Evaluating lncRNA Identification and Risk Management Perspectives for Strategic Decision-Making

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Abstract

The pharmaceutical industry increasingly relies on long non-coding RNA (lncRNA) identification for drug development, precision medicine, and therapeutic advancements. However, the strategic decision-making process regarding lncRNA adoption requires a structured evaluation of its key determinants. Moreover, the significance of the risk management practices being followed by such an industry can be viewed from their managerial implications and subsequent decision making. This study examines the impact of lncRNA identification and risk management on strategic decision-making in pharmaceutical organizations using Structural Equation Modeling in SmartPLS. The measurement model's reliability and validity were confirmed, ensuring the robustness of the results and the adopted items for the estimation purpose. The findings confirm that both lncRNA identification and risk management have a positive and significant impact on strategic decision-making, reinforcing their critical role in shaping business strategies. These insights provide pharmaceutical executives and decision-makers with a data-driven foundation for evaluating and integrating lncRNA identification into strategic frameworks while managing associated risks effectively.

Keywords

lncRNA Identification, Strategic Decision-Making, Risk Management, Pharmaceutical Industry, Structural Equation Modeling.

1. Introduction

The mRNAs, which serve as the building blocks for protein synthesis, have been created from about 1.5% of the human genome, out of which 90% are transcribed, which is the majority of the genome (**Dunham *et al.***, 2012). A subset of RNAs known as non-coding RNAs (ncRNAs) is those that cannot be translated into proteins (**Xu *et al.***, 2009). The ncRNAs originate from the "black stuff" of the genome, or the regions of the genome that do not code for proteins, have received less attention in later studies. Using high-throughput technologies, it has been demonstrated that non-coding RNAs (ncRNAs), and in particular long ncRNAs (lncRNAs), play crucial roles in several biological functions. Understanding the traits and functions of lncRNA transcripts depends on their accurate identification. Long non-coding RNAs (lncRNAs) are non-coding RNAs (ncRNAs) that have transcripts that are at least 200 nucleotides long (**Johnson *et al.***, 2005; **Kornienko *et al.***, 2013). The larger sizes of lncRNA transcripts, which are otherwise indistinguishable from mRNA transcripts, complicate their separation. Long noncoding RNAs (lncRNAs) and messenger RNAs (mRNAs) are remarkably similar concerning their transcription from genomic locations and the associated chromatin states. There may be subtle distinctions between the two of them (**Szcześniak; Makałowska**, 2016; **Zhou *et al.***, 2016). Figure 1 shows the overview of lncRNA identification pipeline.

Risk management has got much recognition in the modern literature of different field of studies due to its direct connection with the organizational strategic decision making in every field of business and operations. Therefore, it is recognized that risk management should ideally start early in the planning stage of a formulation development project

and other strategic decision-making phrases (**Charoo; Ali**, 2013). This trend will allow the teams and several functional areas of the organizations to identify potential risks, prioritize them, and take steps to minimize their impact. By focusing on key areas and using resources wisely, companies can better manage risks related to different stages. Moreover, the understanding which process steps and quality factors are most critical helps in developing a solid control strategy. Over the passage of time, as experience and knowledge grow, it is believed that the companies become better at applying risk management on effective grounds. Meanwhile, the concept of the risk assessment is an ongoing process throughout the project, having a reliable system for managing knowledge and documentation is essential for making informed decisions and ensuring compliance.

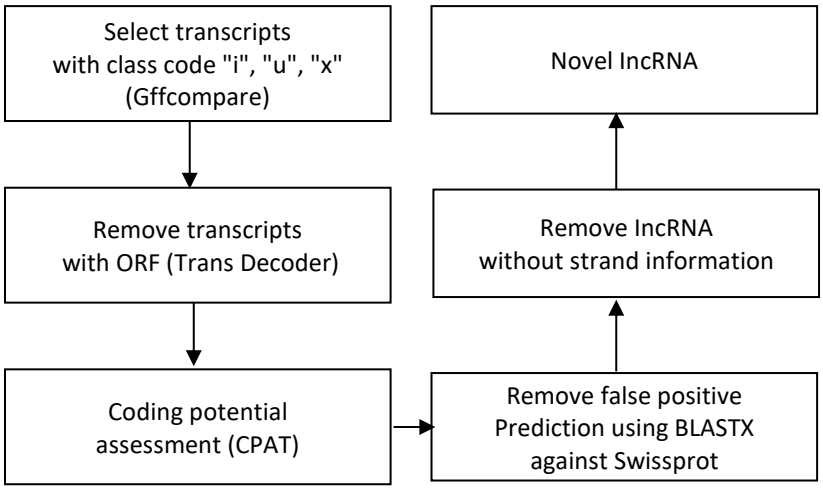

Figure 1: Overview of lncRNA identification pipeline.

