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Structuring the Decision-Making Process Using Quantitative Options Valuation

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ABSTRACT

This study focuses on enhancing decision-making processes in the construction industry by investigating quantitative decision-making models. The construction industry is known for its diverse projects and inherent risks. Effective decision-making is crucial for project success, but it faces challenges due to various factors. The research explores biases and heuristics in decision-making, specifically in entrepreneurial and managerial contexts, with a focus on two biases: overconfidence and representativeness. Data collection involved surveys administered to entrepreneurs and managers in prominent industrial sectors. The surveys measured the levels of overconfidence and representativeness in decision-making. Additionally, the study examined commonly used decision-making models in construction, including multi-criteria decision analysis, decision support systems, decision trees, and mathematical optimization techniques. The objective was to gain insights into applying quantitative models and improve the understanding of decision-making processes in construction projects. The survey achieved a response rate of 54%, and participating managers were categorized based on their two-digit Standard Industrial Classification (SIC) codes, specifically in the 1300, 3400, 3500, 3600, and 3800 categories. Rigorous statistical analyses were conducted to evaluate potential response bias. Comparing usable responses to non-respondents using chi-square tests, no significant evidence of bias was found (χ^2 (4) = 3.973, p = .59). Moreover, a further analysis explored potential response bias across the broader set of five two-digit SIC categories, and again, no significant evidence of bias was observed (χ^2 (5) = 1.782, p = .878). The findings of this study contribute to the improvement of decision-making in construction projects and provide valuable insights into the practical application of quantitative models. By addressing biases and exploring effective decision-making approaches, this research aims to enhance project success within the complex construction industry.

INTRODUCTION

The construction industry is a multifaceted sector that encompasses many projects, including residential, commercial, infrastructure, and industrial developments. The construction sector is a dynamic, complex environment with many risks and uncertainties (Haarhaus & Liening, 2020) . Within this industry, decision-making plays a crucial role in determining project success, as it involves selecting the most suitable options and strategies at various stages of a project's lifecycle (Jin *et al.*, 2019). However, decision-making in construction projects is often a complex and challenging due to several factors. To effectively and efficiently complete the set project objectives in this hostile environment, managers must make critical decisions to carry out the core managerial tasks of planning, organising, leading, and regulating (Hoseini *et al.*, 2021).

Unfortunately, traditional management has always seen decision-making as a skill or art that can only be developed over time through experience. Managers used to judge exclusively by using trial and error, a general rule of thumb, common sense, intuition, or quick judgement. These techniques are deceptive and could have negative effects (Kaaronen *et al.*, 2021). A single bad choice could have an impact on the economics of the country in addition to being damaging. Therefore, in order to improve the likelihood of making wise decisions, the science of decision-making must be augmented (Sorko & Brunnhofer, 2019). This method requires that decisions be based on thorough data analysis that identifies correlations, trends, and rates of change in the pertinent variables. Since the early 19th century, scientific management has developed to offer a variety of quantitative methodologies capable of addressing challenging managerial issues. Construction projects are inherently complex, involving numerous interrelated activities, stakeholders, and technical requirements. Decisions need to be made regarding project design, material selection, procurement strategies, resource allocation, scheduling, risk management, and many other aspects. The interdependencies among these factors make decision making in construction projects inherently intricate (Loftus *et al.*, 2020).

The construction industry operates in an uncertain environment characterized by factors such as changing market conditions, regulatory requirements, weather conditions, labor availability, and technological advancements. These uncertainties introduce risks that decision makers must consider when selecting options. Failing to adequately account for risks can lead to cost overruns, delays, and project failures. Construction projects often face strict time and cost constraints (Asiedu

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& Adaku, 2020) . Decisions need to be made efficiently and effectively to meet project deadlines and budgetary limitations. The pressure to make quick decisions under time constraints can lead to suboptimal outcomes if not supported by robust decision-making processes. Construction projects involve multiple stakeholders with different interests, including clients, architects, engineers, contractors, subcontractors, regulators, and local communities (Pasaoa *et al.*, 2023).

Decision-making needs to consider the perspectives and requirements of these diverse stakeholders, which can be challenging due to conflicting priorities and varying levels of influence. Each phase of the project life cycle-Project Origination, Project Initiation, Project Planning, Project Execution and Control, Project Closeout, and Post-Project Evaluation-changes the nature of the project. New intermediate goods are produced at each level of the project life cycle, with the crucial output from one stage serving as a crucial input for the subsequent one (Bahadorestani *et al.*, 2020). Costs, activities for planning and scheduling projects, and a control for change management should all be included in the project control system. The different types of building construction projects influence the project life cycle and management choices.

