

Machines Meet Minds: AI-Assisted Capital Budgeting, Managerial Overconfidence, and Investment Efficiency

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ABSTRACT

AI is being increasingly used in corporate finance to equip businesses with more advanced forecasting capabilities, real-life scenario simulations, and investment risk quantification. However, the impact of AI decision support systems on managerial judgment has not yet been extensively researched. Based on the Ability – Motivation – Opportunity (AMO) model and the concept of behavioral finance, the paper constructs a conceptual model to test the interactions between the quality of the AI-assisted capital budgeting tool and managerial overconfidence and their relationship to investment efficiency. The model suggests that the use of high-quality capital budgeting tools improves managers' analytical skills, resulting in better investment decisions, but at the same time may result in the extent of their managerial overconfidence due to automation complacency, causing biased capital allocation. The relationship of overconfidence and investment efficiency is thought to be moderated by organizational slack; additionally, resource-rich firms have more room for overconfident investment. The paper proposes eight theoretical propositions on the topic, outlines the entire conceptual framework, and outlines specific mechanisms by which the use of AI tools helps or hinders cognitive bias in capital allocation decisions in business organizations. Theoretical work includes putting AI decision-support research into a behavioral corporate finance framework in the AMO framework, and addressing the conflicting effects of AI on judgment quality. The practical considerations provide recommendations for CFOs, boards of directors, and regulators looking to leverage the efficiency of AI and prevent it from fostering hazardous overconfidence. Empirical directions for future research provide the research methods for testing the propositions with survey, archival, and experimental research.

Keywords: AI-assisted capital budgeting; AMO framework; automation complacency; behavioral finance; corporate finance; investment efficiency; managerial overconfidence; organizational slack.

INTRODUCTION

One of the most important decisions made by any management team is related to the capital budget, which is the way in which the company uses its limited monetary resources and assets over the long term. These decisions affect the firm's growth path, competitive position and ultimately the long term value of the shareholder (Graham & Harvey, 2001). Traditional techniques for capital budgeting have been based on discounted cash flow (DCF) methods, real options analysis, and comparisons of precedent transactions, all of which are fundamentally limited by the cognitive capabilities and biases of the managers who implement these techniques (Kahneman & Lovallo, 1987).

With the advent of artificial intelligence, there has been a new dimension to this process. The speed and level of detail with which AI-driven capital budgeting tools conduct predictive analytics, Monte Carlo simulations, machine learning revenue forecasting, natural language processing of regulatory documents, and real-time risk assessment are far beyond the cognitive power of humans (Duarte et al., 2021). Many big financial institutions and corporations have incorporated these tools into their treasury functions, M&A valuations and strategic planning. Deloitte's recent survey shows that more than 70% of large CFO offices are investing in AI in the coming five years (2023). AI tools can analyze huge amounts of data, identify patterns that analysts can't see, and mitigate systematic errors in financial forecasting.

This has a significant impact because one of the most important determinants of the economic performance of a firm, industry or the economy is capital allocation efficiency. Hubbard (2017) has shown that capital misallocation between firms is one of the biggest contributors to productivity loss in today's economies. Bad investment decisions, whether it involves making too many risky investments in small projects or missing out on good investments in big projects, have an impact that propagates through supply chains, labor markets and capital markets. If these decisions are really improved by these AI tools, then the macroeconomic impact can be significant. On the other hand, if AI technologies develop new avenues for bias, the fallout can be just as disruptive.

There are two separate, but related, fields of literature. The first one is about the adoption of AI and analytics in corporate finance, reporting efficiency benefits, better forecasting accuracy, and better risk management capabilities (Duarte et al., 2021; Li et al., 2022). The second considers the managerial cognitive biases, especially overconfidence, and their distorting impact on investment decisions, capital structure and strategic resource allocation (Barber & Odean, 2009; Malmendier & Tate, 2005). Such literatures have evolved virtually in isolation. Behavioral corporate finance research views human cognition as the main cause of decision error, and AI adoption research views the technology as a neutral efficiency gain. Both the tradition of AI decision support and that of managerial psychology have not

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explored the impact of the interplay between these two factors on investment results.

This lack of synergy indicates a key gap. This issue of whether the use of AI tools increases or decreases managerial overconfidence is both theoretically unexplored and of great practical significance. There is some evidence that decision-support systems enhance the accuracy of judgment, due to their ability to correct for cognitive errors (Dietvorst et al., 2015). Studies have shown that overconfidence can be exacerbated by automation complacency, which is the tendency to overconfidently accept inputs from automated systems without proper verification (Parasuraman & Manzey, 2010). Such conflicting results have been observed in the human factors and decision science literatures but have not been combined into corporate finance theory.

The theoretical problem is a basic one of interaction effects. The organization performance is a multiplicative product of an ability (A), a motivation (M) and an opportunity (O) in the AMO framework (Appelbaum et al., 2000). The main dimension that AI capital budgeting tools focus on is the Ability dimension, which involves improving analytical skills. Managerial overconfidence is manifested in two ways: Ability (a high level of self-perceived analytical ability) and Motivation (a low level of diligence in checking AI output). Opportunity is captured with organizational slack, which can either facilitate or hinder the link between ability bias and real capital allocation decisions. There is no current model that combines these three aspects in the context of AI-backed capital budgeting.

This paper introduces an AI adoption-behavioural corporate finance intersection conceptual framework that builds on the AMO model. In the first pathway, the quality of the capital budgeting tools that AI provides is expected to increase management's analytical capabilities, which leads to improved investment efficiency. In the second pathway, it is hypothesized that the quality of the capital budgeting tools provided by AI will increase management's self-confidence, thereby reducing investment efficiency. Organizational slack serves as a buffer on the overconfidence pathway, and helps to buffer against biased decision making in resource-rich settings. The framework addresses conflicting results in the area of decision support, identifying when AI enhances versus diminishes quality of judgement in capital budgeting situations.

