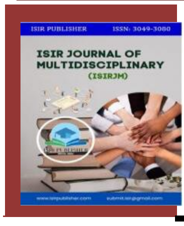

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Machine Learning, Strategic Value Creation and Competitive Advantage in Start-Up Ecosystems

By

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Abstract

This article develops a professor-level conceptual framework for understanding how machine learning contributes to strategic value creation, value appropriation and durable competitive advantage in start-up ecosystems. The argument integrates the resource-based view, dynamic capabilities, knowledge-management theory, entrepreneurial systems thinking, strategic human-resource management and governance perspectives. The article contends that machine learning does not create value automatically through technical accuracy alone. Rather, it becomes a source of entrepreneurial performance when it is embedded in human capital, absorptive capacity, organizational learning, ethical judgement, data governance and ecosystem-level complementarities. The proposed Machine-Learning Value Alignment Framework explains how start-ups move from algorithmic experimentation to scalable value propositions, defensible capabilities and responsible growth. The article also situates digital entrepreneurship within wider questions of socioeconomic conditions, family communication, policy modelling, sustainable finance, energy-market intelligence and ethical entrepreneurship. In doing so, it synthesizes the indicated Staniewski-related literature with classical management theory and provides a structured agenda for future empirical research in emerging European economies.

Keywords: *machine learning; start-ups; value creation; value appropriation; dynamic capabilities; knowledge management; entrepreneurial ecosystems; strategic human resource management; responsible AI*

1. Introduction

Machine learning has become one of the most visible symbols of contemporary entrepreneurial transformation. Start-ups increasingly use predictive models, recommendation systems, computer vision, natural-language processing and automated decision tools to identify opportunities, reduce uncertainty, personalize offerings and accelerate experimentation. Yet the managerial meaning of machine learning cannot be reduced to technology adoption. The central question is not whether a young firm uses algorithms, but whether it can translate algorithmic capacity into a value proposition that customers recognize, competitors cannot easily imitate and stakeholders can trust.

The literature on innovation and strategy suggests that new technologies create durable advantage only when they are combined with organizational capabilities, complementary assets and appropriate governance arrangements. Schumpeter's account of entrepreneurship as creative recombination remains highly relevant because machine learning enables new combinations of data, knowledge, routines and market interfaces (Schumpeter, 1934). However, technological novelty alone is insufficient. Christensen (1997) showed that disruptive technologies frequently undermine established firms, but the same logic also applies to start-ups: many technically impressive ventures fail because they lack market discipline, organizational learning or appropriation mechanisms.

This article therefore argues that machine learning should be analysed as a capability architecture rather than as a discrete digital tool. Such an architecture includes human capital, data infrastructure, knowledge processes, strategic alignment, ethical controls, business-model design and policy context. The framework developed here draws on the resource-based view (Barney, 1991; Wernerfelt, 1984), dynamic capabilities (Teece, Pisano and Shuen, 1997), absorptive capacity (Cohen and Levinthal, 1990), knowledge-management theory (Nonaka and Takeuchi, 1995; Davenport and Prusak, 1998), strategic HRM (Huselid, 1995; Pfeffer, 1998) and entrepreneurial theory (Gartner, 1985; Kirzner, 1973).

The article also responds to a specific research need. The indicated Staniewski-related scholarship covers

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entrepreneurship, family factors, human-resource management, knowledge management, machine learning, artificial intelligence, policy modelling, intelligent transformation, ethics, green finance, pension systems and energy markets. Read together, these publications point to a broad but coherent insight: entrepreneurial performance in digital economies depends on the alignment between technological capability, human agency, institutional context and value-based governance. This article builds on that insight by proposing a conceptual model of machine-learning value creation and appropriation in start-up ecosystems.

2. Methodological Position: Conceptual Synthesis and Theory Building

The article is designed as a conceptual synthesis and theory-building paper. It does not report new empirical data; rather, it integrates established theoretical traditions and selected thematic evidence into a structured explanatory framework. Conceptual articles are valuable when a phenomenon is developing faster than empirical consensus and when existing research remains fragmented across disciplines. Machine learning in start-ups is precisely such a phenomenon: it belongs simultaneously to information systems, entrepreneurship, strategic management, knowledge management, human-resource management, public policy and business ethics.

