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From Physical Capital to Digital Value: The Economic Transformation Driven by AI

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من رأس المال المادي إلى القيمة الرقمية: التحول الاقتصادي المدفوع بالذكاء الاصطناعي

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Abstract

Artificial intelligence is changing how economies create value. Older growth models placed factories, machines, and transport systems at the center of production. AI shifts attention toward data, software, algorithms, cloud infrastructure, and organizational learning. This paper explains the move from physical capital to digital value. It uses a theoretical lens, supported by published experiments and public data. The main claim is simple. AI does not remove the need for physical capital. It changes how physical assets are used, measured, and rewarded. Digital value grows through prediction, automation, personalization, and scale. These features can raise productivity and open new markets. They can also concentrate gains in firms that control data, compute, talent, and platforms. Evidence from writing, coding, consulting, and customer support studies shows strong task-level gains from generative AI. Public data also shows rising AI investment, fast firm adoption, and growing electricity needs for data centers. These results show that AI value is both digital and material. The paper argues that national gains depend on complementary investment. Skills, competition, infrastructure, trust, and measurement systems shape outcomes. The paper concludes that AI will reward economies that treat digital assets as productive capital. It will also test policy systems built for a factory-based economy. A fair AI economy needs broader access to data, tools, training, and digital infrastructure.

Keywords: artificial intelligence, digital value, physical capital, intangible capital, productivity, data, innovation, economic transformation.

الملخص

يغير الذكاء الاصطناعي طريقة توليد الاقتصاديات للقيمة. لقد وضعت نماذج النمو القديمة المصانع، والآلات، وأنظمة النقل في مركز العملية الإنتاجية، في حين ينقل الذكاء الاصطناعي الاهتمام نحو البيانات، والبرمجيات، والخوارزميات، والبنية التحتية الحوسبية (السحابية)، والتعلم المؤسسي. تشرح هذه الورقة الانتقال من رأس المال المادي إلى القيمة الرقمية، وتستخدم منظوراً نظرياً مدعوماً بتجارب منشورة وبيانات عامة. إن الأطروحة الأساسية للورقة بسيطة؛ فالذكاء الاصطناعي لا يلغي الحاجة إلى رأس المال المادي، بل يغير طريقة استخدام الأصول المادية، وقياسها، ومكافأتها اقتصادياً.

تنمو القيمة الرقمية من خلال التنبؤ، والأتمتة، والتخصيص، والتوسع (مقياس الإنتاج). ويمكن لهذه الميزات أن ترفع الإنتاجية وتفتح أسواقاً جديدة، لكنها قد تحصر المكاسب أيضاً في الشركات التي تسيطر على البيانات، والقدرات الحوسبية، والمواهب، والمنصات الرقمية. وتُظهر الأدلة المستمدة من دراسات الكتابة، والبرمجة، والاستشارات، ودعم العملاء تحقيق مكاسب قوية على مستوى المهام بفضل الذكاء الاصطناعي التوليدي. كما تكشف البيانات العامة عن ارتفاع الاستثمار في الذكاء الاصطناعي، وتسارع تبنيه من قِبل الشركات، وزيادة الاحتياجات من الطاقة الكهربائية لمراكز البيانات. تُبين هذه النتائج أن قيمة الذكاء الاصطناعي ذات طبيعة رقمية ومادية في آن واحد.

وتجادل الورقة بأن المكاسب الوطنية تعتمد على الاستثمار التكاملي (المكمل)؛ إذ تشكل المهارات، والمنافسة، والبنية التحتية، والثقة، وأنظمة القياس هذه المخرجات. وتخلص الورقة إلى أن الذكاء الاصطناعي سيكافئ الاقتصاديات التي تتعامل مع الأصول الرقمية كأرصدة رأس مال إنتاجي، كما أنه سيختبر السياسات والأنظمة التي بُنيت في الأصل لاقتصاد قائم على المصانع. إن تحقيق اقتصاد ذكاء اصطناعي عادل يتطلب إتاحة أوسع للبيانات، والأدوات، والتدريب، والبنية التحتية الرقمية.

الكلمات المفتاحية :الذكاء الاصطناعي، القيمة الرقمية، رأس المال المادي، رأس المال غير الملموس، الإنتاجية، البيانات، الابتكار، التحول الاقتصادي.

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1. Introduction

Economic growth was long explained through physical capital. Factories, machines, ports, roads, and energy systems shaped national wealth. They still matter today. Yet the source of value is changing fast.

Artificial intelligence now turns data and software into productive assets. Firms can improve decisions, speed up routine work, and create new services. A model trained on data can support many users at once. This gives digital assets a scale that factories rarely have.

The paper studies this shift from physical capital to digital value. The phrase digital value means economic value created through data, software, algorithms, digital networks, and AI-enabled knowledge. It is not separate from the real economy. It changes how the real economy works.

A warehouse with AI forecasting can hold less inventory. A hospital with diagnostic support can use expert time better. A bank with machine learning can price risk more quickly. A school with adaptive tools can support more learners. These examples show one pattern. AI often raises the value of existing assets.

The shift is not only technical. It is economic and social. Digital value can spread quickly because software has low marginal cost. It can also become concentrated because data, compute, and networks create strong advantages. Haskel and Westlake (2018) call this a central feature of the intangible economy.

This topic matters because many policy tools still fit an industrial age. Accounting systems often measure buildings better than data. Bank lending often favors collateral over code. Tax systems can reward machines more than worker training. Education systems often lag behind digital skill needs.

This paper develops a theoretical view of AI-led economic transformation. It also adds practical evidence from published studies. The paper does not run a new human-subject experiment. Instead, it reviews public experiments and field studies with clear results.

The main research question is direct. How does AI move economic value from physical capital toward digital assets? A second question follows. What conditions decide whether this shift raises broad welfare or increases concentration?

The paper argues that AI creates value through four linked channels. These are prediction, automation, augmentation, and recombination. Prediction lowers the cost of decisions.

Automation shifts tasks from labour to systems. Augmentation makes workers faster and more accurate. Recombination creates new products from existing data and tools.

The argument also stresses limits. AI needs chips, energy, networks, and data centers. Digital value sits on a physical base. The new economy is not weightless. It is a mix of software, infrastructure, skills, and governance.

