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The Influence of Artificial Intelligence on Budgeting and Financial Forecasting: A Conceptual Perspective on Accuracy, Efficiency, and Strategic Planning.

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Abstract

Budgeting and financial forecasting occupy a peculiar theoretical position within management accounting: they are simultaneously among the most heavily criticized organizational practices in the field and among the most persistently retained. Artificial intelligence (AI) enters this contested territory carrying a specific promise — more accurate prediction, less manual effort, and closer integration between forecasting and strategic planning — and a specific risk, that improved prediction is mistaken for improved decision-making. This paper offers a conceptual analysis of AI's influence on budgeting and forecasting that takes both the promise and the risk seriously. Integrating the Beyond Budgeting critique of traditional annual budgeting, Mintzberg's classical argument against the predictability formal planning presumes, and recent empirical evidence on AI-enabled forecasting and decision authority, the paper argues that AI improves forecasting accuracy and budgeting efficiency in ways that are now reasonably well evidenced, but that these improvements translate into better strategic planning only under specific organizational conditions that much of the applied literature leaves implicit. Chief among these conditions is the allocation of decision authority: recent field evidence shows that superior algorithmic predictions do not automatically improve organizational decisions when human decision-makers retain, and exercise, override authority. The paper develops an integrated model distinguishing accuracy, efficiency, and strategic value as related but analytically separate outcomes, and considers what this distinction implies for how organizations should structure AI-enabled budgeting and forecasting processes going forward.

Keywords: artificial intelligence; budgeting; financial forecasting; forecast accuracy; strategic planning; rolling forecasts; decision-making; management accounting.

Introduction

Few management accounting practices have attracted as much sustained criticism as the traditional annual budget, and few have proven as durable. Hope and Fraser (2003), founders of the Beyond Budgeting movement, argue that conventional budgeting is fundamentally poorly suited to volatile business environments: fixed annual targets, negotiated months in advance and rarely revisited, encourage gaming, discourage adaptation, and consume disproportionate organizational effort relative to the strategic value they produce. Yet Libby and Lindsay (2010), surveying North American organizations, find that despite two decades of this critique, most firms continue to use budgets for control and performance-evaluation purposes and consider their budgeting systems value-adding —

evidence that the gap between budgeting's theoretical reputation and its practical persistence is real and has not closed on its own. Artificial intelligence enters this long-running debate carrying a specific promise: that AI-enabled forecasting can resolve much of what critics have found wrong with traditional budgeting, by replacing static annual targets with continuously updated, more accurate predictions generated with less manual effort than conventional forecasting required.

The empirical evidence on AI's contribution to this promise is genuinely encouraging on its own narrow terms. Ding, Lev, Peng, Sun, and Vasarhelyi (2020), studying insurance loss reserve estimates, find machine-learning predictions outperforming the managerial estimates firms actually reported in the majority of lines examined — direct evidence that AI can improve the accuracy of a specific, consequential financial forecast. Yoshioka and Ishii (2025) propose integrating generative AI with data-science techniques specifically to strengthen simulation, prediction, and scenario analysis within management accounting, arguing that this combination supports a more continuous and responsive planning process than the periodic, backward-looking reporting cycle traditional budgeting depends on. Taken at face value, this evidence suggests AI is well positioned to deliver much of what Beyond Budgeting has argued for since 2003: less rigid, more accurate, more continuously updated financial planning.

This paper argues that taking the evidence at face value in this way is premature, for a reason the applied forecasting literature has generally underexamined. Its central claim is that **AI's demonstrated improvements in forecasting accuracy and budgeting efficiency do not automatically translate into improved strategic planning, because strategic value depends on a further condition — the allocation of decision authority between algorithm and human — that accuracy and efficiency gains alone do not resolve**. Mintzberg's (1994) classical critique of formal strategic planning, developed decades before AI-enabled forecasting existed, anticipated part of this problem: he argued that formal planning systems mistake the ability to process data for the ability to predict genuinely discontinuous change, and that this mistake has organizational consequences independent of how sophisticated the underlying data processing becomes. This paper connects Mintzberg's critique to recent evidence on algorithmic decision authority to develop a more complete account of what AI actually changes, and does not change, about the relationship between financial forecasting and strategic planning.

