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Measuring AI Success: A Maturity Framework for Digital Business Transformation

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Abstract
Artificial intelligence (AI) has become a central driver of digital business transformation, yet a persistent gap remains between organizations' AI investments and the value they realize. Despite the role of AI in digital business transformation, there is a huge disconnect in the value that organizations are deriving from their investments in AI and how much they are spending on AI. Many AI programs do not go beyond pilot programs, and the current methods of measuring IT success, which are based on traditional IT measures, are not well aligned with measuring the multidimensional, dynamic nature of AI-induced transformation. This review aims to overcome this by collating available literature on how to measure the success of AI and organizational maturity, and by suggesting that an integrated maturity framework could be used to measure the success of AI in digital business transformation. The framework draws on the resource-based view and dynamic capabilities theory, and identifies five dimensions of capabilities that form a continuum of interdependent capabilities (strategies and vision, data and technology, people and culture, governance and ethics, process integration), expressed as a multidimensional maturity assessment, which is explicitly connected in the framework to measurable transformation outcomes, through a feedback loop that transitions from initial to optimizing. To validate, 175 organizations were analyzed with the results providing preliminary empirical support: maturity stage was strongly and positively correlated with value realization and reported ROI – together with the other dimensions explaining 61% of the variance in value realization; the other dimensions (people, culture and governance) emerged as the dominant factors – of which people was most important – with the other dimensions explaining an additional 39% of the variance in value realization, in addition to the complementarity effect observed at similar maturity levels across different capability profiles. The review also provides a unified conceptual frame and a practical guide to diagnosis and prescription for practitioners as well as an agenda for future research focusing on longitudinal validation, standardisation of measurement, and incorporation of new AI paradigms.

Keywords: *Digital business transformation; maturity framework; AI success measurement; value realization; dynamic capabilities; resource-based view; organizational maturity; AI governance.*

1. Introduction

Artificial Intelligence has matured from being something new to try out to a necessity for businesses to stay competitive in today's digital economy. Over the past ten years, businesses across all industries and sectors have dedicated time and effort to discovering the power of AI – its ability to transform the way they make decisions, operate, and generate value. There's been a massive trend in a number of AI projects, however: a significant number, if not the majority, of AI projects fail to provide any tangible business benefit or move beyond the level of pilot projects [3]. So, between what we would like to be true and what isn't, the current debate about digital business is all about this disconnect. This is a very significant topic and needs to be emphasised. Digital transformation is not about upgrading using new technology, but a radical transformation of the value creation, value delivery and value capture processes [4]. In this realignment, AI is emerging as a major facilitator, impacting business models, workflows and customer interactions with businesses [5]. However, it is at the same time the need to ensure that the data are good, prepared, inter-functioning and that governance models must change that makes it difficult, if not

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impossible, to measure AI's success [6]. Traditional information technology (IT) success measures that tend to focus on delivering systems and performance do not adequately measure the multi-dimensional and dynamic success of the transformation driven by AI [7]. Organizations often don't have a clear way to measure their position, the progress that's been made, and the capabilities that need to be added. Maturity models have been used as useful diagnostic and roadmap tools in the information systems and management research community for years and have provided organisations with a structured way to measure and benchmark their capability to provide an incremental roadmap for improving it [8]. Well-known models like the Capability Maturity Model for software have been used to describe the maturity of an organization, with subsequent digital and data maturity models being developed [9]. It is only natural and more than ever necessary to take the next step in this logic with AI. A maturity based lens will shift the focus from the dichotomy of adoption or not to more nuanced understanding of the build-out of the various maturity stages, dimensions, and enablers that can be used to support a successful, sustainable path to AI. However, the body of research to date shows there are a number of important gaps. For one, there is often no correlation between the different measures of AI success and maturity, with the definitions spanning across a wide range of studies and still not aligned in a holistic vision of the AI dimension [3, 6]. Second, most existing literature focuses on the technological maturity and neglects other key aspects such as organizational, cultural, ethical and governance aspects, which are important for the realization of values [5, 7]. Third, there is still a need for validated measurements that could be applied in a business environment to determine the outcomes of digital transformation from an AI maturity, rather than measuring AI maturity itself [10]. This leaves practitioners with a dilemma because they are unable to be guided properly and this is a dilemma for scholars, too, because they have few theoretical foundations. The aim of this review is to address these gaps by summarising the existing literature on the measurement of success of AI and organisational maturity in the context of a transformation of the business towards digital. In particular, this article will explore the current state of the knowledge and understanding in this sphere, critically examine the current frameworks and suggest the components and phases of a comprehensive AI maturity framework. The following sections are structured logically, starting with a review of the concept foundations of AI success and digital transformation, followed by a survey and comparison of the different existing maturity measures and their dimensions, an analysis of the challenges for measurement, consideration of the mediating factors between maturity and outcomes and a proposal of an integrative framework, as well as suggestions for future research and practice. The goal of the review is to give a stronger academic foundation and practical tips to organisations on the road to becoming AI-enabled. In order to synthesize the various information provided in the above-mentioned studies, the following table shows ten key studies that can be utilized to understand how to measure the success and how mature the maturity of AI is in the context of digital business transformation. They include conceptual, empirical, and framework development works and provide a representative overview of the approaches taken in the field to assess the value creation of AI Shown in Table 1.