Among several steps and components linked with the risk management practices, the term risk assessment is a crucial in developing a strong risk management system as a whole. The ability to identify, evaluate, and address potential risks determines how effectively risks can be minimized or eliminated. According to guidelines as provided by ICH the idea of risk assessment is a structured process that helps gather and organize information to support decision-making. It involves identifying potential hazards, analyzing their impact, and evaluating the risks associated with them. The main goal of risk assessment is to clearly define the problem or objective covering the main queries like "What could go wrong with the critical quality attributes (CQA)?" where the CQAs can be expressed as physical, chemical, biological, or microbiological properties of a product that are essential for its safety and effectiveness. Therefore, after the identification of the risks factors, they are further analyzed based on how severe they are, how likely they are to happen, and how easily they can be detected in a given situation. For this reason, a clear definition of these risks allows companies to choose the most suitable risk management tools and gather the right information to address them effectively. Moreover, the risk management process also includes the risk mitigation and related strategies which have their potential benefits to the organizations over a longer period of time.

In addition, strategic decision-making (SDM) is an essential component to gain the business growth because it helps companies to determine the best path to achieve their goals and long-term objectives (**Kumar**, 2024). However, for this process to be effective enough, organizations need to determine a set of clear policies that guide decision-making and ensure consistency across all functional areas and departmental levels (**Kumar**, 2024). In competitive industries, companies are consistently relying on strategic decisions to gain an edge over their rivals (**Das; Canel**, 2023) as working in the similar industry. Such an effort to gain edger over industry rivals is normally whether by expanding their market presence, improving operations, or by adapting to new challenges having their influence on the organizations. Typically, these decisions are made by the top-level management, who not only set the direction for the company but also ensure that strategies are executive on effective grounds. By making well-thought-out choices and following a structured approach, businesses can position themselves for long-term success (**Adam; Humphreys**, 2008).

It is quite evident to claim that most studies focus on the scientific and technical side of lncRNA, where there is big literature gap to fill in terms of its connection with the strategic decision making. This research fills up this gap by connecting the lncRNA identification, risk management, and strategic decision-making in the pharmaceutical industry. This study looks at how pharmaceutical companies can use this knowledge to make better business decisions having their longer influence not only on them but also for the overall industry. By using Structural Equation Modeling methodology in SmartPLS, the study shows that lncRNA identification and risk management factors like risk identification, assessment and mitigation play their important role in strategic decision-making. This means companies that understand and manage these factors well can make stronger investment choices, improve innovation, and stay compliant with regulations. The research also confirms that the methods used are reliable, making it a helpful resource for business leaders, researchers, and policymakers.

2. Literature Review

2.1. Theoretical Foundation

This study is grounded in Resource Based View (RBV) theory introduced by **Barney** (2001) which offers a fundamental framework for comprehending how pharmaceutical companies navigate risks and formulate strategic decisions accordingly by utilizing their resources and competencies. According to this theory, companies attain competitive advantage through the possession of inimitable, precious, unalterable and unique resources. In the pharmaceutical sector, these resources encompass patented medicinal formulation, regulatory acumen, innovative technological expertise, and patents. This theory elucidates why companies having substantial funds, and innovative capabilities are more adept at managing risks related to clinical trials, and supply chain upsets (**Li**, 2024). Furthermore, it elucidates the rationale for substantial investments by prominent pharmaceutical corporations in R&D, digital progression, and strategic alliances to augment their resource base and maintain market dominance (**Schuhmacher *et al.***, 2023). Organizations that proficiently employ AI-driven medication research, predictive modelling for risk management attain competitive benefits by alleviating monetary and operational risks. Moreover, companies with robust regulations may adeptly maneuver through intricate compliance settings, hence diminishing the probability of sanctions and medicine recall. Hence, RBV, provides a robust theoretical base to elucidate how pharmaceutical companies strategically distribute resources to mitigate risks, drive innovation, and attain sustainable growth (**Furr; Eisenhardt**, 2021).

2.2. Risk Management

Risk management underscores the vital necessity for assuring drug safety and efficacy, which is pivotal in pharmaceutical sector (**Damayanti**, 2023). It helps this sector in evaluating regulatory, operational, and financial threats. This literature review elucidates the multifaceted dimensions of risk management encompassing clinical trial hazards, supply chain vulnerabilities and emergent risks stemming from technological progression. The firms have to comply with stringent regulations forced by agencies, otherwise these have to face hefty penalties, product recalls, and reputational damage (**Provost *et al.***, 2022). Risk management associate with legal compliance entails the execution of through framework to control quality, and sophisticated pharmacovigilance systems (**Olawale**, 2024).

Firms also dedicate funds to adhere management software's and monitoring systems to preemptively tackle regulatory concerns. Clinical trials are crucial for drugs progression; nonetheless, they entail significant risks owing to elevated failure rates, safety issues, and regulatory scrutiny. Pharmaceutical forms implement empirical evidence and utilize AI powered information analytics to curb trial risks, enhance patient choice, and optimize trial oversight (**Kardas**, 2024). Moreover, organizations diversify trial venues to mitigate geographically as well as regulatory hazards, while ensuring larger demographic representation in the investigation. Pharmaceutical supply chains are intricate connecting several stakeholders, distribution networks, raw material procurement, and production procedures. Disruptions in the supply chain can lead to pharmaceutical shortage, monetary losses, and quality concerns. Risk management strategies in supply chain encompass diversification, blockchain based traceability systems and predictive analytics. The companies enforce stringent quality control protocols and regulations at each stage of production to reduce risks linked with contamination and counterfeiting (**Oriekhoe *et al.***, 2024).