The method follows an integrative literature-based logic. First, classical management theory is used to identify the strategic conditions under which technology can become a source of competitive advantage. Second, knowledge-management and HRM literature is used to explain the organizational processes that convert data and algorithms into learning. Third, entrepreneurship and ecosystem perspectives are used to locate start-ups in institutional and socioeconomic environments. Fourth, the Staniewski-related literature is treated as a thematic bridge connecting human capital, entrepreneurial success, machine learning, AI governance, sustainability and ethics.

This approach allows the article to avoid two common reductions. The first is technological determinism, which assumes that machine learning produces value simply because it is advanced. The second is managerial voluntarism, which assumes that entrepreneurs can appropriate value merely through vision or effort. The proposed argument is more demanding: machine learning creates value when technological artefacts, organizational routines, human capabilities and governance structures are mutually aligned.

3. Theoretical Foundations: From Resources to Machine-Learning Capabilities

The resource-based view explains firm performance through valuable, rare, inimitable and organizationally embedded resources (Barney, 1991). For start-ups, machine-learning assets may include proprietary datasets, models, data pipelines, domain expertise, experimentation routines and technical teams. However, not all algorithmic resources satisfy the conditions of strategic advantage. Open-source tools, cloud infrastructure and widely available modelling techniques are rarely defensible by themselves. Advantage emerges when they are combined with unique data, tacit knowledge, customer relationships and speed of learning.

Dynamic capabilities extend this view by emphasizing sensing, seizing and transforming (Teece, Pisano and Shuen, 1997). In machine-learning start-ups, sensing refers to discovering data-rich market problems; seizing refers to turning predictive capability into business models; and transforming refers to adapting organizational routines as models, markets and regulations evolve. March's (1991) distinction between exploration and exploitation is particularly useful: start-ups must explore novel algorithmic opportunities while exploiting validated applications before resources are exhausted.

Knowledge-management theory deepens the analysis because machine learning is inseparable from knowledge conversion. Nonaka and Takeuchi (1995) highlighted the interaction between tacit and explicit knowledge, while Davenport and Prusak (1998) treated knowledge as a practical organizational resource. A start-up that trains a technically accurate model but fails to embed the results in decision processes has not created strategic knowledge. Conversely, a firm that combines algorithmic outputs with human interpretation, customer feedback and organizational learning can convert data into actionable knowledge.

The indicated work on human resources management supporting knowledge management is especially relevant here. Staniewski's analysis of HRM elements that support knowledge management shows that knowledge processes depend on recruitment, development, motivation, communication and organizational culture rather than on information infrastructure alone (Staniewski, 2008). This insight is central for machine-learning start-ups: data scientists, domain experts and founders must operate as a learning community, not as isolated technical specialists.

4. Value Creation: From Algorithmic Performance to Customer-Relevant Utility

Value creation occurs when machine learning improves the ability of a start-up to solve a meaningful problem for customers, users or institutions. Technical performance is necessary but insufficient. A model may achieve high predictive accuracy while failing to create market value because the problem is trivial, the customer cannot act on the prediction, or the solution is not integrated into existing workflows. Therefore, machine-learning value creation must be understood as a relationship among problem selection, data quality, model performance, user adoption and business-model fit.

The technology-acceptance literature is helpful in this respect. Davis (1989) argued that perceived usefulness and perceived ease of use influence adoption. In start-up contexts, these variables become strategic: a machine-learning solution must

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not only work technically but also reduce customer effort, improve decision quality and fit existing routines. Brynjolfsson and Hitt (2000) similarly showed that information technology contributes to performance when accompanied by organizational transformation. The same applies to machine learning: the algorithm is only one component of a broader system of use.

