Hardware, Software, and the Future of Economic Growth

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Outline

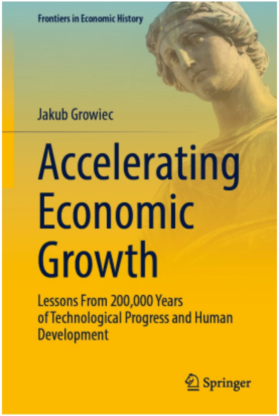
1. The **hardware–software framework**
   - Based on first principles
   - Generalizes standard macro frameworks
   - Guides the narrative of economic growth and technical change throughout human history (Growiec, 2022a)
   - Helpful for predictions of future growth: secular stagnation – balanced growth – accelerating growth – singularity
2. An **empirical application**
   - USA, 1968–2019
   - We construct the time series of L, H, K, Ψ.
   - We document the progress of mechanization and automation
   - We carry out a growth accounting exercise
3. **Scenarios for the future**
   - Partial vs. full automation
   - With vs. without R&D capital
   - Impacts of artificial superintelligence

Outline (2)

1. "Hardware and Software over the Course of Long-Run Growth: Theory and Evidence" (2023), with Julia Jabłońska and Aleksandra Parteka
2. "Automation, Partial and Full" (2022), **Macroeconomic Dynamics** 26(7), pp. 1731-1755
3. "What Will Drive Global Economic Growth in the Digital Age?" (2023), **Studies in Nonlinear Dynamics and Econometrics** 27(3), pp. 335-354
4. "Industry 4.0? Framing the Digital Revolution and Its Long-Run Growth Consequences" (2023), **Gospodarka Narodowa. Polish Journal of Economics**, 4/2023 (316), pp. 1-16

The Broader Context

- “Accelerating Economic Growth: Lessons From 200 000 Years of Technological Progress and Human Development" (2022), Springer.



Related Literature (1)

1. **Production function specification and estimation**, in particular with capital–skill complementarity, unbalanced growth, investment-specific and skill-biased technical change
(Gordon, 1990; Jorgenson, 1995; Greenwood, Hercowitz, and Krusell, 1997; Krusell, Ohanian, Ríos-Rull, and Violante, 2000; Henderson and Russell, 2005; Caselli and Coleman, 2006; Klump, McAdam, and Willman, 2007, 2012; Mućk, 2017; McAdam and Willman, 2018);
2. **Accounting for the accumulation of information and communication technologies (ICT)** and their broad growth-enhancing role as a general purpose technology
(Bresnahan and Trajtenberg, 1995; Timmer and van Ark, 2005; Jorgenson, 2005; Brynjolfsson and McAfee, 2014; Gordon, 2016; Brynjolfsson, Rock, and Syverson, 2019; Aum, Lee, and Shin, 2018; Jones and Tonetti, 2020; Farboodi and Veldkamp, 2019; Nordhaus, 2021);
3. **Automation** and its impacts on productivity, employment, wages and factor shares
(Acemoglu and Autor, 2011; Autor and Dorn, 2013; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018; Andrews, Criscuolo, and Gal, 2016; Arntz, Gregory, and Zierahn, 2016; Frey and Osborne, 2017; Barkai, 2020; Autor, Dorn, Katz, Patterson, and Van Reenen, 2020; Jones and Kim, 2018);

Related Literature (2)

4. **Macroeconomic implications of AI**
(Yudkowsky, 2013; Graetz and Michaels, 2018; Sachs, Benzell, and LaGarda, 2015; Benzell, Kotlikoff, LaGarda, and Sachs, 2015; DeCanio, 2016; Acemoglu and Restrepo, 2018; Aghion, Jones, and Jones, 2019; Berg, Buffie, and Zanna, 2018; Korinek and Stiglitz, 2019; Trammell and Korinek, 2021; Davidson, 2021; Eloundou, Manning, Mishkin, and Rock, 2023);
5. **R&D-based endogenous growth**
(Romer, 1990; Jones and Manuelli, 1990; Aghion and Howitt, 1992; Jones, 1995; Ha and Howitt, 2007; Madsen, 2008; Bloom, Jones, Van Reenen, and Webb, 2020; Kruse-Andersen, 2023).

