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RESEARCH ARTICLE

Reviewing the Key Factors Influencing Selection of Stochastic Business Decision Modelling Under Uncertainty

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ABSTRACT

Decision-making under uncertainty is a pervasive challenge impacting individuals, organizations, and societies across diverse fields. While existing research has extensively explored the technical intricacies of stochastic models, it frequently underemphasise critical influences such as organizational dynamics, contextual constraints, and individual skill limitations that shape model selection and practical application. This study, reviews the extant literature to uncover insights into how individual predispositions, situational factors, and contextual conditions collectively drive stochastic model choice in uncertain decision-making scenarios. The study adopts the narrative content review methodology of existing decision science literature through the google scholar search engine; selecting peer-reviewed scholarly journals, conference proceedings, and opinion papers related to the utilisation of stochastic decision making models in business. Findings indicate that while all the factors influence stochastic model selection, contextual conditions- especially organizational culture and resource availability—are the most significant. The principal conclusion is that supportive environments with ample resources enhance SBDM adoption and adaptability, whereas resource constraints or resistant cultures often hinder effective SBDM utilization. The study provides valuable insight to decision scientist, managers, and policymakers to foster an open and supportive organizational culture, ensure adequate resource investment in relevant software, tools, and training for staff, and address contextual constraints.

INTRODUCTION

In contemporary business situation, steering through uncertainty presents substantial challenges for organizations, especially when selecting and implementing appropriate stochastic decision model (Varathan, 2024). Stochastic modelling involving the use of probability theory to manage randomness in decision-making, are critical for informed choices under unpredictable conditions. These models support strategic planning, financial analysis, and operational management across industries by enabling decision-makers to weigh multiple outcomes and their likelihoods (Szollosi *et al*., 2023; Shone et al., 2021). In real-life situations, uncertainty is often caused by limited information, ambiguity, variability, or the availability of several possible outcomes. There have been problems over the years on how organisations make decisions under an uncertain scenario. Uncertain situations are conditions that the decision maker has little or no prior information about the potential occurrence of state of nature (Dane & Pratt, 2017; Cao et al., 2021). Therefore, selecting decision making models that align with specific business needs, situational dynamics, and environmental factors is often challenging, especially given the complexity of these models and the ever-evolving state of nature. Understanding the factors that influence the choice of decision model in a stochastic business scenario is worth investigating.

Prior studies have primarily focused on the technical details and mathematical complexity required in stochastic models (Keith & Ahner, 2021; Carmeli & Halevy, 2017; Shone *et al*., 2021). Yet, these studies frequently overlook critical influences such as organisational culture, budget limitations, and the individual skills necessary to interpret complex outputs, which significantly impact model choice and utilisation in real-world contexts (Leal-Rodríguez *et al*., 2023). Moreover, many organizations lack adequate data infrastructure or analytical capacity, limiting their ability to fully leverage sophisticated stochastic models. This gap between theoretical development and practical application often results in the underutilization of models that could otherwise enhance business decision-making (Koehler *et al*., 2018).

Further complicating this scenario is the volatility, uncertainty, complexity, and ambiguity (VUCA) that characterize today's global economy (Kaikkonen *et al*., 2021; Muhammad et al., 2012). Rapid technological advancements, shifting regulations, and market volatility add layers of complexity, requiring decision models that are both precise and adaptable (Muhammad *et al*., 2021). However, due to their inherent complexity, stochastic models can be time-consuming and resource-intensive to recalibrate as conditions evolve, posing a challenge for organizations that must balance accuracy with agility (Dane & Pratt, 2017; Ezbakhe & Pérez-Foguet, 2021). Prior studies have not adequately addressed how businesses can manage this dual need for accuracy and adaptability, especially under constraints like limited resources or time pressures.

Situational factors, including time constraints, resource availability, and environmental complexity, further influence the decision-making process (Muhammad *et al*., 2021). For example, limited time can restrict information gathering, while constrained resources can reduce available options and tools (Lim & Hui, 2020). Environmental complexity, with its unpredictable dynamics, requires more flexible and adaptive decision-making approaches. While some research has acknowledged these situational elements, studies often fall short in exploring how these constraints shape the selection and suitability of stochastic models for specific business needs.