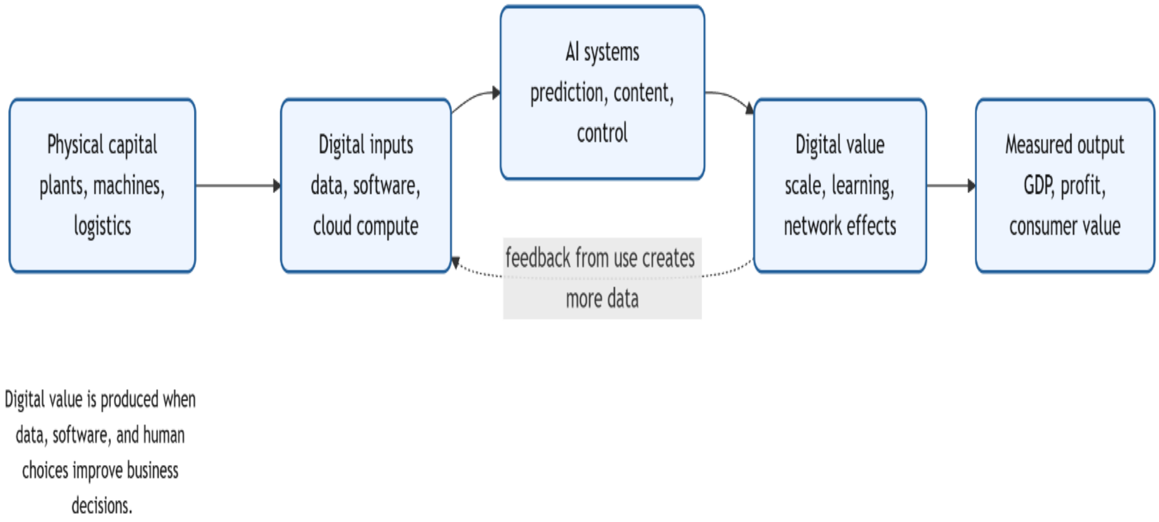

Figure 1 From physical capital to digital value in an AI economy. Source: Created by author based on Corrado et al. (2009), Haskel and Westlake (2018), and Agrawal et al. (2019).

2. Background: From Machines to Digital Assets

Physical capital is easy to see. It includes buildings, machinery, vehicles, and infrastructure. It helps workers produce more output. Standard economics placed this capital inside the production function.

Digital capital is harder to see. It includes software, data, models, brands, processes, and organizational knowledge. These assets often do not appear fully on balance sheets. They can still explain large market values and productivity gains.

Corrado, Hulten, and Sichel (2009) show that intangible capital changes the way growth is measured. They include software, research, design, brand equity, and firm-specific training. Their work shows that economies invest heavily in assets not built from steel or concrete.

Brynjolfsson, Hitt, and Yang (2002) also show that computers gain value through organizational capital. A computer alone does little. Value rises when firms redesign tasks, incentives, and information flows around it.

AI deepens this pattern. AI systems are not just tools for storing information. They generate predictions, text, code, images, and recommendations. They can also learn from use and improve workflows over time.

Agrawal, Gans, and Goldfarb (2019) describe AI as a fall in the cost of prediction. This idea is useful because prediction sits inside many decisions. When prediction becomes cheaper, the value of judgement, data, and complementary systems changes.

Physical capital loses some of its old role as the main sign of firm strength. A small software firm can serve millions of users. A platform can coordinate work without owning many assets. A model can be copied across markets at low cost.

Yet digital assets have special risks. They can be hard to value, hard to regulate, and hard to tax. They can also produce winner-takes-most outcomes. Network effects let large platforms gain more data, users, and revenue.

This is why AI is not only a productivity tool. It is a new way to organize economic power. The owners of data, chips, cloud platforms, and models can capture large returns. Workers and smaller firms may gain less without access and skills.

Table 1 Economic Shift from Physical Capital to Digital Value

Dimension	Physical capital economy	AI-driven digital value economy	Main implication
Core asset	Factories, machines, roads, and vehicles.	Data, models, software, cloud systems, and skills.	Value becomes less visible in standard accounts.
Cost pattern	High fixed cost and high variable cost.	High fixed cost and low marginal cost.	Scale can rise quickly after development.
Growth source	More equipment raises output.	Better predictions and automation raise output.	Decision quality becomes a growth input.
Competitive edge	Ownership of land, machines, and supply chains.	Ownership of data, compute, talent, and platforms.	Market power may shift toward digital leaders.
Main policy need	Infrastructure and industrial investment.	Skills, data rules, competition, and digital infrastructure.	Policy must protect access and trust.

