Online Appendix 1: Explaining how we learnt what we posit

This paper draws on earlier evolutionary work that considers sectoral evolution (e.g. Jacobides, 2005). It is an 'history-friendly' account of the global AI industry which draws on a set of different sources, and relies both on published cases and direct observation. In terms of published sources, we consider both research and industry (and "grey") literature on this area, expanding on Simon (2019) who offers a compendium of existing sources. Our focus was aimed at arriving at a consistent image of the sector, while employing caution for the evidence, understanding that sources may be inescapably biased, whether consciously or unconsciously, and need to be treated as such. The writing team, supported by a team of consultants from BCG, gradually came to converge, triangulating reports, the (limited and fragmentary) systematic empirical evidence, and primary research. If questions arose, we engaged in further interviewing.

Our primary investigation drew on our own experience and that of colleagues who have been involved in AI projects, both in Evolution Ltd, a boutique consultancy, and, primarily, the Boston Consulting Group (BCG) and its thought leadership arm, the Henderson Institute (BHI), where the first author is an Academic Advisor and the third Author is the Global Managing Director. We had the opportunity of using the data that had been collected by BCG, BHI in the context of its current work on both client engagements and research initiatives, which have helped us triangulate the evidence. The primary data which BCG had collected came from recent surveys, including one done in 2020 (with MIT's *SMR* administered to over 3,000 managers from various sectors across the globe), and, more directly pertinent, from a set of 32 semi-structured interviews with AI specialists, outlined in Online Appendix Table below, which ranged from 30 to 90 minutes, and lasted an average of 60 minutes. The interviews, intended to provide a solid understanding of the sector, were complemented from engaging with BCG's data science division, BCG GAMMA, who provides data science consulting combined with deep business expertise.[1] While client projects were confidential, BHI staff which contributed to this project analyzed outcomes of over 30 projects and drew on senior members at GAMMA and some of their main clients, through in-depth interviews, which helped considerably arrive to a consistent and comprehensive picture of the AI ecosystem and its evolutionary dynamics. Our understanding was further refined from those on the Acknowledgment list who reviewed and commented on our evolving drafts.

[1] BCG GAMMA is composed of over 850 data scientists and software engineers, conducting over 200 projects per year worldwide, helping clients with their digital transformation.

Online Appendix 1 Table: Informants / Sources for the Study

Company/Institution	Interviewee / Role
H&M	Head of advanced analytics and AI
DHL	Vice president of innovation and head of Americas Innovation Center
Mercer	Global chief digital officer
Baidu	Director, deep learning platform
Stanley Black & Decker	Director of analytics, Industry 4.0
Repsol	CIO and chief digital officer
Walmart	Vice president of machine learning
Bharti Airtel	CIO and head of cloud and security business
Novo Nordisk	Senior director, advanced analytics and AI
Anglo American	Chief data officer
Porsche Digital	CIO of Porsche, CEO of Porsche Digital
Lyft	Former vice president of science; Head of LyftML
J.P. Morgan	Managing director, head of AI research
Partnership on AI	Head of fairness, transparency, and accountability research
Google Cloud	Managing director, Cloud CTO office
Humana	Senior vice president of enterprise data and analytics
World Economic Forum	Head of AI and machine learning
OECD	Administrator; Innovation economist/policy analyst
BCG GAMMA	Global leader; Leader of GAMMA in the UK; Leader of GAMMA in Australia and New Zealand; Leader of GAMMA in Northeast Asia; Leader of big data and advanced analytics in North America; Leader of GAMMA in Canada
The Wharton School, University of Pennsylvania	Professor of Technology and Digital Business
Harvard Business School	Professor of Business Administration
INSEAD Business School	Professor of Decision Sciences and Technology Management; Professor of European Competitiveness and Reform and Professor of Economics
Carroll School of Business, Boston College	Professor of Information Systems