The Project life Cycle

Various project life cycle approaches exist in the literature, e.g., control-oriented model, quality-oriented model, risk-oriented model, a fractal approach to the project life cycle, as well as some company-specific project life cycles (Mishchenko, V. Y. 2022). Each of these approaches has a different number of phases, as well as different phase names. Industries, or even businesses within the same industrial sector, are unable to agree on the stages of a project's life cycle due to the complexity and diversity of projects. It has since been suggested that a project should follow the theoretical system life cycle phases, which are Conceptual, Planning, Testing, Implementation, and Closure. Seven generic life cycle phases for projects that have been suggested are included in Table 1 along with a brief description and alternate titles for each phase (Nascimento, G. H. P. 2022). The Phases of this general project life cycle can be mixed, for example, the development and execution phase was frequently combined with the commissioning phase, to suit the needs of specific projects based on these suggested readings in the literature and discussions with manufacturers in South Africa.

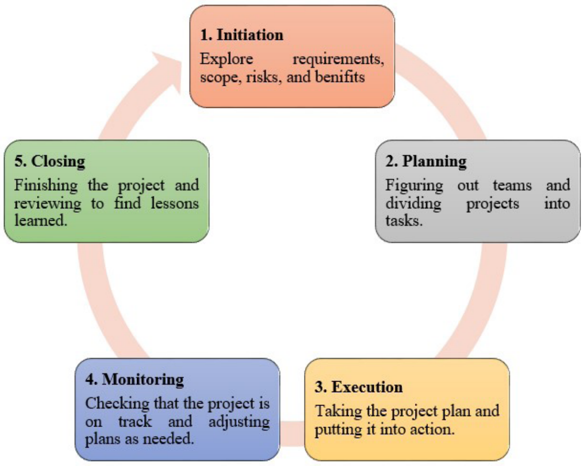

Figure 1: Shows five stages of project life cycle, Figure 1 Demonstrate different stages of project life cycle of Initiation, Planning, Execution, Monitoring and Closing briefly

Table 1: Life cycle phases in a project

Phase Names	Alternative Names	Description of Phase
Idea generation	Proposal	In this phase, the idea for a new project was generated, and the initial proposal that describes the business need must be prepared. This phase does not require a formal project plan.
Pre-feasibility	Initial investigation	The goal of this phase is to evaluate the existing proposal in terms of financial, operational, and technical viability, as well as against the company's strategy. Overlapping or synergy with other projects should also be checked out.
Feasibility	Detailed investigation	The optimum solution to address the business need must be identified and defined. All areas of this solution must be analyzed and assessed to determine killer concerns and risks.
Development and execution	Implementation	This phase involves the design, development, creation, and building of the chosen solution. The supporting system, manuals, business processes, and training for the solution must also be developed during this phase.
Commissioning	Trial	In this phase, the solution was tested in an operational environment. The purpose is to validate the acceptance and capabilities of the solution.
Launch	Release	The project was handed over to the business units and thus released to the operational environment during this phase. This phase also marks the beginning of operational support.

Post Implementation Review	Business review	After sufficient time (9–15 months), the project should be assessed to determine if the benefits were delivered and what the impact of the project was on the business. Lessons learned should be captured for future reference.

Table 2: Characteristics of a project and an operational activity

Phase	Phase Names	Alternative Names	Description of Phase
1	Idea generation	Proposal	In this phase, the idea for a new project was generated, and the initial proposal that describes the business need must be prepared. This phase does not require a formal project plan.
2	Pre-feasibility	Initial investigation	The goal of this phase is to evaluate the existing proposal in terms of financial, operational, and technical viability, as well as against the company's strategy. Overlapping or synergy with other projects should also be checked out.
3	Feasibility	Detailed investigation	The optimum solution to address the business need must be identified and defined. All areas of this solution must be analyzed and assessed to determine killer concerns and risks.
4	Development and execution	Implementation	This phase involves the design, development, creation, and building of the chosen solution. The supporting system, manuals, business processes, and training for the solution must also be developed during this phase.
5	Commissioning	Trial	In this phase, the solution was tested in an operational environment. The purpose was to validate the acceptance and capabilities of the solution.
6	Launch	Release	The project was handed over to the business units and thus released to the operational environment during this phase. This phase also marks the beginning of operational support.
7	Post Implementation Review	Business review	After sufficient time (9–15 months), the project should be assessed to determine if the benefits were delivered and what the impact of the project was on the business. Lessons learned should be captured for future reference.

Flow Chart for Main Groups of Professional Management Processes

Figure 2. Shows a pyramid (hierarchy) of different available approaches, which were applied to select the proper project option.