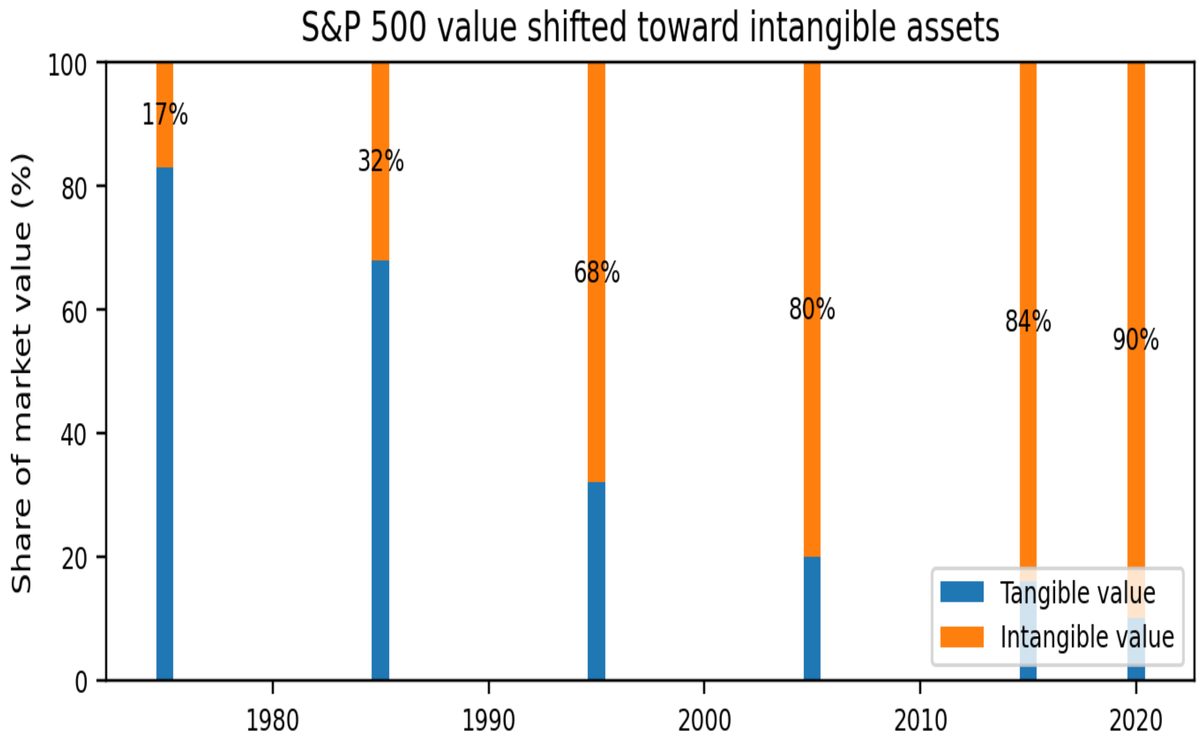

Figure 2 S&P 500 value shifted toward intangible assets. Source: Created by author using Ocean Tomo intangible asset market value study data.

3. Theoretical Framework

The paper uses a simple theoretical frame. AI changes production by changing the role of information. It also changes value capture by changing control over digital assets.

In a physical economy, a firm expands output through labour and capital. A factory adds machines. A logistics firm adds trucks. A farm adds tractors. Productivity rises when these assets work with labour.

In an AI economy, a firm expands output through labour, physical capital, and digital capital. Digital capital includes data, software, models, and organizational routines. These assets do not replace all machines. They make machines and workers more useful.

A basic production relationship can be written in words. Output depends on labour, physical capital, digital capital, and institutional quality. Institutional quality includes trust, competition, skills, and rules.

AI raises output when digital capital improves decisions. It can reduce search costs, forecast demand, plan maintenance, detect fraud, and personalize services. These tasks appear across sectors, not only technology firms.

Aghion, Jones, and Jones (2017) model AI as a form of automation. Their view helps explain growth effects. Automation can raise output by letting capital perform more tasks. The total effect depends on new tasks, wages, and demand.

Acemoglu and Restrepo (2019) add a useful warning. Automation can displace labour if new tasks are not created. Growth then becomes less inclusive. The same point applies to AI, especially in routine cognitive work.

Digital value also depends on complementarity. A model has low value without useful data. Data has low value without clean systems. Software has low value without workers who use it well. Skills and redesign are part of the asset.

The framework has four channels. First, AI makes prediction cheaper. Second, it automates parts of tasks. Third, it augments human judgement. Fourth, it creates new combinations of services and products.

The distribution of gains depends on ownership. Firms that own models, data, and platforms may capture rents. Workers may gain when AI raises their productivity and bargaining power. Consumers may gain when services become cheaper or better.

There is also a measurement channel. Free digital tools may create welfare outside GDP. Internal data assets may not appear as investment. Productivity may look weak while firms build digital capabilities. Brynjolfsson, Rock, and Syverson (2021) call this the productivity J-curve.

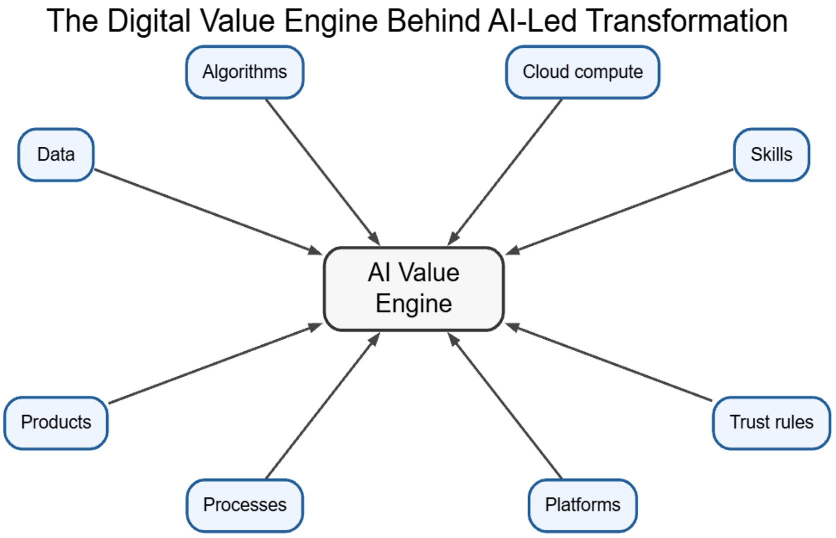

Figure 3 The digital value engine behind AI-led transformation. Source: Created by author based on Brynjolfsson et al. (2002), Agrawal et al. (2019), and Brynjolfsson et al. (2021).

4. Literature Review

The literature on intangible capital is a base for this paper. Corrado et al. (2009) argue that growth accounting should include intangible investment. Their work shows that measured capital is too narrow when knowledge assets are ignored.

Haskel and Westlake (2018) explain why intangible assets behave differently. They describe scalability, spillovers, sunk costs, and synergies. These features fit AI well. A model can scale quickly and improve through related data.

Brynjolfsson et al. (2002) connect computers with organizational change. They show that market value reflects more than hardware. It also reflects new work systems and hidden capabilities. This point matters for AI adoption.

The economics of AI literature adds a decision view. Agrawal et al. (2019) argue that AI lowers the cost of prediction. This makes data and judgement more important. It also changes where firms place responsibility.

Growth theory gives a wider frame. Aghion et al. (2017) present AI as automation with broad growth effects. Their model shows possible gains, but it does not promise equal benefits. The outcome depends on tasks and institutions.

The labour literature warns against a simple technology story. Acemoglu and Restrepo (2019) show that automation can displace tasks. New tasks must grow for labour to share gains. AI may follow the same pattern.

The firm adoption literature stresses uneven use. OECD evidence shows that firm-level AI use is rising. It also shows gaps by firm size and capability. Larger firms can adopt earlier because they have data, managers, and capital.

