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From Algorithmic Capital to Algorithmic Management: A Theory of Algorithmic Management Emergence

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Abstract:

This study explains how algorithmic management emerges within organizations by developing the Algorithmic Management Emergence Theory (AMET) and conceptualizing algorithmic capability as a multidimensional mediator linking algorithmic capital to managerial practice under specific governance conditions. Methodologically, the study adopts a conceptual, framework-based theory-building approach and synthesizes literature grounded in the resource-based view, intellectual capital theory, the SECI model, and scholarship on algorithmic management and governance. The analysis draws primarily on peer-reviewed studies published between 2019 and 2026, supplemented by seminal theoretical contributions. The findings suggest that algorithmic management should be understood not merely as a technological system adopted by organizations, but as an emergent organizational capability enacted through computational artifacts. The study identifies algorithmic capability as the key mechanism through which algorithmic capital is transformed into managerial practice and introduces the Algorithmic Capital-to-Management Framework (ACMF) to explain the micro-level formation of this capability. At the macro level, AMET specifies causal and moderating relationships among algorithmic capital, algorithmic capability, governance conditions, and algorithmic management through five theoretical propositions. The study contributes by shifting attention from the operation and consequences of algorithmic management toward its organizational antecedents and emergence mechanisms. Future research should empirically validate the proposed constructs and relationships and examine their implications for governance, organizational performance, competitive advantage, and ethical outcomes.

Keywords: algorithmic management; algorithmic capital; algorithmic capability; emergence; computational agency; conceptual theory building.

1. Introduction

The locus of competitive advantage has gradually shifted over the past decades towards knowledge-based and other intangible resources, taking the place of tangible ones (Benlian et al., 2022; Josan & Alpopi, 2024). With the accelerating pace of digital transformation and the integration of artificial intelligence into organizational routines, a new type of intelligent asset has emerged. This category is a collection of data, algorithmic models, computing infrastructure, and autonomous systems that can generate knowledge, aid decision-making, and, in a few instances, implement decisions. These resources are no longer just technical means, but they are also becoming strategic organizational resources capable of redefining how things are organized, observed, and managed in daily operations (Keegan & Meijerink, 2025).

However, the fact that they have intelligent assets does not mean that they are effectively utilized within organizations. There is a disjuncture between having resources in the form of algorithms and the actual application of algorithmically mediated managerial practices. The phenomenon of algorithmic management has been studied extensively in the past, with studies addressing the mechanisms of control and platform work, worker surveillance, and algorithmic decision-making (Baiocco et al., 2022; Andonova, 2019; Bowdler et al., 2025; Wood et al., 2019; Duggan et al., 2020). The more logical prior question: what is algorithmic management about in the first place? is comparatively little researched. Though numerous studies explain how algorithmic management works and affects individuals and processes, they do not clarify the origin of the same in the organizations or how it is formed.

To fill this gap, the current study changes the analysis focus from a logic of direct transformation to a logic of emergence by mediation. It is believed that algorithmic management does not come as a direct offshoot of algorithmic assets. Instead, with the right conditions of governance, algorithmic capital can trigger a multidimensional algorithmic capability, and it is this capability that can bring about algorithmic management as an organizational practice. This stance is in line with the core idea of the resource-based view, which believes that organizational performance is not created by the mere presence of resources but the ability created out of these resources (Barney, 1991; Teece, 2007).

In this respect, the research is aimed at answering the following main research question: How does algorithmic management arise from algorithmic capital? To answer this question, the study further discusses how algorithmic capital governance emerges, the nature and dimensionality of algorithmic capability as a mediating construct, and the theoretical limits of the proposed explanation for the organizational outcomes.

Five objectives are aimed at in the study. First, it develops a clear theory, the Algorithmic Management Emergence Theory (AMET), to address how algorithmic management emerges out of its organizational origin. Second, it theorizes algorithmic capability as a multidimensional mediating construct and defines its four dimensions. Third, it rebrands the Algorithmic Capital-to-Management Framework (ACMF) as an internal account of the formation of capabilities as opposed to a rival theory. Fourth, it obtains a collection of conceptually based propositions that reveal the distinction between causal pathways and moderation impacts. Fifth, it outlines the limitations of the theory, explains the location of the performance outcomes, and outlines the ethical and governance implications of algorithmic management.

This paper is a conceptual paper methodologically, as it does not provide empirical testing to develop its theory but rather builds up on the existing literature. It combines the understanding of the resource-based view, intellectual capital theory, the SECI model of knowledge creation, and the literature on algorithmic management and governance following a framework-based theory-building approach (Jaakkola, 2020; Whetten, 1989). The resultant theory is purposely constrained at the emergent level; the issues of organizational performance and competitive advantage are approached as the empirical consequences to be studied as opposed to theoretical requirements.

The research adds value to the literature in three aspects. First, it moves the focus of algorithmic management as a managerial practice to the conditions in an organization that create it. Second, it adds an algorithmic capability as the unaccounted factor between algorithmic resources and managerial practice. Third, it establishes a multilevel theoretical framework that separates a macro-level causal structure and a micro-level operational mechanism, thus providing a more detailed explanation of how algorithmic management is a phenomenon that occurs in organizations.

