Modeling the AI-Driven Age of Abundance: Applying the Human-to-AI Leverage Ratio (HAILR) to Post-Labor Economics

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Abstract

This paper explores the transformative impact of AI on automating knowledge work leading to the anticipated 'Age of Abundance' in a post-labor society where work is performed by machines rather than human labor. Through a detailed model incorporating variables such as cost of computing, AI model efficiency, and human-equivalent production output (derived from the human-to-AI leverage ratio, or HAILR), we provide a nuanced albeit tentative analysis of future productivity trends and economic realities.

The model, integrating conservative estimates like a 30% annual improvement in AI model efficiency, projects a substantial increase in productivity; by 2044 it indicates that just four hours of productive human labor could yield as much as 636 years of equivalent output. The model is not intended as a precise prediction, rather a framework to allow scientists and laypersons to visualize the inevitability of the coming Age of Abundance. The assumptions are incidental. If work is automated at scale, one may reasonably change the assumptions in the model and still arrive at the same conclusion: extreme abundance.

This research also critically examines the potential job displacement in knowledge and office work sectors, suggesting a loss of 9 out of 10 jobs by 2044 due to AI automation. The model also shows how the remaining workers will be empowered with their efforts “leveraged” by AI technologies.

We highlight the economic and societal implications of these findings, including the need for proactive public policy and corporate strategy to navigate the challenges and opportunities presented by AI-driven transformations. The study underscores the criticality of grasping these shifts in timely ways for future workforce planning and societal adaptation. Although the model will certainly need to be revised to accommodate technological, political, and social changes, we believe that its simplicity, flexibility, and clarity can earn it a significant role in policy discourse.

Literature Review

The notion of 'knowledge worker' was developed by Peter Drucker in his 1959 book, *The Landmarks of Tomorrow*[1]. Drucker was a pioneer in contrasting knowledge work with manual labor in his managerial analyses. In our paper, the phrase "knowledge work" includes cognitive work generally performed on a computer. This includes the efforts of programmers, scientists, writers, and engineers who produce and handle information.[2] Office work (from simple clerical tasks to complex, multi-stage efforts) is especially amenable to AI automation. AI capabilities are also making many knowledge work efforts involving high-level thinking (such as medical and legal jobs) amenable to automation.

Many early efforts to analyze and understand the dimensions of knowledge work from economic perspectives were inspired by the 1970s writings of Marc Porat[3], following the lead of Fritz Machlup[4] in the 1960s. Mapping the impact of particular technologies such as AI on the productivity of workers has been an activity of many researchers in the decades that followed, as outlined in the sections to come. The modeling effort described in this paper is intended to use straightforward terms and common-sense concepts in ways that make the models usable in public policy deliberations as well as in community outreach or business planning. Providing clear yet powerful data visualizations and conceptual tools in these forums will focus these discussions and stimulate the production of useful insights.

Introduction

The idea that artificial intelligence will transform the working lives of people worldwide is not a new one. AI practitioners and thought leaders such as Elon Musk[5a] and Kai Fu Lee[6] have argued that AI will bring about an "Age of Abundance" that will dramatically decrease the cost of goods and services through efficiency and economy of automation. The model in this paper presents one perspective on how these dramatic cost reductions will take place. The productive clout of individual workers will also expand dramatically as it is leveraged by AI technologies. Just as the philosopher Archimedes reportedly said "Give me a firm place to stand and a lever and I can move the Earth," workers in the years to come will have their efforts dramatically enhanced by the leverage of automation.

Automation through AI will supplement and then eventually replace many human workers[7] once the technology is adopted, particularly in knowledge work where jobs are conducted solely on a computer. Discussed here is the critical question of just how much work will be accomplished by AI systems within the next two decades, how many net jobs will be displaced and what the impact will be upon the cost of goods and service. Jobs will go away, but exactly how many? Predictions about the "disruption" that AI will cause have been expressed by many corporate and public policy leaders, but specifics are often missing.

Developing and integrating AI systems into the workplace will come at a cost, but the data show how catastrophic it will be for corporations and governmental agencies that do not adopt AI technology and how imperative it is to get started immediately. Specifically, the present paper introduces a new concept termed the Human-to-AI Leverage Ratio, or *"HAILR,"* to describe how much productive output AI automation can accomplish for each minute of human input. Using HAILR, our model predicts AI output will be so large in the coming years that a single minute of human labor could produce 2.7 years in human-equivalent output. Whether this increase in output will provide for societal "abundance" or produce less optimal results depends on how corporate leaders, public administrators, and community members engage with each other in planning and disbursement efforts.

