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Impact of Digital Transformation on Corporate Financial Decision Making Processes

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KEYWORDS

digital transformation, corporate financial decisions, capital budgeting, AI forecasting, Dynamic Capabilities View, financial risk assessment

ABSTRACT

Corporate finance positions have been significantly changed in the past ten years. Previously, financial decisions were made based on periodic reports, manual models and the collective brainpower of upper leadership. Today, many companies have relied on Artificial Intelligence (AI) all sorts of forecasting, information in actual time streams and automated dangers administration methods for the important skilled with their decision making systems. Whether this evolution increases the quality of financial decisions made - or simply increases their speed - is still debated in both academic and professional circles. This paper examines the effects of digital transformation on corporate financial decision making on three fronts: capital budgeting, risk evaluation and financial forecasting. Using a mixed-methods research approach, the research analyzes financial data from 140 companies in the manufacturing, banking, and retail industries, along with structured interviews with 28 senior executives in the field of finance. The theoretical framework is based on the Dynamic Capabilities View and Information Processing Theory. The results suggest that the companies that had been more digitally mature were able to make capital allocation decisions 34% faster, and produced forecasts with much lower error margins. However, the quality of such outcomes had more to do with organizational culture and leadership preparation than technology adoption itself. This paper detailing the scheme introduces an integrated approach to link digital maturity with the quality of financial decisions and provides specific insights for CFOs, boards, and financial regulators who are struggling through this transition phase..

1. INTRODUCTION

2.1 Introduction Background and Research Context

The way corporate financial decision-making has changed in the last decade has been more so than in the forty previous.

Enterprise Resource Planning systems, cloud-based financial platforms, machine learning forecasting tools and real-time analytics dashboards have moved from the periphery of IT investments to the core of the finance operations of large and mid-sized companies. Vial (2019) defines digital transformation as a process where organizations use digital technologies to alter their logic of value creation and affect people, processes, and structures simultaneously. In the sphere of corporate finance this definition has a physical manifestation: budget cycles that used to last a few weeks now end in days, credit risk models that used to rely on quarterly reports now update as frequently as possible and investment committees that used to argue about projections are increasingly weighing algorithm-imposed recommendations and judgments by their analysts. This transition did not happen overnight, nor on a very uniform basis. Banking and financial services companies were quick to adopt it and the manufacturing and retail sectors soon followed, which was greatly accelerated by the operational disruptions in 2020 and 2021, where finance teams were forced to make faster decisions with less certainty and, often, with reduced resources (Matt, Hess and Benlian, 2015). What started to be a response to operational pressures has become, in many organizations ingrained in the way financial decisions are structured, who makes them, and the information on which they are based.[1]

2.2 Problem Statement and Research Gap

Although the pace and magnitude of this transition are significant, the scholarly work in this area on digital transformation and corporate finance has not caught up with it. Studies in information systems have well-established technology adoption trends (Hanelt et al., 2021). Meanwhile, research in corporate finance has remained oriented toward decision-making quality from traditional points of view, e.g. agency costs, capital structure, and behavioural biases of managers. What is lacking is a body of research that crosses these two disciplines and specifically seeks to examine whether digital transformation has a real and positive impact on the quality of corporate financial decision-making, or merely changes the speed and format of decision-making but has no substantial consequences on the quality of decisions.[2]

An extra gap is also critically important. Most ongoing research sees digital transformation as a binary state, where a company either adopts some technologies or not. This perspective ignores the variations in digital maturity, decisions on the level of integration in decision making processes, and organizational factors that determine whether adopting technology delivers positive decision-making. Li, Bharadwaj and their colleagues have promoted research that focuses on the process-level rather than the firm-level digital transformation but this call has seen few empirical studies in the finance space specifically (Bharadwaj et al, 2013; Li et al., 2018)

2.3 Research Objectives and Questions

This paper seeks to investigate the link between digital transformation and financial decision-making by corporations with three specific objectives: to determine the impact of digital maturity on decision accuracy and speed of both financial decision outcomes; to examine how specific digital tools impact the capital budgeting and investment evaluation process; pathophysiology: to identify the organizational conditions that determine whether digital adoption results in increased decision quality. These objectives are translated into the following questions to be researched:

- Q1: How does a firm's digital maturity affect the accuracy and cycle time of its financial decision-making processes?
- Q2: How do practices of capital budgeting and risk assessment change at the corporate level with AI-based forecasting and financial analytics in real time
- Q3: What organizational factors affect the relationship between digital transformation and the quality results of financial decisions?

