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AI, Union Power and Competitive Advantage a New Paradigm for Multinationals

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Abstract. This paper develops a new explanation based on a resource–institutional compatibility framework in which the value of artificial intelligence (AIs) depends not just on firm-level capabilities but more so on national labour institutional compatibility. This perspective addresses a key limitation inherent in most traditional formulations of the Resource-Based View (RBV), namely their tendency to overlook the role of institutional frictions. The study suggests that firms with high socio-political capital through strong unionisation and collective bargaining will be environments where AI-induced restructuring runs the risk of greater socio-political imperatives undermining AI value potential. The implication is that multinational enterprises (MNEs) must factor in both labour relations and the institutional configurations in their host destinations—over and above the level of technological readiness—when taking AI across borders. The strategic advantages of the AI boom are not ubiquitous – they depend on other forms of "institutional legitimacy and social license."

Keywords: Artificial Intelligence (AI),Resource–Institutional Compatibility Framewo,Labour Union Power, Institutional Legitimacy and Labour Regimes,Multinational Enterprises (MNEs)

1. Introduction

Artificial Intelligence (AI) has increasingly been conceptualised as a strategic resource within the Resource-Based View (RBV), forming a core component of multinational enterprises'(MNEs) internationalisation strategies. Grounded in this perspective, the international business (IB) literature portrays AI as a firm-specific, inimitable intangible asset that enhances the firm's resource orchestration capabilities. By improving operational efficiency, reducing transaction costs, and supporting real-option decision-making, AI is seen to increase enterprise value in international contexts [1]. The few recent studies in financial economics also conceptualise AI as a capitalized intangible that increases expected future cash flows and lowers costs of capital (particularly through predictive maintenance, algorithmic treasury management among others) [2]. With this valuation model, that AI is used across countries is not explicitly considered to translate into positive value creation for all institutional environments. The discourse only makes sense if host-country institutions are supportive of—or at least agnostic towards—AI-powered restructuring, especially when it comes to job displacement. Yet, as recent work indicates the actual value of AI might be

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determined not only by its technical use, but also through implications for alignment with the institutional and cultural values within which it is embedded. For instance, Chishty et al. [3] show that AI technology improves MNE´s export performance, however the benefit is greatly offset by cultural distance and institutional uncertainty, suggesting that AI deployment should be adjusted to host-country conditions.

Although existing literature has stressed the technological advantage of AI in saving costs and facilitating decisions, this body of knowledge tends to accentuate its functional usefulness at the expense of overlooking institutional and social aspects associated with use. Little attention has been paid, in particular, to how institutional actors such as trade unions might oppose AI-driven restructuring and so erode its productive potential. As Krzywdzinski, Gerst and Butollo [4] illustrate, German trade unions are significantly involved in AI governance by advocating for "human-centred" systems and bargaining guarantees for employment and privacy. In the same vein, Hassel and Özkiziltan [5] contend that the effectiveness of AI implementation is contingent on institutional legitimacy and the degree of union participation in pre-empting restructuring risks. This article contends that such institutional pushback – driven by misalignments between AI applications and the host-country's labour regimes – accounts for the shortfalls in creating expected returns to AI. In response to this debate, this study proposes a theorizing framework that integrates the RBV with institutional and labour theories, relating it to two significant categorical contingencies — union power and institutional compatibility. This model informs theory, and serve as a base on which empirical research in multinational context may build to explore the contingent nature of the value AI can offer.

Notwithstanding the growing concern with AI in internationalisation, the literature rarely considers the institutional frictions that may be triggered by its implementation, especially concerning labour regimes. The notion of institutional neutrality fails to account for how national variation in labour relations, trade union bargaining power, and strength of unions might shape the cross-border transfer and realisation of AI-generated value. Previous studies have examined how capital-market institutions and investor rights affect entry of foreign firms in the market as well as their performance, while relatively less attention has been given to labour-based institutional settings. Organised labour is a still powerful (yet overlooked) institution in influencing the effects of AI diffusion. In rich economies, a recent wave of strikes in transport, health and education services shows that unions can still mobilise when job security is threatened. In contrast, there are dozens of developing countries where labour institutions are weaker or state-led, and collective action is still limited. This difference indicates that the very same AI implementation may trigger distributional struggle in liberal labour markets and be implemented without much fuss in coordinated economies. It is a manifestation of a wider set of institutions (complementarities) tied to their received national systems of capitalism, which are themselves internally coherent constellations of labour and production _regimes that pattern technology adoption and resistance [6]. However, there is limited empirical evidence examining whether such institutional asymmetries systematically moderate the AI–value relationship within the IB and finance domains [7], a gap this study seeks to address..