The pharmaceutical sector encounters substantial financial risks due to market uncertainties, high R&D costs, mutable drug prices. Risk management comprises mergers and acquisitions, portfolio diversification, and managing robust intellectual stuff (**Li**, 2024). Moreover, pharmaceutical companies employ risk-sharing treaties with governments and insurers to mitigate financial acquaintance (**Li**, 2024). The market entry approaches, like strategic licensing agreements, tiered pricing models also play a crucial role in managing financial risks With the rise in digital evolution, efficiency enhances in the pharmaceutical sector, algorithm introduction of new risks relating to cybersecurity, AI ethics and data privacy (**Damayanti**, 2023). The firms must invest in cybersecurity outlines, data encryption, and regulations implementation, and AI applications to alleviate risks linked with digital health solutions and larger data statistics (**Oriekhoe *et al.***, 2024). The incorporation of AI in patient monitoring and drug detection has raised apprehensions about algorithmic bias and transparency in making decisions. Approaches concerning ethical risk management embrace creating regulatory strategies, AI models, assuming transparent for AI-driven medicines advancement, and assuring human oversight in decision-making procedures (**Aguinis *et al.***, 2024). Pharmaceutical firms embracing risk mitigation frameworks, and comprising diversified supplier networks, flexible manufacturing, and accelerated regulatory approvals, are can effectively navigate the crisis (**Kardas**, 2024).

2.3. Strategic Decision Making

Strategic Decision Making is crucial in the pharmaceutical sector because of its intricate regulatory framework, substantial R&D spending, and a continually varying competitive environment. The related companies must execute strategic framework to enhance innovation, assure market viability and address ethical issues and policy challenges. This literature unveils critical elements of strategic management decision regarding pharmaceutical sector, encompassing regulatory adherence, competitive tactics, and R&D investing along with digital evolution (**Miozza *et al.***,

2024). The critical strategic decision in the pharmaceutical industry revolves around R&D investments. The industry is highly research-intensive, with firms allocating substantial financial resources to the discovery and development of novel medication. Prior studies argue that pharmaceutical firms must balance their R&D portfolios between high-risk, high-reward innovative drugs and safer, incremental enhancements (**Razi *et al.***, 2023; **Schuhmacher *et al.***, 2023). The implementation of data-driven decision-making and predictive analytics has further enhanced the strategic allocation of R&D funds The organizations increasingly rely on artificial intelligence (AI) and machine learning to forecast drug efficacy and optimize the clinical trial procedures (**Longo *et al.***, 2024).

Moreover, an emergent trend in R&D investment strategy is the focus on personalized medicine (**Razi *et al.***, 2023). Progress in genomics and biotechnology have enabled pharmaceutical companies to develop treatments tailored to individual genetic profiles, requiring strategic partnerships with diagnostic companies and regulatory authorities (**Isoko *et al.***, 2024). The change toward targeted therapies necessitates a reevaluation of traditional business models, with firms exploring novel pricing strategies and reimbursement outlines (**Michos *et al.***, 2021). The Pharmaceutical companies operate in one of the most regulated industries worldwide, where compliance with stringent regulatory frameworks meaningfully shape strategic decisions. Guidelines set by agencies such as the U.S. Food and Drug Administration (FDA), the European Medicines Agency (EMA), and China's National Medical Products Administration (NMPA) influence the drug development lifecycle and market penetration approaches (**Olawale**, 2024).

Longo *et al.* (2024) argued that firms adopt proactive regulatory strategies, including early-stage engagement with regulatory bodies and adaptive clinical trial designs, to mitigate approval perils. Also, patent expiration and generic drug competition have prompted firms to extend exclusivity through strategic patenting, licensing agreements, and product reproducing. Also, regulatory acquiescence extends beyond drug approval processes to include post-market surveillance and pharmacovigilance. Firms must ensure robust monitoring systems to track adverse drug reactions and maintain compliance with evolving safety protocols. The implementation of digital pharmacovigilance systems, utilizing AI and big data analytics, has become a key strategic decision to enhance regulatory adherence and patient wellbeing (**Aguinis *et al.***, 2024). Competitive advances in the pharmaceutical industry often drive strategic decisions regarding mergers, acquisitions, and strategic coalitions. **Isoko *et al.*** (2024) specifies that strategic alliances with biotech firms and research institutions have become increasingly prevalent, as large pharmaceutical companies seek to leverage external invention. Open innovation frameworks, where firms collaborate with academic institutions and contract research organizations (CROs), have also emerged as key strategic decisions to accelerate the discovery of medicines (**Treiblmaier; Rejeb**, 2023).