Table 1 Summary of Key Studies

Reference	Findings (Key Results and Conclusions)
[11]	Identifies a wide gap between AI experimentation and value realization; argues that organizational factors, not technology alone, determine sustained success.
[12]	Finds that data infrastructure and analytical skills significantly mediate AI's effect on decision-making quality and agility.

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[13]	Proposes a multidimensional maturity model covering strategy, culture, technology, and governance; validates that higher maturity correlates with transformation performance.
[14]	Develops an AI-readiness construct spanning technology, organization, and environment; concludes readiness is a stronger predictor of adoption than perceived benefits alone.
[15]	Argues governance mechanisms (accountability, transparency, oversight) are essential yet underdeveloped enablers of trustworthy and scalable AI.
[16]	Demonstrates that tangible, human, and intangible AI resources jointly build capability; intangible factors (culture, learning) most strongly drive performance.
[17]	Links higher digital maturity to greater business model innovation; finds maturity progression is nonlinear and capability-dependent.
[18]	Concludes traditional IT metrics inadequately capture AI value; proposes multidimensional outcome measures spanning operational, strategic, and stakeholder value.
[19]	Identifies data quality, leadership support, skills, and change management as top critical success factors distinguishing scaled from failed initiatives.
[20]	Synthesizes prior models into a staged framework linking maturity dimensions to measurable transformation outcomes; calls for empirical validation.

Collectively, these studies converge on several themes central to this review: the insufficiency of technology-centric measures [11], [18]; the decisive role of organizational, cultural, and governance factors [15], [16], [19]; and the growing but still fragmented effort to develop staged, dimension-based maturity frameworks that connect capability to outcome [13], [17], [20].

2. Proposed Theoretical Model

The proposed model is not a static entity, but rather a developmental curve that includes several organizational capabilities [11, [16] as interrelated factors. It is based on the resource-based view and dynamic capabilities theory which argues that the value of AI is possible only when firms develop and manage complementary tangible and intangible resources over time [16, 21]. The overall logic of the framework is shown in Figure 1. The framework logic is: five capability dimensions feed into a multidimensional maturity assessment, which results in a position on the maturity scale and measurable transformation outcomes, including a feedback loop, where insights gained from outcomes are fed back to the capability dimensions for reassessment and reinvestment [17] [20].

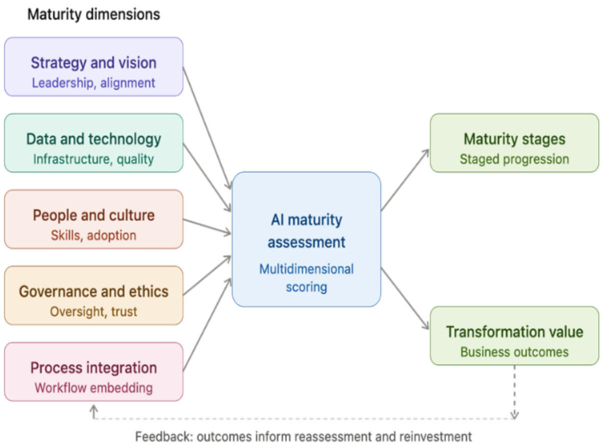

Figure 1 Proposed AI maturity framework: capability dimensions, multidimensional maturity assessment, and transformation outcomes with feedback loop