Furthermore, contextual influences, such as cultural norms and organizational structures, play a pivotal role in decision-making (Wiklund, 2020). Cultural expectations, for instance, may dictate whether decisions prioritize group consensus or individual autonomy, while institutional rules might determine stakeholder involvement levels (Shone et al., 2021). Despite the relevance of these contextual factors, existing research often treats stochastic model choice in isolation, failing to address the broader social, organizational, and cultural environment that affects decision processes (Ezbakhe & Pérez-Foguet, 2021; Bhatti *et al*., 2024). Without considering these contextual influences, decision models risk being misaligned with the organizational setting, potentially hindering their effectiveness and adoption.

This study addresses these gaps by systematically reviewing the individual, situational, and contextual factors that influence the selection of stochastic business decision models (SBDMs). By identifying these driving forces, this study seeks to advance understanding of how organizations can address uncertainties more effectively through tailored decision model selection.

Specifically, this research aims to answer the question: *What are the individual, situational, and contextual forces driving the selection of stochastic business decision modelling (SBDM)?* Answers to this research question through this review would contribute to a more holistic approach to stochastic model adoption, fostering models that are both practically viable and contextually relevant for dynamic business environments.

2. LITERATURE REVIEW

2.1 Individual Influences

Decision-making under uncertainty, where there is no guarantee of the outcomes, is an advanced process influenced by numerous personality traits. The purpose of this review is to highlight how cognitive biases, expertise, attitude to risk, and personality traits impact decision-making and the selection of decision-making models. Decision-making models can be chosen with significant impact from cognitive biases, which are systematic departures from rational decision-making. Confirmation bias individuals, for instance, could favour models that support their preconceived notions while ignoring opposing data (Varathan, 2024; Szollosi *et al*., 2023). On the other hand, people who are conscious of their biases might look for models of decision-making that take cognitive constraints into account or include debasing strategies (Abdel-Basset *et al*., 2020). Cognitive biases as highlighted by Al-Sharqi *et al*., (2022), can impact decision-making under uncertainty by potentially leading individuals to deviate from rational decision-making.

The choice of decision-making models is also influenced by an individual's risk attitudes, which express their inclination towards either taking or avoiding risks. Models like the minimax regret model, which emphasizes minimizing potential losses or making cautious assumptions, may be preferred by risk-averse people (Huang, 2010; Hauser *et al*, 2004). On the contrary, risk-takers might favor models like the prospect theory (Gigerenzer & Gaissmaier, 2011) that include more aggressive assumptions or optimize future gains.

The choice of decision-making models can also be influenced by personality qualities including neuroticism, conscientiousness, and openness to new experiences. For example, those with high openness to experience might be more open to new or unusual models of decision-making, while people with high conscientiousness might favour ordered and scientific methods (Djulbegovic et al., 2012). People with high neuroticism tend to favor models that consider aspects of emotions or allow for greater degrees of uncertainty (Ezbakhe & Pérez-Foguet, 2021).

The degree of knowledge and experience one possesses in a given field, or expertise, can have a big impact on the models used to make decisions. Based on their acquired knowledge and aptitude for seeing patterns, experts may rely on heuristics and intuitive decision-making models (Dinbabo *et al*., 2021). On the other hand, inexperienced users could favour more analytical and structured models to make up for their lack of knowledge (Kannan et al., 2017).

Studies have highlighted how individual characteristics influence the choice of decision-making models. For instance, a study conducted by Baucells & Heukamp, (2012) found that those who were more averse to risk and loss were also more inclined to use models based on prospect theory when making financial decisions. People with greater degrees of neuroticism tend to favour decision-making models that take uncertainty and emotional considerations into account (Celona, 2017; Brace, 2023).