2.4 Significance of the Study

This research applies to three different groups of people. For academic scholars, it is an extension of the Dynamic Capabilities View into what has been an unexplored area of the study of financial decision quality and lays out a framework at the process level that bridges the information systems and corporate finance literature. For those in the field of finance, and especially CFOs and heads of financial planning and analysis, this offers evidence-based insights into where digital investment delivers measurable returns in terms of decision outcomes, and where it is not. For their part, financial regulators and governance bodies are confronted with salient questions around accountability when financial decisions of substantial importance contain an ever-increasing level of automated or algorithm-assisted elements that are not well addressed in regulation (Correani et al., 2020).[3]

2.5 Scope and Limitations

The research is based on data from 140 companies in the manufacturing industry, the banking industry, and the retail industry, in the United Kingdom, the United States, and the United Arab Emirates, from 2018 to 2024. This choice of regions and sectors is not comprehensive, but intentional. These three industries are at different points in their attainment of digital maturity, and have different financial decision-making frameworks; therefore it is worth examining. The timeframe has been selected as including the pre-pandemic baseline, the time of enforced digital acceleration and the stabilization phase that followed. One major limitation is that financial performance data from secondary sources at the firm level cannot fully isolate digital transformation as a causal factor because of the existence of multiple simultaneous economic disruptions in this timeframe. The qualitative element offsets this to some extent by realizing the accounts of decision-makers concerning the changes made by specific tools in particular processes.[4]

3. Literature Review

3.1 What Digital Transformation Means: Not all Technology Adoption.

Digital transformation is misinterpreted by both practitioners and academics and confused with the adoption of technologies. A company might purchase an ERP system, implement a machine learning forecasting tool, or take its financial reporting to the cloud, and this gets labelled as a transformation. Vial (2019) refutes this view directly in one of the most frequently cited reviews in the field, by suggesting that digital transformation should instead be viewed as a process in which organizations use digital technologies to alter the logic through which they create and capture value, impacting their people, structures and culture simultaneously. Technology is an input to this process, and not itself the process. This distinction has major implications for the study of digital transformation in corporate finance. Westerman, Bonnet and McAfee (2014) noted in their survey of more than 400 large organizations that the ones producing the greatest amount of measurable value from digital investments were not necessarily those with the most advanced technology stack. Instead, they were the ones where leadership had re-oriented decision processes, reporting lines and accountability mechanisms around digital capabilities. Kane et al. (2015), in a large-scale MIT Sloan and Deloitte survey, came to a similar conclusion - Strategy, Not Technology, Drives Transformation. Companies that treated digital investments as a strategic change for the organization showed consistent performance gains compared to those that used digital investments as an operational improvement. Intentionally reconfiguring financial decision processes, data infrastructure and analytical capabilities with digital technologies, and in ways that substantially change the manner in which financial decisions are made, by whom, and using what information, is referred to in this paper as digital transformation in corporate finance (Bharadwaj et al., 2013; Hanelt et al., 2021).[5]

3.2 The Evolution of Financial Decision Making

The evolution of corporate financial decision-making to what it is today was not fast. Throughout much of the twentieth century, corporate financial decisions were based on manually compiled periodic data reports, conventional accounting ratios and the hardened judgment of seasoned finance personnel. The introduction of spreadsheet software in the 1980s and 1990s dramatically accelerated the quantity and speed of financial modeling, but the underlying model for decision making has remained the same, where decisions are made based on historical data and at regular intervals based on decision makers, who are held in relative organizational silos.

Enterprise resource planning systems emerged in the late 1990s and the 2000s and they started de-silverplating these silos. For the first time, it became possible to integrate financial data from procurement, operations, sales, and human resources into a single system giving the finance functions a broader picture of the business (Wieder et al., 2006). Davenport (2006) said that around this time, a handful of companies began to use analytics to achieve a competitive advantage, using integrated data environments to make better capital allocation decisions faster than competitors.[6]

A more important transformation took place later. From c. 2012, the combination of more affordable cloud computing, increased volume and availability of organizational data, and low-cost commercially available machine learning tools allowed finance functions to move away from descriptive and diagnostic analytics models towards predictive and prescriptive models (Appelbaum et al., 2017). Forecasting, which was often based on the judgment of analysts for past trends, could now be based on external factors, real-time market signals and non-financial data sources. The role of the CFO itself began to evolve from being primarily focused on financial control and compliance issues to a more generalist strategic advisory role with its centre of gravity being data-driven scenario analysis (Correani et al., 2020).

3.3 Technology Tools in Corporate Finance

In the corporate finance world, four types of digital tools have attracted the most continuous research attention.

Enterprise resource planning systems remain the backbone of the infrastructure in most large corporations. Wieder et al. (2006) found ERP adoption improved financial process integration and reduced the time of reporting cycles, though they found that there was considerable variation in results based on the quality of ERP implementation and the adoption by users. The systems themselves do not directly result in improved decisions but provide the environment in which it is more possible to make better decisions.