2. Theoretical Foundations

2.1. Intelligent Assets and Algorithmic Capital

Intelligent assets are digital objects based on information, algorithms, and machine-learning capabilities that can create knowledge and make or assist with decisions semi-autonomously (Simić & Stojković, 2024). Recent scholarship identifies them as new classes of resources that add value to creation (González et al., 2025). The definition of algorithmic capital is operational; that is, it is the stock of intelligent assets endowed with computational agency possessed by an organization coupled with the organizational capabilities necessary to transform them into value.

Theory building involves the justification of the choice of terminology, not just its adoption. Digital capital is too general, consisting of passive, immobile digital properties that are inert but hold value.

AI capital is simultaneously more specific and more ambiguous, anchoring the concept to a specific, rapidly outmoded technology and suggesting that value lies in the model itself as opposed to the organizational ability to implement it. The nature of the phenomenon being studied can be best characterized as the so-called "algorithmic capital": an asset based on an executable, learning procedural logic, regardless of the carrier technology. As the unit of analysis in this case is the algorithm as an organizational actor, the algorithmic term is the most specific and the most robust to technological change, and it is also the term where the critical algorithmic-management literature gathers.

The whole analysis is based on the property of a computational agency that makes the algorithmic asset stand out amongst other intangibles (Wusono et al., 2025).

This definition is related to three streams of theory. The former is the broader social sense of agency theory (Kadolkar et al., 2024), which views agency as a distributed ability to generate effects, but not necessarily a uniquely human ability; the algorithmic asset is thus bestowed with a delegated agency by designers and organizations. The second is sociomateriality (Zhang & Zhengwei, 2025), which denies the distinction between the social and the technical. Consistent with the more general traditions of actor-network and distributed agency, sociomateriality assumes that the action of organizations is the result of an entanglement of people and technologies in one practice. In this perspective, agency is a consequence arising from a web of human and non-human actors and not a property of any actor. The algorithm thus does not exist in isolation but exists as a part of the sociotechnical assemblage where agency is shared between the user, the model, and the data and is renegotiated with each change of configuration. The third literature is the human-AI interaction literature (Liu et al., 2024), which looks at how the decision-making process is transformed when the system becomes a partner, as opposed to an instrument, and questions trust, transparency, explainability, and delegation limits. Based on this, algorithmic capital is identified as a separate form of asset, as the traditional structural assets are still at the zero point of this gradient (Sfetcu, 2024; Yang, 2025; Stark and Vanden Broeck, 2024).

2.2. The Resource-Based View (RBV)

The Resource-Based View (RBV) offers a reference point in terms of how to frame algorithmic capital as a strategic organizational resource. In RBV, valuable, rare, inimitable, and non-substitutable resources help organizations to gain competitive advantage (Barney, 1991). RBV, however, does not, in itself, clarify how resources are converted into organizational behavior. This gap is filled by the dynamic capabilities perspective, which believes that value is not stored in resources but in the capabilities of the organization that mobilize, rearrange, and create new ones over time (Helfat et al., 2007; Woodcock, 2024). This capability-based reasoning has lately been applied to AI-enabled organizations in the form of the Organizational AI Capability concept, which elucidates how organizations convert AI resources into superior organizational capabilities (Abuhaimed, 2026c).

2.3. Intellectual Capital Theory

Intellectual Capital Theory offers a systematic approach to categorizing intangible organizational resources into human, structural, and relational capital (Edvinsson and Malone, 1997). Human capital is individual expertise, structural capital is codified systems and processes, and relational capital is external networks and relationships. In this context, algorithmic capital can be placed in the first place as a type of developed structural capital that combines information, computational infrastructure, and machine learning models. Nevertheless, the conventional methods of intellectual capital are constrained by the fact that they are based on fixed accounting representations that tend to miss the dynamic and responsive aspects of intangible assets (Noponen, 2025). This drawback is especially typical of algorithmic capital, which is dynamic and somewhat autonomous due to the process of constant learning and adaptation (Jarrahi et al., 2021).

2.4. The Knowledge-Conversion Model (SECI)

The SECI model describes knowledge creation as an endless cycle of transformation between tacit and explicit knowledge through four stages: socialization, externalization, combination, and internalization (Nonaka and Takeuchi, 1995). This model is used in an analogical way in order to explain how the algorithmic systems are involved in knowledge transformation in the organizations. The tacit human know-how may be externalized and coded into computational models along with structured data and finally incorporated into algorithmic capital. The outcome is a recursive trend whereby knowledge is constantly revised and updated in a two-way communication between human and algorithmic agents. Recent research contributes to the utility of SECI in digital environments where AI systems facilitate such knowledge channels (Mufti et al., 2026).

2.5. Algorithmic Management and Governance

The term "algorithmic management" is used to describe the application of computer-programmed processes to the organization of labor inputs in organizational contexts, especially platform-based ones where actors are not directly ordered, contracted, or networked (Szajczyk, 2026; Möhlmann et al., 2021). Such coordination changes managerial control to be based on human discretion rather than

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computational systems that organize, assess, and distribute work (Lee et al., 2015). The concept of critical scholarship, especially the idea of surveillance capitalism (Mittelman, 2022), emphasizes the logic behind data mining and stalking in order to maximize profits. Empirical studies have shown that organizations have mostly implemented algorithmic systems in a control-based fashion, thus neglecting their opportunities for augmentation and empowerment (Röttgen et al., 2024). Governance, in this regard, serves as a boundary condition, which is influenced by the new AI regulatory frameworks that focus on responsible deployment, transparency, and accountability (Röttgen et al., 2024). This theoretical gap encourages the emergence of the Algorithmic Management Emergence Theory (AMET), which describes how controlled algorithmic capital is converted to organizational capabilities and, furthermore, algorithmic management practices.