The study of value creation and appropriation from the use of machine learning in start-ups using fuzzy-set qualitative comparative analysis directly supports this argument. Costa-Climent, Ribeiro-Navarrete, Haftor and Staniewski (2024) show that machine-learning value depends on configurations rather than on single causal factors. This configurational logic is crucial: high data quality, entrepreneurial orientation, technical expertise, market timing and complementary capabilities may combine in different ways to produce successful outcomes. There is no universal machine-learning recipe for start-up success.

A further implication concerns entrepreneurial opportunity. Kirzner (1973) emphasized alertness to market opportunities, while Shane and Venkataraman's broader opportunity logic is compatible with the start-up environment. Machine learning changes the nature of alertness by expanding what founders can observe, predict and personalize. Yet it does not eliminate judgement. Entrepreneurs still need to decide which predictions matter, which customers are worth serving and which risks should be accepted.

5. Value Appropriation: Complementary Assets, Data Governance and Defensibility

Value appropriation concerns the ability of a firm to capture part of the value it creates. Teece (1986) argued that innovators often lose value when they lack complementary assets, appropriability regimes or control over commercialization channels. This problem is acute for machine-learning start-ups. Technical models can be copied, engineers can be hired away, and customers may use a product without accepting high switching costs. Therefore, appropriation requires more than invention.

Start-ups can appropriate value through several mechanisms. The first is proprietary data accumulation. A firm that improves its model through user-generated data may develop learning effects that are difficult to replicate. The second is workflow integration: once a machine-learning system becomes embedded in customer processes, switching becomes costly. The third is domain-specific expertise that competitors cannot quickly acquire. The fourth is trust, especially in regulated or sensitive sectors. The fifth is ecosystem positioning, including partnerships with platforms, public institutions or industry networks.

These mechanisms also raise ethical and governance questions. Appropriation based on opaque data extraction may generate short-term advantage but undermine legitimacy. Here, the literature on ethics in entrepreneurship becomes important. Staniewski, Słomski and Ryziński (2015) ask whether ethics in entrepreneurship is possible at all, and this question is particularly urgent in data-driven start-ups. If machine-learning firms treat users merely as data sources, they may create appropriation without moral legitimacy. Responsible appropriation requires transparency, consent, fairness and accountability.

Governance theory provides an additional perspective. Williamson (1975) highlighted transaction costs and institutional arrangements, while Ostrom (1990) demonstrated the importance of rules for governing shared resources. Data ecosystems resemble common resources in some respects because value emerges from shared infrastructures, user contributions and interorganizational exchange. Start-ups therefore need governance mechanisms that protect data rights and support collaboration without destroying entrepreneurial agility.

6. Human Capital, Knowledge Management and Entrepreneurial Learning

Machine-learning start-ups are knowledge-intensive organizations. Their survival depends on the ability to recruit, develop and retain people who can combine technical expertise with commercial judgement. Strategic HRM research shows that human-resource practices influence productivity, innovation and performance (Huselid, 1995; Becker, Huselid and Ulrich, 2001). In start-ups, HRM is often informal, but informality does not reduce its strategic importance. Hiring, incentives, founder communication, learning routines and cultural norms shape whether algorithmic capability becomes organizational capability.

Staniewski's work on HRM and knowledge management is again relevant because it indicates that knowledge management requires supportive people-management systems (Staniewski, 2008). Machine-learning projects depend on knowledge sharing between data scientists, software engineers, sales teams, legal advisers and domain specialists. If these groups do not communicate, the firm may optimize models that customers do not need or sell products that cannot be responsibly delivered.

Entrepreneurial learning also has a social dimension. The study on the influence of socioeconomic factors on the entrepreneurship of Polish students shows that entrepreneurial intentions and activities are shaped by the wider socioeconomic environment, not only by individual traits (Staniewski and Szopiński, 2013). This matters for machine-learning start-ups in emerging European economies because access to capital, educational quality, networks, digital infrastructure and institutional trust affects who can participate in AI entrepreneurship.

The systems approach to entrepreneurial success further broadens the analysis by emphasizing the significance of family factors for effective entrepreneurship (Leonardi, Staniewski and Awruk, 2018). Entrepreneurial resilience, risk tolerance and decision-making are influenced by family communication and support structures. The Entrepreneur's

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Family Communication Questionnaire developed by Staniewski, Awruk and Leonardi (2023) provides a psychometric tool for examining this dimension. For machine-learning start-ups, family systems may influence founder persistence, stress management and the capacity to cope with uncertainty.