Much has been said about how AI tools will increase the speed and reduce the cost of production, but little has been documented about human-performance and the role it plays in the future productivity boom. We predict that HAILR will increase rapidly over the next twenty years, and surprisingly, that the high rate of productivity will come to be even more dependent on the efficiency of the humans who work to support the AI systems, as one minute of lost human productivity will initially mean the loss of hundreds, and ultimately thousands of minutes of productive output. Thus human capital will become far more important in the creation of value and competitive advantage than it is today, which is consistent with the conclusions of some managerial consulting firms such as McKinsey: "we'd argue the need for excellent management will grow even greater."[(8)]

Figure 1 shows human labor decreasing as automation of work increases.

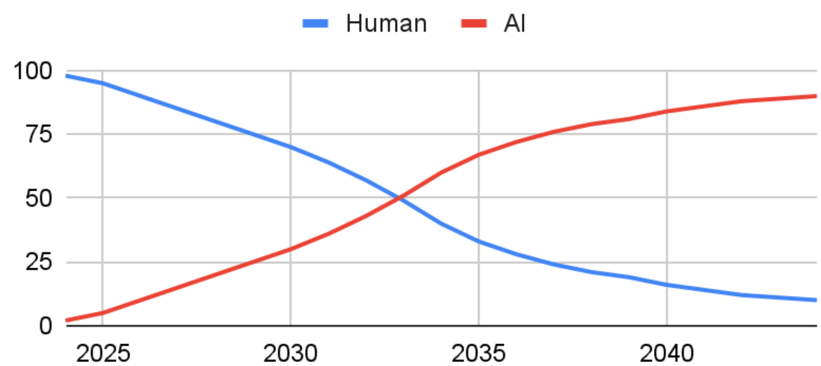

Figure 1: Percentage Human vs AI Output
Source: Inspira AI Corp. analysis

Three Categories of Work

Three categories of work are presented.

Human-centric work

This is work that does not include any automation. It is singularly human. The journey towards automation has only just begun and we anticipate that by the end of 2024, the vast majority of all work will still be performed by humans alone.

Human-assisted work

This is work where humans play a role, but much of the productive output is produced by AI systems. In this category of work, humans may participate by planning or providing input, giving AI ‘leadership’. Today this looks like creating prompts to generate articles or images, then reviewing the work and fine tuning the output. However, in the future, the library of tasks in this category will expand to many thousands of use cases.

As shown in Figure 2, this category of work will grow rapidly over the next decade but will eventually shrink, as the next category of fully autonomous work takes over an increasing share of the workload. The model in figure 2 illustrates 20% of the work currently performed by humans on computers will be performed by this category of human-assisted work by 2044.

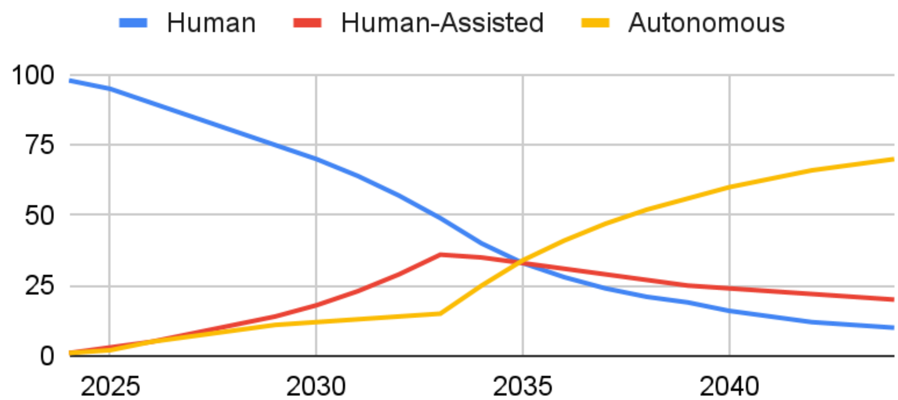

Figure 2: Human, Human-Assisted and Autonomous
Source: Inspira AI Corp. analysis

AI-Autonomous work

This is work initiated and performed solely by AI systems, without any human involvement at all. If the server doesn’t go down, this work will never stop. Today the number of items on this list is small, and mostly invisible to us humans. Think of the clock on your phone changing to daylight savings time automatically. The list of fully autonomous tasks will grow rapidly over the next two decades, taking more and more of the load from the above two categories. Our calculations project that 70% of work currently performed by humans on computers will be performed by this fully autonomous category by 2044.