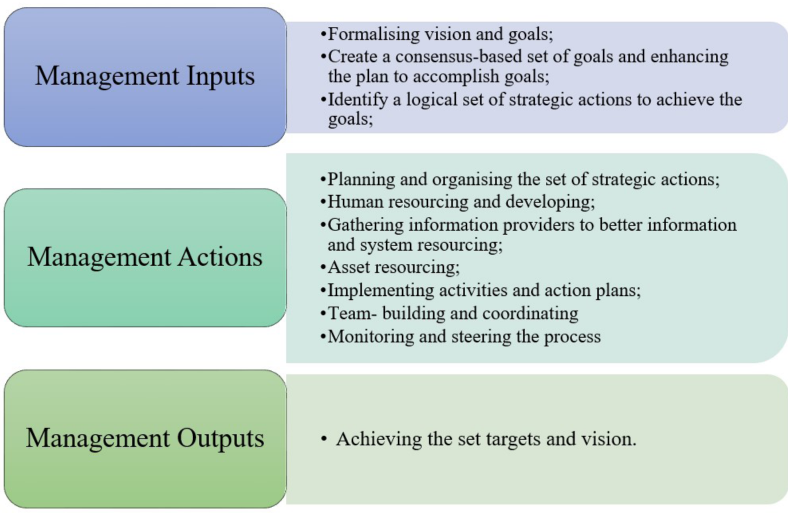

Figure 2: Main groups of professional management processes

Pyramid of Decision Maker

The pyramid of decision-makers in the construction industry represents a structured hierarchy that ensures effective communication, collaboration, and alignment of decisions throughout the project lifecycle.

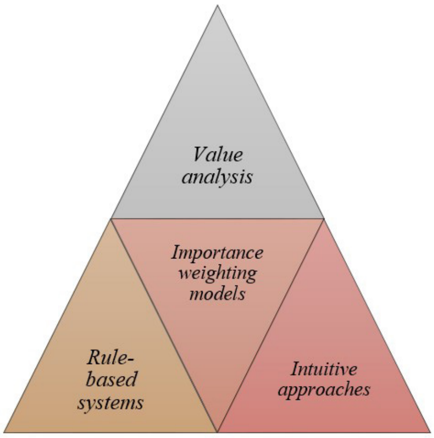

Figure 3: A pyramid of decision approaches

Subjectivity and Bias

Historically, decision making in the construction industry has been influenced by subjective factors, personal biases, and heuristics. These subjective influences can lead to inconsistent decision outcomes and suboptimal project results. Objective decision-making approaches are necessary to reduce subjectivity and enhance the transparency and fairness of decision processes (Santos, J. P., 2020).

Given these challenges, there is a growing recognition of the need for structured and objective decision-making processes in the construction industry. This has led to the exploration and development of quantitative decision-making models that provide a systematic framework for evaluating options, considering multiple criteria, and reducing subjectivity in decision-making(Yan & Sviridova, 2024).

Quantitative decision-making models in the construction industry advantage mathematical and analytical techniques to analyse complex options, assess risks, weigh trade-offs, and prioritize decision criteria (Skitmore, M., & Kabir, G., 2019). These models integrate quantitative data, stakeholder preferences, and decision analysis methodologies to arrive at informed and rational decisions. By applying these models, construction professionals can improve project outcomes, optimize resource allocation, mitigate risks, and enhance stakeholder satisfaction. The background of decision making in the construction industry underscores the importance of developing quantitative decision-making models to address the complexities and challenges faced in project planning, execution, and management. By utilizing these models, construction professionals can make more informed, transparent, and objective decisions, leading to improved project performance and better outcomes for all stakeholders involved (Kabir, G., 2019).

This study aims to further investigate the distinctions between entrepreneurs and managers in big businesses. This study, however, analyses differences in the decision-making processes employed by entrepreneurs and managers in large industries rather than concentrating on previously examined individual differences. Our argument, which is based on behavioural choice theory's nonrational decision-making models, is that the employment of bias and heuristics may account for a sizable amount of the variability in strategic decision-making. More precisely, we contend that business owners make more strategic decisions using biases and heuristics than managers in large organisations. We look at how two biases and heuristics affect differences between entrepreneurs and managers in large organisations: exaggeration and representativeness.

LITERATURE REVIEW

This literature review aims to explore existing research and scholarly works related to the development of quantitative decision-making models for complex options with multiple attributes in the construction industry.

Prior Work on Biases, Heuristics, and Entrepreneurial Decision-Making

Organisational researchers have acknowledged that managerial decision-making frequently deviates from the completely rational model since their early research in 2019. The high costs of such decision-making efforts, the decision-makers' limited ability to process information, differences in the management styles adopted, and differences in the decision-makers' values, and more have all been cited as obstacles to purely rational decision-making (Frau, L., 2022). Biases and heuristics are the subject of one of the most significant families of models that explain departures from rational decision-making. Decision-making aids, cognitive mechanisms, and subjective judgements used by people include biases and heuristics. Biases and heuristics are frequently used to produce effective and efficient answers to challenges for individuals. The term "biases and heuristics" in this study refers to various decision-simplifying techniques that people employ, particularly in complex and difficult situations (Ihalainen, L., 2021). Despite the fact that the majority of prior research has been done in lab settings, a wide range of empirical findings indicate that most decision-makers use biases and heuristics to make decisions more straightforward most of the time, and that research into this behaviour is crucial for understanding strategic decision-making (Mechelli, A. 2022).