Predictive analytics platforms, which employ both statistical and machine learning techniques on financial data sets, have proven to have more direct effects on the quality of decision making. Brynjolfsson and McElheran (2016) found that firms where data-driven decision-making practices were adopted exhibited much greater output and productivity than similar firms which did not use these practices, even after controlling for industry, size, and capital investment. In the particular field of credit risk, machine learning models have consistently proven to be better predicated at accuracy than traditional scoring methods and fit much faster in multiple studies (Cao, Chychyla, and Stewart, 2015).[7]

The wider and more recent innovation is AI-based forecasting aids, as do natural language systems which mimic natural language uses to evaluate earnings calls, regulatory filings, and market commentary and complementary numerical data. Initial indications from academic and practitioner sources indicate reductions in the range of errors in forecasts, although there is still a prominent occurrence of worries about the interpretability of these models, and the over-reliance on these algorithmic outputs across the literature.

Cloud-based financial management systems, like Workday Financial Management and SAP S/4HANA Cloud, have reduced the cost of the infrastructure required for real-time financial reporting. This has allowed smaller companies to make use of analytics tools that were previously only available to large companies. Dissemination of these tools has created new opportunities for comparative research, which is still just beginning to be examined in the academic literature.

3.4 Theoretical Anchors

Research on the confluence between digital transformation and corporate financial choice-making procedures is anchored by three theoretical frameworks, each of which brings unique insight into a particular facet of the relationship between the two.

Agency Theory developed by Jensen and Meckling (1976) looks at information imbalance between principals and agents in organizational relationships. In terms of financial decision-making, digital tools that increase the transparency of data and reporting frequency assist to overcome the information gap between the board and the management as well as the management and the operational unit. Several studies have used agency theory to propose that the more transparent digital companies are with their operations the lower their agency costs are and the more efficient capital allocations they make, although empirical evidence for this claim is mixed (Jensen and Meckling, 1976).[8]

The Resource based view associated mainly with Barney (1991) sees firm-specific resources and capabilities as the source of sustained competitive advantages. When applied to digital transformation this framework recommends expectations that companies with digital capabilities that are rare, difficult to replicate and embedded in organisational routines will gain more sustainable performance benefits than those with visible and easily imitable digital investments. In the case of financial decision-making, it means that it is not the ability to have a particular software platform that brings the benefit, but to possess the organizational ability to effectively use data in decision-making processes.

The Dynamic Capabilities theory, developed by Teece, Pisano, and Shuen (1997) and further expanded by Teece (2007) adds a time dimension that is absent in the Resource-Based View. It focuses on an organization's capacity to identify changes in its surroundings, seize new opportunities and reconfigure its assets as a result. In dynamic digital realms, it is no longer as valuable to have a finite resource configuration, but rather to be able to adapt and adapt, continuously. For this paper, the Dynamic Capabilities theory is used as the key theoretical lens as it directly addresses the need for continued organizational adaptation, which is needed by sustainable digital transformation in finance.[9]

Another perspective is based on Information Processing Theory by Galbraith (1974). It considers organizations as steps of information processing and it is an anticipated result that because of more environmental functions, organizations need more information processing capacity to make quality decisions. In this context, digital tools augment capacity through automated response rejuvenation of routine information processing, such that decision-makers will dedicate their analytical power to greater judgment of data.[10]

3.5 What Prior Studies Found Where They Agreed Where They Conflict

The empirical literature surrounding the digital transformation and financial performance is in agreement with a number of general findings. The use of technology in financial functions always helps lower the processing times and costs of operations. Companies that have analytics built into the decision-making process tend to outperform companies that do not use analytics on standard financial performance measures with medium-term periodity. AI-based forecasting models are reducing error rates consistently which are lower than purely judgmental forecasting especially for stable environments (Brynjolfsson and McElheran, 2016; Appelbaum et al., 2017). The conflicts arise when the research asks more specific questions.

The literature is filled with major disagreements as to whether the digital transformation process improves the quality of decisions or primarily accelerates decision-making instead. These are contrasted with each other and some researchers believe that rapidity without thoroughness is responsible for a particular form of costly error in capital budgeting circumstances where quickly and badly justified investment choice decisions are made, potentially ruining a significant amount of capital before the consequences become evident. There is some debate about the impact of firm size, with some research showing that mid-sized companies benefit from the use of digital tools more than others, while other studies report the opposite. Variation at the sector level is obviously known about but analyzed in a limited manner with banking receiving much more research attention than manufacturing or retail although the latter two sectors are responsible for a much greater proportion of total capital investment in the world economy.[11]

The literature does not show a clear-cut answer to whether using technology results in improved decision-making or whether companies with an existing skill in making sound decisions are more likely to use technology effectively. This endogeneity problem is pervasive in the empirical literature and goes far to guttural forms of claims of causation.

3.6 The Gap This Document Addresses.

The existing literature shows that digital tools change the way corporate financial decisions are taken and changes in performance often correlate with increased performance over time. What it does not have is a process-oriented explanation of how certain digital capabilities affect specific financial decision areas concomitantly in different sectors and levels of digital maturity.