This paper makes three contributions to the theory of corporate finance. Firstly, it combines AI adoption research and behavioural finance into one model to understand when and how AI can be beneficial or detrimental in investment decisions. Second, it raises automation complacency as a way to increase the level of automation quality to amplify its impact into a cognitive bias, thereby counteracting the prevailing view that AI always makes better decisions. Thirdly, it provides a contingency model of organizational slack, and a basis for understanding why the same AI tools can generate varying investment results in different organisations.

The rest of this paper can now be continued. Section 2 provides a critical, comprehensive literature review that merges the AI in corporate finance, managerial overconfidence and decision-support literatures. The theoretical foundations are presented in

Section 3. The conceptual framework is developed in section 4. Theoretically derived propositions are given in Section 5. The conceptual model is presented in Section 6. Theoretical contributions, practical implications, future research directions, and limitations are discussed in sections 7–10. This is the end of the paper (section 11).

LITERATURE REVIEW

AI and Analytics in Corporate Capital Budgeting

AI's role in corporate financial decision making is one of the biggest tech changes in finance in recent years. The traditional capital budgeting (CB), which relies on discounted cash flow (DCF) and sensitivity analyses, and managerial judgment, is complemented by machine learning (ML) algorithms that can predict revenues, forecast demand, evaluate counterparty risk, and analyze investment patterns of millions of potential investments (Duarte et al., 2021). They leverage big data analytics, NLP for earnings calls and regulatory filings, neural network-based scenario modeling and real-time market signal integration.

Several efficiency benefits from adopting AI have been documented in the corporate finance literature. Companies that use advanced analytics say they have greater forecasting accuracy, shorter time from project identification to approval, and better risk-adjusted return measurement (Duarte et al., 2021). Li et al. (2022) showed that companies that invest in AI-enabled financial systems have a higher level of capital efficiency as reflected in their Tobin's Q and ROIC. Bakos et al. (2022) conclude at the macroeconomic level that use of AI in financial management is linked to a decrease in cost of capital, indicating that markets reward firms that use AI for decision making.

Most of the capital budgeting literature, however, has approached AI as an ability-augmenting technology that enhances the accuracy and speed of current processes. The basic premise is that with improved inputs, (more accurate forecasts, more complete data) better decisions are made. This is an intuitive guess, but one that doesn't consider the human judgment layer that sits between the AI-generated output and the actual capital allocation decision. AI tools give recommendations, managers make decisions on whether to take them. The quality of that mediation is rooted in managerial psychology—specifically the mental biases that have been documented over the years from behavioral finance research.

Managerial Overconfidence and Investment Decisions

One of the most consistent findings in behavioral corporate finance is managerial overconfidence, the tendency of the decision maker to overestimate his knowledge and to underestimate risks and overestimate the control he has over outcomes. Overconfident CEOs, determined by how they talk about their own superior abilities and respond to market signals, spend a lot more than rational CEOs, resulting in greater excess acquisition activity and higher offers for target firms, according to Malmendier and Tate (2005). In their seminal work, they have proven that cognitive bias is not just an annoyance, but a systematic force that affects corporate investment.

Later studies continued in this direction for several parameters. Barber and Odean (2009) reported overconfidence is associated with excessive trading, portfolio concentration, and market

participation of individual investors and similar effects have been shown among corporate managers (Malmendier & Tate, 2005). Based on their research, Kahneman and Lovallo (1987) created the "threat of paranoia" model which demonstrates that decisionmakers can be too optimistic (oversized investment) or too pessimistic (oversized withholding) and that the net result of these fluctuations is determined by the context of the decision. Graham and Harvey (2001) found that more than 60% of the CFOs surveyed admitted to cognitive biases affecting capital budgeting that included being overconfident in projected cash flows.

There are a number of specific forms of overconfidence in capital budgeting. Project managers may be overly optimistic about the odds of success, underestimate the costs and timeline of implementation, overestimate the value of strategic synergies in acquisitions, and underestimate the likelihood of bad risk scenarios (Kahneman & Lovallo, 1987). The result of these biases is the systematic overinvestment in marginal projects, over-diversification into related but value-neutral projects and overpayment in mergers and acquisitions (Malmendier & Tate 2005). Importantly, there has been little literature that has considered the interaction between organizational tools and technologies and managerial overconfidence. There are studies that have used overconfidence as a relatively stable individual trait, and others that have investigated whether it can be considered as a characteristic of a firm's culture; however, the moderating (or aggravating) effect of decision-support technologies has not been theoretically explored.

Decision Support Systems and Quality of Judgment

The most direct evidence on the interactions between AI decision-support tools and human judgment comes from the human factors and decision science literatures. This literature portrays a positive side to the role of decision-support systems, suggesting that they can correct for human judgment problems, limit arithmetic errors, and offer a systematic way of considering alternatives (Dietvorst et al., 2015). Evidence on clinical decision making suggests that algorithmic approaches are useful in minimizing diagnostic errors associated with the human expert (Topol, 2019). Likewise, research into financial analysts shows that on average, quantitative models are more accurate than human forecasting (Sparks & Heese, 2018).

But a countervailing literature exists describing situations in which decision support systems fail to enhance judgment. Parasuraman and Manzey (2010) identified automation complacency, a phenomenon in which operators decreased their monitoring efforts when they felt the automated systems they used were likely to be working correctly, thus allowing system errors to go undetected. This is especially harmful when there is silent failure of the automation or when automation generates a confident output that seems to be correct. Specifically, Egan and Zwiebel (2015) discovered humans who trade using algorithmic signals grew too confident in their own abilities even when the algorithm gave them false signals, indicating that the use of AI signals makes humans feel more competent than they really are.

In a lab environment, Shin and Grant (2018) showed that decision makers who receive AI-generated recommendations are more confident of the decisions they made, even when the

recommendations were correct or incorrect. This discovery is particularly alarming in the context of capital budgeting, as it indicates that the use of AI tools could lead to overconfidence even when the results they produce are not accurate or correct. The takeaway is that while AI can aid capital budgeting, it can also lead to poorer capital budgeting decisions because managers may be less careful in examining AI-generated forecasts and scenarios.