This view was supported by the studies as well. We do, however, recognise that not all decision-makers may be equally susceptible to these biases and heuristics in their decision-making. Recent findings that decision-makers follow diverse cognitive paths provide credence to this line of inquiry. The prospect that there might be variations in the degree to which decision-makers are susceptible to heuristics and biases raises an intriguing possibility for research on the distinctions between entrepreneurs and managers in large organisations. Heuristics and biases may be especially important in explaining why different strategic decisions are made. The degree to which these two groups of people exhibit biases and heuristics in their decision-making may be a key distinction between them.

Particular Differences in Decision-Making

As was previously mentioned, a significant number of biases and heuristics have been investigated in the literature on non-rational decision-making. We selected two biases and heuristics-overconfidence and representativeness-to study differences between these groups of people out of all of these biases and heuristics. Overconfidence was chosen since it is viewed as having certain characteristics with other biases and heuristics that have been documented in the research (Wagner, H., & Taubert, M., 2022). One of the more popular heuristics, representativeness, is a decent measure of how quickly one is likely to extrapolate from a single or small set of events.

Overconfidence

It has been demonstrated that overconfidence can occur in a variety of contexts. Overconfidence occurs when decision-makers overestimate the likelihood of a circumstance occurring in the first place and, as a result, take a long time to update their evaluation after learning more details. For instance, it was discovered that only 81% of individuals who gave odds of 1000:1 were accurate. Most decision-makers overestimate their capacity for estimation and fail to recognise the true level of uncertainty. Additionally, because they are confident in their current assumptions and attitudes, decision-makers typically take their time incorporating new information (Fischhoff, B., & Broomell, S. B., 2020). A priori, overconfidence is more likely to show up in entrepreneurial decision-making than it does in managerial decision-making in large organisations. Overconfidence enables a businessperson to move forward with a concept before all the details of that particular enterprise are completely understood. A higher level of confidence is likely to encourage an entrepreneur to act before it makes complete sense, even though there are a great deal of unknowns in this decision-making scenario (e.g., is there a real economic opportunity to be exploited, how should that opportunity be exploited, how big is this opportunity, how will competitors react to this opportunity, etc.) (Osazevbaru & Amawhe, 2022). On the other hand, managers in vast industries do not have to depend as heavily on their own judgement when making decisions. Instead, these managers can persuade senior management that their projects should be given priority by using decision-making tools and historical performance trends. These findings support the following hypothesis:

HI.' Entrepreneurs will display more overconfidence than by managers in huge industries.

This research simply suggests that entrepreneurs do display overconfidence, albeit being suggestive. The majority of research on nonrational decision-making, however, reveals that most decision-makers exhibit a variety of biases and heuristics, including overconfidence, to some extent. Unfortunately, this earlier study did not investigate whether or if business owners have higher levels of overconfidence than managers in large corporations do.

Representativeness

Tversky and Kahneman to describe one of the most prevalent biases and heuristics in decision-making first used the term "representativeness". Decision-makers display this heuristic when they are ready to generalise about a person or a phenomenon based on just a few of that individual's traits or just a handful of observations of a particular phenomenon. Studies regularly reveal that people frequently disregard base rate information, which has led to the development of a wide range of challenges to measure representativeness. Consistently, decision-makers undervalue the inaccuracy and liability that come with using only limited samples of evidence. According to the rule of big numbers, it is possible to draw accurate conclusions about population statistics using large random samples. However, occasionally, decision-makers are prepared to draw such conclusions from smaller, nonrandom samples rather than from large random samples.

Personal experience is, of course, the most typical kind of tiny nonrandom sample utilised as a foundation for generalisation. One more time, there is cause to suspect that representativeness, and specifically the willingness to generalise from small, nonrandom samples, is a decision-making shortcut that may be especially prevalent in entrepreneurial settings. Large random samples are rarely available in such a situation to accurately anticipate customer demand, production costs, and other crucial pieces of information. Additionally, few business owners have the time or resources to collect data in such a methodical manner. In fact, these methodical data collection efforts may expose an entrepreneur's ideas and technology to rivals before they are ready, lowering their potential for return on investment. Entrepreneurs must be prepared to make decisions in this situation based on small, non-random samples, particularly their personal interactions with present and potential clients. Naturally, managers in large organisations have to rely less on these nonrandom samples and will thus, generally, be able to make decisions that are closer to being fully logical. These findings support the concept that:

H2: Compared to managers in large industries, entrepreneurs will exhibit representativeness more frequently in their decision-making.