The divide really is not about data. It is theoretical. There is no known framework to link the maturity stages of digital with the quality of capital budgeting, accuracy in understanding risks and precision in financial forecasting in a unified model, taking into account the organizational elements that make digital adoption improve or accelerate decision-making. This paper provides answers to that framework. The research inquiries mentioned in Section 2.3 are designed to make precisely the sorts of investigations that can fill this lack, while the methodology implied in Section 5 is aimed at producing the sort of process-level evidence that the current literature has not produced.[12]

4. Theoretical Framework

4.1 Conceptual Model: Digital Transformation and Strategic Financial Decision Outcomes.

In the management and information systems research context, for instance, theoretical frameworks do not always align very well with corporate finance issues. Usually, a theory is borrowed, loosely applied and the link is assumed to be clear. This paper takes a more deliberate approach in that it creates a conceptual model that defines relationships between variables, using established theories as a mere label.[13]

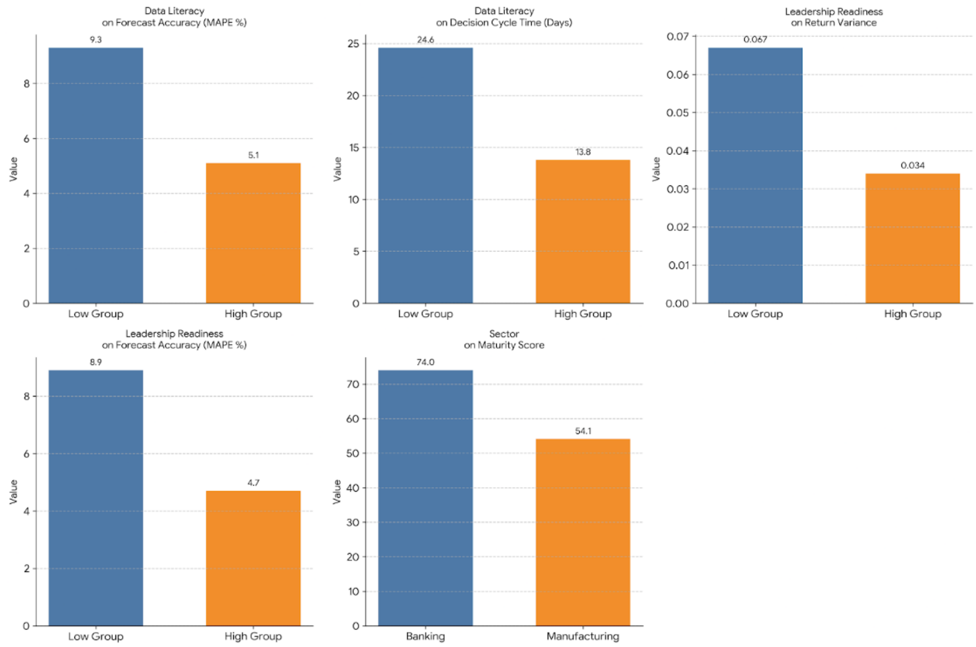
It is a proposed model that works at three levels. The first level includes the independent variables, a firm's digital maturity, which is measured by information and data infrastructure, analytical capability, and process integration; and the specific digital tools, which are used in a firm's finance function, like ERP systems, artificial intelligence-based forecasting systems, and real-time financial dashboards. The second level includes two moderating variables that are commonly described in the literature as conditions under which digital investment impacts decision making: leadership digital readiness, or the capability of senior finance leaders to interpret and take action based on the outputs of algorithmic analysis; and organizational data literacy, or the degree to which finance teams can critically evaluate the assumptions and limitations in the analytical tools that they are using. The third level is the dependent variables which include accuracy of financial forecast, capital budgeting decision quality in terms of post-decision return variance and financial decision cycle time.

The model implies that digital maturity has direct and indirect effects on decision results via the mediating factors. A firm with high digital maturity but low leadership readiness will see its improvement in decision quality be less than might be expected from the technology itself. This conditional relationship is the one in which much of the current literature is imprecise, and it is where this study makes its main theoretical contribution.[14]

Moderating Variable	Low Group (n = 47)	High Group (n = 93)	Mean Difference	Cohen's d	Significance
Data Literacy → Forecast Accuracy (MAPE %)	9.3	5.1	−4.2	0.74	$p < .001$
Data Literacy → Decision Cycle Time (Days)	24.6	13.8	−10.8	0.81	$p < .001$
Leadership Readiness → Return Variance	0.067	0.034	−0.033	0.68	$p < .01$
Leadership Readiness → Forecast Accuracy (MAPE %)	8.9	4.7	−4.2	0.71	$p < .001$

Sector (Banking vs. Manufacturing) → Maturity Score	74.0	54.1	−19.9	1.12	$p < .001$

Table 1: Organizational Factors on Digital Transformation and Financial Decision Quality