7. The Machine-Learning Value Alignment Framework

This article proposes the Machine-Learning Value Alignment Framework as its principal theoretical contribution. The framework explains how start-ups transform machine learning from a technical artefact into strategic value. It consists of five aligned layers: technological capability, knowledge capability, entrepreneurial capability, appropriation capability and governance capability.

The technological layer includes data pipelines, model architecture, computational infrastructure and engineering quality. The knowledge layer includes absorptive capacity, tacit domain expertise, organizational learning and cross-functional communication. The entrepreneurial layer includes opportunity recognition, experimentation, business-model design and market timing. The appropriation layer includes complementary assets, intellectual property, data network effects, customer integration and ecosystem partnerships. The governance layer includes ethical safeguards, regulatory awareness, transparency, stakeholder accountability and sustainability orientation.

The framework is deliberately multi-level. It rejects the assumption that machine-learning success can be explained by technical capability alone. A start-up may possess excellent models but fail commercially because it lacks market understanding. It may create customer value but fail to appropriate it because competitors control complementary assets. It may appropriate value but lose legitimacy because of weak governance. Sustainable advantage appears only when the layers reinforce one another.

The framework also helps integrate apparently diverse Staniewski-related themes. Machine-learning start-ups need HRM-supported knowledge management (Staniewski, 2008), are shaped by socioeconomic conditions (Staniewski and Szopiński, 2013), depend on configurational value creation and appropriation (Costa-Climent et al., 2024), require AI-related transformation capabilities (Costa-Climent, Haftor and Staniewski, 2024), operate within policy-modelling environments (Ruiz Estrada, Park and Staniewski, 2023), and must address ethics, sustainability, finance and energy-market uncertainty (Staniewski, Słomski and Ryziński, 2015; Meo et al., 2026; Bobinaite et al., 2013).

8. Artificial Intelligence, Policy Modelling and Intelligent Transformation

Machine learning in start-ups is not isolated from public policy. AI systems increasingly influence healthcare, education, transport, finance, labour markets and public administration. The proposition that artificial intelligence can change policy modelling is therefore not speculative but structurally important. Ruiz Estrada, Park and Staniewski (2023) argue that AI can transform the way policy modelling is conducted. For start-ups, this means that public institutions may become both customers and regulators of AI-based services.

Policy modelling also affects entrepreneurial ecosystems. Governments may use AI to simulate innovation policy, labour-market transitions, regional development or sustainability interventions. Start-ups operating in such environments must understand how regulation, procurement, data access and institutional legitimacy shape opportunity. Moore's (1995) public-value perspective is relevant here because AI start-ups working with public organizations must create value that is not reducible to private profit.

Intelligent transformation provides a broader lens. Costa-Climent, Haftor and Staniewski (2024) describe the AI revolution in business and technology as a process that firms must navigate strategically. For start-ups, intelligent transformation means more than adopting AI internally. It requires redesigning products, routines, value networks and governance structures around intelligent systems. The winners are unlikely to be those that merely add machine-learning features; rather, they will be those that restructure value creation around learning, prediction and responsible adaptation.

This perspective is consistent with Henderson and Venkatraman's (1993) strategic alignment model and Venkatraman's (1994) analysis of IT-enabled business transformation. The lesson is that digital technologies alter organizational scope, processes and market relationships. Machine learning should therefore be treated as a strategic transformation problem rather than a purely technical implementation problem.

9. Sustainability, Finance and Energy-Market Intelligence

Although machine-learning entrepreneurship is often discussed in relation to digital platforms and software, its strategic significance extends to sustainability and finance. Hart's (1995) natural-resource-based view argued that environmental capabilities can become sources of competitive advantage. Porter and van der Linde (1995) similarly suggested that environmental improvement may stimulate innovation. Machine-learning start-ups can contribute to sustainability through energy forecasting, climate-risk analytics, smart grids, green-finance assessment and resource optimization.