According to Abuhaimed (2026b), the shift towards algorithmic management is a more significant change in organizational design, in which digitally enabled structures, AI-based processes, and business engineering concepts redefine the way managerial activities are structured and performed. Although this view describes how organizations are changing in the digital landscape, it fails to describe the organizational process by which the very concept of algorithmic management comes into existence.

2.6. Grounding the Concept of "Emergence"

Due to the name of the theory (emergence) and its supporting role, its definition needs to be defined to prevent its informal meaning. The term is used in its narrow meaning in the context of the multilevel organizational theory (Kozlowski and Klein, 2000): a phenomenon is emergent when it is created by lower-level factors (assets, processes, interactions) and then exhibits itself (through interaction and composition) as a higher-level phenomenon whose characteristics cannot be reduced to those of its components.

Here, emergence in AMET is not a causal precedence between two variables but an upward compositional process at two levels: lower-level elements (the components of algorithmic capital and the processes of the ACMF mechanism) interact and compose to form algorithmic capability, where algorithmic management then emerges as an organization-level practice. The model, therefore, involves two consecutive emergences and not one: the emergence of algorithmic capability is the critical mediating moment in the chain, and the emergence of algorithmic management, which is taken up by both the title of the paper and the name of the theory, is the explained end (Mufti et al., 2026; Schmid & Wiesche, 2026).

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Table 1. Theoretical Positioning of AMET Relative to Prior Literature

Study	Primary Focus	Gap: Why Emergence Remains Unexplained	AMET Contribution
Kellogg et al. (2020)	Algorithmic management as managerial control	Treats control as already in place, leaving its organizational origin unexplained	Explains how algorithmic management emerges within organizations
Duggan et al. (2020)	Algorithmic management in platform work	Examines labor and HR consequences, not the asset base from which the practice arises	Identifies algorithmic capital as the generative organizational asset
Meijerink & Bondarouk (2023)	Governance and HR perspectives	Specifies governance but not the capability through which emergence occurs	Introduces algorithmic capability as the mediating mechanism
Stark & Vanden Broeck (2024)	Principles of algorithmic management	Normative and principle-based; offers no causal account of how the practice emerges	Develops a causal explanatory theory of emergence
AMET (Present Study)	Organizational emergence of algorithmic management	Addresses the identified emergence gap	Explains the transformation from algorithmic capital to algorithmic management through governance-enabled algorithmic capability

Table 1 illustrates the theoretical placement of AMET relative to prior literature. Unlike past research that has mainly focused on the operation, governance, or the impact of algorithmic management, AMET describes the emergence of algorithmic management by referring to algorithmic capital as the generative asset, algorithmic capability as the mediating mechanism, and governance as the enabling condition.

3. Methodological Positioning:

The current paper takes a conceptual theory-building approach as opposed to an empirical research design; the paper does not test any hypotheses using primary data. It tries to build in a theoretically sound way an explanation of the creation of algorithmic management in organizations. In line with the traditional strategies of conceptual scholarship (Jaakkola, 2020; Whetten, 1989), the research is based on the systematic analysis and synthesis of the literature on the topic to construct a consistent explanatory framework and derive propositions that can then be tested in empirical studies.

The study material will be the literature that is relevant to algorithmic assets, organizational capabilities, artificial intelligence, governance, knowledge creation, and algorithmic management. It was found in the literature of Scopus, Web of Science, ScienceDirect, SpringerLink, Wiley Online Library, and Google Scholar with a mixture of keywords such as algorithmic management, algorithmic capital, AI capability, algorithmic governance, and computational agency. The preference was made for peer-reviewed articles published in 2019-2026, along with seminal theoretical articles that were critical in the development of theories. The literature was chosen purposely based on three main criteria: relevance to the research problem in terms of concept, theoretical power in the field of its development, and input into the comprehension of the connections between the main constructs of the study. Classical papers were given preference as well as recent papers that are indicative of the current trends in artificial intelligence and algorithmic governance. The inclusion criteria were that the sources had to be peer-reviewed and conceptually relevant to at least one of the main constructs of the study, whereas the exclusion criteria were non-scholar sources, discussion of algorithmic systems, and duplication of more substantial contributions, which were already included in the corpus. The theory-building framework approach was deemed more suitable than either a systematic literature review or a scoping review, as the aim of the study is theory construction, not evidence synthesis, and, thus, the PRISMA protocol was not used (Snyder, 2019; Torraco, 2016).

The analytical process entailed the identification, comparison, and synthesis of concepts, constructs, and causal relationships in the literature that was selected. The emphasis was particularly placed on the spheres of convergence and divergence between the theoretical streams, and the aim was to create a self-sufficient explanation of a phenomenon that was being studied.

The result of such a methodological approach is the creation of the Algorithmic Management Emergence Theory (AMET), along with its conceptual model and propositions. Since the research paper is theory-building research, operationalization of constructs, scale development, and empirical testing are deliberately postponed to later research.

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4. Development of the Algorithmic Management Emergence Theory (AMET)

Here, the Algorithmic Management Emergence Theory (AMET), which is the main theoretical contribution of the research, is formed. It is beneficial to explain the relationship of the concepts presented in the paper to the reader to orient them, as the paper presents a number of concepts. This is the only theory that is being promoted, AMET; the other concepts are not separate contributions, but components of AMET. The generative asset is called algorithmic capital; the property that makes the generative asset stand out is called computational agency; the construct that bridges the two is called algorithmic capability; and the internal mechanism that enables the formation of the capability is the ACMF. They are all there to help a single explanatory claim on how algorithmic management comes about. Continuing the work of the previous literature review, AMET elaborates how algorithmic management comes into being based on its organizational origin.

