

A Value Chain Perspective on AI and Transfer Pricing

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In this article, the authors examine how AI is reshaping business and operating models and the resulting implications for tax and transfer pricing.

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Introduction

Artificial intelligence is rapidly being integrated across industries and business functions, supporting activities ranging from product development and customer engagement to internal decision-making and operational efficiency. Multinational enterprises may pursue AI-related strategies through proprietary model development, foundation model customization, and the integration of proprietary and third-party tools to improve performance, achieving scalability, and generate potential cost savings.¹ These AI-related strategies raise fundamental questions concerning operating models, taxation, and transfer pricing: What divisions within an organization make and track investments?

Who within an organization makes strategic AI-related decisions? Which entities exercise control over those decisions? In which jurisdictions are those decisions made? How should AI-driven income streams be characterized? How and where should AI-driven efficiencies and cost savings be taxed? How should transfer pricing policies adapt to determine which entities are entitled to AI-driven efficiencies, cost savings, and the resulting returns?

AI-driven changes to business models are increasingly recognized as warranting a reassessment of value creation and allocation. For example, the OECD's recent public consultation document proposing revisions to Chapter VII of the transfer pricing guidelines includes illustrative examples involving AI as a service.² This reinforces the importance of analyzing AI through a value chain lens.

Ultimately, how value is created, deployed, and commercialized will drive the alignment of crucial tax and transfer pricing frameworks. As AI adoption accelerates, companies tend to fall into three broad models, depending on the role AI plays in a business and how it contributes to value creation:

1. **AI product companies** derive their primary commercial value from offering AI-based products or services to customers. These businesses generate new revenue streams, such as subscription or usage-based access to proprietary AI platforms or models. In this model, AI capabilities — whether trained models, compute power, or AI services — form the core value proposition and are central to the company's ability to generate profits.
2. **AI-enabled companies operating under a value enhancement model (value enhancement model)** deploy AI to enhance or differentiate customerfacing products and services without selling AI as a stand-alone offering. AI is embedded into front-office or product-adjacent activities. Examples include personalization, recommendations, pricing, advertising effectiveness, fraud prevention, and customer support. These activities aim to improve customer experience, influence customers' willingness to pay, and support monetization. The company typically does not charge customers separately for AI functionality, though AI use may materially affect revenue performance and pricing.
3. **AI-enabled companies operating under an operational enablement model (operational enablement model)** deploy AI primarily to improve internal operations, decisionmaking, and execution efficiency across backoffice and support functions. Many companies use AI tools to automate existing workflows, enhance controls, and reduce costs. Value is generated through productivity gains, margin improvements, or risk mitigation rather than through direct customer monetization.

These models are not mutually exclusive, and many MNEs operate under more than one simultaneously. Nonetheless, distinguishing between them is analytically useful because each model involves different sources of value, distinct AI value chains, and unique tax and transfer pricing considerations. While there is a myriad of taxation issues surrounding AI — including income characterization as services or royalties and permanent establishment — this article primarily focuses on the classification of AI activities within evolving operating models and the resulting transfer pricing implications for businesses whose offerings combine sales of goods, services, and AI.

The following sections provide examples and raise unresolved transfer pricing questions. We do not attempt to provide answers; rather, we raise the questions because tax authorities, taxpayers, and practitioners continue to grapple with the challenges presented by these emerging business models.

The models discussed above may have a material impact on intercompany profit allocation.

AI Product Companies

In the first category, AI product companies present distinct transfer pricing considerations, though they represent only a relatively small subset of multinational enterprises. Like other technology companies, AI product companies face similar transfer pricing issues, including intercompany reseller or distribution arrangements, the sale of hardware with embedded software or AI capabilities, and the characterization of third-party and intercompany payments as services or royalties for tax purposes. Within this model, AI-related intangibles — such as trained models and data — generate nonroutine returns, with pricing closely linked to ownership, control, and deployment of proprietary models, data, and associated risks.

Value Enhancement Model

Under the second category, the value enhancement model, AI is embedded in customer-facing activities that influence demand or monetization. This raises questions about whether AI-related contributions, such as data or embedded systems, warrant returns beyond routine remuneration and, in some cases, separate from any native IP. The broader challenge lies in these AI-enabled revenue streams.

For AI-enabled revenue streams, value is not created at a single point but instead emerges through a series of interrelated activities, stretching from strategic intent and use-case design to operational execution and deployment, and ultimately to business outcomes. The AI value chain for AI-enabled companies can be viewed across five broad, nonlinear categories:

1. **Use-case design and value definition**, whereby businesses determine how AI can support strategic, operational, or commercial objectives;
2. **Data activation and readiness**, which involves sourcing, governing, and preparing data to support those use cases;
3. **Model integration and operational deployment**, through which AI capabilities — whether developed in-house or sourced from third parties — are embedded into business workflows and systems, often relying on underlying compute infrastructure, cloud platforms, specialized hardware, or industry-specific solution providers acting as technical or operational enablers;
4. **Continuous improvement and process optimization**, through which AI-enabled processes are monitored, refined, and scaled over time; and
5. **Business value realization and scaling**, whereby successful use cases are expanded and translated into sustained financial and operational outcomes.