The Hardware–Software Framework

In any technological process, output is generated through purposefully initiated physical action:

1. the physical action requires expending **energy**,
2. the set of instructions, or code, is **information**.

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2. the set of instructions, or code, is **information**.

Hence, based on first principles, the postulated production function is

$$Output = \mathcal{F}(X, S), \tag{1}$$

where X – hardware, S – software. The function $\mathcal{F}$ is increasing in both factors. Both X and S are **essential** and mutually **complementary** ($\sigma < 1$).

What's Inside Hardware and Software

$$Output = \mathcal{F}(X, S) = \mathcal{F}(L + K, H + \Psi). \quad (2)$$

Hardware X	Human physical labor	$L = \zeta N$
	Non-programmable physical capital	$(1-\chi)K$
	Compute	χK
Software S	Human cognitive work	$H = AhN$
	Pre-programmed software (including AI algorithms)	$\Psi = A\psi\chi K$

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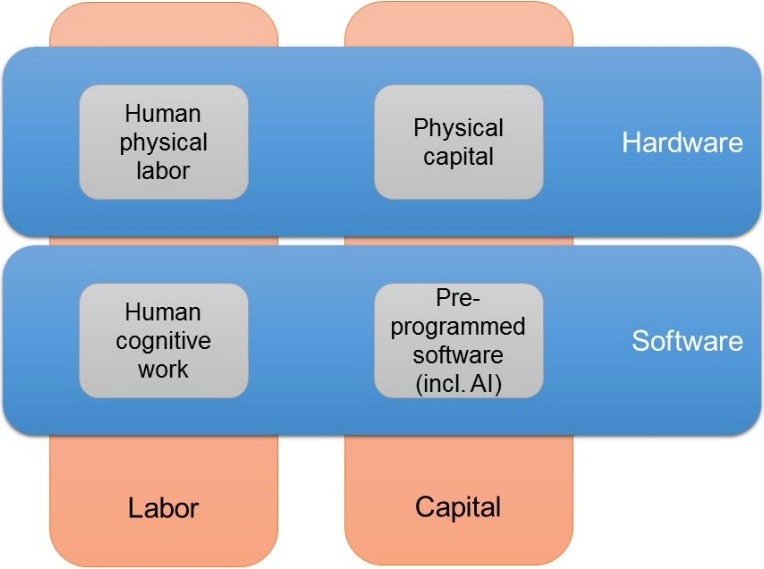
Within hardware and software, factors are substitutable(*)

(*) beware of complex, multi-step processes, Growiec (2022b)

Hardware and Software vs. Capital and Labor



Technological Progress

$$Output = \mathcal{F}(X, S) = \mathcal{F}(\zeta N + K, A(hN + \psi\chi K)). \quad (3)$$

Technological progress (growth in A) expands the "repository of codes"

- New technologies are information and not actual *objects* or *actions*. It is precisely this informational character that makes technologies non-rivalrous (Romer, 1990).
- All technological progress is naturally modeled as software-augmenting.

The Hardware–Software Framework vs. Established Models

The hardware–software framework:

$$Output = \mathcal{F}(X, S) = \mathcal{F}(\zeta N + K, A(hN + \psi\chi K)) \quad (4)$$

encompasses as special cases:

- a standard treatment of the industrial economy (respecting Kaldor's facts),

$$Output = \mathcal{F}(K, AhN),$$

- a model of capital–skill complementarity and skill-biased technical change,

$$Output = \mathcal{F}(\zeta N + K, AhN),$$

- a theory of Industrial Revolution,
- a theory of Digital Revolution.