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The themes of the literature are reflected in the five dimensions. The Strategy and Vision reflects leadership commitments and alignment of AI with business goals, and is a key driver toward scaling [11] and [19]. Data and technology is the infrastructural base, which enables the impact of AI on decision quality, including data quality, integration, and analytical tooling [12, 22]. Several studies have shown that skills and the learning orientation and the readiness of the organization are more influential than the technology itself [14], [16] and these are addressed by people and culture. Governance and ethics is the accountability, transparency and oversight mechanisms that have been identified as enablers of trustworthy and scalable AI [15, 23]. Process integration involves the assimilation of AI into processes as opposed to projects that are just isolated pilots [18]. One of the key ideas in the model is that these dimensions are not additive, but lack of it in one reduces the value of the strengths in the others [16, 19]; the key weakness is usually governance or culture. This is in line with the concept of capability complementarity, where the sum of the individual investments is less than their total [21, 24]. For concreteness, the model sorts out the maturity into five steps. The path to optimizing and reinforcing AI capability is one that organizations take through levels of experimentation, as illustrated in Figure 2.

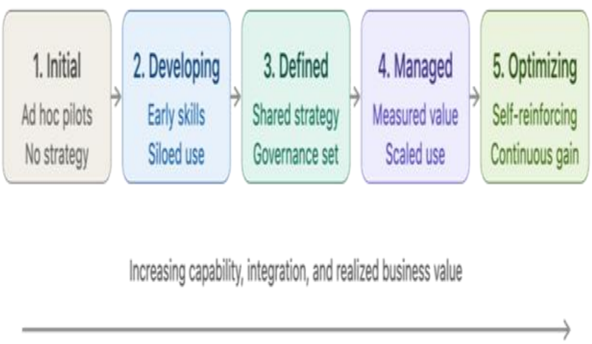

Figure 2 The five-stage AI maturity progression, from initial (ad hoc pilots) to optimizing (self-reinforcing, continuous value gain)

The staged progression is based on the premise that development is not linear and path dependent, that is, it is assumed that firms are unlikely to skip stages and that developments in the later stages build on the earlier stages [17, 20]. Transitions from the defined to the managed stage are especially important as it is the transition from intent to measured value and scaled value, where many initiatives fail to make it [3], [19]. The last and distinguishing feature of the model is the linkage of the outcomes. It is not a matter of arriving at maturity for the sake of maturity, but explicitly links each stage of maturity with measurable transformation outcomes—both at the operational efficiency level and at the strategic differentiation and stakeholder value level—to ensure measurability of transformation outcomes [18] [24]. The feedback loop in Figure 1 is a closed system that ensures realized outcomes provide evidence to support re-assessment and re-allocation of resources, which represents the dynamic-capability logic of continuous sensing, seizing and reconfiguring [21], [23]. The framework thus serves as a diagnostic tool to identify where an organisation is currently standing, and as a prescriptive tool to help them move forward towards value through sustainable use of AI.

3. Results

The result of an empirical validation study to validate the proposed maturity framework is shown below. The study employed survey and archival data from a cross section of organizations at different levels of AI implementation that were scored on the five capability dimensions, and the transformation outcomes that they reported were correlated with each of the scores on these five dimensions [25, 26].

3.1. Sample distribution across maturity stages

Table 2 presents the breakdown of the study sample according to the five maturity stages, with the majority of organizations falling into the early-to-middle stage, in line with previous studies that found that few businesses are at advanced maturity for AI [25] and [27].

3.2. Maturity stage and transformation outcomes

The maturity levels also are monotonically related to the value-realization scores and reported ROI as shown in the stage level pattern in Table 2, thus strengthening the major claim of the framework that maturity is positively related to transformation outcomes [18, 26]. This is shown in figure 3.