The public finance literature raises another issue. Digital value can move across borders. Data, software, and intellectual property can be located away from users. This can weaken tax systems built for physical assets.

The measurement literature also matters. Brynjolfsson, Collis, Diewert, Eggers, and Fox (2019) argue that free digital goods can create value outside GDP. AI tools may expand this gap because many benefits appear as time saved.

Recent AI experiments offer clearer task-level evidence. Noy and Zhang (2023) find that ChatGPT reduces writing time and raises output quality. Peng et al. (2023) find that GitHub

Copilot speeds a coding task. Dell'Acqua et al. (2023) show that AI helps within its frontier and harms outside it.

These studies point to one shared lesson. AI raises value when tasks are well matched to its strengths. It can reduce value when users trust it in the wrong setting. Human judgement remains part of digital value.

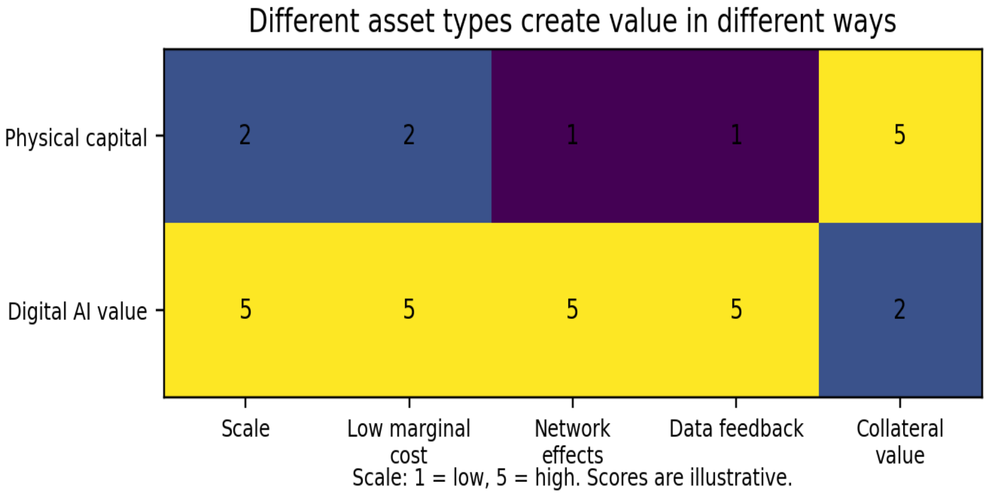

Figure 4 Different asset types create value in different ways. Source: Created by author based.

5. Methodology and Evidence Base

This research uses a theory-led evidence review. It combines published experiments, field studies, and public economic datasets. The aim is not to estimate a new causal model. The aim is to explain a structural change.

The evidence is selected through three rules. First, studies must report practical AI use or public economic data. Second, studies must be available through journals, working papers, or official reports. Third, evidence must link AI to value creation, capital, work, or measurement.

The paper treats experiments as task-level evidence. They show what happens when AI is added to a defined activity. The paper treats public datasets as economy-level evidence. They show investment, adoption, exposure, and infrastructure trends.

This design fits the topic because AI is still spreading. Many long-run effects are not yet observable. However, early experiments and public datasets already show key mechanisms. These mechanisms include speed, quality, concentration, and infrastructure demand.

The analysis avoids invented data. Figures are original charts created from published values. Captions give the source and download links. This makes the paper practical and easy to verify.

Table 2 Public Experiments and Practical Evidence Used in the Paper

Study	Setting	Method	Main result	Relevance
Noy and Zhang (2023)	Professional writing tasks	Randomized online experiment	Time fell by 40%. Quality rose by 18%.	Shows fast digital value in text work.
Peng et al. (2023)	Software coding task	Controlled experiment	Copilot users finished 55.8% faster.	Shows AI raises output in coding.

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Brynjolfsson et al. (2023, 2025)	Customer support agents	Staggered workplace adoption	Productivity rose 14% in early paper. Novices gained 34%.	Shows digital tools transfer tacit knowledge.
Dell'Acqua et al. (2023)	Management consulting	Preregistered field experiment	AI improved tasks inside its frontier. It hurt some outside tasks.	Shows limits and need for judgement.
IMF (2024)	Global labour markets	Task exposure and readiness analysis	AI exposure is 60% in advanced economies.	Shows broad macro exposure.
OECD (2025)	Firms in OECD economies	Firm adoption evidence	Firm use of AI rose from 8.7% to 20.2%.	Shows diffusion into business practice.
IEA (2025)	Global data centers	Energy demand modelling	Demand may reach 945 TWh by 2030.	Shows digital value needs physical energy.

6. Results: Evidence of the Shift to Digital Value

6.1 AI Investment and Market Concentration

The first sign of transformation is investment. Capital is moving toward AI models, data services, cloud platforms, chips, and related infrastructure. These investments look different from older industrial investment.

A steel mill invests in furnaces and buildings. An AI firm invests in data, model training, talent, and compute. Some assets are physical. Many are intangible. Their value depends on learning and scale.

The Stanford AI Index reports that generative AI attracted $33.9 billion in private investment in 2024. That was 18.7% above 2023 and more than 8.5 times the 2022 level. This growth shows a rapid shift of capital toward digital systems (Stanford HAI, 2025).

The same source shows strong country concentration. In 2024, U.S. private AI investment reached $109.1 billion. China received $9.3 billion, and the United Kingdom received $4.5 billion. This gap matters because AI capabilities need large fixed costs.

Concentration can create benefits. Large firms can fund models, safety teams, and infrastructure. Yet it can also reduce competition. If model access is controlled by few firms, smaller firms may pay rents to use essential digital inputs.

This changes the meaning of capital ownership. The factory owner once controlled machines. The AI platform owner may control data, models, compute, distribution, and user feedback. That control can shape value creation across many industries.