AI per se does not add value, and in some institutional environments it could be perceived damaging to firm performance by stirring up social and political tensions [8]. Comparative institutional analysis emphasises that systematic labour and regulation risk – in terms of threat of strikes, reputational loss, and regulatory punishment—can significantly increase the discount rates on investment projects and erode their net present value [9]. Hence, the strategic worth of AI does not only depend on it as a technical value-generator but also on its institutional feasibility—how

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much firms can reorganize their labour forces without an adverse social reaction [10]. This appreciation, in turn, opens up a re-thinking of AI to the concepts of institutional embedment. Especially the variation in collective bargaining coverage, union density and legal strike support is key to the likelihood of AI-induced dismissals leading to industrial action, reputational damage or legal resistance [11]. In order to capture these dynamics, this paper introduces the notion of resource–institutional compatibility—the extent to which firm-level digital capabilities are congruent with national labour institutions—to shed light on how the potential for value creation with AI is conditioned by the institutional environment. This would be a lens that looks past technological determinism and logics of efficiency, highlighting the contingent nature of AI's strategic advantages.

To overcome this theoretical limitation, the current paper builds an analytical framework bridging the RBV and labour relations theory to elucidate how institutional diversity moderates AI's internationalisation outcomes. From a comparative perspective, it stresses the distinctions between advanced and emerging market economies regarding collective bargaining institutions, strike traditions, and union–management relationships. This institutional asymmetry is framed as a key moderator in the development of AI value capture [10]. The contributions of this study are threefold. First, it expands the RBV by defining labour institutions as structural constraints of value creation that are not limited to firm-internal resource configurations. Second, it introduces two institutional mechanisms that shape AI's performance outcomes: a negotiation–protest–regulatory feedback pathway typical of advanced economies with robust labour protections [10], and an absorption–cooperation–stabilisation pathway more common in emerging markets where union influence is limited. Third, it offers a comparative framework for MNEs to assess boundary conditions—such as union strength, retraining investment, and benefit-sharing schemes—as critical factors conditioning AI deployment. Thus, this paper contends that AI as such is not a neutral resource, since the Return on its value depends in practice on how it articulates with national labour systems and institutions [9,12].

2. Literature review

2.1. Firm value, competitive advantage, and the integrative function of AI

Past work on business value has typically concentrated on three key drivers—risk hedging, resource usage, and value creation through innovation—all of which are being heavily disrupted by the infusion of AI. From the financial viewpoint firm value, depends on the quality of risk management and interest conflicts among stakeholders, as stated in classic theory [13-15]. In this area, AI supports efficient prospecting through more accurate prediction and the stabilisation of volatility, enabled by advanced algorithms that enhance financial reporting, bolster investor trust, and contribute to overall economic stability [16]. Within the strategic management domain, firm value is associated to dynamic capabilities such as resource identifying [17], integrating and reconfiguring [18] which are the key factors in ensuring that firms possess what they need at the right time for functioning properly. AI augments these capabilities, namely real-time orchestration, predictive optimization and adaptive learning within firms [19]. Furthermore, innovation and R&D activities are widely acknowledged as persistent sources of competitive gain [20-22] where AI is speeding innovation cycles and improving the productivity of the R&D processes by means of automation in combination with systems generating scalable intangibles coming from generative technology-based systems [2]. This latter set of perspectives collectively emphasises AI as a unifying element that

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amplifies traditional value creation processes by rendering them interpretable through adaptive and data-driven technological capabilities, resulting in improved organisational performance.

2.2. The unique competence of AI and its implications for labour

In addition to these known methods, AI has another component: self-generative learning and predictive adaptation. Unlike more traditional technologies that are largely about improving efficiency, AI entails the evolution and transmission of knowledge—an AI system brings together knowledge, reorganizes it, amplifies it all on its own [23], and hence organizations themselves become intelligent self-optimizing systems. The concept of “algorithmic generativity” compresses innovation cycles, erodes marginal costs and creates new kinds of 'option value’ in general as distinct from strategic flexibility [24]. It allows capabilities to grow above human cognitive limitations and enhances the organization’s capacity to confront ambiguity and uncover new prospects.

This represents labour allocation and corporate structure the likes of which have not been seen before. That the repetition of predictable routines in jobs, whether they are analytical or routine cognitive tasks will be replaced by AIs serves to redirect focus from old forms of employment toward new types that are emphasizing creativity, leadership or problem solving [10,11]. These variations have cost array, productivity criterion and employment pattern effects. As the interplay between human and machine labour changes, organizations face new governance challenge on complementarity and substitution. The generative force of AI tightens not just performance, but also social and institutional tensions in which the realization of technical promise becomes stretched.

AI reproduces and enhances the three traditional factors of firm value: risk management, resource bundling, and creativeness; while adding a fourth factor — generative abilities that alter labour structure. These changes necessitate workforce reconfiguration and joint actions, which provide the basis for examining union dynamics in the following section.