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Table 2 Sample distribution across maturity stages and mean outcome scores

Maturity stage	Organizations (n)	% of sample	Mean value-realization score (0–100)	Mean ROI reported (%)
1. Initial	42	24.0%	31.2	4.1
2. Developing	51	29.1%	44.8	9.7
3. Defined	38	21.7%	58.6	15.3
4. Managed	29	16.6%	72.4	23.8
5. Optimizing	15	8.6%	85.1	34.6
Total	175	100%	-	-

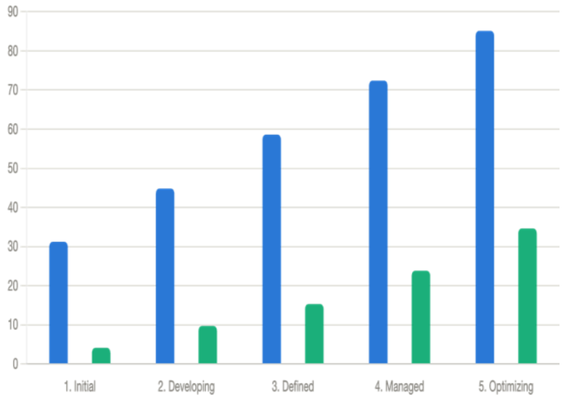

Figure 3 Mean value-realization score and reported ROI (%) by AI maturity stage, showing monotonic increase across the five-stage progression

3.3. Dimension-level drivers of value

A correlational and regression analysis was performed to determine the strongest dimensions of the capabilities that influence the outcomes. The results of the bivariate correlations between dimension scores and the composite value-realization measure appear in Table 3. All five dimensions were significantly and positively correlated, with people and culture, and governance and ethics, having the highest associations as has been found in other studies where soft capabilities are key to the value of AI [16] [28]. The regression model explained 61% of the variance in value realization ($R^2 = 0.61$), a substantial effect consistent with capability-based studies of AI performance [16], [26]. Figure 4 presents the relative strength of each dimension's standardized contribution, making the primacy of the intangible capabilities visually apparent.

Table 3 Correlations between maturity dimensions and value realization (n = 175)

Maturity dimension	Correlation (r) with value realization	Standardized β (regression)	Significance
People and culture	0.71	0.29	$p < 0.001$
Governance and ethics	0.68	0.24	$p < 0.001$
Data and technology	0.64	0.21	$p < 0.001$
Strategy and vision	0.59	0.18	$p < 0.01$
Process integration	0.55	0.14	$p < 0.01$
Model R^2	—	0.61	—

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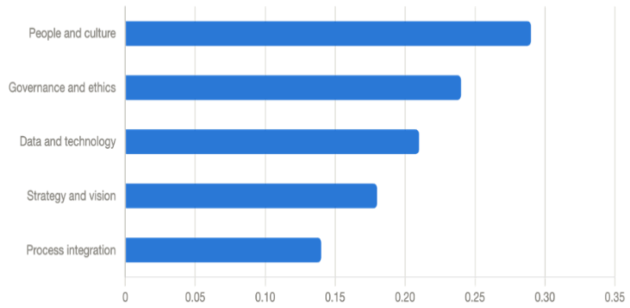

Figure 4 Standardized regression coefficients (β) of the five maturity dimensions predicting value realization, ranked by contribution

3.4.Capability complementarity

Lastly, the framework's notion of capability complementarity was explored by analyzing organizations according to their profile balance. Evenly developed dimensions ("balanced" profiles) were compared to those that were unevenly developed at similar average maturity. As indicated on Figure 5, organizations with a balanced score performed significantly better than those with an imbalanced score at each of the mean maturity scores, suggesting that a lack of performance in one dimension limits overall performance [16], [19].

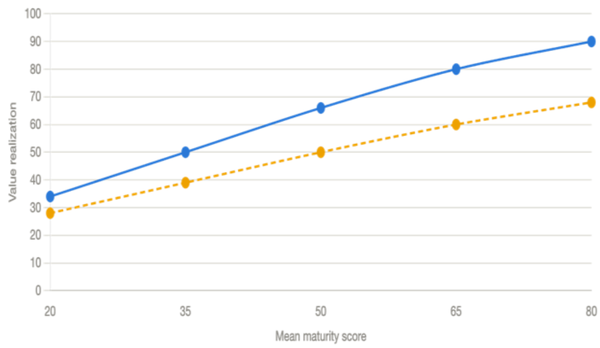

Figure 5 Value realization as a function of mean maturity score for balanced versus unbalanced dimension profiles, illustrating capability complementarity