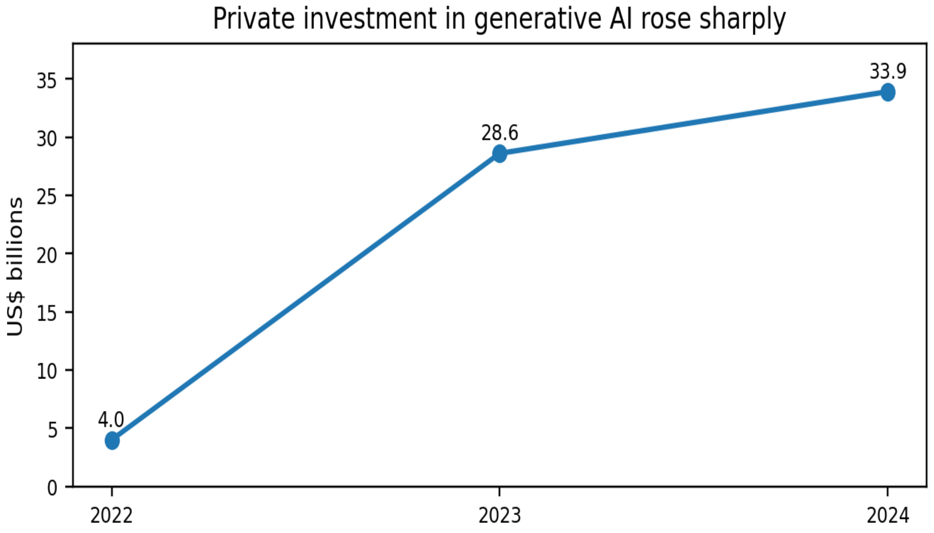

Figure 5 Private investment in generative AI rose sharply.

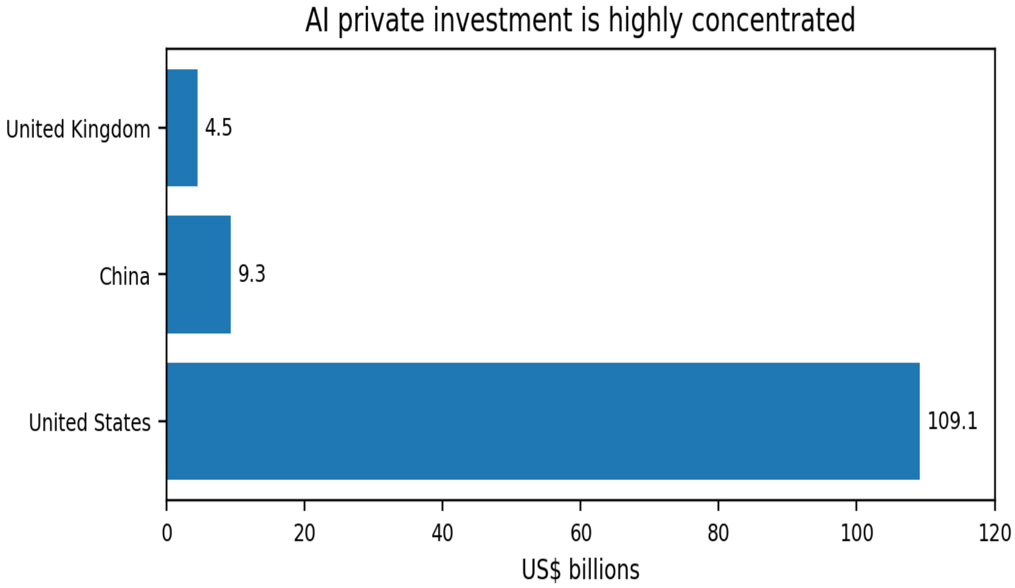

Figure 6 AI private investment is highly concentrated.

6.2 Firm Adoption and Business Diffusion

Investment alone does not prove economic change. Adoption matters because value appears when firms use AI in real tasks. OECD data show that AI use by firms has risen quickly.

Across available OECD country data, 8.7% of firms used AI in 2023. The share reached 14.2% in 2024 and 20.2% in 2025. The adoption rate more than doubled in two years (OECD, 2025). This pattern suggests that AI is leaving the laboratory. It is becoming part of normal business operations. Firms use it for customer service, marketing, forecasting, coding, document review, and process control.

Adoption will remain uneven. Larger firms often have more data and better digital systems. Smaller firms may lack clean records, skilled workers, or safe procurement channels. This gap can widen productivity differences.

The key issue is not whether AI is available. Many tools are already available. The issue is whether firms can redesign work around them. Digital value appears when new tools meet better routines.

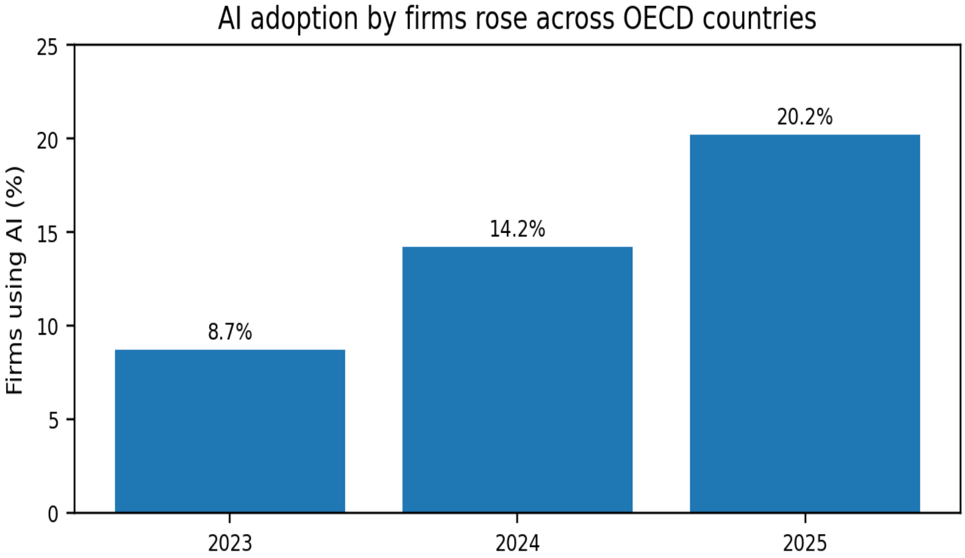

Figure 7 AI adoption by firms rose across OECD countries.

6.3 Task-Level Productivity Evidence

Published experiments give direct evidence on AI productivity. They also show that gains depend on task design. The strongest results appear when tasks have clear goals and evaluation criteria.