Online Appendix 2

Looking ahead: The evolving landscape of AI use and its evolutionary dynamics

Looking beyond Big Tech, AI is already having a significant impact on other sectors, such as healthcare. As Benaich & Hogarth (2020) report, publications dealing with AI methods in biology have grown exponentially, over 50% year-on-year since 2017; papers published since 2019 account for 25% of all output since 2000. In pharma, 2019 saw the first AI-developed drugs (generated by AI healthcare platform Excentia) enter production from Sanofi, confirming that, at the sectoral level, AI may represent an "innovation in the method of innovation" per Griliches (1957), as Cockburn et al (2019) remarked. Investments in *downstream* AI applications differ quite sharply at the sectoral level, making us again mindful of the importance of a sectoral system approach. With more than $67.9 billion investment in 2020 (1.4 times higher than 2019, NetBase Quid), there is a clear if evolving sectoral concentration pattern, illustrated in our Online Appendix Figure.

Focusing on to how AI might affect the drug development process, it is worth considering how AI-powered firms approach drug development. While the numbers are small yet, we can already see that firms with healthcare AI solutions work on developing drugs, and once they are successful, create subsidiaries to commercialize specific drugs or drug families. Inference in medical science is incredibly complex, and AI is being used to analyze connections between genetics and diseases. For example, GlaxoSmithKline, a London-based drug giant, partnered with 23andMe to help accelerate their drug development through unsupervised learning and discovery, as well as a platform with which to test their drugs (Herper, 2018; Candelon et al, 2021).

Thus, AI powers an alternative model for drug discovery, with its own (new) downstream industries, whereby outsiders are funded by venture capital and benefit from creating dedicated subsidiaries, as Recursion did when it created Cerexis (for treatments for rare brain cancers), and Atomwise (supported by Velocity) spun off X37 (treatments for endodermal cancers). [2] Pharma incumbents have reacted by trying to integrate AI into their own processes, leveraging their own data, and attaining the organizational independence and scale to compete through AI. In particular, European drug manufacturers, concerned that they lack the skills

[2] Interestingly, while AI does offer a new method for innovating, the mantle is picked up by AI specialists, suggesting that AI requires different capabilities from those of incumbent firms. It is also interesting that Big Tech firms, although they have AI-based subsidiaries in healthcare (such as Google's Verily), did not pioneer this new approach; AI firms needed to combine their unique skills with an understanding of context, despite relying on Big Tech for infrastructure and potentially additional services.

and capacity to develop similar approaches in-house, have opted to create an AI platform called MELLODDY.[3] This platform is revolutionary, since it anonymously pools the data of key competitors from Merck to Bayer, GSK to AstraZeneca, and Amgen to Novartis. MELLODDY aims to complement the traditional drug-development process and leverage AI downstream.[4]

In other sectors, AI is leading to a host of new opportunities. For example, autonomous driving, along with other developments in the mobility ecosystem, is being driven by the "Cambrian explosion" in computer-enabled vision. Beyond driving, AI has also raised a myriad of ethical and pragmatic considerations around the issue of responsibility. It has been used in areas from facilitating credit allocation to (contentiously) making prison sentencing recommendations, as well as the ubiquitous uses of computer-aided vision, chatboxes, and other decision-support systems.

Drilling down further to consider how AI is affecting performance *within* firms, evidence is sparser. As Ransbotham et al (2020) find, many organizations seem to recognize AI's value in obtaining competitive advantage (87%), entering new businesses (78%), and reducing costs (72%). However, AI has not led to significant benefits yet. A mere 11% of organizations achieved significant financial benefits with AI in 2020, and sectors vary widely in the positive impact from AI. This is consistent with the (very limited) academic evidence. The Babina et al (2020) study finds that AI-investing firms see growth in market share but *not* in productivity measures—at least, as assessed by Total Factor Productivity (TFP). This might also be because of the challenges of integrating IT into existing processes.[5] Thus, AI requires significant changes at the organizational level, as von Krogh (2018) and Tambe et al (2019) posit. With natural language processing (NLP), for example, enterprises have encountered significant time, talent, and cost barriers while building solutions in-house. Similarly, for deep learning, the high volume of accurate data required constitutes another significant barrier.