4.1. Core Assumptions of AMET:

Similar to any explanatory theory, AMET is based on a series of underlying assumptions establishing its area of applicability and the logic behind it.

To start with, the theory presupposes distributed agency. Organizational action is not considered purely human but can be delegated in part to algorithmic assets with computational agency. This agency is on a spectrum between decision support and autonomous decision-making (Kadolkar et al., 2024; Liu et al., 2024).

Second, the theory presupposes the primacy of resources. Algorithms' capabilities do not come into existence but are a result of existing algorithmic capital. This means that without a stock of algorithmic assets, there is no possibility of an algorithmic capability (Simić & Stojković, 2024).

Third, the theory is based on upward composition. The phenomena at the organization level are the result of interaction and aggregation of the lower-level phenomena. Both algorithmic capability and algorithmic management can thus be seen as emergent phenomena that are caused by underlying assets, processes, and interactions (Rilinger, 2024; Zhang & Zhengwei, 2025).

Fourth, the theory presupposes the conditionality of governance. The establishment of a credible and effective algorithmic capability lies in the regulation of algorithmic resources before their implementation. Lack of governance undermines the quality of the ensuing capability (Bowdler et al., 2025; Stark and Vanden Broeck, 2024).

Lastly, the theory presupposes non-determinism of outcomes. The advent of algorithmic management does not always mean better organizational performance or competitive advantage.

The results are also always conditional on circumstances and governance and thus are empirical questions that are not within the scope of explanation of the theory (Woodcock, 2024; Noponen, 2025).

4.2. Theory Statement and Scope:

An organizational causal chain that starts with algorithmic capital as the generative asset, is mediated by governance, leads to the rise of algorithmic capability as a multidimensional mediating construct, and culminates in the emergence of algorithmic management as an organizational practice gives rise to algorithmic management (Rilinger, 2024; González et al., 2025).

In AMET, algorithmic management is a theoretical conceptualization of an emergent organizational managerial practice, as opposed to a technological artifact, software application, or set of algorithms. The theory does not support a direct relationship between assets and practice. Rather, it states that algorithmic assets have a latent potential only. They can only be felt in their organizational impacts when transformed into a capability that can coordinate, interpret, deploy, and continuously enhance algorithmic resources. The ability to create algorithms thus acts as the explanatory variable that links the ownership of algorithmic resources to the development of algorithmic managerial practices (Jarrahi et al., 2021; Wusono et al., 2025; Uğurlu Kara, 2026).

Clarification of Governance Constructs.

In AMET, the conceptualization of governance takes place at two levels of analysis. The term "algorithmic capital governance" is used to describe the management of algorithmic assets, such as data, models, agents, and learning infrastructure, in a way that they are of quality, have integrity, are accountable, and are capable of forming capabilities (Abuhaimed, 2026a). In comparison, good governance is the wider organizational governance context, which is transparent, has oversight, is accountable, and is ethically controlled. The former is an antecedent that influences the formation of capabilities, and the latter is a moderator that operates within contexts and that affects the intensity and the quality of emergence.

4.3. Algorithmic Capability as a Multidimensional Construct

One of the key contributions of AMET is the introduction of the mediating construct, algorithmic capability, between algorithmic capital and algorithmic management. The latest theoretical literature proposed "organizational AI capability" as the organizational ability to create and implement AI resources to create organizational value (Abuhaimed, 2026c). In its development, algorithmic capability will be understood here as a particular higher-order capability that is particularly interested in how agency-bearing algorithmic assets can be converted into coordinated managerial practice as opposed to AI deployment itself.

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The notion is founded on a long history of research on capability. The previous literature proposed IT capability, then big-data analytics capability, and AI capability (Gupta & George, 2016; Rai et al., 2019) as the ability of the organization to transform technological resources into value-creating processes (Simić & Stojković, 2024; González et al., 2025). The emergence of algorithmic management is, however, justified in a separate construct since what is theoretically at stake in the current labels is not reflected in the current labels. The capability of AI is bound to a specific and rapidly developing technological family and is generally focused on predictive or analytical value instead of coordination of work, so it tells us little about how computational systems develop to have managerial roles like assigning, overseeing, and assessing labor.

Table 2. Algorithmic Capability Dimensions and Their Correspondence with Algorithmic Capital Components

Algorithmic Capital Component	Capability Dimension	Description
Data	Data Capability	Ability to collect, govern, prepare, and utilize data for decision-making
Models	Model Capability	Ability to develop, train, evaluate, and deploy algorithmic models
Agents	Agent Capability	Ability to operate, coordinate, and supervise autonomous agents
Learning Infrastructure	Learning Capability	Ability to continuously improve through feedback and learning processes

The dimensions are calculated based on a principle of structural correspondence between the elements of algorithmic capital and the abilities needed to bring them to life. This correspondence enables the mediating process to be defined in a more specific way and also lays a basis for future empirical measurement.