Noy and Zhang (2023) study professional writing tasks. Participants with ChatGPT completed work faster and received higher quality ratings. Average time fell by 40%, and output quality rose by 18%.

Peng et al. (2023) study a coding task with GitHub Copilot. Developers with AI completed the task 55.8% faster than the control group. This shows that AI can raise speed in well-defined software work.

Brynjolfsson, Li, and Raymond (2023) examine a real customer support workplace. Access to generative AI raised issues resolved per hour by 14%. Novice and lower-skilled workers gained 34%. This suggests that AI can spread tacit knowledge.

Dell'Acqua et al. (2023) study consultants using AI. The tool improved performance on tasks inside its frontier. It also harmed some tasks outside its frontier. This result is important because AI can look confident when it is wrong.

These studies support a cautious claim. AI can produce digital value quickly at the task level. However, the value is not automatic. It depends on task fit, user skill, governance, and feedback.

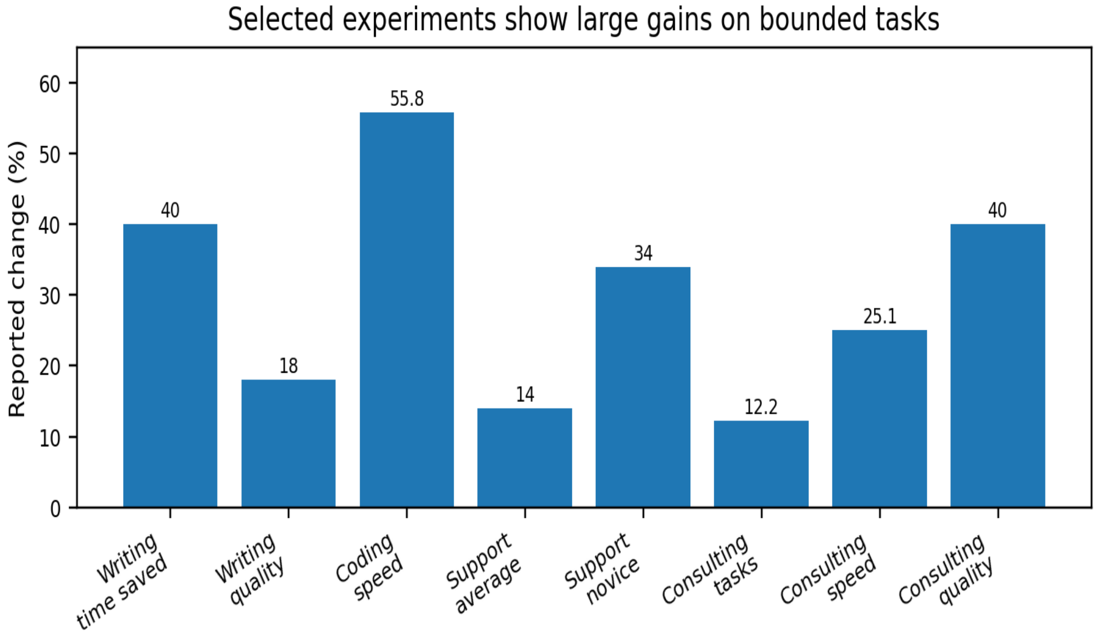

Figure 8 Selected experiments show large gains on bounded tasks. Source: Created by author from Noy and Zhang (2023), Peng et al. (2023), Brynjolfsson et al. (2023), and Dell'Acqua et al. (2023).

6.4 AI Exposure, Labour, and Human Capital

Digital value still depends on people. AI needs workers who know how to ask questions, judge outputs, redesign tasks, and manage risks. Human capital remains central.

The IMF estimates that about 60% of jobs in advanced economies are exposed to AI. The share is about 40% in emerging markets and 26% in low-income countries. Exposure does not mean direct job loss. It means tasks may change (IMF, 2024).

This exposure pattern has two meanings. Advanced economies may gain more from early AI use. They may also face larger disruption. Low-income countries may face less immediate disruption but weaker access to benefits.

The transformation can widen global gaps. Countries with cloud capacity, skills, data systems, and stable institutions can adopt faster. Countries without these complements may remain users rather than producers of AI value.

Skills policy is therefore part of capital policy. Training is not only a social program. It is an investment in the human side of digital capital. Without workers who can use AI well, models remain underused.

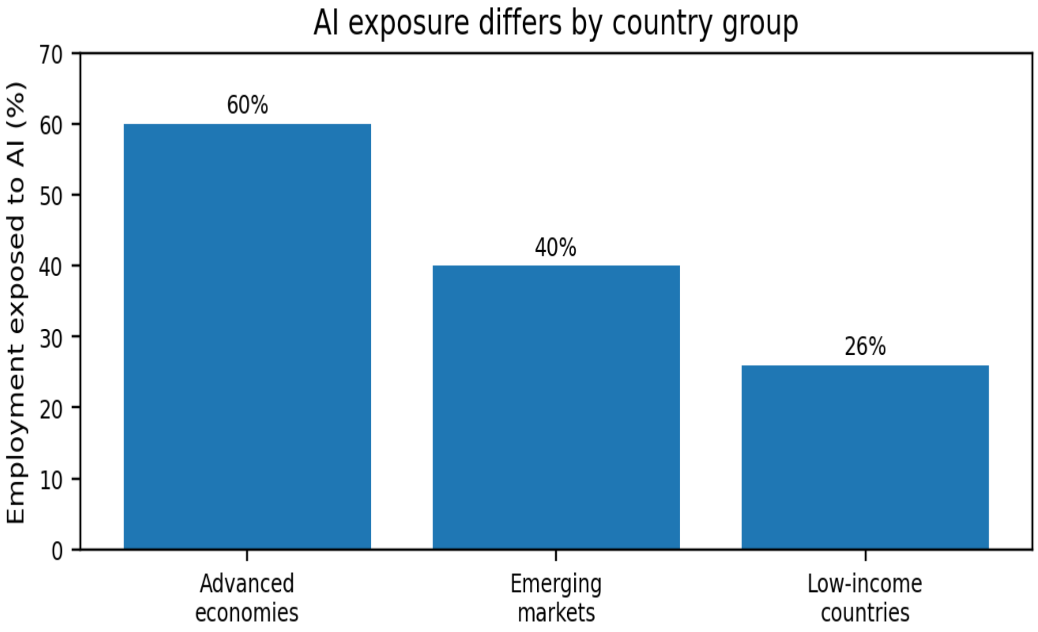

Figure 9 AI exposure differs by country group. Source: Created by author using IMF estimates.