Viewing these activities through a value chain lens helps identify when decisions are made, when resources are deployed, and when economically meaningful contributions arise for transfer pricing

purposes.

In practice, these activities are frequently distributed across multiple entities and jurisdictions within an MNE. Use-case design and strategic control may be centralized in one location while data assets are governed or processed in another. Local business teams may then perform model integration, deployment, and ongoing optimization closer to the business based on physical proximity to relevant markets. Consequently, multiple group members may make economically meaningful contributions at different points along the AI value chain. This has the potential to significantly disrupt established value chains and transfer pricing models.

The OECD's recent public consultation on revisions to Chapter VII of the transfer pricing guidelines includes an AI-focused scenario (Example 16) involving a healthcare MNE that developed and operated an in-house machine learning model using proprietary data sets to provide personalized treatment recommendations to affiliated entities. The example illustrates the potential application of the cost-plus method or the transactional net margin method in circumstances in which AI services rely on unique and valuable intangibles and reliable comparables are unavailable. It further highlights that the entity controlling the AI model — through ownership of proprietary data, the performance of development activities, and the assumption of economically significant risks — may be entitled to returns exceeding routine cost-plus remuneration.

This dynamic under the value enhancement model is also illustrated by the way e-commerce platforms deploy generative AI to enhance customer engagement and monetization. This e-commerce example assumes that centralized data science and engineering teams define personalization use cases and design, train, and continuously refine the algorithms that power product recommendations, search rankings, and content generation. These activities typically rely on large volumes of customer interaction data generated across multiple markets, which are activated and governed through centralized data platforms. Relevant data may be collected in jurisdictions subject to data protection laws. The resulting models are then integrated into local digital storefronts and embedded in the customer purchasing process, where they influence product discovery, cross-selling, and customer engagement. The models may continue to learn from customer data, thereby generating additional value over time. Customers are not charged separately for access to these AI capabilities, but those investments may meaningfully influence commercial outcomes.

Viewed through a value chain lens, these arrangements raise several interrelated operating model and transfer pricing questions, for example:

- To what extent should the centralized development and optimization of recommendation algorithms be considered routine technical support versus influential activity that materially affects demand generation and monetization outcomes across markets?
- How should contributions of centralized AI teams and local operating entities be delineated when local entities control customer relationships, pricing execution, and, in some cases, the market and customer data used to train the centralized models? This question becomes more complex when local entities also control market-specific merchandising, which may be

framed by centrally designed algorithms.³ In those cases, method selection is inherently nuanced and likely does not default to a cost-plus return for the centralized activities.

- Additionally, when AI-driven personalization materially affects conversion rates, considerations are warranted if the associated models and data capabilities represent enhancements to existing marketing or brand-related intangibles, or if they represent distinct, nonroutine contributions (for example, new technology intangibles) that warrant separate consideration in profit allocation.⁴
- If these activities contribute to new or enhanced intangibles, could the new IP be incorporated into the existing IP structure (for example, existing cost-sharing or licensing arrangements) and added to the scope of the intangible development activities? Or is a separate IP structure required to reflect the relevant development, enhancement, maintenance, protection, and exploitation functions and associated returns?
- These questions become more pronounced as recommendation logic improves through global data feedback loops, blurring traditional distinctions between routine execution, local and global marketing activities, and technology-driven value creation.

Operational Enablement Model

Under the third category, the operational enablement model, AI is often used to support productivity gains and operational efficiencies. Gradually, these efficiencies may influence the relevant cost base, with potential implications for benchmarking and pricing for routine functions. To illustrate, AI-powered chatbots may be used to handle a substantial portion of customer service interactions, potentially reducing labor demand and hiring needs as automation capabilities expand. In such models, AI systems — which may be centrally designed, governed, and continuously refined — can perform tasks historically conducted by local service teams. While the primary objectives of these initiatives may include operational efficiency and cost reduction, the resulting operating model changes raise broader transfer pricing questions:

- If customer interactions are increasingly managed through centralized AI systems, taxpayers should consider what functions, if any, are still performed by local service entities, and furthermore, whether a head-count-based, costplus remuneration model still applies.⁵
- If local customer support teams at entities increasingly rely on AI tools, should productivity gains be attributed primarily to the AI tools, the personnel deploying and supervising those tools, or the interactions among these elements? In practice, we expect that tax authorities in some jurisdictions may want to examine the cost base — whether it fully reflects costs that are not explicitly recorded, such as embedded technology costs — to mirror what independent parties would typically include. This approach is broadly consistent with the OECD transfer pricing guidelines, which recognize that cost used in applying cost-based methods may “need some adjustment to make the comparison of the controlled and uncontrolled transactions reliable.”⁶ In this context, the treatment of AI-related efficiencies raises broader questions regarding whether returns should be linked to underlying technology investments (for example, imputed AI-related costs), resulting cost savings, or both.