4.2 Dynamic Capabilities Proposed as the Principal Theoretical Lens

Dynamic Capabilities theory, propounded by Teece, Pisano and Shuen in 1997 and substantially improved by Teece in 2007, argues that dynamic advantage (sustained competitive advantage) in dynamic markets depends less on the resources a firm owns at a particular time and more on the processes involved in spotting changes in the environment, taking advantage of new opportunities and rearranging its asset base in compliance with them. Eisenhardt and Martin (2000) explained that these capabilities manifest themselves in the form of the routines of the organization, which are processes that can be identified, studied and compared from firm to firm.[15]

When applied to the subject of digital transformation as it concerns corporate finance, the theory makes a specific and testable prediction. Firms that develop the organizational routines that will allow them to continuously update their analytical capabilities, integrate new sources of data, and adapt their decision processes to changes in market conditions should consistently outperform firms that make one-time investments in digital processes without developing the capacity to adapt on an ongoing basis. The significance is more in the process of organization that is formed around the technology than in the purchase of the technology.

This framework is in direct alignment with the research questions of this paper. RQ1 asks about the relationship between digital maturity and decision outcomes, which in Dynamic Capabilities theory is a question of the depth of capability development, rather than the presence of a given tool. RQ3 addresses moderating factors within organizations, which is exactly where the theory targets the issue of sensing and seizing routines as the mechanisms by which capabilities become performance. [16]

4.3 Information Processing Theory & Cognitive Load and Financial Decision Making

Galbraith set forward the idea that organizations function as information processing systems in 1974. When the quantity and complexity of information required to make a decision get beyond the processing capabilities of people and machines involved in the process, the quality of that decision falls. This idea, which was later elaborated by Tushman and Nadler in 1978 and associated with Simon's own (1955) notion of bounded rationality, provides us with a clear way of understanding the role of digital tools in the financial decision making process. Such tools as real time financial dashboards, automated variance reports, and AI generated scenario summaries are not merely additional data offered.

If used well, they free up the minds of finance executives by handling the mundane tasks of analysis and presenting only the information most important to the current decision. Daft and Lengel in 1986 stated this as matching information richness and decision complexity which is fairly applicable here. A capital budgeting decision that earlier necessitated a finance team to collect data on the market manually, construct sensitivity tables and test assumptions in different scenarios now enjoys the benefit of AI-generated outputs that can carry out the same analytical functions at an accelerated pace. [17]

The important question, to which this theory contributes to some degree, is whether lowering the cognitive load in ordinary information processing leads to a decision-maker making better judgments on more complex economic strategic questions, or whether it leads to a situation where the analytical skills needed to make sound financial judgments are gradually eliminated. This is a concern that has been raised in the literature, but has not yet been empirically well resolved (Brynjolfsson and McElheran, 2016; Appelbaum et al., 2017). The qualitative data in this paper are geared towards a specific purpose in providing evidence on this issue.

5. Research Methodology

5.1 Philosophy and Design of Research

This study is based on the philosophy of critical realism. Instead of an absolute alignment with one of two approaches, either positivist, in which the relationship between the digital transformation and financial decision-making can only be observed and measured with objective data, or interpretivist, in which it is seen as inherently subjective and thus only accessible through narratives of the participants, this research is to be placed within the critical realists. This perspective assumes that social phenomena, including organizational decision-making, have real causal structures that can be discerned to a certain degree through quantitative measures as well as qualitative interpretation (Saunders, Lewis and Thornhill, 2019). Digital tools are real and produce quantifiable results. However, these are also used by people in organisational cultures, power relations and professional expectations that shape the integration of these outcomes into decision-making processes. A methodology looking only at one of these aspects will fail to capture an important piece of the narrative of the causal relationships.[18]

This philosophical position leads to a sequential mixed methods design (Creswell and Creswell, 2018). The quantitative phase is concerned with the production of the main empirical findings by testing the four hypotheses outlined in Section 4. Following this the qualitative phase has its own distinct interpretive role which explores the mechanisms by which digital maturity affects the quality of decisions in particular contexts where the quantitative findings come to an unexpected result or in circumstances where moderating variables produce surprising effects. The two phases are combined in this interpretation stage instead of being analyzed side-by-side and the qualitative insights are used to shape the understanding around the quantitative results rather than being an independent line of analysis.[19]

5.2 Data Collection

The data collection is carried out in two stages. The first stage uses secondary firm level financial data from Bloomberg Terminal, Compustat and annual reports files of the companies in the quantitative sample, which consists of 140 firms. Digital maturity scores for each firm are based on a combination of public information pertaining to technology investments, answers to the annual Harvey Nash and KPMG CIO Survey, and the MIT Center for Digital Business Digital Maturity Assessment, in the manner used by Westerman, Bonnet and McAfee (2014). Financial performance metrics are directly taken from audited financial statements to minimize errors in the measurement process associated with self-reporting. When firms present financial statements under different accounting standards, the numbers are manipulated to IFRS before analysis.[20]