Besides, globalization has influenced competitive strategies, with firms expanding into emerging markets to capitalize on growing healthcare anxieties. The strategies regarding market penetration include forming joint ventures, local partnerships, and licensing agreements to navigate regulatory and cultural blocks. Adopting the market-specific pricing models and distribution networks is crucial for ensuring sustained profitability in diverse geographical areas. The proliferation of digital technologies has pointedly impacted strategically decision making. The pharmaceutical companies are incorporating data analytics, artificial intelligence in their work to promote openness and productivity (**Miozza *et al.***, 2024). Pharmaceutical businesses are focusing on digital forums for digital marketing and interacting. Moreover, the execution of tangible proof derived from e health data and smart devices in now essential to marking strategies. The literature reveals that pharmaceutical corporations are choosing priced methods to boost medication affordability within low-income markets.

Strategic management decisions are also influenced by corporate social responsibility. The companies are forced to reconcile profits with ethical priorities, especially with prescription pricing, and medication availability. These decisions are also linked with sustainability. The sustainability-driven strategic decisions include reducing carbon footprints in manufacturing processes and investing in green chemistry creativity. Furthermore, ethical considerations encompass the clinical trial designs, with increasing emphasis on diversity and inclusion. The Pharmaceutical companies are executing global recruitment strategies to ensure equitable representation of different demographic groups in clinical trainings (**Michos *et al.***, 2021). Such strategic verdicts not only improve research validity but also align with evolving governing and societal prospects. The pandemic, COVID-19 emphasized the standing of strategic agility in the pharmaceutical industry. Firms had to make rapid decisions regarding vaccine development, supply chain resilience, and global spreading. Pharmaceutical companies adopting swift decision-making outlines, leveraging real-time data and cross-sector collaborations, were more successful in responding to the disaster (**Treiblmaier; Rejeb**, 2023).

3. Methods and Materials

The computational methods for this study comprised at least five different strategies for lncRNA identification (See Table 1). These strategies refer to machine learning tools launched after 2012. Their inclusion criteria were if they (i) accept just sequencing as input, (ii) deliver skilled staff models or genus models, as well as (iii) include publicly released source code or indeed a prepared version of the bundle. Maximum likelihood estimation (MLE) has become an example of a classic statistical tool used by these techniques.

Table 1: Machine Learning Models and Features Employed by the Tools.

Strategies	Classifier	ORF size	Peptide topographies	k-mer profile	Other attributes
1. PLEK	SVM			Frequency of k-mer (k=1–5) patterns	
2. lncRNAnet	CNN + RNN	ORF size, ORF coverage, ORF indicator	-	-	Sequence profile
3. CPPred	SVM	ORF size, ORF coverage, ORF integrity	Isoelectric point, instability index, Gravy	Fickett score, hexamer score, CTD	-
4. lncRNA_Mdeep	DNN + CNN	ORF size, ORF coverage	-	Fickett score, hexamer score, k-mer frequency	Sequence profile
5. LncADeep	DBN	ORF size, ORF Coverage, EDP of ORF	-	Fickett score, hexamer score, EDP of 3-mer from 7 amino acid (codons) groups, EDP of LCDS	HMMER index

Comparable classifiers using distinct feature sets are often used in certain of the aforementioned tools, even though other tools employ classification models that share a similar feature set. To better understand lncRNAs as well as the roles they play, it is helpful to compare several methods side-by-side to learn that classifiers/feature sets offer the greatest amount to lncRNA identification. It should be interesting to see if the excess supply of computing resources is warranted by the effectiveness of deep learning-based algorithms.

For this study, data was gathered from 295 respondents working in the pharmaceutical industry. These respondents represented a diverse mix of professionals based on their job titles, years of experience, functional areas, and decision-making authority to collect the data. A survey questionnaire was designed for the study variables viz., Strategic Decision-Making (SDM), risk identification (RID), risk assessment (RIA), risk mitigation (RMT, and lncRNA identification (LII). The survey aimed to evaluating lncRNA Identification and risk management perspectives for strategic decision-making. The respondents were asked to indicate their level of agreement on a 5- point Likert scale where 1 ranked Strongly Disagree and 5 meant Strongly Agree. Table 2 lists all these items of the questionnaire for each variable.

Table 2: Questionnaire to Evaluate lncRNA Identification and Risk Management Perspectives for Strategic Decision-making.

	Strategic Decision-Making (SDM)
1	Our organization follows a structured decision-making approach for evaluating lncRNA identification.
2	Decision-making for lncRNA identification is based on data-driven insights.
3	The selection of lncRNA identification methods aligns with our long-term strategic goals.
	Risk Identification (RID)
1	We actively identify potential risks associated with lncRNA identification.
2	Our team has clear protocols for recognizing risks in lncRNA-related projects.
3	Early identification of risks helps us make better decisions regarding lncRNA applications.
	Risk Assessment (RIA)
1	We systematically evaluate the impact of risks before implementing lncRNA identification methods.
2	Our organization quantifies the likelihood of risks affecting lncRNA identification processes.
3	Risk assessment plays a critical role in our decision-making for lncRNA adoption.
	Risk Mitigation (RMT)
1	We implement strategies to minimize the risks associated with lncRNA identification.
2	Our risk management policies help reduce uncertainties in lncRNA evaluation.
3	We take proactive measures to ensure that risk factors do not hinder lncRNA adoption.
	Long Noncoding RNAs Identification (LII)
1	Our approach to lncRNA identification is structured and effective.
2	We successfully integrate strategic decision-making and risk management in lncRNA evaluation.
3	Our decision-making framework leads to optimal outcomes in lncRNA identification.
4	Our organization continuously improves its methodologies for lncRNA identification.
5	The adoption of lncRNA identification strategies has positively impacted our decision-making processes.