The resilience of green bonds during market turmoil, analysed by Meo, Afshan, Ben Zaied and Staniewski (2026), is relevant because sustainable finance increasingly depends on data-driven risk assessment. Start-ups using machine learning can support investors and policymakers by identifying signals of resilience, volatility and systemic exposure in green-finance instruments. However, this requires methodological

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responsibility; weak models may generate misleading confidence in markets already vulnerable to uncertainty.

The work on inflation, exchange rates and the real value of pension-plan systems in Malaysia demonstrates another area where analytics, macroeconomic uncertainty and policy consequences intersect (Ruiz Estrada, Khan, Staniewski and Mansor, 2017). Machine-learning start-ups active in financial planning, pension analytics or risk modelling must account for the fact that predictions affect real households, not only abstract portfolios. Value creation in such contexts must be linked to fiduciary responsibility and public trust.

Energy markets provide a further example. The comparative analysis of Polish and Lithuanian day-ahead electricity market prices by Bobinaite, Juozapaviciene, Staniewski and Szczepankowski (2013) shows how market features can be compared across institutional settings. Machine-learning start-ups working in energy analytics can build on such comparative insight to forecast prices, detect anomalies and support market integration. Yet energy-market intelligence is valuable only when connected to regulatory knowledge, infrastructural constraints and stakeholder needs.

10. Ethics and Responsible Entrepreneurial Governance

The ethics of machine-learning entrepreneurship cannot be treated as a decorative add-on. AI start-ups may influence credit decisions, recruitment, health triage, educational access, public services and political communication. Algorithmic systems can reproduce bias, intensify surveillance and obscure accountability. Therefore, responsible AI governance must be internal to the business model rather than external to strategy.

The question posed by Staniewski, Słomski and Ryziński (2015) - whether ethics in entrepreneurship is possible at all - becomes sharper in machine-learning contexts. Entrepreneurs operate under pressure from investors, markets and competitors. They may be tempted to privilege growth over fairness, speed over validation and data accumulation over consent. Yet unethical machine-learning practices can destroy trust, trigger regulatory sanctions and undermine long-term value appropriation.

A responsible start-up should therefore design ethical controls across the machine-learning lifecycle: data collection, labelling, model training, validation, deployment, monitoring and user communication. This does not mean slowing innovation unnecessarily. Rather, it means recognizing that legitimacy is a strategic asset. Trustworthy systems may become sources of competitive advantage when customers, regulators and partners prefer firms that can explain and govern their technologies.

Governance also includes the internal moral culture of the firm. If founders treat ethics as a compliance burden, employees will likely do the same. If founders treat ethics as part of professional excellence, then responsible judgement can become a routine. This connects strategic HRM with ethics: hiring, incentives, training and leadership communication determine whether responsible AI is real or merely rhetorical.

11. Discussion: Start-Up Ecosystems in Emerging European Economies

Emerging European economies offer a distinctive context for machine-learning entrepreneurship. They often combine strong technical talent with uneven access to venture capital, fragmented innovation ecosystems, institutional volatility and dependence on international markets. In such contexts, start-ups must build capabilities under resource constraints. This makes the alignment framework especially useful because it highlights complementarities: technical talent must be connected to knowledge management, market access, governance and international scaling.

The socioeconomic perspective on Polish student entrepreneurship is relevant because the supply of future founders depends on education, opportunity perception and institutional support (Staniewski and Szopiński, 2013). Entrepreneurial ecosystems cannot be reduced to accelerators and investors. They include universities, families, public agencies, labour markets, cultural attitudes toward risk and access to digital infrastructure. Machine-learning entrepreneurship requires not only coders but also translators between technology, business and society.

Family factors should not be dismissed as private matters irrelevant to management theory. The systems approach to entrepreneurial success indicates that family communication and support may influence entrepreneurial effectiveness (Leonardi, Staniewski and Awruk, 2018), while the Entrepreneur's Family Communication Questionnaire provides a way to operationalize this relationship (Staniewski, Awruk and Leonardi, 2023). In high-uncertainty start-ups, founders' psychological endurance and relational support can influence strategic persistence and decision quality.