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Output:

- GDP or value added, Y,
- technological change, $\dot{A}$.

Stages of Economic Development

1. **Pre-industrial production** ($K = \tilde{K} \approx 0$, $\chi = 0$):

$$Y = F(X, S) = F(\zeta N + \tilde{K}, AhN) \approx N \cdot F(\zeta, Ah). \tag{5}$$

2. **Industrial production** ($\chi = 0$):

$$Y = F(X, S) = F(\zeta N + K, AhN). \tag{6}$$

The limit of full mechanization without automation ($K/N \to \infty$) implies:

$$Y \approx F(K, AhN). \tag{7}$$

3. **Digital production**:

$$Y = F(X, S) = F(\zeta N + K, A(hN + \psi \chi K)). \tag{8}$$

The limit of full mechanization and automation ($K/N \to \infty$) implies:

$$Y \approx K \cdot F(1, A\bar{\psi}\bar{\chi}). \tag{9}$$

Empirical Application

We quantify hardware X and software S for the **USA, 1968–2019**.

Data sources:

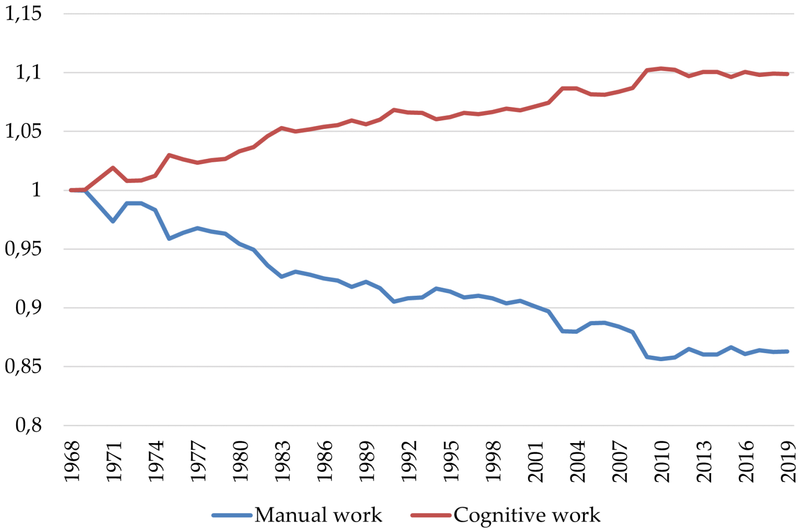
1. O*NET Content Model database – detailed information on work characteristics and equipment used in almost 1,000 occupational groups;
2. CPS IPUMS microdata – hours worked by occupation;
3. US BEA tables – investment in fixed assets by category;
4. aggregate US statistics: GDP, hours worked.

Decomposing Labor: Manual vs. Cognitive Tasks

To compute the share of manual tasks in each occupation, we merge raw O*NET (v.25.3) files on Work Activities, Work Context, Abilities and Skills. We identify manual tasks using a list of selected Work Activities and Work Context Importance scales.

We match these shares with data on hours worked by occupation (CPS IPUMS database). We map the $\sim$ 1000 occupations in O*NET with $\sim$ 450 occupations in CPS IPUMS, using the crosswalk O*NET-SOC 2019 to 2018 SOC from the O*NET Resource Centre.