Research shows that entrepreneurs do exhibit representativeness in their decision-making, although overconfidently. Minimal does not, however, examine the degree to which entrepreneurs exhibit this shortcut when compared to other decision-makers, such as managers in sizable industries.

By reviewing relevant literature, this section provides a comprehensive understanding of the theoretical foundations, methodologies, and practical applications of quantitative decision-making models in the construction context.

Decision-Making Models in Construction

Numerous decision-making models have been proposed and applied in the construction industry. These models encompass various approaches, including multi-criteria decision analysis (MCDA), decision support systems (DSS), decision trees, and mathematical optimization techniques (Papadonikolaki, E., & Liu, Z., 2021). Researchers have explored the benefits and limitations of these models in addressing the complexities and uncertainties involved in construction decision making.

Multi-Criteria Decision Analysis (MCDA) in Construction: MCDA methods, such as Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), have been widely applied in construction decision making (Brinkhoff, P., & Norin, M., 2019). These methods enable the evaluation and ranking of options based on multiple attributes, allowing decision makers to consider trade-offs and prioritize decision criteria.

Decision Support Systems (DSS) in Construction

DSSs have been developed to assist decision makers in construction projects. These systems integrate data, models, and decision rules to provide real-time decision support. They facilitate the analysis of complex options, considering multiple attributes and constraints, and provide recommendations based on predefined decision rules or optimization algorithms (Potdar, V., 2020).

Decision Trees in Construction

Decision tree analysis provides a visual representation of decision alternatives and their potential outcomes. In the construction industry, decision trees have been used to evaluate project risks, assess resource allocation strategies, and support decision making under uncertainty (Costa, V. G., & Pedreira, C. E., 2023). By mapping out various decision paths and their associated probabilities, decision trees help in identifying optimal decisions.

Mathematical Optimization Techniques in Construction

Mathematical optimization techniques, such as linear programming, integer programming, and goal programming, have been employed to optimize resource allocation, schedule planning, and cost management in construction projects. These techniques enable decision makers to formulate decision models as mathematical optimization problems and identify optimal solutions based on predefined objectives and constraints (Verwer, S., & Zhang, Y., 2019).

Integration of Building Information Modeling (BIM) and Decision Making

The integration of Building Information Modeling (BIM) and decision-making processes has gained attention in recent years. BIM provides a digital representation of a construction project, enabling the analysis of various options and their impacts on project performance. The integration of BIM with quantitative decision-making models offers enhanced capabilities for evaluating complex options with multiple attributes (Wu, P., & Yue, T., 2019).

Application of Quantitative Decision-Making Models in Construction

Several studies have applied quantitative decision-making models in the construction industry, focusing on various decision contexts such as project selection, subcontractor evaluation, risk management, sustainable design, and material selection. These studies have demonstrated the benefits of quantitative models in improving decision outcomes, optimizing resource allocation, and enhancing project performance (Edwards, D. J., 2019).

Material and Methods

Samples

As implied by these hypotheses, samples from two populations were drawn: a sample of entrepreneurs and a sample of managers in large organizations. Survey research was used to collect the primary data.

Sample of Entrepreneurs

The researchers utilized the sales tax file from a state comptroller's office as a reliable resource to identify potential entrepreneurs, as previous studies have demonstrated its effectiveness in identifying new businesses. These files contain essential information such as the organization's name, address, owner details, organization type, SIC code, and date of first sale. A targeted sample of firms meeting specific criteria was chosen, including a date of first sale within the past two years and an SIC code in categories such as 4800, 3900, 5000, 2500, 4600, 4700, and 4900, which encompass industries like plastics, electronics, and instruments manufacturing. These categories were selected based on the expectation that they would include a higher proportion of newly emerging firms, given their association with dynamic industries. The sample consisted of 573 firms, and a mail questionnaire was developed and sent to the identified sample.

A total of 176 valid responses were received, resulting in a response rate of 31%. Due to the historical challenges associated with identifying entrepreneurs, we aimed to enhance the precision of our operationalization in this study. Our operationalization involved two key dimensions. Firstly, respondents needed to be founders of the identified firm since being responsible for an independent start-up is widely recognized as a fundamental characteristic of entrepreneurship. Hence, it served as a prerequisite for inclusion in our sample. Secondly, subjects had to be currently engaged in the start-up process. This criterion was defined by requiring participants to have initiated their venture within the past two years or have plans to start another venture within the next five years. Applying these criteria yielded 124 valid responses, and the average time since founding for the included entrepreneurs was 1.7 years. To examine potential response bias, non-respondents were compared to respondents based on the two-digit SIC categories identified earlier. The results of the chi-square test indicated that the usable response was not biased (χ^2 (5) = 1.782, p = .878).