In all, firms will differ in their use of AI depending on their focus on it, their access to adequate digital data, and their size. Smaller and less digital- and data-aware firms focus on consumption of off-the-shelf solutions—which is why libraries might be valuable resources for them, as they replicate some of the resources enjoyed by larger firms. Larger and/or more

[3] https://www.imi.europa.eu/projects-results/project-factsheets/melloddy

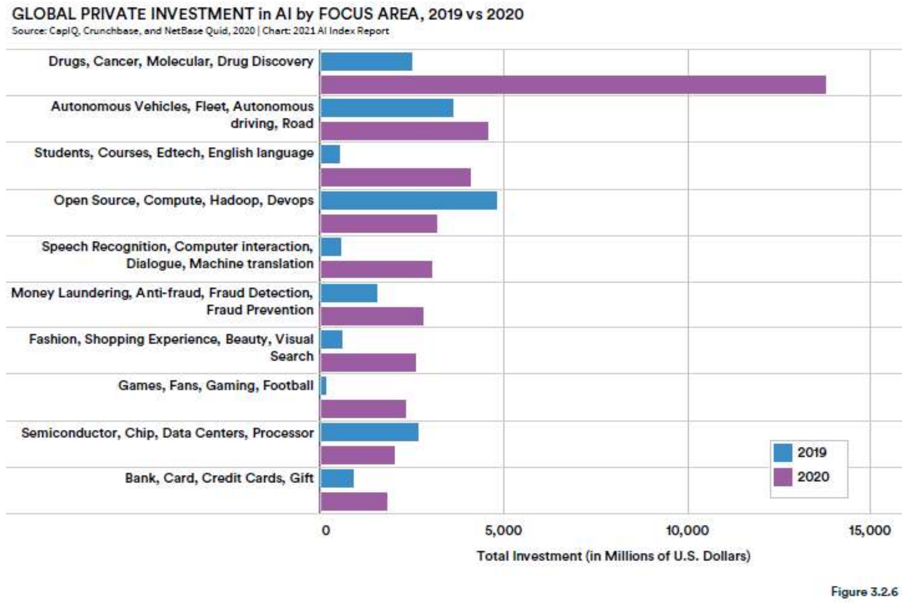
[4] In addition to these new governance forms, we also see new ways in which organizations themselves are structured to respond to these opportunities; see Ransbotham et al (2020) for a review.

[5] The McKinsey study finds, e.g., that Robotic Process Automation and computer vision for creating an expert program (such as tractable's AI system to predict damage costs in vehicle collisions) are the most commonly deployed techniques in the enterprise. Speech, natural language generation, and physical robots, which require more adjustment, are the least common (Bughin et al, 2019).

digitally aware and data-enabled firms may be more sophisticated, and may also have the in-house personnel to customize off-the-shelf AI solutions (such as Uber, which uses multiple tech providers and AI solutions for tech orchestration so that it can focus on producing AI for its core business)[6], and as such potentially being involved in part of the AI stack. Building this expertise may be difficult as well as scale-sensitive, and benefiting from data assets requires significant transformation. These processes will be long, costly, and prone to failure. Heterogeneity will persist, despite the push of data-enabled economies of scale and scope toward concentration, consistent with predictions going back to the origins of the evolutionary approach (e.g. Nelson & Winter, 1982; Dosi, 1988). In this respect, national and regional level differences are pervasive and persistent, and cannot be underestimated.

[6] https://eng.uber.com/tech-stack-part-one-foundation/

Online Appendix 2 Figure



Source: NetBase Quid, Stanford Human-Centered Artificial Intelligence. See https://aiindex.stanford.edu/report/

Online Appendix 3: Mapping the differences in AI between China, the US and the EU

While a full understanding of the differences on how AI operates in the key geographies would require dedicated study, we have provided here a summary of the sources we used to come to the conclusions of section 5.1 and Figure 6, noting some of the sources. For some countries there are more detailed expositions. For China, for instance, see the Triple Helix analysis in Arenal et al (2020). For the EU, see the problem of scattered resources mentioned in Delponte et al (2018). For the U.S., see the phenomenon of "killer acquisition" made by multi-side platforms like Google and Facebook in Kamepalli et al (2020). Our objective, beyond comparing and contrasting the analysis we could see in each setting was to organize information which was available in terms of AI, and this table showcases sources as well as main themes, with the sources and attributes presented in Online Appendix Table 1.