Share of Manual vs. Cognitive Work in the USA



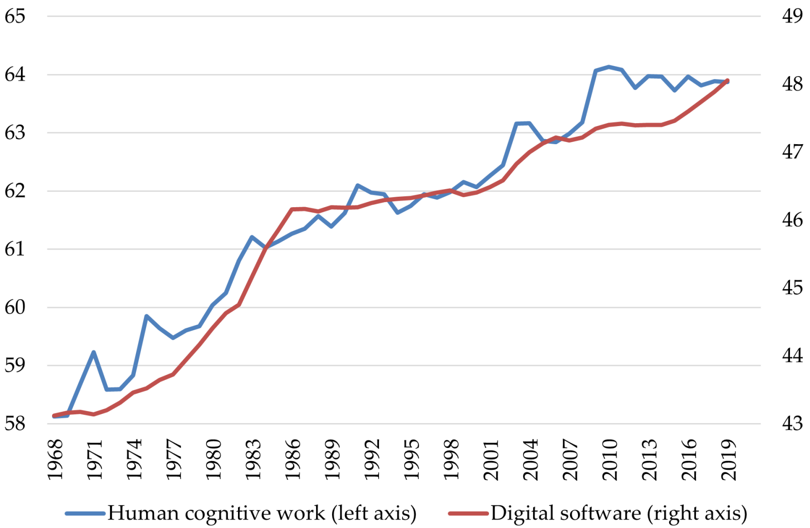
Decomposing Capital: Physical Capital vs. Digital Software

To compute the share of hardware investment we take US Bureau of Economic Analysis data which allows us to divide real investment into structures, intellectual property products and 25 categories of equipment.

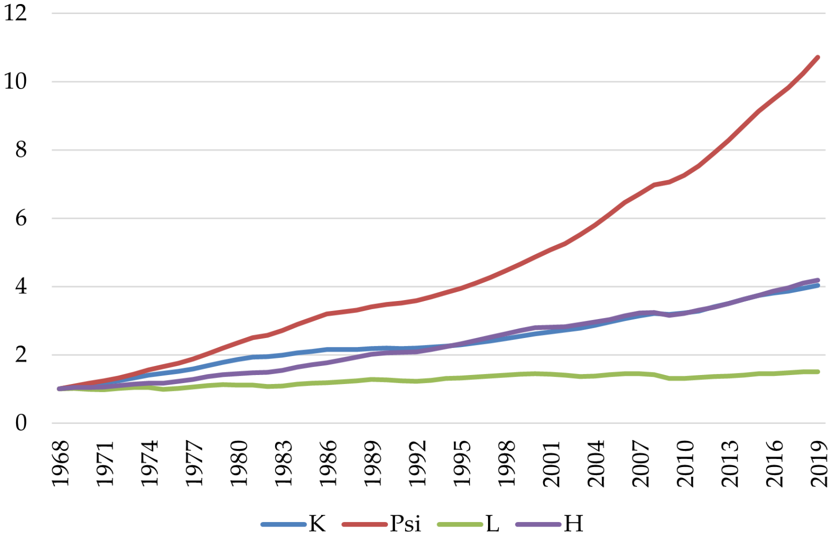
- Structures: 100% hardware;
- IPPs: 100% software;
- Equipment: we proceed via proxy – we assume that the more manual the job is, the more hardware-intensive equipment the worker uses.

We use the standard perpetual inventory method to build up the real stocks of physical capital (hardware) and digital software. We apply asset-specific depreciation rates based on Fraumeni (1997). These rates range from 0.026 per annum (structures) to 0.315 (computers and peripheral equipment).

Share of Human Cognitive Work in Labor and of Digital Software in Capital



Dynamics of Hardware K, Ψ and Software L, H



Calibration of the Aggregate Production Function

We use a normalized CES production function specification:

$$Y = Y_0 \left(\alpha \left(\frac{X}{X_0} \right)^{\theta} + (1-\alpha) \left(\frac{S}{S_0} \right)^{\theta} \right)^{\frac{1}{\theta}}, \qquad \theta \leq 1, \alpha \in (0,1),$$

with

$$X = X_0 \left(\gamma \left(\frac{L}{L_0} \right)^{\mu} + (1-\gamma) \left(\frac{K}{K_0} \right)^{\mu} \right)^{\frac{1}{\mu}}, \qquad \mu \leq 1, \gamma \in (0,1),$$

$$S = S_0 \left(\beta \left(\frac{H}{H_0} \right)^{\omega} + (1-\beta) \left(\frac{\Psi}{\Psi_0} \right)^{\omega} \right)^{\frac{1}{\omega}}, \qquad \omega \leq 1, \beta \in (0,1).$$