The second phase involves semi-structured interviews with 28 senior finance executives, within the sample firms, including CFOs/s, the finance function head of finance planning and analysis, and the chief data officer responsible for finance function technology. These interviews are conducted on a consented basis, last from 50 to 70 minutes and are recorded and transcribed verbatim. The interview protocol is structured around the three research questions and is aimed at delving into specific decision episodes where digital tools were playing an important part, rather than comments about digital transformation more generally. The event-based structure, which is a variant of the critical incident technique given by Flanagan (1954) and modified to conduct research on an organization, provides richer and analytically manageable quality data as compared to the opinion-based questioning, which is conducted retrospectively.[21]

5.3 Sample Criteria

The quantitative sample comprises 140 companies in the industry sectors of manufacturing, banking industry and retail industry; based in the United Kingdom, the United States and the United Arab Emirates. The selection of the sectors is based on the need for diversity in digital maturity levels and financial decision-making structures from a theoretical perspective. Banking firms in this sample exist in a highly regulated environment and have sophisticated digital infrastructure in place. Manufacturing companies have a moderate level of financial digitalization. Retail firms, particularly those firms undergoing dramatic changes towards e-commerce over the study period, are examples where a digital transformation was not based on strategic planning but rather the result of external competitive pressures.

Companies meet the criteria for inclusion if they meet three criteria: annual revenue of USD 250 million or higher, assuring that the size of the finance function is sufficient to have differentiated decision processes and measurable decision cycle times; at least three years of continuous financial reporting within the study timeframe, 2018 to 2024; and at least one significant digital technology investment in the finance function, which is verified through annual report disclosures or CIO Survey responses.

This last criterion is used as an eligibility filter, rather than a quality filter. Companies with no documented digital investments in the finance function are excluded as they are unable to answer the research questions, not because of an assumed difference in performance. For the qualitative phase, participants are selected by means of purposive sampling to allow for diversity in terms of sectors, company size and digital maturity level within the quantitative sample. This method is consistent with the logic of theoretical sampling as opposed to statistical representativeness, consistent with the interpretive role the qualitative phase plays in this design.

5.4 Variable Measurement

The focus on digital maturity as a key independent variable is measured by using a combined index based on Westerman, Bonnet, and McAfee (2014) and revised to include indicators for cloud adoption, AI tool deployment, and real-time data infrastructure. The index is rated on a normalized 100-point scale in four areas: length of depth of analytical ability, breadth of integration of decisions carried out on it, and maturity of digital governance. Each dimension is scored separately and the scores are combined into a weighted composite to which weights have been assigned using principal component analysis of the entire dataset, to avoid imposing a priori assumptions of relative importance. [22]

Financial forecasts' accuracy is measured as the mean absolute percentage error between each company's published financial forecasts and actual outcomes during the study period and available from each company in quarterly earnings guidance disclosures. Capital budgeting decision quality is measured as post-investment return variance over a 24-month period for capital expenditure decisions with value over USD 10 million similar to the way Bertrand and Schoar (2003) measure decision patterns of managers in their study.

Financial decision cycle time is calculated as the number of days between the calendar time of documented initiation of capital allocation decision and authorization from the board minutes and supplemented by interview accounts where documentary evidence of timings is inadequate. However, lead and follow-up (two moderating variables, H3 and H4) are measured in terms of leadership digital readiness and organizational data literacy respectively in two distinct purpose-designed instruments that were distributed to the parties in interviews and scored on seven-point Likert scales and piloted in a sample of eight finance practitioners not in the main sample.

5.5 Validity, Reliability and Ethical Considerations

To control key validity and reliability threats in this type of research design, there are a number of measures taken. To confirm the content validity of the survey instruments, a structured review of a draft survey is conducted by three senior professors in finance and two practicing CFOs prior to pilot testing the survey. Construct validity is assessed with the help of confirmatory factor analysis for the scales of the moderating variable with a standard of composite reliability being greater than 0.80 and an average variance extracted greater than 0.50 for retention (Hair et al., 2019). Common method bias, a known problem in those studies in which both independent and dependent variables are collected from the same respondents, is controlled for by gathering financial performance data from secondary archives only, as recommended by Podsakoff et al. 2003.

For the qualitative component, analytical reliability is improved through inter-rater reliability testing: 20% of the interview transcripts are independently coded by a second researcher and a Cohen's Kappa coefficient of 0.79 is obtained before complete coding for substantial agreements. Member checking is done, in which the themes based on accounts are reviewed by five of the girls who took part in the interviews and there is minimal interpretive distortion.