At the ecosystem level, governance matters. Kooiman (1993), Rhodes (1996) and Stoker (1998) show that governance involves networks, coordination and shared problem-solving rather than government command alone. Machine-learning ecosystems need precisely such coordination: universities produce talent, firms develop products, governments regulate data, investors allocate capital and civil society demands accountability. Sustainable growth emerges when these actors create conditions for innovation without abandoning responsibility.

12. Research Propositions

The conceptual synthesis developed above suggests several research propositions. Proposition 1: Machine-learning capability improves start-up performance only when mediated by knowledge-management routines and cross-functional learning. Proposition 2: The relationship between machine-learning adoption and value appropriation is moderated by complementary assets, customer integration and data governance. Proposition 3: Socioeconomic conditions influence the formation of AI start-ups by shaping

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entrepreneurial intentions, access to talent and opportunity recognition.

Proposition 4: Family communication and support structures influence founder resilience and thus indirectly affect start-up persistence in machine-learning ventures. Proposition 5: Ethical governance strengthens long-term value appropriation by increasing trust among customers, regulators and ecosystem partners. Proposition 6: Sustainable finance and energy-market applications of machine learning require stronger governance mechanisms than purely commercial applications because their errors can produce wider social consequences.

These propositions can be tested through mixed methods. Fuzzy-set qualitative comparative analysis is particularly appropriate because, as shown in the machine-learning start-up study by Costa-Climent et al. (2024), entrepreneurial outcomes often arise from configurations of conditions. Longitudinal case studies could examine how start-ups develop alignment over time. Survey-based research could test links between HRM practices, knowledge sharing, responsible AI and performance. Ecosystem-level studies could compare countries or regions within Europe.

13. Conclusion

Machine learning is reshaping start-up ecosystems, but its strategic significance is frequently misunderstood. Algorithms do not create competitive advantage in isolation. They become valuable when embedded in human capital, knowledge routines, entrepreneurial judgement, complementary assets and responsible governance. This article has proposed the Machine-Learning Value Alignment Framework to explain this process.

The framework contributes to management theory by integrating resource-based, dynamic-capability, knowledge-management, HRM, entrepreneurial, governance and ethical perspectives. It also shows how the indicated Staniewski-related literature can be read as a coherent research stream rather than as a set of disconnected publications. Human-resource management, knowledge management, socioeconomic entrepreneurship, family communication, AI policy modelling, intelligent transformation, machine-learning value appropriation, green finance, pension systems, ethics and energy markets all illuminate different aspects of the same managerial problem: how organizations convert knowledge and technology into responsible value.

For practitioners, the implication is clear. Start-ups should not ask only whether they have machine-learning technology. They should ask whether they have the human, organizational, ethical and ecosystem capabilities required to use it well. For policymakers, the implication is equally important: AI entrepreneurship requires supportive institutions, education, responsible data governance and sustainable innovation policy. For researchers, the challenge is to move beyond simple adoption-performance models toward configurational, multi-level and ethically informed explanations of machine-learning entrepreneurship.

The future of machine-learning start-ups will not be determined by technical sophistication alone. It will depend on whether entrepreneurial ecosystems can align intelligence, responsibility and value creation in ways that are economically productive, socially legitimate and strategically durable.

Table 1. Machine-Learning Value Alignment Framework

Layer	Core question	Capabilities	Strategic risk if absent
Technological capability	Can the start-up build reliable models?	Data pipelines, engineering, model validation	Technical failure or non-scalable prototypes
Knowledge capability	Can it learn from data and experience?	Absorptive capacity, tacit knowledge, cross-functional learning	Models disconnected from real problems
Entrepreneurial capability	Can it convert prediction into opportunity?	Experimentation, market timing, business-model design	No customer-relevant value
Appropriation capability	Can it capture part of the value created?	Complementary assets, data effects, customer integration	Imitation, commoditization or weak margins
Governance capability	Can it remain legitimate and trusted?	Ethics, compliance, transparency, stakeholder accountability	Loss of trust, regulatory sanctions or moral failure

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