6.5 Physical Infrastructure Behind Digital Value

The move to digital value does not end physical investment. AI needs chips, servers, cooling systems, fibre networks, and electricity. These inputs are physical and capital intensive.

The International Energy Agency estimates that data centres used about 415 TWh of electricity in 2024. In its base case, demand reaches around 945 TWh by 2030 and about 1,200 TWh by 2035 (IEA, 2025). This evidence corrects a common mistake. Digital does not mean immaterial. AI value rests on a large physical stack. The new economy needs power systems as much as algorithms.

Energy demand also creates policy trade-offs. Faster AI adoption can raise electricity needs. It can also improve energy systems through forecasting and grid management. The net effect depends on planning. This is why the title of this paper uses from physical capital to digital value, not away from physical capital. AI changes the function of physical assets. It does not make them disappear.

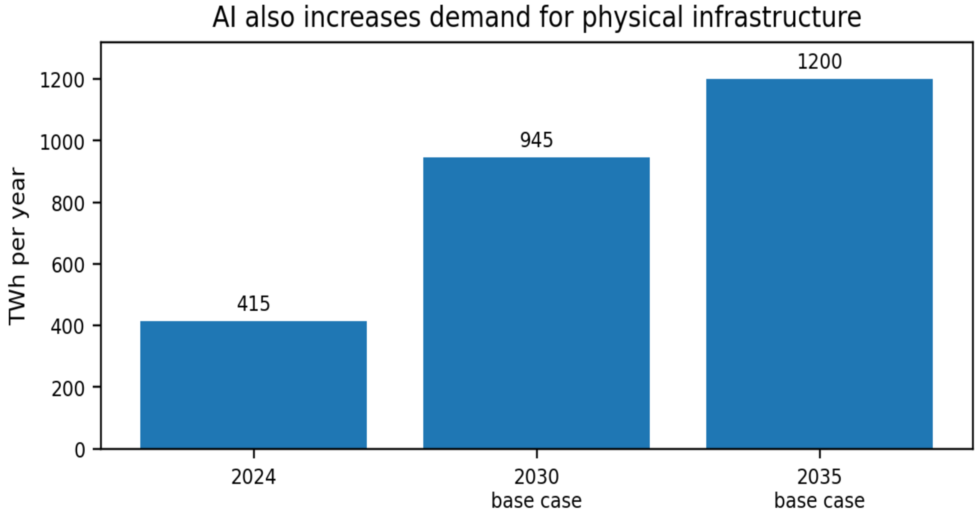

Figure 10 AI also increases demand for physical infrastructure.

7. Discussion

7.1 How AI Converts Physical Capital into Digital Value

AI changes the value of physical capital through better use. A machine becomes more valuable when sensors predict failure. A truck fleet becomes more valuable when routing software lowers fuel use. A store becomes more valuable when demand forecasts improve stock choices. This means digital value often appears as a higher return on existing assets. The firm may not buy more machines. It may use the same machines better. Traditional measures may miss part of this change. AI also changes time. A decision that once took days may take minutes. Faster decisions can reduce waste and improve service. Time saved is an economic gain, even when it is not always priced.

Digital value also changes scope. One model can support writing, coding, customer service, translation, and analysis. This scope gives AI a general-purpose character. It resembles earlier technologies like electricity and computers. Yet general-purpose technologies need complements. Electricity needed motors, factories, and new processes. Computers needed networks and management redesign. AI needs data governance, model evaluation, workflow design, and skilled users.

7.2 Value Capture and the Risk of Concentration

AI can create broad gains. It can also concentrate income and market power. The reason is simple. Digital assets scale faster than physical assets. A leading model can serve many markets at once. Large firms can collect more data from users. More data can improve products. Better products can attract more users. This feedback loop can raise barriers for rivals. Cloud platforms add another layer. Many firms may build AI services on infrastructure owned by a few providers. This can create dependence. It can also turn infrastructure firms into gatekeepers.

Competition policy must therefore understand digital value. It should not only count factories or market shares in old categories. It should also assess access to data, compute, models, and distribution channels.

Open-source models can reduce concentration. Public digital infrastructure can also help. Universities, startups, and small firms need affordable access to compute and data. Without this access, AI gains may remain narrow.

7.3 Measurement Problems in the AI Economy

AI creates value that is hard to measure. Some value appears in paid software and cloud services. Some appears as free tools, faster search, better matching, or time saved by users.

GDP captures market transactions. It does not capture all welfare from free digital services. Brynjolfsson et al. (2019) argue that digital goods can create consumer value beyond measured GDP.

Firm accounts have a related problem. Spending on data cleaning, model tuning, and worker learning may be treated as current cost. Yet these actions can build long-term capability.

This matters for policy. If measurement is weak, investment may be misread. A country may look less productive while it builds digital systems. A firm may look costly while it builds future value.

Better measurement should include data assets, AI capabilities, digital skills, and platform dependence. It should also include energy and environmental costs. Digital value has both benefits and costs.