Table 3. Algorithmic Capability Compared with Adjacent Capability Constructs

Capability Construct	Primary Focus and Value Orientation	What It Leaves Unaddressed for Algorithmic Management
AI Capability	Organizational capacity to deploy AI technologies,	Linked with a quickly changing technological family; geared towards prediction and not to the coordination of

	typically for predictive or analytical value.	work. How systems come to allocate, monitor, and evaluate labor is not specified.
Analytics / Big Data Capability	Capacity to extract insight from data to inform human decision-making.	Thinks of the system as an aid to decision-making by managers, rather than as an agent performing managerial roles. Checks at point of insight, before managerial coordination.
Digital Capability	Broad capacity to use digital assets that store or transmit value.	Includes inert assets that do nothing and dilutes computation agency, the very fact that algorithmic management can be possible.
Algorithmic Capability (AMET)	Capacity to convert agency-bearing algorithmic assets into coordinated managerial practice.	Located very clearly in the area of computational agency and managerial coordination; it is this particular construct that mediates the appearance of algorithmic management.

As Table 3 shows, the neighboring constructs fall short of the property the algorithmic management needs. AI and analytics capability will shift computational systems towards prediction and insight that are used to make human decisions, whereas digital capability is extended to non-acting assets.

4.4 ACMF as the Internal Mechanism of Capability Formation

Although AMET clarifies the reasons why algorithmic management arises, the Algorithmic Capital-to-Management Framework (ACMF) clarifies how the algorithmic capability develops in the organization. The current research consequently relegates ACMF as an in-house explanatory approach as opposed to a competing theory. It plays the role of opening the black box between algorithmic capital and algorithmic capability by defining the mechanisms by which algorithmic resources are converted to organizational capability.

The mechanism comprises four stages that are interrelated:

1. Background: The organization gathers and concentrates its algorithmic capital: data, models, agents, and learning infrastructure, and forms the asset base out of which capability can be constructed.

2. Codification: Tacit knowledge and organizational know-how are externalized and coded into models, rules, and structured data, and the dispersed knowledge is converted into computational form over which algorithmic systems can act.
3. Activation: Codified resources are implemented in operational procedures, and algorithmic systems start to organize, observe, and support the choices, transforming latent assets into operational organizational power.
4. Governance: There are governance systems, accountability, and feedback that govern deployed systems that keep the balance between control and empowerment to ensure that the resulting capability is reliable, transparent, and ethically viable.

4.5. The AMET Conceptual Model

Figure 1: Conceptual Architecture of the Algorithmic Management Emergence Theory (AMET)

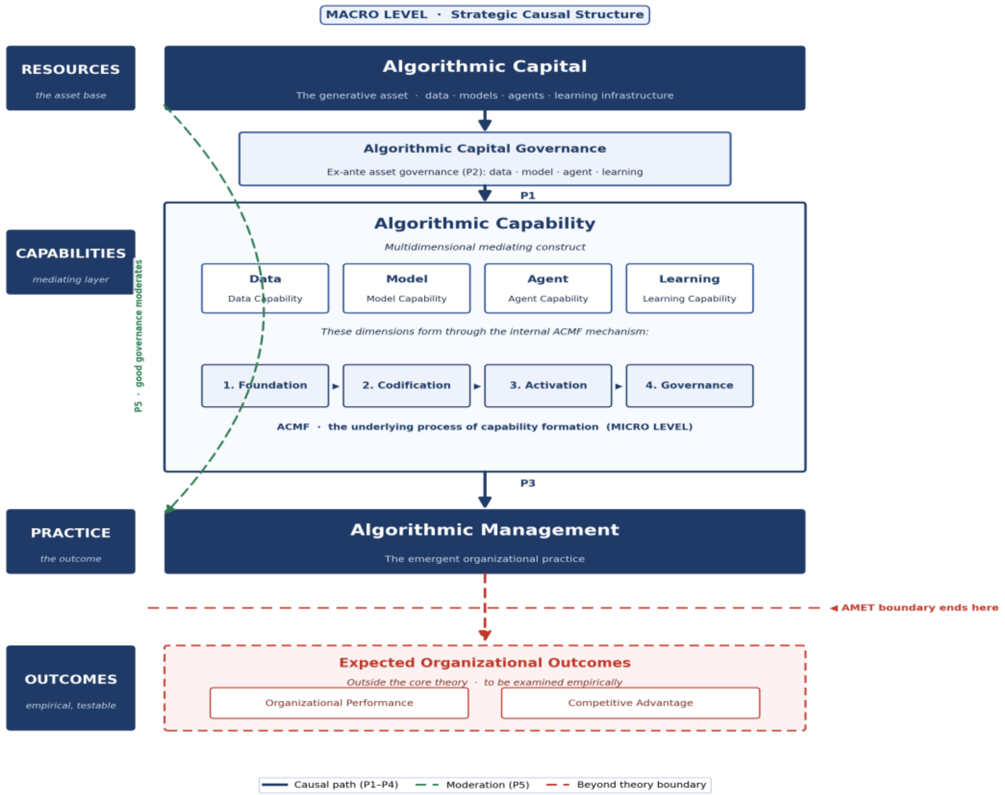

Figure 1. Conceptual Architecture of the Algorithmic Management Emergence Theory (AMET)

Resources → Capabilities → Practice → Outcomes, with governance as antecedent (P2) and moderator (P5)

The model operates at two analytical levels.

The former is the macro level, which describes the cause and effect chain in the development of algorithmic management. The generative asset at this level is algorithmic capital; the ability to form governance conditions is found in the capability of algorithmic capability, and the mediating construct is algorithmic management, which is the form of organizational practice.

