0.000	Accepted
H5	Management Innovation -> Enterprise Performance	0.242	5.728	0.000	Accepted

Table 4.8: Hypothesis Test - Mediating Effects

Hypothesis	Original sample (O)	T statistics (|O/STDEV|)	P values	Decision
H6: Big Data Management -> Management Innovation -> Enterprise Performance	0.074	4.520	0.000	Accepted
H7: Risk Prevention -> Management Innovation -> Enterprise Performance	0.071	4.474	0.000	Accepted

Hair et al. (2019) have provided guidance that provides an assessment of structural model's explanatory power by measuring its coefficient of determination (R^2). According to these guidelines, R^2 values of 0.75, 0.50 and 0.25 can be described as substantial, moderate and weak respectively when used for endogenous latent variables.

Referring to Table 4.9, R^2 values of endogenous constructs in the structural model are as follows. Enterprise Performance has an R^2 of 0.326 which suggests that its exogenous constructs (Big Data Management, Risk Prevention and Management Innovation) explain 32.6% of variance - making this an example of moderate explanatory power. Meanwhile Management Innovation had an R^2 value of 0.252 which suggests they explain 25.2% variance which indicates weak-moderate explanatory power.

Table 4.9: Regression

	R-square	R-square adjusted
Enterprise Performance	0.326	0.322
Management Innovation	0.252	0.249

The predictive relevance (Q^2) values for the endogenous latent variables are presented in Table 4.10. The Q^2 values for Enterprise Performance and Management Innovation are 0.204 and 0.165 respectively, which exceed the recommended threshold of 0 (Chin, 1998). These results indicate that the research model has adequate predictive relevance, suggesting that the exogenous constructs have a satisfactory ability to predict the endogenous constructs of Enterprise Performance and Management Innovation.

Table 4.10: Q^2 Value of Each Endogenous Latent Variable

Variable	Q^2 (=1-SSE/SSO)
Enterprise Performance	0.204
Management Innovation	0.165

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5. DISCUSSION AND CONCLUSION

5.1 Discussion of Main Findings

This study developed and tested a conceptual framework analyzing how big data management and risk prevention influences enterprise performance, with management innovation as mediating role. The results provide strong empirical support for the hypothesized relationships. Big data management demonstrated significant positive direct effects on enterprise performance (0.202, $p<0.001$), Management Innovation ($\beta=0.306$, $p<0.001$). Risk prevention demonstrated significant positive direct effects on enterprise performance ($\beta=0.286$, $p<0.001$), Management innovation ($\beta=0.295$, $p<0.001$). Additionally, Management innovation ($\beta=0.242$, $p<0.001$) positively predicted enterprise performance. Further analysis confirmed the mediating roles of Management innovation. Big data management had indirect effects on enterprise performance through Management innovation ($\beta=0.074$, $p<0.001$) and risk prevention had indirect effects on enterprise performance through Management innovation ($\beta=0.071$, $p<0.001$). Thus, H1-H7 were fully supported. The results highlight big data management and risk prevention's potential, both directly and indirectly, to promote enterprise performance.

5.2 Theoretical and Practical Implications

The results of this research could provide valuable insights for policymakers and businesses in Henan Province. It shows how technologies like big data and innovative management practices can help small and medium enterprises (SMEs) strengthen their resilience and stay competitive. The study highlights how big data solutions can improve risk management. By making better decisions with data, SMEs can work more efficiently and control risks better. This encourages more businesses in the region to adopt these technologies. With big data management, this research has the potential to help SMEs in Henan Province to strengthen their risk prevention practices. The insights generated from big data help companies be better equipped to identify potential risks early. Thus, companies can develop strategic responses to reduce risk. The big data management allows business in the aspect of real-time monitoring market conditions, adapting to technological shifts, and improving operational performance. The timely warning signals enable businesses to swiftly identify issues as they emerge. With the big data technology, impacts can be minimized and quick action is available. This research provides an excellent opportunity to deepen our understanding of such an important topic through an interdisciplinary study. By investigating how small and medium enterprises can integrate big data management, risk prevention and management innovation, valuable insights can be gained for enterprise performance. This integrated approach to the research promotes cooperation in different fields. Data science, management strategies, and risk management are combined to help SMEs in Henan Province. Bringing different perspectives together in this way deepens our knowledge in management.

5.3 Limitations and Future Research

Although this study provides useful insight into how big data management and risk prevention are used to enhance SME performance, certain limitations exist that provide opportunities for

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further study. In the first place, the ability of this study's cross-sectional design limits our ability to draw causal inferences from its results. Because relationships seen may have been affected by unknown variables or reverse causation, so making longitudinal studies would be more ideal ways of better capturing dynamic interactions among key variables over time. Then, this study focused only on Henan Province of China. While providing valuable insights for that region, it might be limited its generalizability to other provinces or countries. Replicating it with different economic and cultural environments would establish external validity for this model. What's more, data were only gathered through self-reported surveys which can lead to bias due to common method deficiency. Integrating objective performance measures or multi-source data (for instance by merging employee assessments with customer assessments) may improve results further. Lastly, this study focused on the main effects and mediating roles of management innovation. Future studies should investigate any possible boundary conditions or moderating factors which might alter these relationships. Factors like industry characteristics, firm size or technological readiness might play a decisive role in improving enterprise performance. Though limited, this study represents an essential first step toward understanding how big data management, risk prevention and management innovation come together to drive SME performance. The findings provide a solid basis for future studies that aim to explore deeper into this complex phenomenon, while offering more precise guidance to SMEs as they tackle digital obstacles.

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