- We set α, β, γ, θ, μ, ω and g so as to roughly match
  - the average GDP growth rate (2.7% in data)
  - the labor share (in data, 0.61 on average)
  - the cognitive wage premium (in data, cognitive work earns $\sim$ 10% more)

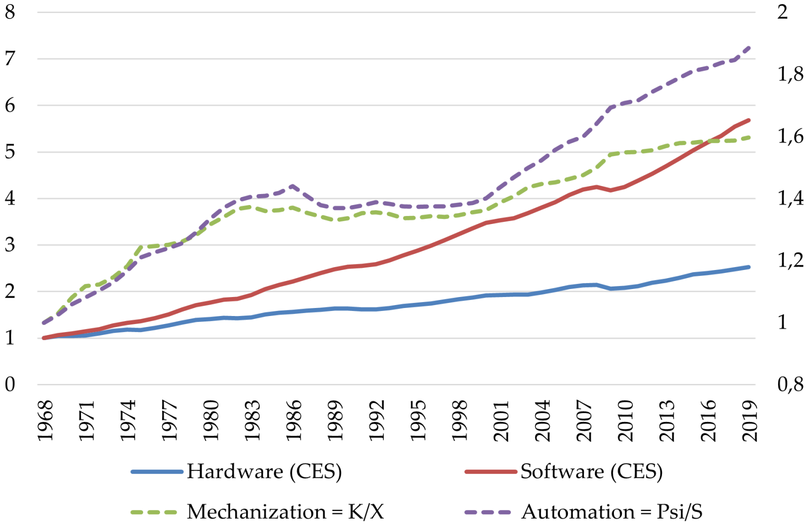
Baseline Calibration

Table: Baseline parameterization of the nested CES production function

Output		Hardware		Software		Tech
α	θ	γ	μ	β	ω	g
0.44	-0.2	0.45	1	0.71	-1.74	0.015

- Hardware and software are gross complements: $\sigma_{X,S} = \frac{1}{1-\theta} = 0.83$
- Physical capital and human physical labor are perfectly substitutable
- Human cognitive work and digital software are gross complements: $\sigma_{H,\Psi} = \frac{1}{1-\omega} = 0.36$

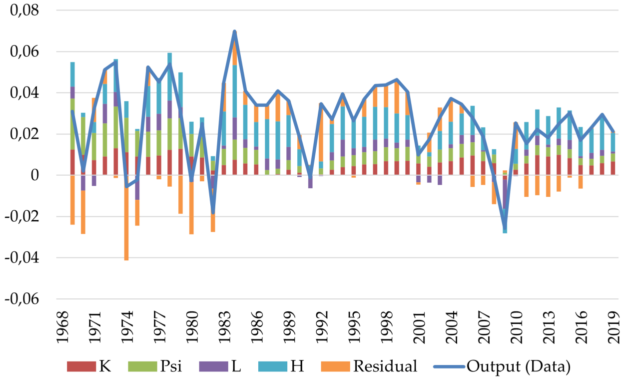
Hardware, Software, Mechanization and Automation



Growth Accounting with Nested CES Production

Table: Contributions to annual GDP growth, 1968–2019 (pp.)

	GDP	K	Ψ	L	H	Residual
pp.	2.71	0.64	0.75	0.17	1.13	0.02
% of total		23.7%	27.9%	6.1%	41.7%	0.8%



The Future of Economic Growth in the Digital Era

Reduced form two-sector growth model with a production and R&D sector:

$$Y = F(G_1(\zeta N, K), G_2(AhN, A\psi\chi K)), \tag{10}$$

$$\dot{A} = A^{\phi}\Phi(G_1(\zeta N, K), G_2(AhN, A\psi\chi K)), \tag{11}$$

$$\dot{K} = sY - \delta K, \tag{12}$$

where the term A^{ϕ} (with $\phi \in [0, 1]$) captures the potentially positive "standing on shoulders" effects in R&D (Jones, 1995).

