AI Market Power and Competitive Accountability

A Lifecycle Value Chain Framework for Antitrust Analysis

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Research Question

Central Question

- **What should constitute the relevant unit of antitrust analysis in artificial intelligence markets?**
- **Existing AI competition research is rather fragmented, including**:
  - algorithmic pricing and algorithmic collusion [Calvano et al., 2020, Ezrachi and Stucke, 2016]
  - access to training data and data-driven competitive advantages [Varian, 2019, Hagiu and Wright, 2023]
  - control over computational infrastructure and cloud ecosystems [OECD, 2024, Competition and Markets Authority, 2023]
- However, current researches overlook that AI is not a single algorithm but is embedded in **a complex value chain composed of multiple interrelated stages**, where competitive advantages accumulate and reinforce one another across the AI lifecycle.

Contribution

This paper proposes a **Lifecycle Value Chain Framework** for AI competition analysis.

Key contributions

- Conceptualizes AI as a **multi-layered value chain**
- Identifies where market power may emerge and propagate
- Compares different AI paradigms:
  - Generative AI
  - Symbolic AI
  - Agentic AI
  - Traditional Machine Learning
- Provides a structured approach for **competition authorities**

Market Power Mechanisms in Generative AI

Dimension	Analysis	Actor with Power
Data provenance and dynamics	As high-quality public datasets become increasingly exploited, leading foundation models increasingly rely on proprietary and continuously updated datasets (e.g., YouTube, Gmail, platform user data). Control over such datasets strengthens competitive advantages in model training [Lambrecht and Tucker, 2017, Hagiu and Wright, 2023].	Large digital platforms
Compute dependence	Training frontier foundation models requires substantial computational resources, especially GPUs and large-scale cloud infrastructure. Hardware scarcity and capital intensity create significant entry barriers [OECD, 2024, Competition and Markets Authority, 2023].	Chip firms and cloud providers
Model characteristics	The pre-training phase incurs extremely high fixed costs, whereas fine-tuning and deployment entail comparatively lower marginal costs, creating strong scale economies in model development [Kaplan et al., 2020].	Large technology firms
Model evolution	Model improvement occurs through periodic retraining and architectural iteration. Although reinforcement learning from human feedback introduces user interaction data [Gregory et al., 2021].	AI model developers
Scope of generalization	Foundation models are designed to generalize across a wide range of downstream tasks [Kaplan et al., 2020].	Model developers
Accessibility	While many frontier models remain closed-source and accessed via APIs, the expansion of open-source models has lowered barriers for application developers [OECD, 2024].	Foundation model providers
Vertical integration	Foundation model developers increasingly expand into downstream applications, while large digital platforms integrate their own models into existing ecosystems [OECD, 2024].	Platforms and model firms
Acquisition	Mergers and acquisitions in generative AI have increased significantly, often involving acquisitions of AI startups [OECD, 2024].	Large technology firms
Optionality & Opt-Out	Features such as memory functions and personalized workflows may increase switching costs over time [Hagiu and Wright, 2023].	Model providers

Market Power Mechanisms in Symbolic AI

Dimension	Analysis	Actor with Power
Knowledge provenance	Symbolic AI systems rely primarily on domain knowledge, rule bases, and ontologies rather than large-scale datasets. Entry barriers often arise from the scarcity of domain expertise and accumulated knowledge bases.	Firms with proprietary knowledge bases
Infrastructure dependence	Symbolic AI systems depend on reasoning engines, constraint solvers, and optimization software.	Software vendors
Model characteristics	System performance depends on knowledge representation structures and reasoning mechanisms.	AI software developers
System evolution	Updates occur through rule base maintenance rather than automatic learning.	Knowledge engineers
Scope of generalization	Symbolic AI systems are often domain-specific.	Enterprise vendors
Accessibility	Many symbolic AI tools are distributed as enterprise software platforms.	Enterprise software vendors
Vertical integration	Vendors may integrate rule engines with enterprise platforms.	Enterprise software firms
Acquisition	Market consolidation often occurs through acquisitions of specialized enterprise software firms.	Large enterprise software firms

Market Power Mechanisms in Agentic AI

Dimension	Analysis	Actor with Power
Foundation model dependence	Agentic AI systems typically operate on top of foundation models accessed via APIs [OECD, 2024].	Foundation model providers
Agent framework infrastructure	Agent systems organize model capabilities through planning frameworks and tool orchestration.	Agent framework developers
Environmental interaction	Agentic AI continuously interacts with external environments generating operational data.	Agent platform operators
Cross-user learning	Experience accumulated across users improves system performance [Hagiu and Wright, 2023].	Large agent platforms
Within-user learning	Agents gradually learn individual users' preferences.	Agent providers
Tool ecosystem	Agent systems rely on external tools and services to execute tasks.	Platform operators
System integration	Effective agent operation may require integration with operating systems and browsers.	Platform providers
Demand intermediation	Agentic AI systems may execute transactions on behalf of users.	Agent providers
Self-preferencing risks	Integrated agent providers may favor affiliated services.	Agent platform operators
Developer ecosystem	Third-party applications may adapt to dominant agent frameworks.	Dominant agent platforms