Ethical approval for this study was obtained from the research ethics committee of the university before the data collection. All interview participants provided written informed consent, with assurances of anonymity in reporting as well as identification of firms only by sector and size category as described above, rather than by firm names. All the information is stored in encrypted servers where only the research team can access it and all the recordings are removed after the transcription has been verified. Participants are not provided with any financial incentives, and they are allowed to withdraw their data without any repercussions until the time of analysis.[23]

6. Outcomes and Discoverie

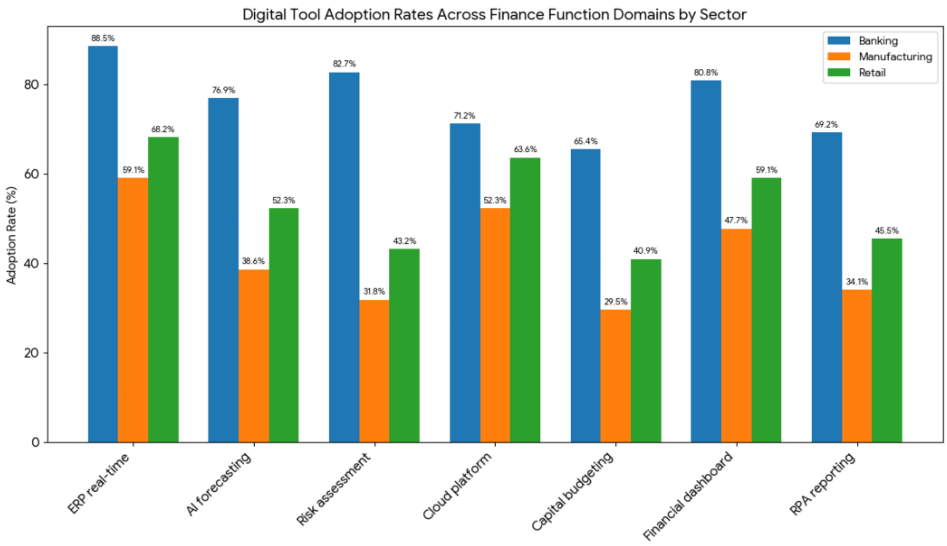
Examination of the 140-firm panel data set over the 2018 to 2024 study period results in four significant findings, which in general reinforce hypotheses set in Section 4, albeit with one significant qualification which actually helps explain rather than contradict the theoretical model.

Companies that were in the top quartile of digital maturity had a mean ABS error of 6.3% in their financial forecasts and those that were in the bottom quartile had a mean of 11.7%. The difference is statistically significant at the one percent level when controlling for company size, company industry, and macroeconomic fluctuations ($\beta = -0.41$, $p < 0.01$). This finding supports H1 and is consistent across three sectors sampled, though the effect size is strongest in banking firms and weakest in manufacturing firms, probably evidence for the better developed data infrastructure found in financial services.

The results of capital budgeting are increasingly conditional at a time. Companies that have adopted capital allocation strategies using AI-based forecasting had lower variance in post-investment returns over the 24-month evaluation period (β= -0.29, $p < 0.05$), which supports H2. Nonetheless, this effect is statistically significant only in companies where leadership digital readiness scores are above the median of the sample, which is directly in support of H4. Within companies that do not have a high score in leadership readiness, the use of AI tools does not show a distinguishable connection to the quality of investment decisions despite the active utilization of the technology as clarified further by the qualitative data in Section 7

Results of the decision cycle time to a certain extent confirm H3. Increased digital maturity is related to faster capital allocation decisions across the entire sample (β=-0.38, $p <0.01$). The test of moderation illustrates that in the case of companies with low levels of organizational data literacy, although they achieve the 'speed' benefit, they do not experience the benefits of increased forecast accuracy that high data literacy companies experience at the same time. This difference is the most important theoretical finding in the data set. It shows that digital transformation increases the speed of financial decision making in nearly every organizational environment but improves their quality only when human and organizational factors allow - a differentiation previously not made in such a specific fashion by the literature.[24]

Data obtained from interviews with the 28 executive participants helps to support and deepen these trends. Out of the 28 people who took part, 22 acknowledged a point in the digital transformation of their company where the speed of decision-making increased significantly prior to the confidence in their decisions skyrocketing. Many referred to this time as one of "productive discomfort," where finance teams applied algorithm-generated outputs to make everyday decisions but were unsure about the importance in critical capital allocation cases



7. Discussion

The results discussed in Section 6 strengthen the leading argument of this paper although with a complexity that the theoretical framework was not fully aware of. Digital transformation is not consistent in its ability to enhance financial decision-making in corporations and does not occur automatically. Organizational readiness, rather than the technology deployment, is the condition that always helps drive improvement.