2.2 Situational Influences

Situational factors such as time pressure, complexity, available information, and decision context significantly influence the choice of decision-making models for handling uncertainty. Understanding these factors and their interplay is crucial for developing effective decision-making strategies tailored to specific contexts and organizational needs. For instance, time is a major factor in decision making quality and is regarded as one of the main resources used in decision making and choosing

(Ezbakhe & Pérez-Foguet, 2021; Gigerenzer & Gaissmaier, 2011). Making decisions in a hurry is something that many individuals deal with on a regular basis. Placing people under time constraints to make judgements can lead to pressure and stress. According to Clifford *et al*., (2023), people may make decisions without considering all of the options when there is a time constraint. Numerous researches have documented the detrimental impact of time constraints on the efficacy of decision-making, and the pattern of outcomes is mostly constant (Crescenzi et al., 2021; Szollosi *et al*., 2023; Shone et al., 2021). Feramani, (2018) postulated that when people are pressed for time, they are more likely to make "good enough" judgements as opposed to the optimal ones. Time constraints in work environments might cause people to rely more on instinctive and heuristic decision-making (Feramani, 2018).

According to Szollosi *et al*., (2023) decision-makers under time pressure use less complex decision rules, give more weight to negative aspects, take fewer risks, and are less satisfied with their decisions than decision-makers who are not under time pressure. Pressure to make decisions quickly leads to a reduction in the amount of information gathered and processed, a reduction in the range of options examined, a failure to take crucial information into account, and poor decision-making.

The quantity of variables, unknowns, and interdependencies in the task is what makes it complicated. More complex decision-making models that can effectively manage uncertainty are required for complex decision tasks (Arijaje & Aizebeokhai, 2024). For example, decision trees are frequently used in strategic decision-making to plot several option routes and the probability that go along with them. Nevertheless, a satisficing model could be adequate for simple decisions. This is choosing an alternative that satisfies a minimal set of requirements as opposed to looking for the greatest possible one.

The amount and quality of information that is readily available has a big impact on how decisions are made. We might apply the bounded rationality model or depend on intuition when the knowledge is insufficient (Odukoya et al., 2018). This model focuses on choosing the optimal option given the information at hand while acknowledging the limits of human decision-making. We may experience information overload when confronted with an abundance of facts. In this case, using scenario planning or decision trees can help us organise the data and make better decision.

Ultimately, the experience of the persons concerned plays a major role in determining the necessity for more information (Ogunmokun et al., 2023; Ogbari *et al*., 2018). One could argue that individuals with a great deal of experience making strategic decisions will not be as overwhelmed by information overload as middle-level or inexperienced individuals. This is because experienced individuals are more adept at picking out the most pertinent data and have a more coherent arrangement of information stored in memory, which allows them to pay attention to and process larger volumes of information than inexperienced individuals. According to Ogbari *et al*., (2018), a variety of external variables, such as stakeholder expectations, organisational culture, and legislative restrictions, influence decision-making techniques. Decision-makers may give preference to conservative models that reduce possible losses or liabilities in risk-averse contexts. On the other hand, in creative and dynamic environments, decision-makers may be more willing to accept risk and uncertainty and use strategies like agile decision-making frameworks or real alternatives analysis.

2.3 Contextual Influences

Contextual factors such as organizational culture, industry norms, regulatory requirements, and market conditions significantly influence the adoption and implementation of decision models under uncertainty. Organizations must carefully consider these factors when selecting and implementing decision models to ensure alignment with their strategic objectives and operational realities. According to Carlos Pinho, et al., (2014), organizational culture refers to culture related to organizations including schools, universities, not-for-profit groups, government agencies, and business entities. A culture that values innovation, risk-taking, and agility is more likely to embrace uncertainty and adopt decision models that support flexible and adaptive decision-making (Kock, & Georg Gemünden, 2016).

Also, a conservative or hierarchical culture may resist change and prefer traditional decision-making approaches, even in the face of uncertainty (Ramos, et al., 2024). For instance, tech startups often have a culture of experimentation and rapid iteration, making them more inclined to adopt probabilistic decision models like Monte Carlo simulations for risk analysis. Kaur, (2024), stated that the leadership style within an organization significantly influences its culture and, consequently, its approach to decision-making under uncertainty.