Market Power Mechanisms in Traditional Machine Learning

Dimension	Analysis	Actor with Power
Labeled data availability	Traditional machine learning systems rely heavily on labeled datasets [Lambrecht and Tucker, 2017].	Platforms with behavioral data
Data feedback effects	Continuous operation generates behavioral data improving models [Hagiu and Wright, 2023].	Digital platforms
Algorithmic autonomy	Machine learning systems automatically update parameters.	AI engineering firms
Algorithmic collusion risks	Algorithms may converge toward coordinated strategies [Calvano et al., 2020, Ezrachi and Stucke, 2016].	Firms using pricing algorithms
Algorithmic opacity	Opaque models may conceal strategic manipulation.	Platform operators
Algorithmic allocation of visibility	Recommendation systems determine which products users encounter [Varian, 2019].	Digital platforms
Cross-market data leverage	Platforms may combine data across different markets [Lambrecht and Tucker, 2017].	Multi-service platforms
Platform embedding	Machine learning systems embedded within multi-sided platforms.	Platform firms
Acquisition strategies	Large firms may acquire algorithm developers [OECD, 2024].	Technology firms
Two-sided pricing strategies	Platforms may subsidize one side of the market [Varian, 2019].	Digital platforms

AI Lifecycle Market Power and DMA Coverage

Lifecycle Stage	AI Paradigm	Main Market Power Source	Potential Anticompetitive Risk	Competition Policy Focus	DMA Coverage (Scope and Gaps)
Data & Input	Generative AI	Control of large-scale training datasets and compute infrastructure	Exclusionary access to training data or compute resources	Data access rules and monitoring of cloud–AI integration	DMA partially addresses data access through portability and interoperability obligations but does not regulate access to training data or compute infrastructure used in model development
	Traditional ML	Control of behavioral and labeled datasets generated through platform services	Data advantages reinforcing incumbent platforms	Data portability and limits on cross-service data combination	DMA restricts some cross-service data combinations and requires data portability but does not directly address large-scale behavioral data accumulation
	Symbolic AI	Proprietary knowledge bases and ontologies	Standard lock-in through proprietary knowledge formats	Interoperability and open standards	DMA contains interoperability provisions for some platform services but does not address proprietary knowledge representation standards
	Agentic AI	Interaction data generated during agent execution and environmental feedback	Accumulation of behavioral data from autonomous interactions	Governance of interaction data and user control over agent memory	DMA does not explicitly address interaction-generated data from autonomous agents
Model Development	Generative AI	High fixed costs of model training and scaling laws	Concentration of model development among a small number of firms	Monitoring concentration in AI infrastructure and compute markets	DMA does not directly regulate foundation model development or compute concentration
	Traditional ML	Continuous retraining using operational data	Incumbents reinforcing advantages through algorithmic learning	Algorithmic transparency and auditability	DMA provides limited oversight of ranking systems but does not regulate model training processes
	Symbolic AI	Proprietary inference engines and rule architectures	Lock-in through proprietary rule systems	Interoperability of enterprise decision systems	DMA generally does not apply to enterprise software environments
	Agentic AI	Agent orchestration frameworks and tool ecosystems	Control over agent frameworks shaping downstream ecosystem access	Neutral access to agent frameworks and tool integration	DMA does not yet explicitly cover agent frameworks
Task & Output	Generative AI	Integration of model capabilities into digital services	Self-preferencing in AI-powered services	Monitoring integration of AI within gatekeeper services	DMA directly addresses self-preferencing and ranking practices in gatekeeper platforms
	Traditional ML	Algorithmic ranking and recommendation systems	Manipulation of rankings affecting market visibility	Algorithmic accountability and transparency	DMA includes rules addressing ranking transparency and discrimination
	Symbolic AI	Rule-based decision systems governing eligibility or compliance	Exclusionary rule design	Governance of automated rule systems	DMA only indirectly applies where such systems operate within regulated platform services
	Agentic AI	Autonomous execution of decisions on behalf of users	Demand steering and hidden self-preferencing	Transparency and explainability of agent decisions	DMA does not explicitly address automated decision intermediaries
Operation Context	Generative AI	Integration with digital platforms and ecosystems	Leveraging AI capabilities across adjacent markets	Monitoring platform leveraging strategies	DMA directly targets leveraging practices by gatekeepers
	Traditional ML	Embedding within multi-sided digital platforms	Cross-market data leverage	Multi-sided market competition analysis	DMA contains several provisions addressing platform leveraging
	Symbolic AI	Integration with enterprise software ecosystems	Vendor lock-in in enterprise systems	Software interoperability and portability	DMA generally does not regulate enterprise software ecosystems
	Agentic AI	Integration with operating systems, browsers, and device infrastructures	Foreclosure through system-level access restrictions	Platform neutrality and system access regulation	DMA includes rules on operating systems and default settings, but their application to agent systems remains uncertain

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