The conflicting findings of AI enhances judgment (Dietvorst et al., 2015) and AI leads to over-confidence (Shin & Grant, 2018) are not yet resolved due to the fact that they were investigated in the two different literatures with different methodologies and different dependent variables. Neither of these findings has been incorporated in a coherent model of the impact of AI on investment efficiency in the corporate finance literature.

Organizational Slack and Capital Allocation

There has been a theory that organizational slack may help or hinder strategic resource allocation (Nohria & Gordon, 1984). On the other hand, slack creates resource cushion to allow for experimentation, risk taking, and long-term investments that may not pay off immediately (Hubbard, 2017). Firms that have excess capacity can, in turn, handle the setback of underperforming projects and continue to invest in downturns. In contrast, however, slack can lead to a managerial entrenchment, a building up of an empire and wasteful expenditure of resources to serve managerial goals, rather than those of the shareholders (Jensen, 1986). Slack is especially relevant to the present model because of its relationship to risk taking. It has been found that companies with greater slack are more likely to be aggressive investors, more likely to take risky projects, and to acquire larger companies (Zattoni et al., 2017). This aligns with the AMO framework dimension of Opportunity, where slack means that an organization has room to move based on the decisions it made, regardless of how well informed or misguided they are. The possibility of capital misallocation is greatest when the manager is overconfident and there is a lot of slack, since the overconfident manager can give in to his or her biases with little or no corrective feedback that would occur if resources were scarce.

Identifying the Research Gap

The proposed framework is warranted by four major gaps. First, there is no such model that incorporates decision-support research from AI and managerial overconfidence in capital budgeting, so the net impact of AI on investment efficiency remains to be theoretically determined. Second, with regard to the working mechanism, an overconfidence effect, commonly referred to as 'automation complacency', is not theorized in corporate finance contexts. Third, the AMO framework (Appelbaum et al., 2000) has not previously been used to explain the interaction between ability and behavior in the context of opportunity in corporate finance. Fourth, organizational slack, as a contingency variable in determining the effect of overconfidence on capital misallocation, has not been included in the behavioral capital budgeting literature.

THEORETICAL FOUNDATION

The AMO Framework

The Ability–Motivation–Opportunity (AMO) framework, developed by Appelbaum et al. (2000), posits that organizational task performance is a multiplicative function of three factors:

$$\text{Performance} = \text{Ability} \times \text{Motivation} \times \text{Opportunity}$$

Ability is the knowledge, skills and competencies that a person brings to the execution of a task. Motivation is defined as the incentives, commitment and effort people invest in a task. Opportunity is the environment and organisational factors that help or hinder performance. Each factor is a must; if any one of them is missing, the others do not contribute to the performance value. The AMO framework has multiple benefits for analyzing AI-driven capital budgeting. First, it captures the individual-level factors (managerial capabilities, cognitive bias) as well as the organizational-level factors (tool quality, resource availability). Second, it defines performance as multiplicative, that is, the higher the quality of the AI tool (Ability), the lower the effectiveness of the overconfidence (motivation toward verification reduction), and vice versa. Third, it offers a language to describe the interaction between technology (AI tools) and psychology (overconfidence) and organization (slack) to create investment efficiency outcomes.

Relevance to the Research Problem

The AMO approach is especially pertinent for three reasons. AMO is relevant for three reasons. First of all, AI capital budgeting tools have an impact on the Ability dimension directly, by improving analytical capabilities and information processing. Second, managerial over-confidence has an impact on both Ability (overconfidence in analytical skills) and Motivation (lower willingness to critically examine AI output). Third, the Organizational Slack specifies the Opportunity dimension by making resources and decisions to allocate resources available or unavailable. The AMO framework also includes the multiplicative interaction, which is at the heart of the present argument. A firm with high ability and overconfident managers but low Motivation (i.e., poor verification of outputs) may make poorer investment decisions than a firm with moderate ability and diligent managers. On the other hand, a company with great AI capabilities and low status managers, working in a tough environment (Small Opportunity for error), can still generate excellent investment efficiency. These contingent outcomes are naturally the result of the framework.

Behavioral Finance as the Psychological Foundation

The psychological underpinning of understanding managerial overconfidence is given by the theory of behavioral finance, which is based on bounded rationality (Simon, 1955), prospect theory (Kahneman & Tversky, 1979) and heuristics-and-biases research (Tversky & Kahneman, 1974). The behavioral finance literature has documented that these so-called "cognitive biases" are systematic, predictable, and consequential, which is why they are not random noise. The managerial overconfidence is not a random deviation from rationality but a predictable characteristic of human judgment under uncertainty, especially in the areas where feedback is not immediate, and is not clearly understood (Malmendier & Tate, 2005).

How Constructs Are Connected Through the Theory

The theoretical logic connecting the constructs operates through three interconnected pathways, consistent with the AMO framework:

Pathway 1 (AI → Ability → Investment Efficiency, Positive):

AI capital budgeting tools empower managers with better forecasting, scenario analysis, and risk quantification. This improved ability directly contributes to the quality of investment decisions which improves the capital allocation and increases the investment efficiency.

Pathway 2 (AI → Overconfidence → Investment Efficiency, Negative):

The very same AI tools which improve capability also incite managerial overconfidence by automation complacency. AI-enabled managers tend to feel more capable of analyzing situations than they should, become less diligent in verifying what AI provides, invest more heavily in projects that are more favorable in their AI projections, and become more even more trusting of algorithmic forecasts. This type of overconfidence leads to less critical analysis of AI recommendations, leading to bias in capital allocation and less investment efficiency.

Pathway 3 (Organizational Slack Moderates Overconfidence → Investment Efficiency):

This is a negative pathway that is moderated by organizational slack. In a setting of abundant resources, the managers can be overconfident, and so take on marginal projects, because they do not need to worry about triggering corrective feedback from resources constraints. As a result, slacked companies are able to sustain the losses associated with overly optimistic investments for longer, and this is the reason that overconfidence continues to run almost unrestricted. (Jensen, 1986).