With the help of expert opinions from the industry professionals and academicians, the questionnaire was given a well-rounded validity and reliability of the factors that influence decision-making processes in the pharma industry. Additionally, a pilot test was conducted to confirm that the questionnaire effectively captured insights into lncRNA identification, risk management, and strategic decision-making. Figure 2 demonstrates the pilot test results. For data analysis, this research applied the two-step method of Smart PLS (Partial Least Squares Structural Equation Modeling). First, the study tested the measurement model to ensure that all the survey items were reliable and valid. Once that was confirmed, we moved to the structural model, which helped us examine how lncRNA identification and risk management factors named risk identification, assessment, and mitigation affected strategic decision-making. Smart PLS was particularly useful because it allowed us to analyze complex relationships and draw meaningful conclusions.

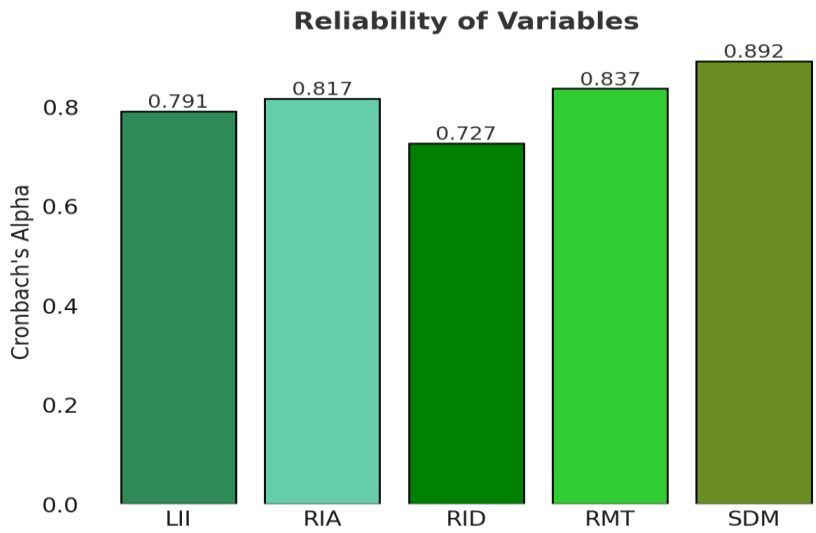

Figure 2: Pilot Testing Results.

4. Results and Discussion

The demographics are known as the key factors to reflect the profile of the respondents. Table 3 depicts job designation, years of experience, functional areas, and level of decision-making at organizational level. For example, overall, the highest responses came from persons who are currently performing their role of Chief Technology Officer (CTO). Conversely, the lowest participation was from the head of regulatory affairs. For example, overall, the highest responses came from individuals with 6–10 years of experience, while the lowest participation was from those with over 10 years of experience. Similarly, when looking at departments, the majority of responses came from those working in Strategic Planning & Decision-Making, whereas the least participation was from individuals in Pharmaceutical Investment & Risk Management. In terms of decision-making authority, the highest number of responses came from those who influence decisions at a medium level, while the lowest participation was from individuals categorized as low-level operational contributors. Table 3 and Figure 3 represent this demographic distribution.

Table 3: Survey Demographics.

1. Job Title / Designation	Frequency	Share
Chief Scientific Officer (CSO)	54	-
Chief Technology Officer (CTO)	82	Highest
Director of Research & Development (R&D Director)	62	-
Head of Regulatory Affairs	23	Lowest
Senior Risk & Compliance Manager	74	-
Overall	295	-
2. Years of Experience		
1–5 years	84	-
6-10 years	162	Highest
10+ years	49	Lowest
Overall	295	-
3. Department / Functional Area		
Research & Development (R&D)	55	-
Regulatory Affairs & Compliance	34	-
Strategic Planning & Decision-Making	98	Highest
Pharmaceutical Investment & Risk Management	25	Lowest
Bioinformatics & Drug Discovery	83	-
Overall	295	-
4. Level of Decision-Making Authority		
High (Final Decision-Maker)	108	-
Medium (Influences Decisions)	168	Highest
Low (Operational Contributor)	19	Lowest
Overall	295	

The investigation for reliability was measured through Cronbach's alpha, Composite reliability (rho_a), Composite reliability (rho_c) as shown in Table 4. The scores for variables LII, RIA, RID, RMT, SDM are 0.820, 0.762, 0.752, 0.884, and 0.914, giving a confirmation of reliability. Similarly for the composite reliability, the values are in the following sequence: 0.857, 0.942, 0.827, 0.886, and 0.914. The last measure is rho_c with the results of 0.879, 0.850, 0.860, 0.928, and 0.959. Average variance extracted were also presented for these variables whose major purpose is to examine the presence of convergent validity (**Cheung *et al.***, 2024). All results are above 0.50 for these variables, showing a clear indication of convergent validity as linked with risk management, strategic decision making, and lncRNA Identification.