Conceptualizing AI's Role in Budgeting and Forecasting

Budgeting and forecasting, though often discussed together, serve theoretically distinct organizational functions. Budgeting is primarily a control and coordination mechanism, allocating resources across organizational units and establishing targets against which subsequent performance is evaluated. Forecasting is primarily an informational mechanism, estimating future financial and operational outcomes to support planning and decision-making, with less inherent connection to performance evaluation. Appelbaum, Kogan, Vasarhelyi, and Yan (2017), proposing a management-accounting data-analytics framework, argue that these functions have historically been treated as separate activities supported by separate systems, even though both depend on essentially the same underlying data and both benefit from the same analytical capabilities — an observation with direct relevance to AI adoption, since AI-enabled forecasting tools increasingly blur the boundary

Appelbaum et al. describe, generating outputs that inform both resource allocation and performance-target setting simultaneously.

Rikhardsson and Yigitbasioglu (2018), reviewing business intelligence and analytics research in management accounting, find that empirical coverage of how analytical tools change budgeting and forecasting practice specifically has historically lagged behind coverage of the tools' technical capabilities — a gap the more recent AI-specific literature has begun to close, but one that leaves considerable room for the conceptual analysis this paper undertakes. This paper treats AI's influence on budgeting and forecasting as operating along three distinguishable dimensions: accuracy, the degree to which forecasts correspond to actual outcomes; efficiency, the resource and time cost of producing budgets and forecasts; and strategic value, the degree to which improved forecasts and more efficient budgeting processes actually improve the quality of strategic decisions made downstream. The central argument developed below is that AI's contribution to the first two dimensions is now reasonably well evidenced, while its contribution to the third remains considerably more conditional than much of the applied literature acknowledges.

Theoretical Foundations

The Traditional Budgeting Critique and Beyond Budgeting

Hope and Fraser's (2003) Beyond Budgeting critique identifies several specific pathologies in traditional annual budgeting relevant to evaluating AI's potential contribution: budgets fixed months before the period they govern quickly become disconnected from actual conditions; the negotiation process through which budgets are set encourages managers to build in slack or sandbag targets; and the annual cycle itself is poorly matched to the pace at which many business environments actually change. Libby and Lindsay's (2010) survey evidence complicates the Beyond Budgeting movement's more radical prescription — eliminating budgets altogether — by finding that most organizations retain budgets specifically because they continue to serve real control and coordination functions, even while acknowledging the pathologies Hope and Fraser identify. This paper reads the Libby and Lindsay evidence as suggesting that the more productive response to traditional budgeting's problems is not elimination but reform of the specific mechanisms producing those problems — which is precisely where AI-enabled forecasting is most plausibly positioned to contribute, by reducing the staleness and manual negotiation cost Hope and Fraser identify as central to what makes traditional budgeting dysfunctional.

Mintzberg's Fallacy of Prediction and the Limits of Formal Planning

Mintzberg (1994) offers a theoretical foundation this paper treats as essential, and as a necessary corrective to overly optimistic accounts of AI-enabled forecasting. His central argument is that formal planning systems rest on what he terms the fallacy of prediction: the assumption that because a system can process large volumes of data systematically, it can therefore predict the future reliably, including the kind of discontinuous change — a new competitor, a technological shift, a shift in customer preference — that most threatens an organization's strategic position. Mintzberg argues that repetitive patterns may indeed be predictable through formal analysis, but genuine discontinuities are not, and that formal planning systems have historically performed best at exactly the kind of incremental, pattern-following forecasting that matters least strategically, while performing worst at the kind of discontinuity-anticipation that matters most.

This critique was developed decades before AI-enabled forecasting existed, but its logic applies with particular force to machine-learning-based prediction specifically, because machine-learning models are, definitionally, pattern-extrapolation systems trained on historical data. Ding et al.'s (2020) finding that machine learning outperforms managerial judgement in insurance loss-reserve estimation is a finding about exactly the kind of repetitive, pattern-governed prediction Mintzberg's framework predicts formal systems should handle well; it is not evidence that AI can anticipate the discontinuous changes Mintzberg identifies as strategically decisive. A theoretically complete account of AI's role in forecasting therefore has to distinguish, more carefully than much of the applied literature does, between AI's demonstrated strength in stable-pattern prediction and its unproven, and on Mintzberg's logic structurally limited, capacity to anticipate genuine discontinuity.