The second level is the micro level, which is embodied by ACMF. The level describes the inner organizational mechanisms through which the capability is formed; in fact, the difference between these levels eliminates possible confusion about governance. On the macro level, governance deals with the quality of algorithmic governance of assets. On the micro level, governance is a process that controls the capability formation and attains the right balance between control and empowerment.

4.6. Boundary Conditions

There are a number of boundary conditions that are applicable to AMET, and these determine the limit of its explanatory power.

To start with, the theory is only applicable to those organizations that have algorithmic assets with a certain level of computational agency. It is less explanatory where digital assets serve as passive storage of information only.

Second, the theory assumes that there are mechanisms of governance that could control algorithmic assets and their use. Capability formation is structurally inadequate in the lack of governance.

Third, the theory is mostly applicable to the situation whereby there are algorithmic systems involved in organizational decision-making, coordination, monitoring, or control. It is less relevant in areas where algorithms are peripherally or solely supportive.

Lastly, the theory is limited to elucidating emergence. It does not assert that algorithmic management is the best way to enhance organizational outcomes. The production of value, resistance, trust, surveillance, empowerment, or competitive advantage by the emergent practice is an open empirical issue outside the precincts of the theory itself.

5. Research Propositions

The propositions are based on the logic of the Algorithmic Management Emergence Theory (AMET). They define the connections between the main constructs of the model and put the theory in the form of empirically verifiable statements. In line with the structure of the theory, the propositions separate the path relationships (P1-P4), which specify the emergence process per se, and a moderation relationship (P5), which specify how governance moderates the strength and direction of the emergence process. This difference prevents the confusion of causal mechanisms with contextual factors and maintains the conceptual clarity. All propositions are derived from the theory's central proposition.

5.1. Central Theoretical Proposition:

Central Theoretical Proposition:

Algorithmic management stems from governance-driven asset potential, not asset ownership alone.

5.2. Path Propositions

Proposition 1 (P1): Algorithmic Capital → Algorithmic Capability

Statement: Algorithmic capital has a positive effect on the emergence of organizational algorithmic capability in its four dimensions.

Grounding*:* This postulation is based on the reasoning of the resource-based perspective, where resources are regarded as inputs in the process of developing capabilities (Barney, 1991). The argument is based on structural correspondence: every element of algorithmic capital, data, models, agents, and learning infrastructure provides the raw material on which a corresponding dimension of capability is built since no capability can be constructed without an underlying asset on which to act.

Proposition 2 (P2): Algorithmic Capital Governance → Capability Formation Effectiveness

Statement: Algorithmic capital governance has a positive effect on how well the algorithmic assets are converted into operational algorithmic capabilities.

Grounding*:* This suggestion is based on the responsible AI and governance frameworks, where the quality of the data, models, and algorithmic systems is often believed to rely on the proper governance mechanisms (NIST, 2023; OECD, 2024). The governance here is a formative condition in the sense that the ability that later becomes is determined by the quality of the underlying assets.

Proposition 3 (P3): Algorithmic Capability → Algorithmic Management

Statement: Algorithmic capability is positively linked to the rise of algorithmic management.

Grounding: This suggestion is based on the dynamic-capabilities perspective, which states that capabilities are constructed on the basis of resources and not resources per se (Teece, 2007).

Proposition 4 (P4): Mediation

Statement: Algorithmic capability mediates the relationship between algorithmic capital and the emergence of algorithmic management.

Grounding: This postulation combines both P1 and P3 into a mediation route in line with the sequence of resources, capabilities, and practices in the capability-based theories of the firm (Barney, 1991; Teece, 2007). The assumption of the proposition is that the algorithmic assets do not create managerial practice, but they create it through the ability created by the assets.

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5.3. Moderation Proposition

Proposition 5 (P5): Good-Governance Moderation

Statement: Good governance moderates the relationship between algorithmic capital and the emergence of algorithmic management in a positive way, with the relationship getting stronger with the rise in the quality of governance.

Grounding: This premise is informed by the fact that there are control-oriented and empowerment-oriented types of algorithmic management (Meijerink and Bondarouk, 2023; Kellogg et al., 2020), and the overall literature on surveillance capitalism and responsible technology governance (Zuboff, 2019).

Clarification on the Dual Role of Governance

Governance in both P2 and P5 is indicative of two analytically different constructs.

Governance in P2 is defined as algorithmic capital governance, which is a resource-oriented construct that is interested in governing data, models, agents, and learning processes.

In P5, good governance is defined as a wider organizational attribute that includes transparency, accountability, oversight, and control versus empowerment. Since it is not directly causative of capability, but rather it forms the context within which emergence takes place, it acts as a moderator not within the primary causal pathway. The possible interdependence between Prop 3 and Prop 4 is prevented by expressly considering P4 as a mediation proposition but not an extra causal relationship. Proposition 3 determines the capability-to-practice route, and the wider mediating framework, in which the algorithmic capital has an effect on the development of algorithmic management as stipulated in the fourth proposition.

6. Discussion:

This part will decode the theoretical implications of the Algorithmic Management Emergence Theory (AMET), place it in the context of the existing literature, and discuss the governance and ethical issues related to the emergence of algorithmic management. With the theory and propositions developed, the discussion is no longer descriptive but rather addresses the explanatory value of the theory and how it relates to other competing views.