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Additional assumptions

- F, G_1, G_2 and Φ are characterized by constant returns to scale
- factors in F, Φ are essential and mutually complementary ($\sigma < 1$)
- factors in G_1 are inessential and mutually substitutable ($\sigma > 1$)
- for G_2 we consider $\sigma > 1$ (**full automation**) vs. $\sigma < 1$ (**partial automation**)
- bounded variables (s, h, ψ, χ) will eventually stabilize
- population N is constant

Key Questions

- **Full vs. Partial Automation.** How are long-run growth predictions affected whether or not all essential tasks can be automated?
- **Automation of Production vs. R&D.** How are long-run growth predictions affected if only production, but not R&D tasks can be automated? And conversely, what if only R&D, but not production tasks can be automated?
- **R&D Capital.** How are long-run growth predictions affected whether or not machines (physical capital) are used in the R&D process?
- **Hardware-Augmenting Technical Change.** How are long-run growth predictions affected whether or not technical change can be (at least partly) hardware-augmenting?

Intuition Behind the Results

- Observe the **relatively scarce factor of production in the long-run limit**
  - hardware or software?
- Industrial economy
  - the scarce factor was human cognitive work
  - the key source of growth was labor-augmenting technological progress, provided by R&D (Romer, 1990; Jones, 1995; Acemoglu, 2009).
- Digital economy with partial automation
  - the scarce factor is human cognitive work complementary to automated tasks
  - dual growth engine: labor-augmenting technological progress + accumulation of R&D capital
- Digital economy with full automation
  - the scarce factor is compute
  - the key source of growth is accumulation of compute (Jones and Manuelli, 1990; Trammell and Korinek, 2021)
- On top of that, the hypothetical force of hardware-augmenting technical change can alleviate the scarcity of compute

Summary of Results

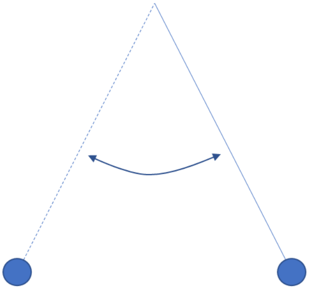
Scenario	Growth engine	Growth rate
	BASELINE (WITH R&D CAPITAL)	
Full Automation in Production and R&D	K acc	$g = s\alpha a_K - \delta$
Full Automation in Production	K acc	$g = s\alpha a_K - \delta$
Full Automation in R&D	K acc	$g = s\alpha a_K - \delta$
Partial or No Automation, $\phi = 0$	K acc + LATC	equation in text
Partial or No Automation, $\phi \in (0, 1]$	K acc	$g = s\alpha a_K - \delta$
	WITHOUT R&D CAPITAL	
Full Automation in Production and R&D	K acc	$g = s\alpha a_K - \delta$
Full Automation in Production	K acc	$g = s\alpha a_K - \delta$
Full Automation in R&D	K acc	$g = s\alpha a_K - \delta$
Partial or No Automation, $\phi \in [0, 1)$	LATC*	secular stagnation
Partial or No Automation, $\phi = 1$	LATC**	$g = b_K \zeta N$

Notes: LATC – labor-augmenting technical change; KATC – capital-augmenting technical change; * semi-endogenous R&D-based growth; ** fully endogenous R&D-based growth.