Sample of Decision Managers in Large Industries

For the purpose of this study, managers in large industries were defined as individuals who hold responsibilities for a minimum of two functional areas within publicly owned organizations employing over 10,000 individuals. These managers are commonly known as divisional managers or general managers, as they oversee multiple functional areas such as marketing, finance, personnel, research and development, and manufacturing. Contact was established with three organizations, and two of them agreed to participate in the study. The data collection process was coordinated through the human resource departments of the respective organizations, accompanied by a company cover letter. To be included in the sample, managers needed to supervise a minimum of two functional areas, with an average of 4.55 functional areas per manager. A response rate of 54% was obtained, resulting in usable responses. The managers' SIC codes in this sample corresponded to the 1300, 3400, 3500, 3600, and 3800 categories. Furthermore, the results of the chi-square test comparing usable responses to non-respondents indicated no significant bias (χ^2 (4) = 3.973, p = .59).

Theory/Calculation

The primary objective of this study was to assess the utilization of biases and heuristics in the decision-making approaches employed by entrepreneurs and managers in large organizations. To achieve this goal, a range of decision problems was intentionally included to ensure a comprehensive understanding of the decision-making styles within the specific context of these two groups of strategic decision-makers.

Overconfidence

A set of five questions was created for this study, focusing on death rates related to various diseases and accidents in the United States. Each question had a dichotomous format, presenting respondents with two options and asking them to determine which cause of death is more prevalent. For example, a question could be: "Which cause of death is more frequent in the United States? A. Cancer of all types, B. Heart disease." The correct option for each question was based on the most recent vital statistics report prepared by the National Center for Health Statistics. Participants were required to provide two responses for each question. First, they had to select their best guess of the correct alternative. Second, they indicated their level of confidence in their answer using a provided scale ranging from 50% to 100%. The instructions clarified that a response of 50% would signify a total guess, while 70% would indicate that they believed they had seven chances out of ten of being correct. A response of 100% indicated complete confidence in their choice. To facilitate analysis, the "level of confidence" responses were grouped into six probability categories: 0.50–0.59, 0.60–0.69, 0.70–0.79, 0.80–0.89, 0.90–0.99, and 1.00. Responses falling within the 0.50–0.59 range were coded as 0.50, those in the 0.60–0.69 range as 0.60, and so on. This categorization allowed for further analysis and interpretation of the collected data.

To facilitate statistical analysis for each participant, an additional score was calculated. This score involved determining the average probability response across all the questions and assessing the percentage of items for which the correct alternative was selected. The difference between these two scores served as an indicator of overconfidence or underconfidence. A positive score indicated overconfidence, while a negative score indicated underconfidence. For example, let's consider a respondent who provided probability responses of 0.50, 0.60, 0.70, 0.70, and 0.90, and correctly answered three out of the five questions. Their overconfidence score would be calculated as 0.08, which is the mean of their probability responses (0.68) minus the proportion of correct answers (0.60). This scoring approach allowed for quantifying the level of overconfidence or underconfidence exhibited by participants based on their responses to the questions.

Representatives

The study aimed to measure representativeness by giving subjects scenarios representing real-life strategic decisions. Two scenarios were presented, one based on quantitative/statistical information and the other on heuristic reasoning. Participants were asked to decide between the two alternatives and describe their reasoning for reaching the designated decision. Coders analyzed these responses to determine if heuristic type reasoning was used. Responses without statistical reasoning were coded "1" and those with statistical reasoning were coded "0." After initial training, all responses were coded blindly by two individuals, with 84% agreement between coders. If disagreement existed, a third coder was used to resolve the disparity. The results were summed across the two problems to create a single three-category variable (0-2). A "0" indicated statistical reasoning, while a "2" indicated only heuristic reasoning.

Control Variables

Research on entrepreneurs and managers in large industries has mixed results, but this study includes measures of economic alertness to explain entrepreneurial activity and impact decision-making.

Personal Demographic Characteristics

Age and education information were collected for entrepreneurship analysis, as age and education levels may influence biases and heuristics. Age was determined by birth year, while education was measured using a five-point scale from high school to graduate degrees.

Economic Factors

The Cronbach's alpha reliability score for the nonverbal search or reading alertness for economic opportunity in this study was 0.81. With a reliability score of 0.52 in this study, a second component assessing openness to new ideas was removed from further analysis.

RESULTS

Entrepreneurs in large organizations were found to be more over-confident than managers in all categories except in the 0.8 range probability, where they were nearly identical. The study conducted analysis using logistic regression to test the overconfidence and representativeness variables. The results showed that both variables were significant and in the expected direction, correctly predicting entrepreneur versus manager more than 70% of the time. However, there was little collinearity among independent variables, suggesting that including control variables in the analysis would be important. The control variables education, conformity, and alertness remained statistically significant, while risk-taking and age were non-significant. These results support the emerging consensus that psychological, personal/demographic, and broader social and economic factors have a limited ability to distinguish entrepreneurs from managers in large organizations.