6.1. Theoretical Implications:

The main contribution of AMET is that it changes the focus on algorithmic management as a current organizational practice to the circumstances that create it. Most of the literature available considers algorithmic management as a visible reality and focuses on its impact on the employees, organizations, and society. The explanatory question of AMET has a logically preceding question: How is algorithmic management created in the organizations? Instead of starting with algorithmic management per se, AMET starts with the organization's asset base, and thus the explanation flows in the opposite direction as is common in much of the literature.

It is this differentiation that is at the center of the theoretical contribution of AMET, and that has more weight than a shift of emphasis. There has been a misidentification of the unit of analysis as far as the prevailing literature is concerned. It frames the phenomenon in the artifact by positioning algorithmic management as a technology that organizations embrace, a system that needs to be implemented, governed, and resisted, thus examining its diffusion and impacts. AMET believes that this framing confounds a manifestation with the phenomenon itself. The concept of algorithmic management is not, fundamentally, a technology, but an organizational capacity that just happens to be implemented by the use of computational artifacts. The identical software implemented in two organizations is not going to give the same algorithmic management since the practice is made of the capability that brings the artifact into action, rather than by the artifact itself.

The theory adds to the literature by providing an explanatory gap in the literature, which is the lack of algorithmic capability between algorithmic assets and algorithmic management. This contribution takes the reasoning of the resource-based view to the level of algorithmic management. In line with RBV, resources do not produce organizational outcomes, but instead, value is created by the capabilities that are built upon these resources. AMET uses this concept to justify why organizations with comparable algorithmic assets still can exhibit considerably different degrees of algorithmic management.

The second contribution is that of separation of macro-level causation and micro-level explanation of processes. The theory at the macro level describes the causal chain between algorithmic capital, governance, capability, and practice. At the micro level, ACMF defines the mechanism that takes place internally by which capability formation takes place. This difference is to prevent a confusion of theory with mechanism and offers a more detailed explanation than models that simply set up statistical relationships between variables.

6.2. Why a New Theory Is Needed

The main question for any theory-building project is whether a new theory is justified or whether the phenomenon can be explained by the existing frameworks. The reason why AMET is justified is that the two closest bodies of theories, the dynamic capabilities perspective and the algorithmic management literature, can explain separately half of the phenomenon but do not provide an explanation of how the phenomenon emerges at the organizational level. The way that AMET is built is to fill this explanatory gap but not to push either tradition out.

The dynamic capabilities school of thought describes how companies perceive opportunities and restructure resources to maintain a competitive edge in a dynamic environment (Teece, 2007; Eisenhardt and Martin, 2000). It provides the overall reasoning that capabilities, and not resources, provide organizational results, and AMET uses it as an assumption. However, the theory of dynamic capabilities is explicitly generic: it is not determined by the unique characteristic of algorithmic assets that are computational agency but rather by the specific capacity in terms of which agency-containing assets are transformed into managerial coordination.

In its turn, the algorithmic management literature is abundant in information about what algorithmic management is and does, what control mechanisms it uses, and what implications it has on workers and what governance issues it brings about (Kellogg et al., 2020; Duggan et al., 2020; Stark and Vanden Broeck, 2024). This literature uses the presence of algorithmic management as its initial point of theorization and theorizes downstream. To answer this preliminary question, AMET can pursue the practice of its generative asset base and the mediating capability. It thus supplements the literature on algorithmic management: while the literature tells how a practice works and what its impacts are, AMET tells how it came into being in organizations. Moreover, the need to develop a new theory is not therefore due to the fact that current frameworks are incorrect but rather that the advent of algorithmic management is in the gray area between them. Dynamic capabilities theory provides the correct logic but not constructs; the algorithmic management literature provides the phenomenon but not its source.

6.3. Theoretical Contributions:

Summarizing the arguments above, the theory contributes to the literature on algorithmic management and organizational capabilities in five ways.

1. It shifts the unit of analysis. AMET redefines algorithmic management as an organization's capability implemented with computational artifacts, rather than simply a technology that organizations adopt. This change focuses on the organizational process that enacts the artifact and reinterprets a body of work where the artifact is assumed to be given.

2. It emphasizes emergence rather than operation. Unlike previous studies that explore the nature of algorithmic management once it exists, AMET identifies the earlier process of creating algorithmic management. This offers a causal explanation for its origin, which is missing in current literature.

3. It identifies the mediating construct that earlier frameworks overlook. The theory describes algorithmic capability as the ability to convert agency-bearing algorithmic assets into managerial coordination. It defines the specific capacity that turns these assets into managerial practice, rather than relying on related concepts like AI, analytics, and digital capability.

4. It integrates two traditions without collapsing into either. AMET merges the logic of dynamic capabilities with insights from algorithmic management literature to bridge the gap between the two, rather than restating either.

5. It sets boundaries. By defining the theory at its point of emergence and separating causal factors from moderating conditions, AMET clarifies what it explains, increasing its testability and readiness for empirical evaluation.

Together, these contributions indicate that AMET is not an alternative to existing capability- and governance-based explanations but clarifies how algorithmic management emerges in organizations.

6.4. Engaging Alternative Explanations:

A theory becomes stronger when tested against other conflicting explanations. Institutional theory, particularly the theory of institutional isomorphism, provides the most significant alternative view on the development of algorithmic management (DiMaggio and Powell, 1983).

In institutional contexts, organizations may adopt algorithmic management due to external influences rather than internal strengths. Factors like competitive imitation, professional norms, regulatory expectations, and stakeholder demands can motivate organizations to implement algorithmic systems.