Knowledge work will be automated faster than manual labor

The model in this paper focuses on knowledge work, specifically work that is currently performed by humans on computers. Broadly this affects any job that involves manipulating or moving information. This would include domains such as engineering, accounting, mathematics, writing, design, clerical, sales, data entry, legal work and much, much more. This includes jobs which require communication as existing AI technology can already demonstrate human-level empathy and emotions during conversation[9]. For the purpose of this paper, knowledge work does not include jobs that primarily require physical labor, such as construction or house keeping. It is anticipated by the authors that knowledge work will be automated at a much faster rate than work which requires manual labor.

While it is widely accepted that the amount of work that is automated will grow, the rate of automation will vary widely for each job role[10,11]. Some tasks are more difficult and expensive to automate. Replacing manual labor requires the development and production of mechanical robots, which are expensive. The operation of robots requires computing hardware, software, and ongoing maintenance, all of which adds to the cost of production. Conversely, the automation of office work requires only computing hardware and software, without the mechanics. Thus, it is far easier and less expensive for white-collar industries to automate than it is for industries that rely upon human labor[11, 12].

The Phases of Automation

Phase I - Automation Potential

Automation potential is the general maturity of technology and its capacity to automate work. Chui et al.[14] refer to this as the *potential for technical automation* - the capacity for automation to complete work conducted by humans. Such potential is the availability of general technology which acts as building blocks which can be customized for specific use cases, then integrated into production environments. It is AI technology that is capable of automating tasks, but which in and of itself, automates nothing. As examples, deep learning and large language models fall into this category. According to Chui, M., Ellingrud, K., et al. of McKinsey, as of 2023, the global Automation Potential is currently between 60 to 70% of all hours worked globally[14a]. This number could reach 90% before 2035[14b]. In theory, at that time 90% of all tasks could be automated, but the actual number depends on Phase II and III.

Figure 3 demonstrates how McKinsey's data for Automation Potential reaches 90% before 2035 and 95% before 2040.