Despite controlling for previously examined factors, the overconfidence and representativeness measures remained statistically significant, helping distinguish between entrepreneurs and managers in large organizations. The results from Model 1 indicate that Risk-Taking does not have a statistically significant effect on the dependent variable, as indicated by the non-significant Wald statistic (Wald = 0.005, p > .05). Similarly, Age also does not show a significant effect (Wald = 1.67, p > .05). The pseudo-R-squared values for Model 1 and Model 2 are 0.21 and 0.37, respectively, suggesting that the models explain 21% and 37% of the variance in the dependent variable. The model fit is relatively better in Model 2 compared to Model 1.

Means, Standard Deviations, and Correlations

Table 3: Means, Standard Deviations, and Correlations

Variable	Mean	SD	1	2	3	4	5	6	7
1. Entrepreneur/Manager	1.6	0.49							
2. Representativeness	1.14	0.78	0.61‘						
3. Overconfidence	.17	0.17	0.20’	—0.05					
4. Risk-taking	5.2	2.38	0.02	—0.04	—0.04				
5. Conformity	2.4	1.86	—0.30°	—0.07	—0.01	—.28’			
6. Education	3.32	1.27	—0.62’	—0.35‘	—0.11	0.06	0.02		
7. Age	44.55	9.7	—0.07	—0.07	0.03	—0.01	—0.11	0.01	
8. Alertness	5.45	1.79	0.09	—0.04	—0.11	0.21’	—0.19’	0.09	0.17”
“P < .05.									

Table 3 suggests little collinearity among independent variables. However, several moderate intercorrelations involving control variables suggest that including these variables in an analysis would be important.

A sub analysis was conducted to avoid confounding results due to industry effect. Eight industries were represented in the two samples, but 62% of entrepreneurs and 86% of managers in large organizations were from three closely related industries. These industries, which are closely related to industrial and commercial machinery, computer equipment, electronic equipment, and measuring instruments, accounted for the majority of the samples. The full logistic regression model was tested with a subsample, and overconfidence and representativeness remained significant at the same levels as the full samples. The only significant change was with the alertness variable, which was significant at the.05 level with the subsample.

Results of Logistic Regression Analysis

Table 4: Results of Logistic Regression Analysis

	Model 1		Model 2	
	Parameter	**Wald**	**Parameter**	**Wald**
Independent Variables	Estimate	x^2	Estimate	x^2
Intercept	2.07’	30.64	6.31’	17.6
Risk-Taking			—0.007	0.005
Conformity			—0.39‘	11.64

Education			—1.09'	31.76
Age			—0.03	1.67
Alertness			0.34’	6.61
Representativeness	1.6"	36.49	1.56'	22.09
Overconfidence	2.68‘	8.36	2.76•	6.21
Pseudo-R’	0.21		0.37	
Model y’	54.43°		108.5'	
Df	198		185	
Hit ratio (%)	70		79'	
° p < .05.				
p < .01.				

Table 4 explain the control variables, education, conformity, and alertness remain statistically significant. The risk-taking and age variables were non- significant. Overall, these results support the emerging consensus that psychological, personal/demographic, and broader social and economic factors have a limited ability to distinguish entrepreneurs from managers in large organizations (the hit ratio reported in table 4 only improved 9% with the inclusion of the control variables). More importantly for this study, continuing support was found for H1 and H2. Even after controlling for previously examined factors, the overconfidence and representativeness measures re-main statistically significant and help distinguish between entrepreneurs and managers in large industries.

DISCUSSION

The discussion focuses on the complexity of decision-making in the construction industry and the implications of biases, heuristics, and quantitative decision-making models. It highlights the challenges faced by decision-makers in this industry and the potential benefits of adopting effective decision-making strategies (Chappin, E. J., 2019). The construction industry is characterised by its multifaceted nature, encompassing a wide range of projects such as residential, commercial, infrastructure, and industrial developments. Within this dynamic and complex environment, decision-making plays a crucial role in determining project success. Decision-makers are responsible for selecting the most suitable options and strategies at various stages of a project’s lifecycle (Urbina, A. (2019). However, decision-making in construction projects is often a complex and challenging process due to several factors. These factors include the inherent risks and uncertainties associated with the construction sector (Haarhaus & Liening, 2020).