The Automation–Augmentation Paradox in Forecasting

Krakowski, Luger, and Raisch (2023), extending resource-based theory to AI adoption through a controlled study of competitive chess, find that AI adoption triggers substitution and complementation dynamics operating simultaneously: certain traditional human competitive capabilities become obsolete even as new, persistent sources of advantage emerge from the specific way particular humans interact with AI systems. Applied to forecasting, this framework suggests that AI does not simply replace human forecasting judgement with algorithmic prediction; it changes what human judgement in forecasting actually consists of, shifting emphasis away from producing the numerical forecast itself and toward evaluating, contextualizing, and deciding how much weight a given AI-generated forecast should receive — precisely the judgement Mintzberg's framework suggests remains most needed exactly where AI-generated predictions are least reliable.

AI and Forecasting Accuracy

Evidence on Predictive Performance

The evidence that AI improves forecasting accuracy on well-specified, data-rich prediction tasks is now substantial. Ding et al. (2020) provide a directly relevant demonstration in an accounting-estimate context, finding machine-learning loss-reserve estimates outperforming reported managerial estimates in four of five insurance lines examined. Ahaggach, Abrouk, and Lebon (2024), systematically reviewing 516 studies on sales forecasting published between 2013 and 2023, find machine-learning and deep-learning approaches increasingly outperforming classical statistical forecasting methods across the reviewed literature, particularly in contexts involving complex, non-linear demand patterns that traditional time-series methods struggle to capture. This body of evidence supports a clear and well-grounded conclusion: for forecasting tasks characterized by rich historical data and reasonably stable underlying patterns, AI-based methods now represent the more accurate default choice relative to either classical statistical methods or unaided managerial judgement.

From Prediction Quality to Decision Quality

The critical theoretical move this paper makes is to separate this well-evidenced accuracy improvement from the question of whether it actually improves organizational decisions. Kim, Glaeser, Hillis, Kominers, and Luca (2024) supply the clearest available evidence on exactly this separation, though from outside the budgeting context specifically. Evaluating algorithms of varying sophistication in a municipal inspections setting, they find both algorithms delivered substantial, measurable prediction gains over the department's existing methods — yet these prediction gains did not translate into improved decisions, because the officials retaining override authority exercised that authority frequently, often citing considerations the algorithm had not been designed to capture, and the resulting decisions were, on average, no better than those made without algorithmic assistance. Applied to budgeting and forecasting, this finding carries a direct and sobering implication: an organization can adopt a demonstrably more accurate AI forecasting tool, exactly the kind Ding et al. (2020) and Ahaggach et al. (2024) document, and see no corresponding improvement in the budgets or strategic decisions that forecast is meant to inform, if the managers using that forecast are inclined to override it in ways unconnected to genuine additional information they possess.

This separation between prediction quality and decision quality gives Mintzberg's (1994) older critique renewed relevance. Mintzberg's concern was that formal planning systems conflate data-processing sophistication with genuine predictive insight; Kim et al.'s (2024) evidence demonstrates a related but distinct organizational failure mode, in which even genuinely superior data-processing sophistication fails to improve decisions because of how organizations structure the human override authority surrounding that sophistication. Both point toward the same conclusion this paper treats as central: forecasting accuracy is a property of the algorithm, but decision quality is a property of the organizational system within which that algorithm's output is used, and improving the first does not automatically improve the second.

AI and Budgeting Efficiency

Rolling Forecasts and Continuous Budgeting

A second, more straightforwardly positive contribution AI makes to budgeting concerns efficiency rather than accuracy — specifically, the cost and speed of producing and updating financial forecasts. Yoshioka and Ishii (2025) argue that generative AI combined with data-science techniques can support continuous, rather than periodic, forecasting and scenario analysis, directly addressing the staleness problem Hope and Fraser (2003) identify as central to traditional annual budgeting's dysfunction. Choi and Xie (2026), documenting AI adoption's effect inside real accounting workflows, find a 7.5-day reduction in monthly close time and a measurable reallocation of accountant time toward business communication and quality assurance — concrete evidence that AI-enabled processes can compress the time between when underlying data becomes available and when a corresponding forecast or budget update can be produced, addressing exactly the lag Hope and Fraser identify as undermining traditional budgeting's relevance.

Efficiency Gains and Their Limits

Zhang, Zhu, Dai, Wu, and Chen (2025), interviewing representatives from forty-one companies about AI adoption in managerial accounting, find institutional and individual factors both shaping whether these efficiency gains are actually realized in practice, rather than efficiency following automatically from the technology's technical capability. This finding is consistent with the pattern this paper has identified throughout: AI's capability to improve a specific input — in this case, the speed and cost of producing a forecast or budget update — does not automatically translate into the organizational outcome that capability is meant to serve, because organizational and individual-level conditions mediate the translation. Efficiency gains, on this account, are more reliably realized than accuracy-to-decision-quality gains, since efficiency is measured closer to the technology itself, but they remain conditional on organizational adoption factors rather than following mechanically from AI's technical capability.