Summary of Results (2)

Scenario	Growth engine	Growth rate
	With Hardware-Augmenting Technical Change	
Full Automation in Production and R&D	K acc + KATC	explosive growth
Full Automation in Production	K acc + KATC	explosive growth
Full Automation in R&D	K acc + KATC	explosive growth
... *With R&D Capital* ...		
Partial or No Automation, $\phi = 0$	LATC	$g = \gamma b_N hN$
Partial or No Automation, $\phi \in (0, 1]$	K acc + LATC	explosive growth
... *Without R&D Capital* ...		
Partial or No Automation, $\phi \in [0, 1 - \kappa)$	LATC	secular stagnation
Partial or No Automation, $\phi = 1 - \kappa$	LATC	$g = b_K \zeta N$
Partial or No Automation, $\phi \in (1 - \kappa, 1]$	LATC	explosive growth

Zooming Out: Revolutions in Energy vs. Information



Hardware
2. Agricultural revolution
4. Industrial revolution

Software
1. Cognitive revolution
3. Scientific revolution
5. Digital revolution

Source: Growiec (2022), Accelerating Economic Growth: Lessons From 200 000 Years of Technological Progress and Human Development, *Springer*.

Waves of the Industrial Revolution

Revolution	Years	Key technologies
1.0	1770-1840	Steam engine, railroad, loom
2.0	1870-1920	Internal combustion engine, electricity, telephone, medicine
3.0	1960+	Digital computer, cell phone, Internet, credit cards
4.0	2010+ ?	Internet of Things, cloud computing, AI

Sources: Gordon (2016); Schwab (2016)

Waves of the Industrial Revolution – Revisited

Revolution	Years	Key technologies
		Industrial Revolution [Energy]
1.0	1770-1840	Steam engine, railroad, loom
2.0	1870-1920	Internal combustion engine, electricity, telephone, medicine
		Digital Revolution [Information]
3.0	1980+	Digital computer, Internet, cell phone, credit cards
4.0	2010+ ?	Internet of Things, cloud computing, AI

Sources: Gordon (2016); Schwab (2016); Growiec (2022a)

Overview of Technologies

Mechanization technologies (≈ since Industry 1.0-2.0)

- Steam engine and applications thereof
- Internal combustion engine and applications thereof
- Electric engine and applications thereof
- Electricity generation: fossils, hydro, nuclear, wind, solar

Key: machines have instant access to an energy source. **Physical action is generated without the input of human physical work.**

Automation technologies (≈ digital)

- Machines with a built-in program (e.g., clocks, old washing machines)
- Jacquard loom with punchcard coding
- Digital computer: programmable hardware / compute
- Software: deterministic vs. AI / machine learning
- Communication technologies: telegraph, telephone, cell phone, broadband
- Network: Internet, smartphone, Internet of Things, cloud computing
- Robots, interfaces: digital computer + physical device (e.g., AR/VR)

Key: machines have instant access to an information source (code, data). **Information is processed without the input of human cognitive work.**

Future of the Digital Era?

1. Does the technology enable full automation of a complex production process? Can production continue without any human input?
   –> breadth of automation; adaptive, general thinking
2. Does the technology contribute to positive knowledge spillovers in R&D? Does it facilitate new innovations or, to the contrary, make "ideas harder to find" (Bloom, Jones, Van Reenen, and Webb, 2020)?
   –> automating R&D, exploiting long-distance links in the knowledge space

Key **game changer**:

- General-purpose, adaptive, powerful AI –> AGI

Necessary auxilliary technologies:

- General-purpose computing power, digital memory, Internet, bandwidth, sensing technologies and other sources of data
- Reliable access to energy

AGI Timelines

- OpenAI (2023): "While superintelligence seems far off now, we believe it could arrive this decade" (until 2030)
- Metaculus.com median forecast: 2032
- Cotra (2022), based on a formal model: $\sim$ 2040
- Grace et al. (2024), survey of AI experts: 2047.
- Miscellaneous singularity estimates (e.g., Kurzweil, Johansen & Sornette, Roodman): $\sim$ 2050

Thank you for your attention.

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OPUS 19 No. 2020/37/B/HS4/01302

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