- As local customer support teams become increasingly reliant on AI tools and centralized teams assume responsibility for AI model governance, deployment decisions, and optimizations, the delineation of value-generating contributions may become less straightforward. In particular, taxpayers may need to evaluate the contributions of local personnel, centralized AI teams, and AI capabilities, as well as whether those centralized activities still constitute routine operational support, or whether they have evolved into nonroutine contributions warranting a different return profile.⁷
- In this context, the reliability of a traditional benchmarking approach under the transactional net margin method may require reassessment, and alternative approaches (for example, profit split or modified cost-based methods) could be considered to reflect AI-related contributions within the group's overall value chain.⁸

Third-Party Arrangements

Distributed value creation extends beyond an MNE's organizational boundaries. Many AI-enabled businesses operate within broader ecosystems of third-party alliances, partnerships, or joint ventures, where different participants contribute complementary elements such as hardware, software platforms, AI capabilities, data, or infrastructure. While these third-party arrangements are often difficult to rely on as comparables for related party pricing, they may provide useful insights into how market participants allocate risks and returns in AI-driven business models. For example, strategic infrastructure partnerships between AI developers and hardware providers may be structured such that investments and related economic benefits are deployed progressively, contingent on the successful rollout and scaling of compute capacity. Even when detailed pricing terms are not publicly disclosed, these structures may suggest that market participants defer or condition economic returns until technological deployment and commercial benefits are realized. This may have significant implications for the allocation of costs and benefits between related parties.

This is not to say that existing transfer pricing paradigms must adhere to these new potential third party comparables. However, as a starting point, careful consideration should be given to the location of the relevant activities. The more fundamental challenges are determining whether and when AI-related activities generate identifiable intangibles, how control and risk over those contributions are exercised, and how resulting returns should be allocated among participating entities, especially if those risks are dispersed in the value chain.

Conclusion

In this context, tax departments may wish to evaluate their companies' value chains to determine whether their existing operating models remain aligned with the business or should be modified or redesigned. The value chain framework outlined here provides a basis for taxpayers and practitioners to identify and assess the key questions relating to value creation and taxation. Subsequent articles will examine the types of intellectual property that may arise in AI-enabled businesses, the operating and transfer pricing models commonly observed in practice, the valuation

considerations that may arise, and the potential direct and indirect tax consequences involving income characterization and PE considerations.

FOOTNOTES

¹ The article draws on a series of illustrative examples to highlight key tax and transfer pricing considerations. These examples are informed by publicly available information but do not reflect the specific facts or circumstances of any particular companies. Rather, the examples are intended solely to help frame and explore the types of questions that tax and transfer pricing professionals may need to consider in practice.

² OECD, "[Public Consultation Document: Revisions to Chapter VII of the OECD Transfer Pricing Guidelines: Special Considerations for Intra-Group Services](#)" (June 2026).

³ The delineation of contributions between centralized and local entities is addressed in the OECD transfer pricing guidelines' guidance on accurate delineation of transactions. Paragraph 1.42 requires that the actual conduct of the parties — including who controls key functions and bears economically significant risks — prevail over contractual form where the two diverge. See OECD, "Transfer Pricing Guidelines for Multinational Enterprises and Tax Administrations," para. 1.42 (2022). The related concept of "control over risk" under the OECD's risk framework is also relevant: Entities that do not exercise genuine control over economically significant risks are generally not entitled to the returns associated with bearing those risks. See *id.* at paras. 1.65-1.106.

⁴ Under the OECD transfer pricing guidelines, the question of whether an activity generates a distinct intangible — rather than merely enhancing an existing one — directly affects profit allocation. The OECD defines intangibles broadly to include nonphysical and nonfinancial assets that businesses may own or control for use in commercial activities, and whose use or transfer would have been compensated in transactions between independent parties. See OECD, "Transfer Pricing Guidelines for Multinational Enterprises and Tax Administrations," para. 6.6 (2022). Under U.S. law, the definition of intangible property for [section 482](#) purposes was expanded by the Tax Cuts and Jobs Act of 2017 ([P.L. 115-97](#)) to include "workforce in place, business methods, goodwill, going concern value, or any other item the value or potential value of which is not attributable to tangible property or the services of any individual." See section 936(h)(3)(B); reg. [section 1.482-4\(b\)](#).

⁵ OECD, *supra* note 4, at paras. 1.33-1.35 (requiring accurate delineation of transactions based on party conduct).

⁶ *Id.* at paras. 7.33 (cost base adjustments for comparability), 2.98-2.99 (cost base determination based on facts, circumstances, and functional analysis).

⁷ See reg. section 1.4821(d)(3)(ii) (emphasizing the relative importance of functions performed, assets employed, and risks assumed in determining arm'slength results).

⁸ OECD, *supra* note 4, at Chapter II (discussing comparability analysis and the reliability of benchmarking when business circumstances change).

END FOOTNOTES