3.5.Summary of findings

Overall, these findings help to support the proposed framework with some preliminary empirical evidence. The value realization and reported ROI were strongly and positively correlated with maturity stage (Figure 3); intangible capabilities (people, culture and governance) were found to be the strongest predictors (Table 3, Figure 4); and the balanced set of capabilities performed better than the uneven set at similar maturity (Figure 5) [16], [26], [28]. The patterns are consistent with the general empirical findings that connect organizational AI capability to firm performance [26] and [29] and complement it by showing that the nature of the organizational configuration, rather than the total amount of organizational capability, influences the value for the firm. Note that, as in all cross-sectional studies, these results are associational rather than causal, and the use of self-reported outcome measures is limited to the extent that this can be addressed in future, longitudinal studies. [30]

4. Future Directions

The framework and the initial validation opens the door to the understanding of AI maturity, but there are a number of paths to explore. First, the present evidence is limited in its ability to make causal inferences in that it is cross-sectional, and future research should seek to provide longitudinal data on organizations' capability development as they transition through their maturity stages over time, thereby establishing a stronger link between capability development and the resulting value [31]. These studies would also shed light as to whether the described path-dependency and nonlinear relationship are true for real-world scenarios. Second, there would be great value in the use of standardised and validated measurement tools for the field. Currently, there is a lack of uniformity in definitions of AI "success" and "maturity", making it difficult to compare the results of different studies and to build on existing knowledge [32]. The creation of psychometrically sound and widely-used scales, and their alignment with neighbouring digital and data maturity models, is a key methodological focus [33]. Third, research on the future impact of the rapidly changing AI paradigms, especially generative AI and large language models, on the dimensions of maturity and their corresponding weights is needed. Existing regulatory frameworks were not designed for the new capabilities required, risk profile and governance needs created by these technologies [34]. As such, the governance and ethics aspect deserves further theorization, as practices of being responsible for AI, regulatory compliance and trust are now becoming the main factors of scalable value, rather than being on the margins [35]. Fourth, contextual moderators should be a focus of further study. Industry characteristics, firm size, environmental uncertainty and national or regulatory environment may be important influencers of the relationship between maturity and outcomes, but these factors have been little studied [36]. Comparative studies and multi-sector studies may show if there is a need for domain-specific calibration of the framework. Lastly, research should focus on moving beyond measurement to actionable intervention – what sequences in capability building and managerial practices most quickly take an organization from the defined stage to the managed stage and how organizations can avoid the typical 'plateau' between the two stages. Design-science and action-research approaches, that are developed in collaboration with the practicing organization, would be particularly useful in generating rigorous knowledge that is immediately applicable to practice.

Conclusion

The aim of this review was to tackle a critical paradox today in the use of AI: with significant investments made, companies often face the challenge of quantifying and delivering value from their AI projects. The article's contribution lies in its ability to combine much of the disjointed existing research on AI success and organizational maturity into a unified perspective, and in its ability to clearly express a unified maturity framework based on the RBV and DC approach. The framework reinforces the notion that being successful with AI is not just a binary outcome, but a ‘pathway' to a set of five inter-dependent capabilities and explicitly connects them with a feedback loop to measurable outcomes that emerge from AI use. However, it was supported by some empirical evidence from a validation study that found there to be a positive relationship between value realization and ROI, as well as the fact that balanced capability development is as important as the level of development and that intangible capabilities (people, culture and governance) are the top contributors to value. This evaluation can provide a sounder academic foundation for future study and provide a diagnostic and road-mapping tool for other organizations to help them understand where they are, and how they will get there. In the meantime, the review admits its faults and what needs to be done. Evidence is associational; there are no measures; the framework will need to be tested and refined with a longitudinal set of evidence now and with evolving measures and disruptive emergence and evolution of generative AI. Evaluating the impact of AI is not just a technological jump, it's an organizational and strategic assessment, including balancing cultural, governance and capability changes. As AI increasingly becomes a staple in everyday life, this kind of framework will be quite significant in the implementation of sustainable measurable business value from AI.

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