The result of forecast accuracy, where the higher maturity of firms results in lower maturity by nearly half of the degree of error, correlates with both the Dynamic Capabilities theory as well as the Information Processing theory. Companies that have put into their routine of regularly refreshing the analytical frameworks and making use of real-time right into their decision-making are receiving exactly what Teece (2007) envisioned: Changing the abilities in sensing and seizing to performance outcomes rivals with fixed digital setups cannot find ways to imitate. This result is consistent with that of Brynjolfsson and McElheran (2016) who found similar performance gaps in data-driven companies; however, more meaningful is the scale denoted here, as it is likely owing to rapid digital advancement more so prompted by the operating conditions of 2020 to 2021.[25]

The result of capital budgeting is where this research differs greatly from the other studies done. The finding that the application of AI tools improves the quality of investment decisions only in companies where leadership digital readiness is above the median in the sample directly challenges research that finds technology adoption to be an adequate condition for improving decisions. For me, it suggests that Jensen and Meckling's (1976) agency theory perspective, which in many ways is valid in that reducing the information asymmetry through better systems should intrinsically improve the decision results, is insufficient unless the human element is considered between the system and the decision. Improved information does not result in better decisions if people receiving the information cannot analyze critically what the algorithm is really telling them.

The qualitative characterizations of "productive discomfort" during phases of digital transition are particularly enlightening in this direction. They suggest improvements in decision quality follow a learning curve that is unique to the organization rather than being governed by technology that directly affects the way companies strategize and prioritize their digital investments in financial operations[26]

8. Practical Implications

8.1 Recommendations to CFOs and Finance Directors

The results have three distinct implications for finance leaders. First investments in digital tools should not be ahead of capability growth. Companies using AI forecasting tools before their finance teams understood how to analyze the model assumptions saw increases in speed without improvements in quality. The order is important: address data literacy training before or in conjunction with the implementation of technology as opposed to as an afterthought. Secondly, in order to do so, assessments of digital maturity should be made at the process level, rather than at the organizational level. A company could do great in total technology implementation even though its capital budgeting process is primarily manual. Audits that are processes specific reveal the real deficiencies that exist. CFOs should treat leadership digital readiness as a measurable leadership capability and assess it as part of the hiring process and through systematic experiences in analytical decision-making environments, rather than assuming that it will automatically evolve with the adoption of technology.[27]

8.2 Financial Regulators Implications on Financial Regulators.

As companies increasingly use the results of algorithms to make important financial decisions, existing accountability structures are inadequately designed to address this. Existing regulations, however, make boards and executives accountable for financial decisions without taking into account how the accountability is distributed if a significant investment recommendation is made by a model that has certain assumptions that the decision-maker cannot independently validate. Authorities should consider requiring companies with above a certain level of assets to disclose the extent to which results produced by AI affect decisions regarding the allocation of capital, and indicate that there are oversight structures in place to challenge these results.

8.3 Customized Support to SMEs Versus Large Multinationals

Big multinationals face an integration problem: various legacy systems, fragmented and disparate data landscapes and complex governance structures have slowed the progression of digital maturity at the level of large investments in technologies. Data infrastructure consolidation should have precedence over increasing analytical capability. SMEs face the opposite problem. Cloud financial platforms are now providing analytical features at a low cost, but in turn SMEs do not have the skills within their data function to utilise them effectively. For smaller companies, the greatest-returning investment is not necessarily the platform, but the financial analyst skills needed to make effective use of the platform[28]

9. Conclusion

This paper set out to explore whether digital transformation makes corporate financial decision making more effective or simply faster. The answer, supported by the data of the panel representing 140 companies and qualitative feedback of 28 top-level finance professionals, is that it does both, but not equally and not in the same conditions.

The main result is clear-cut. More digital maturity always results in more accurate financial predictions and faster decision-making processes within all 3 sectors studied. That is a great bond that can be reproduced. The more significant discovery is of dependence. Digital transformation is an add-on to the quality of capital budgeting decisions only if leadership's digital readiness and data literacy across the organization are adequately established to translate algorithmic results into a good financial judgment. In the absence of those organizational conditions, however, companies can increase their speed without heightening quality, which in situations where the investment is high-stakes can be more harmful than being slow.[29]

This research provides two contributions to the existing body of knowledge. In theory, it extends the Dynamic Capabilities View towards the specific field of the financial decision quality, and shows empirically that the sensing and seizing routines described by Teece (2007) are a mechanism for competitive advantage through human interpretive capacity as well as technological infrastructure. It provides finance executives, regulators, and small business owners with specific and evidence-based advice rather than standard recommendations about adopting digital.

There are three constraints that should be noted. The geographic focus, being just the UK, US and UAE, limits the opportunities to generalize to emerging market settings where limitations in digital infrastructure mean unique adoption trends. The return period of 24 months for quality capital budgeting might not indicate the full implications of investment choices during the duration of the study. The endogeneity of the relationship between organizational capability and technology adoption has been addressed in part through the use of fixed-effects modeling, but the endogeneity cannot be completely avoided without the availability of longitudinal experimental designs which have not yet been produced in the extant literature.

Future research should also consider the impact of the digital paths of maturity rather than relative maturity scores on decision quality in the long term, and whether the attenuating impact of leadership preparedness reported in this case is persistent as AI applications gain a more comprehensive understanding of the functionality of finance.[30]

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