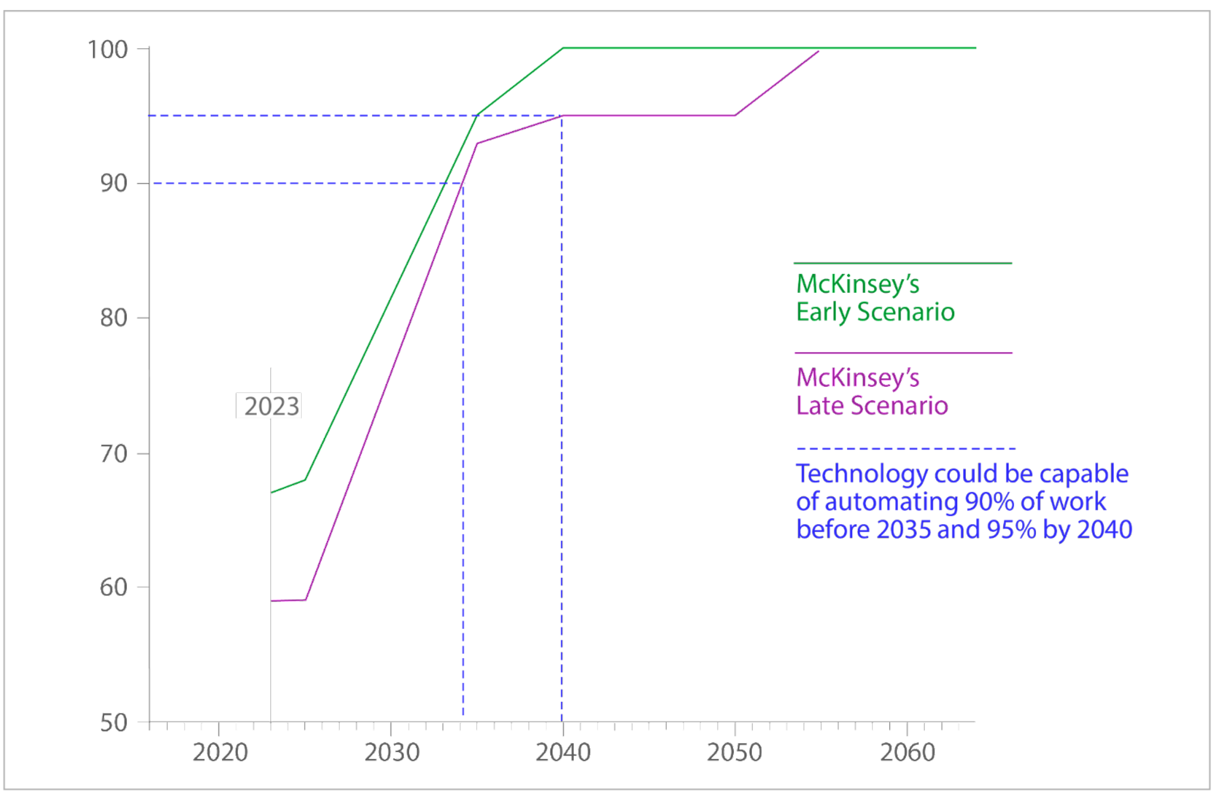

Figure 3 - Automation Potential: Maturity of Technology. Adapted from McKinsey[13]

Even when using McKinsey's Late Scenario, the world will be capable of automating 90% of work before 2035, but capability does not guarantee adoption.

Phase II - Customization

This phase involves tailoring and configuring the technology to suit specific use cases, environments, or operational requirements. During this phase, the general capabilities of the technology are fine-tuned to address the unique challenges and needs of a particular organization, industry or task. This may involve modifying the technology to integrate with existing systems, adjusting it to comply with industry standards or regulations, and ensuring it meets the specific performance criteria of the use case. Third parties may create customized solutions, then make them commercially available to organizations, or companies may, as part of Phase III adoption, initiate the development of custom solutions.

Phase III - Adoption

This phase involves the decision of business executives to adopt automation into their production process. This may involve integrations with off-the-shelf solutions, and/or retaining qualified people or firms to build custom solutions. The development and implementation of strategies for the maintenance and updating of the AI systems follows. As opportunities or serious issues with the systems are identified, the current systems may be optimized, or scrapped and new systems begun (back to Phase I or II). Future AI technology may become capable of self-optimization, so a return to previous phases may not obligate human input.

Chui et al.[14] suggested that the pace of workforce transformation is likely to accelerate. While the trajectory of the potential for automation does suggest acceleration, frictives exist that may result in a more homogeneous pace of adoption. These include the relative cost of automating certain tasks over others, the repetition rate of tasks, the value of completed tasks and the motivation of stakeholders to invest in automation, not to mention unknowns such as regulatory compliance requirements, only just emerging.

Priorities of Automation

We offer for consideration that frequent and high value tasks could bring an economic return faster than their counterparts and thus, highly repetitive tasks are likely to be automated before tasks with less frequent repetition, as are tasks that have high value (think medical diagnosis). The forces of repetition and value are balanced by the difficulty and the cost of customization and integration, as the engineering requirements to automate dissimilar tasks varies widely.

We anticipate the possibility that over time, with the assistance of AI, the pace of automating tasks will increase and the cost of development will decrease for similar tasks. As easy and high value tasks are likely to be automated first, that will leave the difficult and lower value tasks for last, or at least until the cost of development and engineering for automating those remaining tasks drops to a cost-efficient level.

Auto-Automation

A coming scenario on the horizon is when AI becomes capable of creating customizations and integrations with little or no human engineering. Call it ‘auto-automation’. Consider a task that is performed only once. It generally isn’t economically feasible to engineer the automation of such a task, as the automation engineering could easily take longer than performing the task itself. However; a more advanced AI with finetuned domain knowledge could potentially develop a customized solution on demand. We posit auto-automation will be needed to push automation upwards of 90% for all work. In some fields, auto-automation capabilities may emerge more quickly than in others (fields in which the assumptions behind processes are more transparent, for example). However, the trajectory indicates auto-automation capabilities will eventually be widespread, leading to even more extensive and pervasive automation of work.