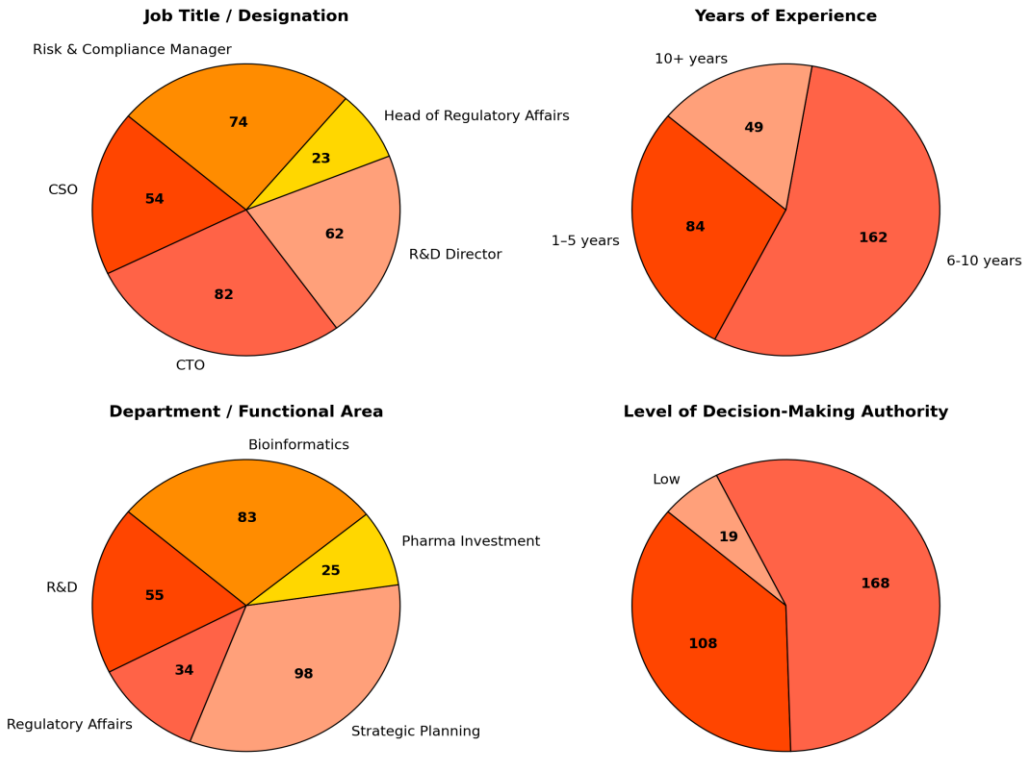

Figure 3: Survey Demographics.

Table 4: Cronbach's alpha, Composite reliability (rho_a), Composite reliability (rho_c), and AVE.

Variables	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted
LII	0.820	0.857	0.879	0.648
RIA	0.762	0.942	0.850	0.655
RID	0.752	0.827	0.860	0.680
RMT	0.884	0.886	0.928	0.812
SDM	0.914	0.914	0.959	0.921
Note RID- Risk identification; LII- Long noncoding RNAs Identification SDM- strategic decision making; RIA- Risk assessment; RMT- Risk management				

This study further presents the loadings using the output of SEM in Figure 4. Some items were deleted because of lower loadings and showing their adverse in terms of affecting the reliability and validity. For instance, RID loading is lowest at 0.594 and highest at 0.924; LII reports loadings with the lowest value at 0.678 and the highest 0.908. Additionally, for SDM, loadings are above 0.90. Moreover, for the RMT and RIA, the loadings are well enough to show their significant presence in this study.