To effectively achieve project objectives in this hostile environment, managers must make critical decisions related to planning, organizing, leading, and regulating (Hoseini *et al*., 2021). Traditionally, decision-making has been seen as a skill or art that is developed over time through experience. Managers would often rely on trial and error, general rules of thumb, common sense, intuition, or quick judgment to make decisions (Kaaronen *et al*., 2021). However, these techniques can be deceptive and may have negative effects. A single bad decision can have significant economic implications and lead to project failures. To improve the likelihood of making wise decisions, the science of decision-making needs to be augmented (Sorko & Brunnhofer, 2019). This involves basing decisions on thorough data analysis that identifies correlations, trends, and rates of change in relevant variables. Scientific management has developed various quantitative methodologies to address challenging managerial issues since the early 19th century (HAQUE, A. U., & Baloch, A., 2019).

Construction projects are inherently complex, involving numerous interrelated activities, stakeholders, and technical requirements. Decision-making in such projects needs to consider various aspects, including project design, material selection, procurement strategies, resource allocation, scheduling, and risk management (Loftus *et al*., 2020). The interdependencies among these factors make decision-making inherently intricate. The construction industry operates in an uncertain environment characterized by factors such as changing market conditions, regulatory requirements, weather conditions, labor availability, and technological advancements. These uncertainties introduce risks that decision-makers must consider when selecting options. Failing to adequately account for risks can lead to cost overruns, delays, and project failures. Additionally, construction projects often face strict time and cost constraints (Asiedu & Adaku, 2020). Decision-makers need to make efficient and effective decisions to meet project deadlines and budgetary limitations.

However, the pressure to make quick decisions under time constraints can lead to suboptimal outcomes if not supported by robust decision-making processes. Moreover, construction projects involve multiple stakeholders with different interests, including clients, architects, engineers, contractors, subcontractors, regulators, and local communities. Decision-making needs to consider the perspectives and requirements of these diverse stakeholders, which can be challenging due to conflicting priorities and varying levels of influence. The project life cycle in the construction industry further complicates decision-making. Each phase of the project life cycle, from project origination to post-project evaluation, presents unique challenges and changes the nature of the project (Bahadorestani *et al*., 2020). Decision-makers need to adapt their strategies and decisions accordingly, considering the evolving project requirements and objectives.

In order to improve decision-making in the construction industry, quantitative decision-making models have been developed and applied. These models offer structured approaches to evaluate options, consider multiple attributes, and optimize decision outcomes. Some of the commonly used models include multi-criteria decision analysis (MCDA), decision support systems (DSS), decision trees, and mathematical optimization techniques. MCDA methods, such as the Analytic Hierarchy Process (AHP), TOPSIS, and PROMETHEE, enable decision-makers to evaluate and rank options based on multiple attributes, facilitating trade-offs and prioritization of decision criteria. DSSs integrate data, models, and decision rules to provide real-time decision support, allowing analysis of complex options and recommendations based on predefined rules or optimization algorithms (Herrera, F., 2019).

Decision trees provide a visual representation of decision alternatives and their potential outcomes, aiding in evaluating risks, resource allocation strategies, and decision-making under uncertainty. Mathematical optimization techniques, such as linear programming and goal programming, optimize resource allocation, schedule planning, and cost management in construction projects, considering predefined objectives and constraints. The integration of Building Information Modeling (BIM) with decision-making processes has gained attention in recent years. BIM provides a digital representation of a construction project, allowing analysis of various options and their impacts on project performance (Bulle, C., & Lesage, P., 2019). The integration of BIM with quantitative decision-making models enhances capabilities for evaluating complex options with multiple attributes. Several studies have applied quantitative decision-making models in the construction industry, focusing on various decision contexts such as project selection, subcontractor evaluation, risk management, and sustainable design. These studies have demonstrated the benefits of quantitative models in improving decision outcomes, optimizing resource allocation, and enhancing project performance.

CONCLUSION

In conclusion, this study contributes to the understanding of decision-making in the construction industry by investigating biases, heuristics, and quantitative decision-making models. The findings highlight the presence of overconfidence and representativeness biases among entrepreneurs and managers, emphasizing their potential impact on decision-making processes and project outcomes. It underscores the importance of adopting improved decision-making approaches that account for uncertainties, stakeholder perspectives, and project constraints. The utilization of quantitative decision-making models, such as multi-criteria decision analysis and mathematical optimization techniques, provides valuable insights for making informed decisions in complex construction projects. Integrating these models with building information modeling enables decision-makers to evaluate options, optimize resource allocation, and enhance project performance. Future research should address the identified limitations and further investigate the interplay between biases, decision-making models, and project outcomes in the construction industry, offering practical implications for practitioners and contributing to the knowledge base of researchers.

LIMITATION

Despite the valuable insights gained from this study, it is important to acknowledge some limitations. Firstly, the data collection relied on surveys, which may introduce response biases and rely on self-reported measures. Additionally, the sample primarily consisted of entrepreneurs and managers from large industries, which may limit the generalizability of the findings to other segments of the construction industry. Moreover, the study focused on a specific set of biases (overconfidence and representativeness) and decision-making models, neglecting other potential biases and models that may influence decision-making in construction projects.

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