In addition to the qualitative evidence noted above, we have mapped the (imperfect) information about AI, presented here in Online Appendix Table 2. We have little systematic evidence on AI activity within corporates but do have information on (a) hyperscalers (ie., firms worth over $500 billion); (b) startups focusing on AI; (c) unicorns (ie., firms worth over $1B) in AI. We provide below these three sets of data, in raw numbers (for 2020), as well as normalized (1) in terms of the total number of firms in the country (e.g., number of unicorns in AI divided by number of unicorns in China) and (2) share of global AI activity (e.g., number of unicorns in AI divided by number of AI unicorns in the world). While this gives us only partial evidence it is the most comprehensive (or at least consistent) data available. This table also features patents in AI to complement our analysis

Online Appendix 3 Table 1

Area of interest	**Issues we focused on**	***US and Canada***	***China***	***European Union (and UK)***	**Source**
Commercial	Current types of pre-existing tech players (tech giants and startups)	Have diversified types of businesses, with tech giants present in the market	Have most diversified types of businesses, with tech giants present in the market	Do not have local tech giants, relatively fewer AI unicorns	CB insights[7], 2019, interview
	Collaboration model with traditional companies	Tech-natives replace traditional companies that can't adapt fast enough	"Transformers" drive AI transformation for traditional companies	Traditional companies reinvent themselves to be AI-powered, by orchestrating their own ecosystems of tech partners	Interviews
	Accessibility and maturity of capital market	Relatively easy access to funding	Relatively easy access to funding	Relatively difficult access to funding but improving	Crunchbase[8], 2019
Academic	Collaboration between universities and businesses	Strong and mature collaboration between academics and businesses	Close connection between academics and businesses driven by government	Limited connection between academics and businesses, most research financed by government	OECD.AI[9], 2020, interview
	Access to AI talents (e.g., graduates and trained workforce)	Strong access to AI talents (both researchers and workforce)	Medium access to AI workforce (trending upward), weak access to AI researchers	Medium access to AI researchers, weak access to AI workforce (varies largely among countries, centered in UK and FR)	OECD.AI[10], 2020, Element AI[11], 2019
Technological	Level of business digitalization	High level of business digitalization in major industries	Relatively low level of business digitalization in major industries	High level of business digitalization in major industries	BCG-MIT survey[12], 2020

[7] See https://www.cbinsights.com/research/asia-startups-most-well-funded/
[8] See https://www.crunchbase.com/
[9] See https://www.oecd.ai/data-from-partners?selectedTab=AIResearch
[10] See https://www.oecd.ai/data-from-partners?selectedTab=AIResearch
[11] See https://www.elementai.com/news/2019/2019-global-ai-talent-report
[12] Source: Ransbotham et al, 2020. The sample size was over 3000 firms globally. Respondents to the questionnaire were executives of companies across industrial sectors including aerospace, agriculture, automobile, chemicals, construction and real estate, consumer goods, electronics, entertainment, financial services, health care services, logistics, manufacturing, oil and gas, pharmaceuticals, retail, telecom, transportation and travel, and utilities