Limitations of Applying AMO to AI-Assisted Capital Budgeting

Multiple modifications are required in order to apply the AMO framework to AI-assisted capital budgeting. First, Ability is viewed as primarily human knowledge and skill in the traditional AMO framework. Tool quality, a non-human, ever-evolving factor—is included in the AI concept of ability. This requires reconceptualizing Ability as a composite of human analytical skill and AI tool capability, and recognizing that these two components may interact non-linearly.

Second, the AMO framework treats Motivation as relatively stable organizational incentives. The effective motivation toward verification and diligence is altered in ways that are not captured by conventional incentive structures by overconfidence. A manager may be fully incentivized to make good decisions (high Motivation in the AMO sense) but still fail to verify AI outputs because overconfidence reduces the perceived necessity of verification.

Thirdly, the AMO framework typically refers to structural conditions like technology, information access, and coordination mechanisms as the Opportunity dimension (organizational slack). Opportunity also includes the degree of AI integration into workflows in the AI context. A company with opportunity structures that differ from those of a company with AI as a peripheral tool offers capital budgeting processes.

How the Proposed Model Extends Existing Understanding

The proposed model extends existing understanding in three significant ways. First, it transforms the question from "Does AI improve investment decisions?" to "Under what conditions does AI improve versus degrade investment decisions?" — a more theoretically rich and productive inquiry. Second, it identifies automation complacency as a specific psychological mechanism that mediates the AI → Investment Efficiency relationship, providing an empirical target for future research. Third, it integrates three literatures—AI adoption, behavioral corporate finance, and organizational capability—that have developed in isolation, generating new theoretical insights at their intersection.

Development of the Conceptual Framework

Textual Representation

The proposed conceptual model can be represented as follows (the corresponding path diagram is presented as Figure 1 in Section 6):
 AI Capital Budgeting Tool Quality (AICBT) → Managerial Analytical Ability (MA) [enhanced by AI] → Investment Efficiency (IE) [+]
 AI Capital Budgeting Tool Quality (AICBT) → Managerial Overconfidence (MO) [amplified by AI] → Investment Efficiency (IE) [-]
 Organizational Slack (OS) moderates the Managerial Overconfidence (MO) → Investment Efficiency (IE) relationship [amplifies]
 AI Capital Budgeting Tool Quality (AICBT) × Organizational Slack (OS) interaction → Investment Efficiency (IE) [interaction]
 P1: AICBT → (↑) MA → (↑) IE
 P2: AICBT → (↑) MO → (↓) IE
 P3: MA → (↑) IE
 P4: MO → (↓) IE
 P5: MO mediates AICBT → IE (negative pathway)
 P6: MA mediates AICBT → IE (positive pathway)
 P7: OS moderates MO → IE (positive moderation: more slack = worse overconfidence effect)
 P8: AICBT × OS → IE (high AI + High Slack = highest risk of misallocation)

Explanation of Proposed Relationships

Relationship 1: AI Capital Budgeting Tool Quality → Managerial Analytical Ability (Positive)

The managerial analytical capacity is directly enhanced by high-quality AI capital budgeting tools that have interpretable outputs, robust validation protocols, high forecast accuracy, and seamless integration into existing workflows. Managers using superior AI tools have access to more comprehensive data analysis, more sophisticated scenario modeling, and more precise risk quantification than managers relying on intuition or simple spreadsheet models. This enhanced ability translates directly into better capital budgeting decisions, including more accurate NPV estimates, better risk-adjusted discount rates, and more nuanced identification of value-creating versus value-destroying projects. This path is in line with the Ability dimension of the AMO framework, which looks at how technology improves human competence.

Relationship 2: AI Capital Budgeting Tool Quality → Managerial Overconfidence (Positive/Amplifying)

At the same time, there is an increase in managerial overconfidence due to the high-quality AI tools. If management employs tools that give impressively precise forecasts and have a confidently-stated probability distribution for the forecasts, they ascribe the results to their own analytical talent, rather than to the analytical capability of the tool. Automation complacency is the psychological superimposition of the competence of the tool onto the manager's self-confidence (Parasuraman & Manzey, 2010). Managers with quality AI products fall in the trap of believing they make the best decisions, despite it actually being the AI who is the most responsible for the analytical quality. This relationship has been identified in the overconfidence literature as when more advanced tools are available, there would be an increase in perceived competence (Shin & Grant, 2018).

Relationship 3: Managerial Analytical Ability → Investment Efficiency (Positive)

Investment efficiency directly improves with improved analytical skills. Managers who are better equipped to evaluate complex investment proposals, identify hidden risks, differentiate between projects that create value and those that destroy it, and allocate capital more effectively have greater analytical capability, whether it is innate or enhanced by AI tools. This relationship corresponds to the AMO framework's prediction that higher Ability produces higher Performance, all else equal.

Relationship 4: Managerial Overconfidence → Investment Efficiency (Negative)

Overconfidence by managers leads to inefficiency in investment for several reasons. Managers who are overconfidence estimate higher the probability of project successes, lower the cost and timelines of implementation, overvalue expected synergies, and are more inclined to use aggressive investment strategies, which are below the risk adjusted value thresholds (Malmendier & Tate, 2005). Most importantly, overconfidence also causes a decrease in the Motivation to verify the AI output—a double whammy, because overconfident managers will also make biased evaluations, and they won't correct the occasional errors of the AI tool. This aligns to the Motivation dimension of the AMO framework, which has a negative impact on diligence motivation. This is in line with the Motivation dimension of the AMO framework, which has a negative influence on diligence motivation.

Relationship 5: Managerial Overconfidence Mediates the AICBT → Investment Efficiency Negative Pathway

The overconfidence mechanism is how AI tool quality affects investment efficiency negatively. Overconfidence is amplified by high-quality AI tools, which in turn reduces investment efficiency. If overconfidence is controlled (held constant), the negative pathway from AI tool quality to investment efficiency is eliminated. The mechanism by which AI tools can paradoxically reduce decision quality while simultaneously increasing analytical capacity is outlined in this mediation hypothesis.