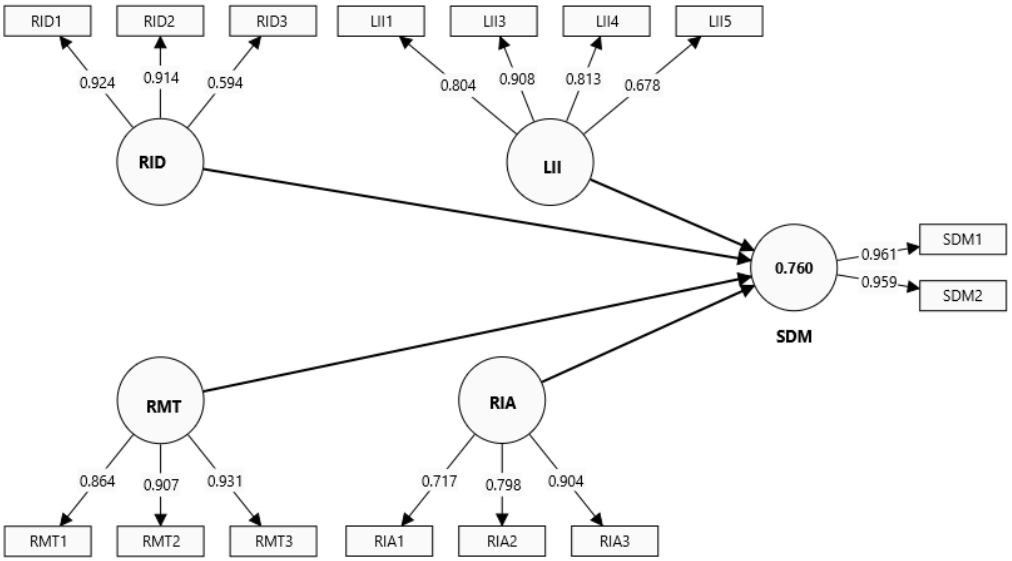

Figure 4: Loadings for the Final Items under Consideration.
Note RID- Risk identification; LII- Long noncoding RNAs Identification SDM- strategic decision making; RIA- Risk assessment; RMT- Risk management.

The HTMT ratio is a good measure of checking the discriminant validity by using the Smart PLS. A matrix for the HTMT ratio is presented in Table 5. It is mentioning that for the RIA <-> LII, the HTMT correlation is .826, and for the RID <-> LII, the given ratio is .833. It is stated that for RID <-> RIA, the HTMT correlation is 0.805, and for RMT <-> LII, the ratio is 0.805. Likewise, the HTMT value for RMT <-> RIA is 0.772, while for RMT <-> RID, it is 0.812. The correlation between SDM <-> LII is 0.675, and for SDM <-> RIA, the value is 0.582. Additionally, the ratio for SDM <-> RID stands at 0.806, whereas for SDM <-> RMT, it is 0.520. Regarding the VIF values, LII1 has a VIF of 2.219, while LII3 is slightly higher at 2.786. LII4 and LII5 show VIF values of 1.860 and 1.606, respectively. In the RIA indicators, RIA1 has a VIF of 1.570, while RIA2 and RIA3 have values of 1.686 and 1.450, respectively. For RID, RID1 has the highest VIF at 2.908, followed closely by RID2 at 2.890, whereas RID3 has the lowest value at 1.158. In the RMT indicators, RMT1 has a VIF of 1.945, while RMT2 and RMT3 are higher at 3.464 and 4.143, respectively. Finally, for SDM indicators, both SDM1 and SDM2 have the same VIF value of 3.427.

Table 5: Heterotrait-monotrait Ratio (HTMT) and VIF Values.

Matrix	Heterotrait-monotrait ratio (HTMT)
RIA <-> LII	0.826
RID <-> LII	0.833
RID <-> RIA	0.805
RMT <-> LII	0.805
RMT <-> RIA	0.772
RMT <-> RID	0.812
SDM <-> LII	0.675
SDM <-> RIA	0.582
SDM <-> RID	0.806
SDM <-> RMT	0.520
Variables	**VIF**
LII1	2.219
LII3	2.786
LII4	1.860
LII5	1.606
RIA1	1.570
RIA2	1.686
RIA3	1.450
RID1	2.908
RID2	2.890
RID3	1.158
RMT1	1.945
RMT2	3.464
RMT3	4.143
SDM1	3.427
SDM2	3.427

The connection between the risk management factors, strategic decision making, and lncRNA Identification are presented by using the results of the SEM. The first relationship between LII and SDM shows coefficient of .193, covering the idea that there is a positive impact of the higher lncRNA Identification on the higher level of strategic decision making in the pharmaceutical industry. The further findings cover the coefficient by getting the sample mean, level of standard deviation which is .081 and T-statistics of 2.371. These scores show the empirical evidence for inferring that LII is leading to SDM in a positive and significant direction. The significance level is 5%. This result concludes that LII is promoting the strategic decision making for the pharmaceutical industry. The second relationship between Risk Identification (the first component of the risk management) and strategic decision making shows a coefficient of 0.772. It is further reinforcing the idea that better risk identification leads to stronger strategic decision-making in the pharmaceutical industry. Additionally, the sample mean is 0.757, with a standard deviation of 0.074 and a T-statistic of 10.417. These values provide strong data-driven empirical support, confirming that risk identification has a significant and positive influence on SDM at a 0.000 significance level. Similarly, the relationship between Risk Assessment (i.e. a second component of risk management) and SDM is reflected in a coefficient of 0.316. It shows that effective risk assessment contributes positively to strategic decision-making. The sample mean remains at 0.316, while the standard deviation is 0.121, and the T-statistic stands at 2.611. With a p-value of 0.009, this result indicates a statistically significant impact of risk assessment on SDM at a 5% significance level. Furthermore, the connection between risk mitigation (i.e., third component of risk management) and SDM demonstrates a coefficient of 0.397, meaning that better risk mitigation strategies enhance strategic decision-making. The sample mean is recorded at 0.383, while the standard deviation is 0.104, and the T-statistic is 3.804. Since the p-value is 0.000, this confirms that risk mitigation has a strong and statistically significant effect on SDM. Overall, these findings provide clear evidence that lncRNA identification, risk identification, risk assessment, and risk mitigation all contribute positively to strategic decision-making in the pharmaceutical industry. These findings are well covered in Table 6. Figure 5 represents P-values and R-square of the same model. R-square value is confirming a variation of 76% in the SDM as reflected by risk management factors, and LII, respectively.