AI and Strategic Planning

Scenario Analysis and Simulation

The most direct connection between AI and strategic planning, as opposed to routine budgeting, runs through scenario analysis and simulation capability. Yoshioka and Ishii (2025) position this capability as central to their proposed framework, arguing that generative AI can support the rapid development and comparison of alternative planning scenarios in a way traditional, manually constructed scenario planning could not match in speed or breadth. This capability speaks directly to one strand of Mintzberg's (1994) critique: he argues that strategic thinking requires synthesis across multiple possible futures rather than extrapolation from a single most-likely forecast, and AI-enabled scenario generation, in principle, expands an organization's capacity to construct and compare the range of alternative futures Mintzberg's framework treats as essential to genuine strategic thinking, rather than the single-point forecasts traditional budgeting processes have historically produced.

Reconciling Mintzberg's Critique with AI-Enabled Planning

Yet this reconciliation is only partial, and the limits are theoretically important. Mintzberg's (1994) deeper argument is not merely that planning should consider multiple scenarios rather than a single forecast; it is that the discontinuities most strategically consequential are, by their nature, not fully anticipatable through systematic analysis of any kind, however many scenarios that analysis generates, because genuine discontinuities are precisely the events that fall outside the pattern space historical data can represent. AI-generated scenarios, however numerous and however rapidly produced, remain constructed from historical data and the model's learned representation of how that data's patterns might vary — which means AI-enabled scenario planning expands the range of anticipatable futures an organization can efficiently consider, without necessarily addressing Mintzberg's more fundamental point about the limits of anticipation itself. Krakowski et al.'s (2023) substitution-complementation framework suggests the appropriate organizational response to this limit: AI should be expected to substitute for the labor-intensive work of constructing and comparing scenarios within the space of historically anticipatable variation, while the distinctly human contribution to strategic planning increasingly concentrates on exactly the kind of discontinuity-sensing and synthesis Mintzberg identifies as strategic thinking's essential and, on his account, fundamentally non-formalizable core.

Toward an Integrated Model: Accuracy, Efficiency and Strategic Value

Bringing the preceding sections together, this paper proposes that accuracy, efficiency and strategic value as related but analytically distinct outcomes of AI-enabled budgeting and forecasting, connected by conditions that are frequently left implicit in the applied literature. Accuracy improves reliably where forecasting tasks are data-rich and pattern-governed, as Ding et al. (2020) and Ahaggach et al. (2024) demonstrate, but this improvement is bounded by Mintzberg's (1994) fallacy-of-prediction critique: accuracy gains are concentrated precisely in the stable-pattern forecasting that matters least for genuinely strategic decisions. Efficiency improves where AI compresses the time and labor cost of producing and updating forecasts, as Choi and Xie (2026) and Yoshioka and Ishii (2025) document, but this improvement remains conditional on organizational adoption factors, per Zhang et al. (2025), rather than following automatically from technical capability. Strategic value, the outcome ultimately at stake in both Beyond Budgeting's critique of traditional practice and this paper's analysis of AI's contribution, depends on a further condition neither accuracy nor efficiency gains resolve on their own: whether the organization's decision-authority structure allows improved predictions to actually change what gets decided, the condition Kim et al.'s (2024) evidence shows is frequently absent even where genuine prediction gains exist.

This model has a specific implication for how Beyond Budgeting's original critique should be updated for the AI era. Hope and Fraser (2003) argued that traditional budgeting's problems stemmed substantially from its rigidity and staleness — problems AI-enabled forecasting is well positioned to address, per the efficiency evidence reviewed above. But this paper's model suggests a further, previously underappreciated problem: even a perfectly current, highly accurate, AI-generated forecast does not by itself solve the strategic-value problem, because Kim et al.'s (2024) evidence indicates organizations frequently fail to let improved predictions change decisions regardless of how current or accurate those predictions are. AI-enabled budgeting reform, on this account, needs to address decision-authority structure as directly as it addresses forecasting technology — a governance dimension the Beyond Budgeting literature, developed before AI-enabled forecasting existed, did not need to theorize in this specific form, but which this paper's synthesis suggests deserves equal billing with accuracy and efficiency in any complete account of AI's influence on budgeting and forecasting.