Relationship 6: Managerial Analytical Ability Mediates the AICBT → Investment Efficiency Positive Pathway

The increased analytical capacity is the mechanism by which the quality of AI tools has a positive effect on investment efficiency. Managers' analytical capacity is enhanced by high-quality AI

tools, which in turn improves investment decisions. The positive path from AI tool quality to investment efficiency is eliminated if analytical ability is controlled (maintained constant). Together, the positive mediation (via Ability) and negative mediation (via Overconfidence) create a tension that determines the net effect of AI on investment efficiency—resolved by the moderation pathways below.

Relationship 7: Organizational Slack Moderates the Managerial Overconfidence → Investment Efficiency Relationship

The negative relationship between overconfidence and investment efficiency is exacerbated by organizational slack. Cash flow constraints quickly correct overconfident investments in resource-constrained environments: projects that consume resources without producing sufficient returns cause resource scarcity, necessitating course corrections (Nohria & Gordon, 1984). Overconfident managers are able to sustain multiple marginal projects concurrently, absorb losses without immediate financial stress, and continue investing based on inflated expectations long after resource discipline would have commanded correction in environments with abundant resources. Slack provides the organizational conditions that enable overconfident Ability to translate into actual capital allocation decisions without constraint, which corresponds to the AMO Opportunity dimension.

Relationship 8: The Interaction of AICBT and Organizational Slack on Investment Efficiency

The combined effect of high AI tool quality and high organizational slack creates the highest risk of capital misallocation. High AI quality amplifies overconfidence; high slack provides the latitude to act on that overconfidence without constraint. If overconfidence effects prevail, this interaction predicts that firms with advanced AI tools and ample slack will have the lowest investment efficiency, while firms with ability effects will have the highest investment efficiency—a prediction that can be empirically tested.

Proposition Development

P1: AI Capital Budgeting Tool Quality (AICBT) is positively associated with Managerial Analytical Ability (MA).

Justification: High-quality AI capital budgeting tools offer better data processing, better forecasting, scenario analysis, and better risk quantification (Duarte et al., 2021). When tools are precise, understandable, and embedded in workflow, managers become more knowledgeable and improve their analytical skills as they can use the tool's results to inform their decision making. This is consistent with the AMO framework's Ability dimension (Appelbaum et al., 2000). Similar observations in medical decision-making have demonstrated that doctors who employ sophisticated diagnostic AI systems over time are able to improve their pattern recognition and clinical judgment (Topol, 2019). Li et al. (2022) show in the financial sector that companies with investments in AI-related financial systems have better managerial analytical efficiency, as expected by P1, the positive Ability effect.

P2: AI Capital Budgeting Tool Quality (AICBT) is positively associated with Managerial Overconfidence (MO).

Justification: The very same artificial intelligence systems that boost analytical skills also boost the self-assessment of managers.

If AI tools generate impressive results with confidence intervals, managers believe that they are as sophisticated as the AI tools (Parasuraman & Manzey, 2010). Shin and Grant (2018) showed experimentally that decision makers' confidence in their judgments are higher when they are given a recommendation by AI, even if the AI is not accurate. Barber and Odean (2009) discovered a positive relationship between access to advanced trading technology and investors' self-assessed skills. It's automation complacency – the perception that decision-making tools are easier and less risky to use, and that managers are more valuable to decision making than they actually are. The proposition highlights one of the crucial negative externalities of the use of AI which is not a part of the prevailing efficiency story.

P3: Managerial Analytical Ability (MA) is positively associated with Investment Efficiency (IE).

Justification: The managers who possess more analytical abilities (either native or aided by AI) are better able to assess projects accurately, identify opportunities for value creation more reliably, and to avoid value destruction investments more effectively (Graham & Harvey, 2001). According to the AMO framework, the higher the Ability, the more the Performance (Appelbaum et al., 2000). Empirical evidence in corporate finance confirms that the more analytically skilled financial managers have better investment efficiency as measured by the investment-to-capital ratio based on the value of the firm's Q and return on invested capital (Hubbard, 2017). In the context of capital budgeting the AMO prediction is the positive core, P3.

P4: Managerial Overconfidence (MO) is negatively associated with Investment Efficiency (IE).

Justification: In essence, managerial overconfidence can cause systematic capital misallocation. Managers are overconfident in their estimates of project profitability, low on estimates of the project cost and time, overpay for acquisitions, and overestimate investment portfolios (Malmendier & Tate, 2005). Overconfidence increases excessive trading which leads to destruction of value, as shown by Barber and Odean (2009). Overconfidence in the capital budgeting context lowers the Motivation to critically examine proposals, validate forecasts and think about worst case scenarios (Kahneman & Lovallo, 1987). Graham and Harvey (2001) reported that more than half of the CFOs recognize that cognitive biases affect their capital budgeting decisions. Theory and empirical evidence from behavioral corporate finance very much back up P4.

P5: Managerial Overconfidence (MO) mediates the negative relationship between AI Capital Budgeting Tool Quality (AICBT) and Investment Efficiency (IE).

Justification: This mediation explanation explains how AI tools could have a negative impact on investment efficiency despite boosting analytical capacity. P2: Overconfidence is enhanced by high quality AI tools, and P4: Overconfidence decreases investment efficiency. When analytical ability is the same, the negative relationship between the quality of AI tools and investment efficiency is fully mediated by overconfidence. This is in line with the multiplicative format of the AMO framework: even high Ability leads to suboptimal Performance at low Motivation (diligence-oriented motivation), when Motivation is degraded by

overconfidence (Appelbaum et al., 2000). Experimentally, however, Shin and Grant have shown that AI recommendations, even when inaccurate, can boost decision confidence, directly supporting this mediation pathway.

P6: Managerial Analytical Ability (MA) mediates the positive relationship between AI Capital Budgeting Tool Quality (AICBT) and Investment Efficiency (IE).