Table 6: Structural Model Results.

Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
LII -> SDM	0.193	0.196	0.081	2.371	0.018
Risk identification -> SDM	0.772	0.757	0.074	10.417	0.000
Risk assessment (RIA) -> strategic decision making (SDM)	0.316	0.316	0.121	2.611	0.009
Risk mitigation -> SDM	0.397	0.383	0.104	3.804	0.000

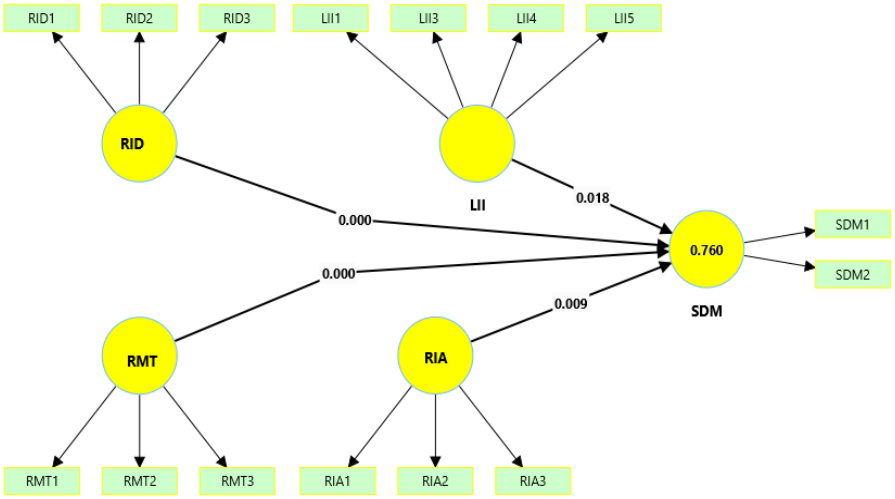

Figure 5: P-values and R-square.

Note RID- Risk identification; LII- Long noncoding RNAs Identification SDM- strategic decision making; RIA- Risk assessment; RMT- Risk management.

5. Conclusion and Suggestions

This study mainly highlights the significant role of lncRNA identification and risk management by using the dimensions like risk identification, risk assessment, and risk mitigation in shaping strategic decision-making for the pharmaceutical industry. The validation of the measurement model strengthens these findings, ensuring that the study's outcomes are reliable and actionable. The study applied the advance statistical techniques of data analysis, for which the results confirm that risk factors like identification, assessment, and mitigation factors are positively influencing how the pharmaceutical organizations formulate and implement their business strategies. The specific finding show that better risk management practices in the form of risk identification, risk assessment, and risk mitigation are reflecting better shape of the strategic decision making for the similar industry. Observing the complexity of pharmaceutical organizations in terms of changing market dynamics and innovative products, decision-makers must recognize the need for structured evaluation frameworks to integrate lncRNA identification on effective grounds. Additionally, a proactive approach to risk management can help significantly in mitigating the associated uncertainties, hence, providing the assurance that strategic decisions align with both scientific advancements and business sustainability. Therefore, by aligning strategic decision-making with scientific advancements and effective risk management practices, the pharmaceutical industry can leverage the potential of lncRNA identification regarding the innovation promotion while safeguarding long-term sustainability.

The policy suggestions of this study are as follows:

1. *Investment in Research and Development:* Governments and pharmaceutical companies are firstly recommended to allocate dedicated funds to enhance the identification and application of lncRNAs. This will ensure the advancements being translated into real-world therapeutic benefits.
2. *Regulatory Guidelines for lncRNA Applications:* the second policy implication determines that regulatory bodies should develop clear and standardized guidelines for the adoption of lncRNA-based technologies, as such guiding principles will address the ethical considerations, patient safety, and commercial viability, etc.
3. *Data-Driven Decision-Making Models:* the third policy suggestion focuses that pharmaceutical firms should adopt data-driven frameworks. It also determines that leveraging AI and big data analytics would aim to improve the predictive accuracy of lncRNA-related outcomes and streamline risk assessment for the similar industry.
4. *Risk Mitigation Strategies:* the fourth policy suggestion states that companies should implement robust risk management protocols, including scenario planning and compliance mechanisms, so that there will be an accurate anticipation of the potential challenges in lncRNA adoption.
5. *Cross-Sector Collaboration:* the fifth policy suggestion is covering the fact that there is a need for encouraging the strategic partnerships between pharmaceutical firms, research institutions, and regulatory bodies. Such collaboration will facilitate knowledge exchange, accelerate innovation, and ensure a smoother transition from research to clinical application and better strategic decisions.

6. *Workforce Training and Capacity Building:* the sixth policy covers that organizations should invest in training programs to equip professionals with the necessary expertise and capabilities linked with the lncRNA technologies and risk management practices.

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