The industry in which an organization operates also shapes its approach to decision-making under uncertainty. Different industries have varying risk profiles, regulatory environments, and competitive landscapes, influencing the choice of decision models (Linnenluecke, et al., 2013). For instance, industries with high regulatory scrutiny, such as finance or healthcare, often require decision models that comply with strict regulatory requirements.

Al-Sharqi, et al., (2022), stated that these industries, decision models must not only provide accurate predictions but also adhere to legal and ethical standards. Moreover, industry norms dictate the level of risk tolerance and the willingness to adopt innovative decision-making approaches. Established industries with long-standing practices may be more resistant to change, preferring tried-and-tested methods despite their limitations in handling uncertainty (Muhammad, et al., 2021). In contrast, emerging industries or disruptors may embrace uncertainty as an opportunity for competitive advantage and be more open to adopting sophisticated decision models powered by artificial intelligence or machine learning.

Regulatory requirements impose constraints on decision-making processes, particularly in highly regulated sectors such as finance, healthcare, and energy (Muhammad, et al., 2021). Decision models must comply with regulatory standards to ensure transparency, fairness, and accountability (Ezbakhe, & Pérez-Foguet, 2021). For instance, financial institutions are required to use risk models that meet the guidelines set by regulatory bodies like the Basel Committee on Banking Supervision. However, regulatory compliance can sometimes be at odds with the need for agility and innovation in decision-making. Stringent regulatory requirements may hinder the adoption of advanced decision models that deviate from established practices or lack interpretability. Therefore, organizations must strike a balance between regulatory compliance and leveraging cutting-edge technologies to enhance decision-making under uncertainty.

Xin & Xin, (2023) stated that market conditions, including competitive dynamics, customer preferences, and economic trends, heavily influence decision-making processes. In highly competitive markets, organizations face constant pressure to innovate and adapt to changing customer demands, driving the adoption of decision models that enable rapid experimentation and scenario analysis. For example, in the retail sector, predictive analytics models are employed to forecast consumer trends and optimize inventory management (Petitet et al., 2021). According to Zhang & Chen, (2022), economic uncertainties, such as fluctuations in exchange rates or commodity prices, also impact decision-making strategies. During periods of economic instability, organizations may prioritize risk mitigation and cost reduction, leading to the adoption of decision models that emphasize scenario planning and sensitivity analysis. Conversely, in times of economic growth, organizations may focus on capitalizing on opportunities and invest in predictive analytics and optimization models to maximize returns.

Table 1: Summary of Factors Influencing Stochastic Business Decision Model Selection

Author and Year	Title of the study	Study objective	Research design	Identified Factors	Findings/outcome