Justification: This mediation hypothesis explains the positive mechanism by which the use of AI tools improves investment effectiveness. Increased investment efficiency (P3) leads to increased analytical ability (P1), which leads to more effective use of AI tools. More effective use of AI tools (P1) leads to increased analytical ability, which leads to increased investment efficiency (P3). With constant level of overconfidence, the positive channel between the quality of the AI tool and the efficiency of the investment goes through improved analytical ability. P6 is the most common position in the literature about the use of AI for decision making which holds that technology increases decision quality by increasing competence. The main theoretical finding of this paper is a tension between P5 (negative mediation through overconfidence) and P6 (positive mediation through ability), such that the overall mediation is either negative or positive depending on which of the two pathways is stronger.

P7: Organizational Slack (OS) positively moderates the relationship between Managerial Overconfidence (MO) and Investment Efficiency (IE), such that overconfidence reduces investment efficiency more strongly when organizational slack is high.

Justification: According to Appelbaum et al. (2000), the Opportunity dimension of the AMO framework indicates organizational conditions either facilitate or hinder the translation of performance. Resource-rich companies create more Opportunity for the overconfident managers to follow their own biases without having to confront them immediately by the constraints of the resources that they have on hand (Nohria & Gordon, 1984). In firms with little slack, over-confident investments are disciplined immediately by cash flow pressures; losses lead to a re-allocation of resources, thus, course corrections (Jensen, 1986). In high-slack companies, managers have the ability to maintain several over-optimistic projects, to handle losses without putting themselves under financial strain, and to invest in the projects despite false hopes. Citing evidence that supports the moderating effect predicted by P7, Zattoni et al. (2017) reports that more slack firms invest more aggressively. There is complementary evidence to support this finding from Hubbard (2017) who shows that abundance of resources allows for risk-tolerant modes of capital allocation.

P8: AI Capital Budgeting Tool Quality (AICBT) and Organizational Slack (OS) interact to influence Investment Efficiency (IE) non-linearly, such that high AICBT combined with high OS produces the greatest deviation from optimal investment efficiency (in either direction).

Justification: This interaction proposition combines the Ability pathway (positive) with the Overconfidence pathway (negative) and the moderation pathway Slack (positive). The positive ability effect and negative overconfidence effect are amplified when the

quality of the AI tools is high and slack is plentiful. The net result will depend on the relative strength of these pathways, an empirical question that can be answered. This also fits the multiplicative nature of the AMO framework: high Ability, high Opportunity, with the Motivation reduced (to overconfidence) creates a broad spectrum of possible outcomes: best-to-worst, depending on the ability enhancement versus bias amplification (Appelbaum et al., 2000). This proposition has an obvious empirical implication, which can help address the conflicting results of the AI adoption research.

Conceptual Model

Figure Specification

Figure Title: "An AMO-Based Model of AI-Assisted Capital Budgeting, Managerial Overconfidence, and Investment Efficiency"

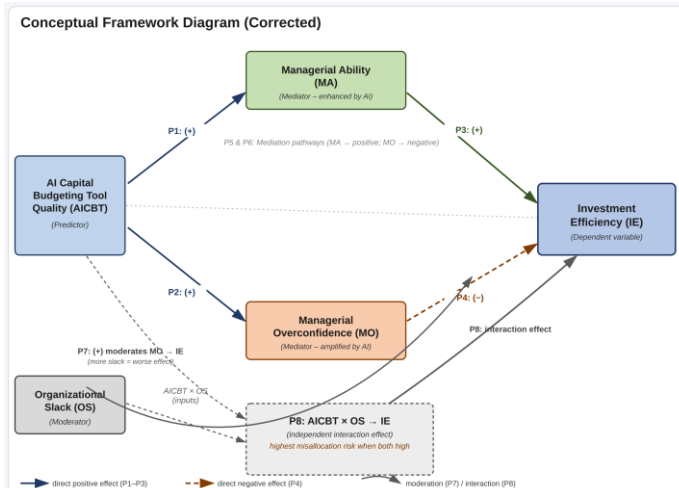
Layout: A directional diagram organized in four vertical panels from left to right: (1) AI Capital Budgeting Tool Quality, (2) Managerial Psychological States (Ability and Overconfidence), (3) Moderator (Organizational Slack), (4) Investment Efficiency.

Variables and Boxes:

- **Panel 1 (Far Left):** AI Capital Budgeting Tool Quality (AICBT) — oval, labeled "AI Capital Budgeting Tool Quality (AICBT)" with sub-elements: Forecast Accuracy, Interpretability, Integration Depth, Validation Rigor.
- **Panel 2 (Center-Left):** Two boxes side by side. Box A (Top): "Managerial Analytical Ability (MA)" — rectangle, with arrow from Panel 1 labeled "+". Box B (Bottom): "Managerial Overconfidence (MO)" — rectangle, with arrow from Panel 1 labeled "+". Both boxes feed into Panel 3.
- **Panel 3 (Center-Right):** "Organizational Slack (OS)" — oval, positioned to the side with curved arrows pointing to the MO → IE arrow and the AICBT → IE composite arrow, labeled "moderates (+)" on MO → IE and "moderates (×)" on AICBT → IE interaction.
- **Panel 4 (Far Right):** "Investment Efficiency (IE)" — rectangle, receiving arrows from MA (+) and MO (−), and moderated by OS.

Arrows:

1. AICBT → MA (solid arrow, labeled "+")
2. AICBT → MO (solid arrow, labeled "+")
3. MA → IE (solid arrow, labeled "+")
4. MO → IE (solid arrow, labeled "−")
5. OS → MO → IE path (curved arrow, labeled "amplifies")
6. AI × Slack → IE (dashed curved arrow, labeled "interaction")



Caption: "Figure 1. An AMO-Based Model of AI-Assisted Capital Budgeting, Managerial Overconfidence, and Investment Efficiency. AICBT = AI Capital Budgeting Tool Quality; MA = Managerial Analytical Ability; MO = Managerial Overconfidence; OS = Organizational Slack; IE = Investment Efficiency. Solid arrows represent direct relationships; curved arrows represent moderating effects; dashed arrows represent interaction effects. The model integrates the AMO Framework (Appelbaum et al., 2000) with behavioral corporate finance theory."