Implications for Practice

For organizations implementing AI-enabled forecasting, the model developed here suggests a specific and actionable distinction: evaluate accuracy and efficiency gains using the kind of benchmarking evidence Ding et al. (2020) and Ahaggach et al. (2024) demonstrate is now available, but evaluate strategic value separately, using evidence about how forecasts actually change subsequent decisions rather than assuming improved accuracy automatically implies improved decisions. Kim et al.'s (2024) finding that override behavior was the norm rather than the exception across the departments they examined suggests organizations should track override rates and reasons explicitly, treating a pattern of routine override without clear justification as a signal that the organization's decision-authority structure, not the forecasting technology, requires attention.

For strategic planning specifically, Mintzberg's (1994) enduring distinction between planning and strategic thinking suggests AI-generated scenarios should be positioned as an input to synthesis performed by people, rather than as a replacement for that synthesis. Organizations that treat AI-generated scenario output as itself constituting strategic planning, rather than as raw material for the distinctly human strategic thinking Mintzberg describes, risk reproducing at greater speed and scale the same fallacy of prediction Mintzberg identified in the formal planning systems of the 1960s and 1970s — a risk this paper's synthesis suggests is real precisely because AI's fluency and apparent comprehensiveness make it easier, not harder, to mistake sophisticated pattern-extrapolation for genuine anticipation of strategic discontinuity.

Directions for Future Research

Several gaps follow from the model developed above. First, Kim et al.’s (2024) override evidence comes from a public-sector sector inspections context rather than corporate budgeting specifically; research directly testing whether the same override pattern occurs when managers evaluate AI-generated budget or forecast recommendations would extend this paper's central claim into its actual domain of application.

Second, Ahaggach et al.'s (2024) review finds machine-learning forecasting methods outperforming classical approaches primarily in aggregate, cross-study terms; research examining specifically where the accuracy advantage narrows or disappears — which the Mintzberg-derived theory developed in this paper would predict occurs near genuine discontinuities — would test this paper's boundary-condition claim more directly than aggregate accuracy comparisons currently allow.

Third, the relationship this paper proposes between Beyond Budgeting's efficiency-oriented critique and this paper's decision-authority-oriented extension has not been tested empirically in combination; research examining organizations that have both adopted AI-enabled forecasting and redesigned decision-authority structures explicitly, relative to those that have adopted the technology alone, would test whether the combination this paper's model predicts is necessary for strategic value actually produces better outcomes than technology adoption alone.

Finally, Krakowski et al.'s (2023) substitution-complementation framework was developed in a competitive-game setting; research examining whether the same dynamic — human forecasting capability becoming simultaneously obsolete in some respects and newly valuable in others — characterizes the specific case of corporate financial forecasters as AI adoption proceeds would connect that framework more directly to the budgeting and forecasting context this paper address.

Conclusion

Artificial intelligence is demonstrably improving two of the three outcomes this paper has examined: the accuracy of financial forecasts, particularly for data-rich, pattern-governed prediction tasks, and the efficiency with which forecasts and budgets can be produced and updated. Both improvements speak directly to problems the Beyond Budgeting movement identified in traditional annual budgeting two decades before AI-enabled forecasting existed. Yet this paper has argued that these two improvements do not automatically deliver the third and ultimately more consequential outcome — improved strategic value — because strategic value depends on an organizational condition, the allocation and exercise of decision authority, that recent evidence shows is frequently unresolved even where genuine accuracy gains exist. Mintzberg's decades-old critique of formal strategic planning, read alongside this recent evidence, suggests the gap between accurate prediction and good strategic decisions is not a temporary implementation problem AI will eventually close as the technology matures, but a structural feature of the relationship between systematic prediction and genuine strategic thinking that organizations need to actively manage rather than expect the technology to resolve on its own.

The practical implication follows directly: organizations adopting AI-enabled budgeting and forecasting should evaluate that adoption along all three dimensions this paper distinguishes — accuracy, efficiency, and strategic value — rather than assuming that demonstrated gains on the first two dimensions imply corresponding gains on the third. **Better forecasts do not produce better strategy on their own; they produce better strategy only where organizations have also addressed who has the authority to act differently because of them**, and it is this governance question, more than any remaining question about forecasting-model sophistication, that this paper's synthesis suggests should occupy the center of both future research and organizational practice in this area.

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