	Penetration of digital infrastructure	High penetration of digital infra.	Relatively low penetration of digital infra.	High penetration of digital infra. (especially in Nordic countries)	OECD[13], 2020; World bank[14], 2019
Regulatory	Level of data protection	High level of data protection	Relatively low level of data protection, "view citizen's data as public good"	Soundest regulation on data protection	Chuvpilo, 2020[15]
Political	The extent to which governments drive the development of AI (Role of governments)	Government is dedicated to drive the development of AI, with large amounts of gov. funding, direct purchases, etc.	Government is dedicated to drive the development of AI, with significant funding direct purchases, etc. (accelerated by "Sputnik moment")	Government has mixed attitude towards AI development, with relatively smaller amount of gov. funding, more regulations, and highest openness of gov. data	OECD[16], 2019, interviews
Cultural	Public trust in data and data science	Relatively low public trust (39% of US/Canada users)	Highest public trust (86% of CN users)	Medium public trust (45% of EU users)	BCG-MIT survey[17], 2020
	Overall knowledge/ understanding of AI	Relatively low understanding of AI (35-39% of US users)	Highest understanding of AI (86-88% of CN users)	Relatively low understanding of AI (28-42% of EU users)	BCG-MIT survey[18], 2020
Socio-economic	Single market size	Medium market size (around 330 Mn population)	Largest market size (around 1,400 Mn population)	Overall medium market very fragmented and immobile (c 450 Mn population across 28 nations)	United Nations[19], 2020
	GDP per capita	High GDP per capita (around $65,300)	Low GDP per capita (around $10,200)	Medium GDP per capita (around $35,000)	World bank[20], 2019

13 See http://www.oecd.org/digital/oecdkeyictindicators.htm
14 See https://data.worldbank.org/indicator/IT.CEL.SETS.P2?locations=CN
15 See https://chuvpilo.medium.com/ai-research-rankings-2020-can-the-united-states-stay-ahead-of-china-61cf14b1216
16 See https://www.oecd.org/digital/digital-government/open-government-data.htm
17 Source: Ransbotham et al, 2020. The sample size was over 3000 firms globally. Respondents to the questionnaire were executives of companies across industrial sectors including aerospace, agriculture, automobile, chemicals, construction and real estate, consumer goods, electronics, entertainment, financial services, health care services, logistics, manufacturing, oil and gas, pharmaceuticals, retail, telecom, transportation and travel, and utilities
18 Source: Ransbotham et al, 2020. The sample size was over 3000 firms globally. Respondents to the questionnaire were executives of companies across industrial sectors including aerospace, agriculture, automobile, chemicals, construction and real estate, consumer goods, electronics, entertainment, financial services, health care services, logistics, manufacturing, oil and gas, pharmaceuticals, retail, telecom, transportation and travel, and utilities
19 See https://population.un.org/wpp/
20 See https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

Online Appendix 3 Table 2

Measurement	Definition	China	US and Canada	EU	Source
Number of hyperscalers[21]	absolute value	2	6	0	CRSP[22]
	global share: number of hyperscalers in China divided by number of hyperscalers worldwide	25%	75%	0%	CRSP[23]
Number of AI startups	absolute value	827	7,154	3,844	Crunchbase[24]
	normalized value: number of AI startups in EU divided by number of startups in EU	6%	5%	4%	Crunchbase[25]
	global share: number of AI startups in EU divided by number of AI startups worldwide	5%	42%	23%	Crunchbase[26]
Number of unicorns	absolute value	121	241	59	CB insights[27]
	global share: number of unicorns in EU divided by number of unicorns worldwide	25%	49%	12%	CB insights[28]
Valuation of unicorns	absolute value (billion USD)	499	709	126	CB insights[29]
	global share: valuation of unicorns in EU divided by valuation of unicorns worldwide	32%	46%	8%	CB insights[30]

[21] Hyperscalers in the U.S. are Apple, Microsoft, Amazon, Google, Facebook, and Tesla. Hyperscalers in China are Alibaba and Tencent
[22] See http://www.crsp.org/
[23] See http://www.crsp.org/
[24] See https://www.crunchbase.com/
[25] See https://www.crunchbase.com/
[26] See https://www.crunchbase.com/
[27] See https://www.cbinsights.com/research/asia-startups-most-well-funded/
[28] See https://www.cbinsights.com/research/asia-startups-most-well-funded/
[29] See https://www.cbinsights.com/research/asia-startups-most-well-funded/
[30] See https://www.cbinsights.com/research/asia-startups-most-well-funded/

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