Explanation of the Model

The conceptual model combines the AMO framework (Appelbaum et al., 2000) and behavioral corporate finance theory, aiming to provide a comprehensive understanding of the dual nature of AI capital budgeting tools on investment efficiency. At the same time, the quality of the AI tool strengthens managerial analytical skills (positive AMO pathway) and boosts managerial overconfidence (negative AMO pathway). The net impact on the efficiency of investment is dependent on the relative strength of these competing pathways, with organizational slack influencing the relative strength of these pathways. In poor, resource scarce conditions, the distorting impact of overconfidence is more likely to manifest itself in the actual misallocation of resources, and in rich conditions, financial discipline partially reduces the impact of overconfidence. The model yields eight propositions that can be tested, and addresses the contradictory evidence in both the AI adoption literature and behavioral finance literature by establishing boundary conditions where AI will be beneficial versus detrimental to investment decisions.

Theoretical Contributions

Integrating AI Adoption Research with Behavioral Corporate Finance

This paper is one of the basic papers that brings together two literatures that have been developed independently. The adoption of AI in the literature is considered as a neutral or positive efficiency-enhancing technology (Duarte et al., 2021) and behavioural corporate finance literature considers human cognition as the key driver of decision error (Malmendier & Tate, 2005). Both of these traditions have not investigated the impact that the interaction between cognitive biases and the use of AI tools has on how capital is allocated. This paper fills this gap by

hypothesizing that AI tools boost ability and amplify overconfidence at the same time, with the net result of whether they are net benefit for investment efficiency being the tension between these. This integration creates a new research frontier on the intersection of technology, cognition and corporate finance.

Extending the AMO Framework to Technology-Cognition Interactions

A second contribution is extending the AMO model (Appelbaum et al., 2000) to the realm of AI-based decision making. The AMO framework has been extensively used in organizational behavior and human resource management to analyse the performance of teams, the design of work systems and work productivity. In this paper, it is extended to the corporate finance domain, with the ability of the AI tool as the measure of the Ability dimension, the level of overconfidence as a measure of the Motivation dimension, and the organizational slack as a measure of the Opportunity dimension. The examples shown in this extension illustrate the versatility of the AMO framework and create a new application domain of great practical relevance for CFOs and corporate boards.

Resolving Contradictory Findings Through a Contingency Model

Third, this paper addresses this conflicting evidence from the decision-support literature by outlining circumstances in which AI aids, and hinders, judgment. The positive effect of AI on investment efficiency is through increased ability (P6), while the negative is through increased overconfidence (P5). These pathways will have varying strengths, as moderated by organizational slack (P7), and thus the net effect. This contingency model helps to account for the contradictory results of some studies that show AI enhancing judgment and others that show it degrading judgment (the Ability pathway and the Overconfidence pathway, respectively). These two results are correct for different boundary conditions and would not be either of them from literature alone.

Identifying Automation Complacency as a Capital Budgeting Mechanism

Lastly, this paper suggests a particular mechanism, namely automation complacency, in corporate finance settings. That automation complacency has been known to exist in human factors and safety research (Parasuraman & Manzey, 2010) but has not been theorized in the context of capital budgeting. This paper posits that AI capital budgeting tools give rise to a new type of automation complacency: not laziness on the part of the managers, but a psychological fusion of the analytical skills of the AI tool with the manager. This mechanism produces predictions that can be evaluated for the relationship between the quality of the AI Tool, managerial confidence, and the accuracy of capital allocation.

Practical Implications

For CFOs and Corporate Finance Executives

The framework offers practical advice on how CFOs can implement AI capital budgeting solutions. Firstly, CFOs should be aware that AI tools are not decision makers, but decision aiders; the analytical quality of the AI (AICBT) leads to making them better, while at the same time causing overconfidence. A

mandatory verification process should be part of investment processes, especially for high-value and high-uncertainty projects, to verify AI-generated forecasts. The protocols should be tailored to battle automation complacency; for instance, asking managers to make their own assumptions of the important factors before they look at what AI has produced. Secondly, CFOs need to adjust the implementation of AI tools to their organizational context. The framework suggests that capital misallocation is most likely to be an issue when high-quality AI tools are used in slack-rich, resource-rich settings (P8). In such settings verification and governance processes should be particularly strong. However, in resource-limited settings, the built-in discipline of scarcity helps mitigate the overconfidence effect and AI tools can provide a higher overall benefit. Third, CFOs need to become "AI-literate" with financial managers, which means they must be able to critically assess the output of AI and understand its limitations, and the conditions in which algorithmic forecasts can be wrong. This directly tackles the Ability part of the AMO framework and is also an antidote to the overconfidence effect since it brings awareness of the tool's limitations to the attention of managers.

For Boards of Directors and Governance Bodies

Boards should ensure AI governance is embedded within their capital allocation oversight. In particular, boards should: (a) create committees to validate the outputs of their AI capital budgeting tools against actual project results, (b) provide disclosure of the use of AI in investment decision-making in materials before their boards, and (c) track whether the use of AI is associated with greater capital investment but lower investment return, indicative of overinvestment due to overconfidence.

For AI Tool Developers

To prevent automation complacency, the interfaces of AI capital budgeting tool developers must be designed to withstand it. Confidence interval displays, model uncertainty indicators, scenario deviation warnings and required "second opinion" prompts before committing large capital dollars can mitigate managers' inclination to blindly believe the output of AI (Parasuraman & Manzey, 2010). It is important to use tools that clearly state their limitations, such as "This forecast is based on historical data which may not be indicative of current market conditions", so as to lessen the overconfidence amplification effect identified in P2.