Sproten et al., (2018)	Decision making and age: Factors influencing decision making under uncertainty	Examine the age effects of decision maker on the choice of decision model choice	Card game (N=200; older adults: 97)Balloon Analogue Risk Task (BART)	Ambiguity, Age and risk and The role of feedback	The study found no significant age variations in decision making situation and choice of model
Bai et al., (2022)	Where business networks and institutions meet: Internationalization decision-making under uncertainty	To investigate how business networks and institutional forces concurrently affect internationalization decision making under uncertainty	Survey methods using 758 manufacturing SMEs in Brazil (103 firms), China (198), Poland (140), Italy (154), and Sweden (163), complemented with secondary data		
Abdel-Basset, et al., (2020)	A novel decision-making model for sustainable supply chain finance under uncertainty environment	To evaluate the set of measurements to provide sustainable supply chain finance in the gas industry under uncertainty	The Best-Worst method, TOPSIS, and TODIM	Price and cost information, Product/service level, technology constraint and demand factor	The most important criteria for improving a company's performance and obtaining sustainable supply chain financing are financial qualities and product/service management.
Zong, et al., (2022)	Decision-making under uncertainty in the early phase of building façade design based on multi-objective stochastic optimization.	A multi-objective stochastic optimization (MOSO) framework was developed to evaluate decision-making under uncertainty in the early phase of building façade design.	Qualitative research design is used. A case study with solid timber and brick construction types,	Design decisions and environmental uncertainty.	The insulation and exterior wall cladding are the most variable parameters of the Pareto-optimal options for building façade design, according to the results.
Zong, et al., (2022)	Decision-making under uncertainty in the early phase of building façade design based on multi-objective stochastic optimization.	A multi-objective stochastic optimization (MOSO) framework was developed to evaluate decision-making under uncertainty in the early phase of building façade design.	Qualitative research design is used.	Design decisions and environmental uncertainty.	The insulation and exterior wall cladding are the most variable parameters of the Pareto-optimal options for building façade design, according to the results.
Dinbabo et al., (2021)	Socio-economic inequity and decision-making under uncertainty: West African migrants' journey across the Mediterranean to Europe.	To determine why migrants make decisions in conditions of uncertainty, to travel from West Africa, crossing the Mediterranean Sea to the ultimate destination of Europe.	The qualitative research design was used. The study employed a mix of secondary data analysis and field data collection.	Rationality of cost maximisation and risk reduction, sources of information at migrants' disposal.	Youth population expansion, poor access to opportunity, poverty, and unemployment amid precarious problems with development.
Gleißner, et al., (2021).	EU's ordering of COVID-19 vaccine doses: political decision-making under uncertainty.	Evaluate EU's political decision in general and the decisions of the German government to procure vaccine doses against the background of modern economics decision under uncertainty	Qualitative research methods. Case study of COVID-19 Pandemic in Germany.	Hindsight Bias, Production Capacities and Production Processes, Time of Decision, Uncertainty, and Incomplete Information	EU's choice to purchase the COVID-19 vaccine was, for once, a clear one: it would have made sense to get from all prospective vaccine providers the quantity of vaccine in the EU.
Pappas, & Glyptou, (2021)	Accommodation decision-making during the COVID-19 pandemic: Complexity insights from Greece.	To explore the decision-making attributes driving their accommodation purchasing preferences in times of increased uncertainty in Athenian,	The mixed approached was used involving the quantitative and qualitative methods. The study was carried out in Athens, Greece, in April 2020, and included	Health and safety, the price-quality nexus, risk aspects, and quality related health and safety,	The findings provide market data on consumer goals, attitudes, and intentions connected to lodging during the pandemic, and they have numerous significant management ramifications for the lodging sector.

			adult Athenian inhabitants.		
Ming, et al., (2016).	Decision-making model of generation technology under uncertainty based on real option theory.	To evaluate the stochastic model with main effective valuables considering relative risk and uncertainties.	The quantitative method was used in this paper. The study was conducted at trading electricity market of Inner Mongolia using the irreversible investment concept and real option theory	Price uncertainties	The findings reveal that taking a full consideration of uncertainties may reduce the economic potential of different generation system.

3. METHODS AND DATA

Building on the approach used by Owolabi *et al.*, (2023) a narrative content review was conducted to examine the range of factors influencing the selection of stochastic decision-making models in organizations. This methodological choice was essential for guiding the selection of relevant studies from prominent databases and respected peer-reviewed journals. The narrative review approach was specifically chosen for its effectiveness in comparing and synthesizing findings across studies (Yevu & Yu, 2019).

Data were gathered from major academic sources, including Google Scholar, Scopus, Web of Science, and published reports from esteemed organizations in data science and operations research, such as INFORMS, the International Institute for Applied Systems Analysis, the World Bank, and the OECD. The search utilized keywords such as "stochastic model," "decision analysis," "decision-making under uncertainty," "state of nature," and "decision environment." Articles were initially screened by titles and abstracts, then selected based on specific inclusion and exclusion criteria. Exclusions included non-English publications, dissertations, book chapters, duplicate publication, and conference proceedings not published in peer-reviewed journals. In contrast, only relevant, English-language, peer-reviewed studies focusing on factors influencing model selection under uncertainty in a business context were included.

Selected studies meeting these criteria underwent data extraction to capture essential details, including study characteristics (authors, year, and methodology), sample sizes, major findings, and identified factors affecting model choice. The final analysis involved categorizing recurring themes such as resource allocation, ethical considerations, risk tolerance, organizational nature and culture, and decision-maker expertise. This synthesis helped identify existing research gaps and suggested potential directions for future studies.