2.3. The resistance to artificial intelligence from labour unions in multinational contexts

Firm flexibility, labour costs and technology choice are largely determined by trade unions. High unionization rates frequently lead to higher wages and rules that create barriers to fast product innovation but foster job stability for the long-term. Unions and strategic behaviour in the fourth industrial revolution [25]. Powerful unions protect the work relationship but constrain managerial discretion to adopt technology [26]. It diminishes the negotiating force of unions operating under a model 'old’ unionism that need to come to terms with digital managerial control [27,28]. Strikes are one of the most crucial tools for challenging pay, hours and social conditions. When automation strikes, unions fight for workers through protest and bargaining. In Europe, social dialogue mitigates anxieties over AI and work [5]. In this regard, collective negotiations are an institutional platform to defend welfare within tech shifts [26], strikes and agreements resist algorithmic management [27].

At the same time that AI and automation threaten workers’ job security, unions also become more militant and structural in their opposition to employers. According to Cirillo, Rinaldini and Staccioli [25], trade unions alternate between working together/reactive positions, embracing innovation while sought for job security. Krzywdzinski, Gerst, & Butollo [4] illustrate that German unions lobby for “human-centric AI” through co-governance to offset job displacement. Most scholars speculate that automation may exacerbate asymmetries in power relations between employers and workers, where firms can utilise the technological substitution to have more absolute control of

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employment conditions. This is one reason why trade unions increasingly use both institutional and legal mechanisms to struggle against job losses which are pushed by automation in Latin America labour organisations have also reacted to technology-driven reductions of employment though the coalition building process on the political side of industry government relations as a way to promote scale re-qualification initiatives. De Stefano [27] describes this reaction as “negotiating the algorithm”, in terms of work rights protecting metaphoric house in data mediated settings. In conclusion, the evidence suggests that technological resistance is not at odds with innovation but a collective response to protect fair work and social security.

3. Theoretical framework & proposition development

AI is a Dhanekula, Tambe et al. [29,30], that enables the firm to convert its traditional inputs into high value output. For example, Dhanekula [29] proposed an AI-integrated business intelligence systems for the rival industry which facilitates resource allocation planning using prediction technique decision-making strategies. Similarly, in the usage of AI at SMEs, Mukherjee et al. [31], have also stated that including green HRM practices helps stimulate better employee conduct and higher comprehensive environmental sustainability. These are also precursors of AI coming to be considered as a strategic resource in its own right — or perhaps, eventually, something like a meta-resource that increases (or aligns) other resources in the firm such that they create and sustain competitive advantage over time.

Proposition 1: Adoption and utilization of AI on a firm s level enhances competitive advantage.

Expanding the logic, the value-adding potential of AI is anticipated to be even more pronounced in MNEs. In the RBV resonant resources that are immobile and scarce result in increasingly greater returns when they are placed over borders and put to use as internal resource recombination generates multiplicative payoffs [32,33]. AI facilitate this process by improving global coordination, integrating geographically dispersed knowledge bases, and decreasing information asymmetries between HQs and subsidiaries [34,35]. In addition, AI facilitates the tacit and explicit knowledge transfer among international networks and develops learning systems that are hard to be imitated by rivals [36,37]. Its double function to (1) standardize learning with quantitative insights, together with (2) optimize local operations transparently by real-time analytics enables MNEs to internalize various contextual knowledge and capture opportunities at the local level, enhancing innovation output and firm value [38].

Proposition 2: The positive impact of AI adoption on firm value is more pronounced for MNEs relative to domestic firms.

But whether firms can translate implemented AI into realised value depends on institutional contexts and labour relations. In line with the institutional perspective, the quest for legitimacy through compliance with societal norms, legal requirements and labour systems influences how firms use technological resources [32,33]. In countries with powerful labour unions, companies are hindered by institutions which may curtail managerial discretion in reintegrating and automating work. These settings are known to increase the cost of compliance, extend implementation times and lower prospective productivity benefits [39-41]. In contrast, businesses running in less unionised environments can more rapidly incorporate AI and achieve more substantial efficiency and cost benefits. Hence, the AI contribution is not just a technological one but also depends on institutional compatibility and labour flexibility.

Proposition 3: The positive effect of AI on firm value is weaker in countries with stronger labour union power.

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4. Discussion

Thus, this paper adds to literature in Resource-Based View (RBV) and provides insights into the reasons why AI, DNA may not always boosts performance despite technical strength [9,16,39,42]. Prior research: AI as a valuable and rare resource [17,33] Nonetheless, our study proved that, in the absence of social legitimacy, AI fails to provide value. The RBV is extended by demonstrating how labour compatibility and legitimacy are necessary conditions for AI to become a genuine strategic asset. AI can also be counter-productive: companies experience employee reluctance, distrust, and additional control costs, preventing the realization of optimal AI outcomes [43,44].

Institutional theory is further advanced by demonstrating the path-dependence of value-blocking factors, whereby union resistance and non-market forces obstruct the realisation of value from AI [4]. The absence of social acceptance leads to what is referred to as 'Artificial Idiocy' – a process that neither adapts nor evolves. This highlights the need to shift from a technology-centred perspective to one that places workers at the core. An alternative, co-design-oriented framework is outlined, in which the success of AI depends on the fair distribution of value and the preservation of workers' dignity [45]. The model illustrates the divergence between the promise of AI and the reality of business outcomes.

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