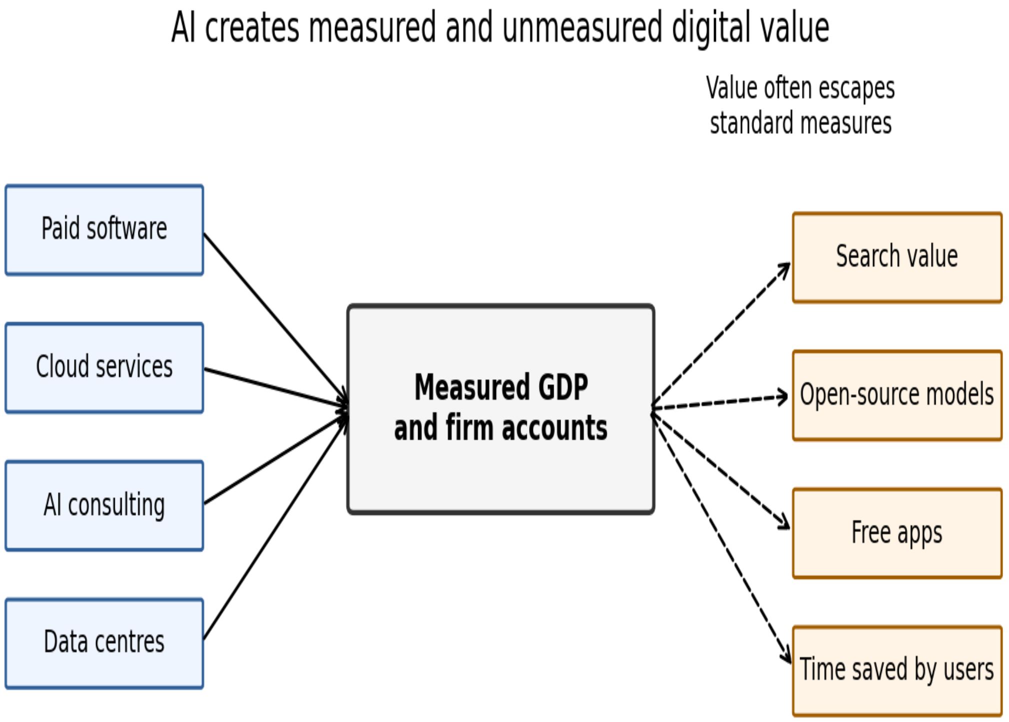

Figure 11 AI creates measured and unmeasured digital value. Source: Brynjolfsson et al. (2019), BEA (2024), and UNCTAD (2024)

7.4 Development, Inclusion, and National Strategy

The shift to digital value has a development dimension. Countries that lack physical infrastructure also face digital gaps. These include weak broadband, costly electricity, low cloud access, and limited technical training.

Low-income countries may have fewer exposed jobs in the short run. That does not mean they are safe. It may mean they have fewer chances to gain from AI-led productivity growth.

A national AI strategy should therefore be more than a model strategy. It should include education, public data systems, competition policy, energy planning, and public procurement. These areas turn tools into value.

Public sector use can also matter. Governments hold large data resources. Safe use of AI can improve tax collection, service delivery, health planning, and disaster response. Poor governance can create bias and surveillance risks.

The goal should be productive access. Citizens and firms need safe access to tools. Workers need training. Smaller firms need practical support. Public institutions need clear rules and skilled staff.

8. Policy Implications

AI policy should treat digital assets as productive capital. This does not mean every dataset should be privatized. It means that data, skills, and compute must be governed as core economic inputs.

The policy challenge is to raise innovation while keeping markets open. It is also to share gains across workers, firms, and regions. This requires practical action in several areas.

Table 3 Policy Actions for an AI-Driven Digital Value Economy

Policy area	Problem addressed	Proposed action	Expected effect
Skills policy	Unequal access to AI skills.	Fund task-based AI training for workers and managers.	Raises adoption and worker bargaining power.
Digital infrastructure	Weak cloud, data, and broadband access.	Invest in broadband, compute access, and public data systems.	Lets smaller firms join digital value chains.
Competition policy	AI market concentration.	Review data, model, cloud, and platform gatekeeping.	Keeps markets open and lowers rents.
Accounting policy	Hidden digital investment.	Improve reporting for data, software, and AI capabilities.	Makes investment and productivity clearer.
Energy policy	Higher data centre electricity demand.	Plan clean power, grids, cooling, and demand response.	Supports AI growth with lower environmental cost.
Public procurement	Slow public sector adoption.	Buy safe AI tools with open standards and audits.	Improves services and builds local capability.
Tax policy	Profit shifting through intangible assets.	Align tax rules with location of users and value creation.	Protects public revenue in the digital economy.

Skills policy should be close to tasks. General awareness is not enough. Workers need to learn how AI changes writing, coding, accounting, logistics, teaching, and health work.

Infrastructure policy should avoid a narrow focus on apps. AI services need broadband, reliable power, cloud access, cybersecurity, and local language data. These inputs are part of modern capital formation. Competition policy must watch bottlenecks. A firm can dominate through models, user data, cloud credits, or distribution. Regulators should examine the full digital value chain. Accounting reform can help managers and governments. Firms often build digital capability through spending that looks like ordinary cost. Better reporting can make long-term investment easier to see. Energy policy is also economic policy. Data centers can support growth, but they need power and water. Planning should link AI investment with clean electricity and grid capacity.

9. Limitations and Future Research

This paper has limits. It uses published studies and public reports. It does not estimate a new model with microdata. Its contribution is theoretical synthesis supported by practical evidence. AI is also changing quickly. Some figures may change within a year. Investment, adoption, and model performance move fast. Future research should update the evidence regularly. The experiments reviewed here study bounded tasks. They do not prove the size of long-run GDP gains. A task gain can be large while economy-wide effects remain smaller. Diffusion, redesign, and demand matter. Future research should connect firm-level AI adoption with balance sheet data. It should also study smaller firms and developing economies. These groups may face the largest barriers. More work is also needed on measurement. Researchers should estimate the value of free AI tools, time savings, public service quality, and data assets. These are central to digital value.

10. Conclusion

AI is changing the economic meaning of capital. The old economy was built around machines, buildings, and transport networks. The new economy adds data, models, platforms, and learning systems. This does not remove physical capital. It changes its role. Physical assets now gain value through digital control, prediction, and coordination. Data centers and power systems also become core inputs. The evidence shows that AI can raise productivity on defined tasks. Writing, coding, consulting, and customer support studies report clear gains. These gains are strongest when work fits the AI frontier. Public data shows another pattern. AI investment is rising fast. Firm adoption is spreading. Country and firm concentration is high. Data centre energy demand is also growing. The main lesson is that digital value is created through complements. Models need data. Data needs systems. Systems need skilled workers. Workers need institutions that share gains fairly. A successful AI economy will not simply buy more tools. It will redesign work, update measurement, build skills, protect competition, and plan infrastructure. It will also protect trust. The future of economic transformation depends on choices made now. AI can deepen concentration if access is narrow. It can broaden prosperity if digital capital is shared, governed, and used well. From physical capital to digital value is therefore not a story of replacement. It is a story of recombination. The economies that learn this fastest will shape the next era of growth.

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