4. FINDINGS AND DISCUSSION

An increasing amount of research identifies individual qualities as important elements influencing decision-making under uncertainty. Individuals with higher risk tolerance tend to gravitate towards models stressing prospective rewards (Weber et al., 2018). Cognitive biases also have a significant impact. For example, overconfidence might cause an overestimation of one's capacity to deal with uncertainty, thereby biasing decision-makers toward models that need less information processing. Individuals with higher degrees of neuroticism, on the other hand, may be more risk-averse, selecting models that prioritize avoiding possible losses (Wang et al., 2021). Additionally, experience in the given decision area might impact model selection. Experienced professionals may use their experience to make informed decisions under uncertainty, perhaps selecting less structured models that allow for incorporating this expertise (Shmueli, 2019).

When considering situational factors, the decision-making context substantially impacts the uncertainty model selection. Time constraints might cause heuristic decision-making, favoring simpler models that need faster processing (Dane & Pratt, 2017). In contrast, situations with ample information may allow for the employment of more complicated models that encompass a broader range of data points (Yao et al., 2019). Furthermore, decision framing can impact model selection. When a decision is portrayed as a possible gain, people may be more prone to embrace optimistic models (Koehler, et al., 2018). Social impact might also be important. Conformity bias can drive decision-makers to choose models that the majority prefer, even if they do not entirely agree with their preferences (Herlocker et al., 2019).

Cultural influences influence risk tolerance and decision-making methods. Individualistic cultures may choose models that emphasize personal benefit and agency, whereas collectivist cultures may prefer models that consider community well-being (Singh et al., 2018). Additionally, organizational structures and decision-making hierarchies might have an impact on model selection. Individual-based models may benefit more from decentralized organizations, whereas hierarchical systems may prefer standardized, top-down approaches (Carmeli & Halevy, 2017). Finally, the availability of resources (both financial and technological) might have an impact on model selection. Resource-constrained scenarios may need simpler, less data-intensive models, whereas sufficient resources may allow for the use of more sophisticated, computationally demanding models (Lim & Hui, 2020).

5.1 Conclusion and Suggestion for Future Research

In conclusion to the study, it is very necessary to understand the varied characters of human choices when making a decision under uncertainty in an organization. Each person brings a distinct set of cognitive biases, preferences, and experiences to the table, which influence how they perceive and assess options. In addition, situational characteristics such as time limits, resource availability, and stakeholder interests can have a substantial impact on the decision-making process.

Larger contextual considerations such as cultural norms, organizational structures, and legal frameworks have a significant impact on the appropriateness of various decision-making techniques. Ignoring any of these factors may result in inferior outcomes or even decision failures in any organisational settings. Thus, a thorough awareness of individual, situational, and contextual elements is required for selecting an effective decision-making model that is tailored to the unique demands and complexity of the scenario at hand.

In the light of the findings, the following recommendations becomes essential: *Foster a Supportive Organizational Culture:* Encourage a culture that is open to change and innovation. This can be achieved through regular training, workshops, and open communication channels that promote the benefits of adopting stochastic decision models. *Ensure Adequate Resource Allocation:* Allocate sufficient resources, including time, budget, and personnel, to support the implementation and utilization of stochastic decision models. This includes investing in necessary software, tools, and training for staff. *Address Contextual Constraints:* Identify and mitigate any contextual constraints that may hinder the effective use of stochastic decision models. This could involve tailoring models to fit specific organizational needs or addressing individual skill gaps through targeted training programs.

Future researchers could delve deeper into specific aspects of the interplay between individual, situational, and contextual factors, exploring how they interact across different decision contexts and populations. Additionally, longitudinal studies could shed light on the evolving nature of decision-making preferences and the effectiveness of interventions aimed at optimizing decision-making processes in uncertain environments. Overall, the findings reveals an underscores the importance of a holistic approach to understanding and enhancing decision-making in the face of uncertainty.

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