For Regulators and Standard-Setters

The regulators should take into account the disclosure requirement of the role AI plays in the capital budgeting process, akin to the requirement for firms to disclose ESG. It is proposed that AI-induced overconfidence could lead to systemic risk: When many companies make excessive investments in AI due to their positive expectations, market corrections might be deeper and more widespread. The provisions on disclosure would allow market participants and regulators to evaluate this risk.

Future Research Directions

Empirical Testing of Propositions Using Survey and Archival Data

Each of the eight propositions results in a clear testable prediction. P1–P4 can be assessed with validated scales for the quality of AI tools (from the literature on technology quality), managerial

overconfidence (e.g., Malmendier and Tate, 2005 scales), and self-reported investment efficiency, respectively, in a cross-sectional survey study of CFOs and financial controllers. At the firm level, studies of the P3 and P4 can be tested using archival research, including 10-K filings, proxy statements and Capital IQ data, all in relation to investment efficiency, as measured by the Q-based investment ratio, excess capital expenditures, and return on invested capital (Hubbard, 2017).

Experimental Studies of AI–Overconfidence Interaction

P2 and P5 can be causally tested in the lab or field by randomly assigning participants to each group and measuring the levels of overconfidence and investment decision after using the different qualities of AI capital budgeting tools. The experimental design should include the following variables: manipulation of the quality of the AI tool (high vs. low accuracy), and the measurement of overconfidence before and after using the AI tool, as well as the actual investment decisions made. This would be the most convincing causal evidence for the overconfidence amplification mechanism.

Longitudinal Studies of AI Adoption Effects

Longitudinal panel studies of firms before and after using the AI capital budgeting tool can be used to assess the systematic changes in investment efficiency, as well as whether the changes are dependent on organizational slack. Early AI adopters and matched non-adopters can be used in difference-in-differences designs to identify causal effects, while controlling for confounders.

Cross-Industry and Cross-Country Comparisons

Predictions of the framework may differ between industries (e.g., technology companies that are significantly more mature with AI than manufacturing companies) and countries (e.g., varying country corporate governance regimes, ownership structures, and cultural views on technology). Cross industry and cross country tests of boundary conditions and generalizability.

Qualitative Investigations of Managerial Experience

Qualitative interviews with CFOs and financial managers who have been using AI capital budgeting solutions over the past few years can uncover the real experience of automation complacency, the approaches implemented to prevent overconfidence, and the organizational cultures that either foster or hinder a critical evaluation of AI. Qualitative data can be used to further develop the theoretical constructs and to develop new propositions to be tested quantitatively.

Research on Different Types of AI Tools

Not all AI capital budgeting tools are created equal. Research needs to differentiate between the prediction capabilities of AI (machine learning forecasting), the ability of AI to create scenarios (LLM-based scenario generation) and the ability of AI to provide recommendations for optimization-based allocation (prescriptive AI). The impacts of various tools on ability and overconfidence may be varied, producing a more differentiated typology than the binary (AI vs. non-AI) classification.

Limitations

The above conceptual paper has some limitations. First, the model has not been tested with data. The propositions are supported by established theory and evidence, but need to be validated using

solid empirical research. The competing mediation pathways (P5 and P6) are not formally tested and we do not have a concrete empirical answer to the relative strength of each pathway. Second, the model is very specific in that it deals only with capital budgeting decisions. The use of AI in the entire corporate finance spectrum: capital structure, working capital management, mergers and acquisitions, and treasury operations. The way in which ability–overconfidence tension found here extends to the latter domains is an empirical issue that needs to be addressed separately. Thirdly, the model assumes that managerial overconfidence is a relatively stable individual trait. In fact, overconfidence can vary according to the market, to recent good or bad luck and to the organization. There are several interesting directions for future studies, including temporal dynamics, e.g., whether high expectations will become more inflated as individuals spend more time using AI. Fourth, the model takes no account of the interaction among team members. Committees, discussions, and negotiations are involved in capital budgeting in large firms. Group processes such as social comparison, dialectical inquiry, and collective wisdom (Ring & Van de Ven, 1994) might enhance or reduce the impact of overconfidence. There are no studies theoretically examining how overconfidence is affected by the use of AI tools in group decision-making. Fifth, the conceptualization of organizational slack as a moderator may have simplified the multidimensionality of organizational slack. Slack has the possibility to be monetary, human or temporal. The interaction between the various forms of slack and overconfidence and AI quality can be different, and therefore, more detailed theorizing is needed in future research. Sixth, the model has been created mainly in the context of publicly traded corporations in developed economies. It needs to be considered for the applicability of privately held firms, family businesses, emerging market corporations and non-profit organizations where there is a significant difference in the capital budgeting processes.

CONCLUSION

In this paper, the author has developed a theoretical framework with a solid theoretical foundation to examine the impact of using AI in capital budgeting on investment efficiency, based on the AMO framework (Appelbaum et al., 2000) and the theory of behavioral corporate finance. The framework also captures a central paradox in the current literature by proposing a positive pathway (increased analytical capability of managers) and a negative pathway (increased managerial overconfidence) of the use of AI capital budgeting tools, with the net impact on capital budgeting efficiency depending on the relative strength of those two competing forces, which is moderated by organizational slack. The model theoretically contributes in four ways: Combines AI adoption research with behavioral corporate finance under the AMO framework; Extends AMO framework to the technology–cognition nexus in corporate finance; Overcomes contradictory findings by adopting a contingency model; Identifies automation complacency as a mechanism in contexts of capital budgeting. The implications of the practical side are significant. CFOs need to use AI tools as analytical partners and have strong verification systems in place to mitigate against automation complacency. Capital allocation accountability should include AI governance. Tool

developers need to create interfaces that are not susceptible to overconfidence amplification. Regulators should take AI disclosure into account when evaluating system risks. Empirical testing of the eight propositions using experimental, survey, archival and longitudinal methods is a key recommendation for future research. With AI increasingly being part of the corporate finance landscape, the debate over when AI adds or detracts value to capital allocation decisions will become more pressing than a theoretical discussion. This paper offers the conceptual blueprint to direct such research and to shape the responsible use of AI in one of management's most impactful decisions.

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