Knowledge Integration Patterns in AI: A Firm-level Taxonomy and Performance Implications

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Extended Abstract

As a general-purpose technology, artificial intelligence (AI) offers multiple pathways for value creation and capture (Cockburn, Henderson, & Stern, 2018). The economic impact of AI varies substantially depending on how firms choose to implement it: while using AI primarily for process automation may yield efficiency gains, deploying AI to enhance innovation capabilities appears to enable higher productivity growth through continuous technological improvements (Brynjolfsson & Unger, 2023). Recent research points to the fact that different paths in how firms benefit from AI are based on their endowment with different types of AI-related knowledge (Grashof & Kopka, 2023; Kopka & Fornahl, 2024).

This knowledge, however, is not uniformly distributed. The AI industry exhibits distinct patterns of knowledge creation and diffusion across different types of organizations: basic research producers, industrial intermediaries, and end-users (Franco, Graña, Flacher, & Rikap, 2023). Recent findings suggest that knowledge access is governed by the position in inter-firm networks (Dahlke et al., 2024) leading to technological dependencies (Lundvall & Rikap, 2022; Rikap, 2023).

This study investigates how the combination of basic and applied AI knowledge affects firm performance, with particular attention to the role of inter-firm networks in knowledge acquisition and exploitation. Our research addresses three sequential questions:

1. What distinct patterns emerge in how firms combine basic research, applied technological developments, and practical AI implementation capabilities?

2. How do these different knowledge combinations impact firm economic outcomes, particularly productivity?

3. To what extent can firms compensate for limitations in their internal AI knowledge base through external collaborations?

The empirical strategy leverages a unique dataset combining publication data (capturing basic research), patent statistics (representing applied research), and web-based indicators (measuring AI implementation) at the firm-level. Publication data is provided by the SCOPUS database, where based on a keyword search string, AI-related publications where identified. Based on author information, these publications are then attributed to organizations. To assess patent statistics, the autumn 2024 version of PATSTAT is used. AI patents are identified through a classification as well as keyword approach using both CPCs and IPCs for the classifications and patent titles and abstracts for the keywords. Both the SCOPUS search string and the patent identification strategy are derived from the World Intellectual Property Organization (WIPO, 2019). This approach has two major advantage in comparison to other patent and publication identification strategies. On the one hand, it provides a single strategy to both identify patents as well as publications on a worldwide level and on the other hand, it allows to separate different AI technologies from each other. While other strategies may have a higher accuracy (Giczy, Pairolero, & Toole, 2022, for an overview), the WIPO algorithm allows for a more holistic approach to assess formalized AI knowledge. The web-based indicators are based on the website text of companies and also assess the proficiency of their AI knowledge by not only doing a simple keyword search but also to include the embeddedness of these keywords in the text (Dahlke et al., 2024). Based on these three data sources, we identify patterns in the co-occurrence of the three AI-knowledge types and establish a taxonomy of AI firms based on their knowledge integration patterns.

In addition to firms internal knowledge and capabilities base, we also take a relational perspective and consider the external collaborations of firms. We distinguish two types of network relating to knowledge on AI applications and knowledge on AI implementation, respectively. For the former, we identify a firm's connection to external AI knowledge based on co-patenting networks (Cantner & Graf, 2006). For the latter, we measure firm linkages by analyzing inbound and outbound hyperlinks connecting company websites within our sample (Krüger, Kinne, Lenz, & Resch, 2020; Dahlke et al., 2024). The analysis distinguishes between unidirectional and reciprocal connections and identifies whether these links involve firms with expertise in implementing AI into their business model. We create a ratio variable representing the proportion of a firm's links that connect to sources of AI knowledge relative to its total links. This ratio serves as an indicator of the firm's intensity of direct exposure to knowledge on AI implementation, rather than an absolute measure of its overall connectivity.

In general, the aim of this study is to estimate how membership in different taxonomical categories affects productivity (through a production function approach) and whether external collaborations can

compensate for limitations in internal knowledge. This research therefore contributes to innovation economics by (1) establishing a novel taxonomy of how firms combine different types of AI knowledge, (2) revealing whether certain knowledge integration patterns lead to different economic outcomes, and (3) assessing how these patterns relate to firm network positions. Our findings will provide guidance for firms' AI knowledge development strategies and inform policy discussions about fostering balanced AI ecosystem development.

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