This explanation is not contradicted by AMET. Instead, it asserts that institutional and capability-based explanations address different issues. Institutional theory explains why organizations seek algorithmic management and how it spreads across industries. AMET details the actual emergence of algorithmic management, highlighting that not all organizations facing the same external pressures adopt it.

This distinction is particularly important when considering variations among organizations within the same institutional environment. Organizations facing similar competitive and regulatory challenges often differ greatly in the sophistication, performance, and scope of their algorithmic management practices. Such differences rarely stem from institutional pressures but can be explained by variations in algorithmic capital, governance quality, and algorithmic capability.

The theory thus positions institutional pressure as a potential external factor influencing investment in algorithmic assets. Meanwhile, the internal processes of algorithmic capital, governance, and capability are seen as crucial steps in creating algorithmic management.

6.5. Ethical and Governance Risks:

The emergence of algorithmic management (AM) is inseparably accompanied by acute ethical and governance dilemmas, although AMET is more of an explanatory theory. The processes that ensure smooth coordination may be very dangerous when they are not strictly supervised. There are four main risks that are identified:

- Excessive Surveillance and Loss of Privacy: AM systems are based on huge datasets, which tend to push the monitoring activity beyond the reasonable organizational requirements. Governmental structures should set clear limits to data collection, storage, and downstream use.
- Bias Reproduction and Amplification: The algorithms used to train on historical data have the risk of amplifying existing disparities. To counter this, it is necessary to have sustained auditing, model evaluation, and strong accountability to identify and prevent discriminatory effects at the initial stage.
- The Digital Iron Cage: Systems can become overly efficient and restrictive to employee autonomy, creativity and professional judgment. Instead of substituting human empowerment, organizations need to strike the right balance between algorithmic direction and human empowerment.
- The Scaling Gap: It happens when investments in algorithmic assets progress faster than the ability of the organization to re-architect its workflows, governance, and underlying processes. As a result, high technological investment does not translate into a real managerial capability and a functional AM reality.

7. Recommendations

1. Empirical & Research Level:

- Empirical Testing: Future research needs to empirically confirm AMET propositions, namely, exploring algorithmic capability as a mediating variable and governance as a moderating variable. These causal relationships are suggested to be analyzed with the help of Structural Equation Modeling (SEM) in different industries.
- Construct Standardization: There is an urgent requirement to grow, validate, and test the reliability of measurement scales of the four dimensions of algorithmic capability: data, model, agent, and learning capabilities.
- Performance Outcomes: The connection between algorithmic management (AM) and the performance or competitive advantage of an organization should be viewed as an open empirical question, and not as a given finding, following the boundary conditions of the theory.

2. Academic & Conceptual Level:

- Curriculum Integration: Concepts of algorithmic capability and computational agency should be integrated into Management, Information Systems (IS), and Digital Transformation curricula.
- Interdisciplinary Collaboration: The integration of strategic management, knowledge management, IS, and critical technology studies is necessary to integrate the disjointed research streams.

3. Practical & Organizational Level

- Capability Assessment: To determine the gaps that prevent success in the implementation of AM, organizations should perform a systematic audit of the health of their algorithmic capability in its four dimensions.
- Proactive Governance: Governance mechanisms need to be put in place at the asset level before being deployed instead of as retroactive corrective measures.

8. Limitations and Future Research:

- Non-Empirical Design: The research is conceptual only; AMET propositions need to be empirically tested with both quantitative and qualitative methods.
- Emphasize Only Emergence: The model only goes as far as emergence. Further studies need to investigate downstream implications (e.g., organizational performance, employee well-being, trust, and resistance).
- Early Theoretical Phase: The four dimensions of algorithmic capability, the core constructs, and the processes of the ACMF require tight operationalization and measurement scaling.
- Uncontrolled Control/Contextual Variables: Due to the parsimony requirement, the contextual variables, such as firm size, industry, digital maturity, and culture, were not included; they should be tested as moderators or control variables.
- Purposive Literature Selection: Due to the use of English, authoritative papers might have missed new or non-English work.
- Technological Dynamism: The fast progress of Generative AI and autonomous agents requires ongoing theoretical changes to make AMET topical.

9. Conclusion:

The paper fills an important gap in the literature as it moves the discussion on how algorithmic management works to how it is actually created in an organization. Whereas the current research has placed a lot of emphasis on the downstream effects, the implementation, and control of the algorithmic systems, this study proposes the Algorithmic Management Emergence Theory (AMET). This theoretical framework determines algorithmic management as an emergent organizational practice that is motivated by algorithmic capital that is directly mediated by algorithmic capability and strictly constrained by certain governance conditions.

The research makes a significant contribution to the scholarly literature in several respects, as it combines the resource-based view, intellectual capital theory, and knowledge-conversion theory into a single explanatory model. It adds algorithmic capability as the crucial missing element that fills the gap between passive technological resources and active managerial implementation. Moreover, it provides a micro-level formation of capability and a macro-level causal explanation via the ACMF framework, providing a very detailed and dual-perspective view of the emergence of these systems.

Finally, AMET changes the research paradigm, which is studying the existing algorithmic systems, to explaining the dynamic organizational processes that make them up. In this way, the framework will offer a solid, coherent base to subsequent empirical testing and conceptual development on the subject of algorithmic organizations. It provides a clear and prospective scholarly plan for the measurement of algorithmic capabilities, assessment of structural governance, and monitoring of the maturation of algorithmic management in the new institutional context.

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