Methods

The model utilizes the metrics below. Certain assumptions made, such as the rate at which AI automation will be adopted. It is important to note that changing the assumptions changes only the timing and depth of the societal changes involved with the Age of Abundance. The general outcome of monumental reduction in the cost of services remains extreme, changing by only a matter of degree.

For example, the current assumptions in the model predict that one person will be able to produce over 600 years of productive output in a single day of work. This is achieved due to the massive leverage that automation will be capable of delivering. Computing hardware continues to get faster and AI models continue to get more efficient. As more and more work is fully automated, the output is less tightly constrained by human input.

One may change the model assumptions enough to reduce the projected output from 600 years worth of production down to 1 year of production, (for a single day worked by a human). But regardless of the weights applied to the model, it mathematically demonstrates how the cost of goods and services will plummet, resulting in an Age of Abundance. If we continue on the trajectory towards full automation, the general directions and dimensions of the outcome appear to be certain. Each variable of the model is described below:

1 - Cost of Computing

Cost of Computing refers to the cost of storage, bandwidth, networks and computational calculations performed by CPUs, GPUs, memory and the like. We used an annual decay rate of 15%. Our model begins in 2024 with a cost of $1 for 1 unit of computing, but the starting place is irrelevant to the outcome, as a cost per unit of $100 produces the same output.

2 - Computing Units

As the cost of computing decreases, the number of Computing Units one can purchase for the same amount of money increase. If the cost of computing decays by 15% per year, in twenty years we can purchase 16.37 units for the same money as will purchase 1 unit of computing in 2024.

3 - AI Model Efficiency

AI Model Efficiency refers to the ability of a model to take advantage of computational capacity. The efficiency of AI models is growing at a pace that can often be well characterized as exponential, with some experts predicting a 100x increase in efficiency over the next 5 years. This is due to a number of factors, including advances in hardware, software, maintenance strategies, and algorithms.

For example, the development of new hardware technologies such as neuromorphic chips is specifically designed to accelerate AI workloads. Additionally, software advances such as compiler optimizations and new programming languages are making it easier to develop and deploy efficient AI models. Improved strategies for system maintenance are eliminating many problematic issues, keeping systems running. Finally, algorithmic advances such as model pruning and quantization are helping to reduce the size and complexity of AI models without sacrificing performance.

These factors are all contributing to an increase in the efficiency of AI models, which is enabling new applications, and potentially accelerating the adoption of AI across industries.

It was reported that OpenAI's GPT4 model was ten times more efficient than their previous model, GPT3.5. Elon Musk has stated in an interview with Rishi Sunak that the capability of AI is growing at the pace of five-fold or ten-fold per year.(5b)

Statements by thought leaders indicate the trajectory of development, but are not predictions of what will happen next, and certainly not over the next twenty years, so we opted for a conservative estimate of model efficiency improvement at 30% each year.

The starting parameter value for Model Efficiency was 1, which gives us a relative mathematical starting point for the schematic.

4 - HAILR Multiple

The Human to AI Leverage Ratio illustrates the productivity-leverage obtained through automation, where one minute of human input produces multiple 'Output-Minutes' by AI systems. The multiple is the reciprocal of HAILR.

Example;

- Human works 1 minute
- AI system outputs 100 minutes of human-equivalent productivity
- HAILR = 1 to 100
- The reciprocal in this example is 100, which is used as the starting multiple in the model, demonstrating the leverage afforded by the AI system

The use of 100 as the model's starting parameter satisfies the intention of the model, which is to demonstrate that automation at scale results in abundance. The actual multiple in production depends highly on the specific use case. E.g. In just one minute of prompt engineering by a human, an LLM may produce several hours worth of writing, or several days worth of artwork. The number of variables that influence the output minutes, and even the human input, are diverse across use cases. Starting with a multiple of 100 demonstrates the intention of the model, while still being observable by readers in their experience with available automation tools.

We posit that HAILR will increase over time, as the cost of computing drops and the efficiency of AI models increase.

5 - Proportion of Automation (PoA)

The Proportion of Automation is the proportion of human labor that will be automated, with the PoA projected to increase over time.

Many previous sources forecast ultimate job displacement of net 40%-50%, notably the Oxford Study[12] as far back as 2013. We do not challenge these previous predictions, however, we point out that they are generalized across all industries, whereas knowledge work is far easier and less expensive to automate than manual labor. The reduced friction in the automation of knowledge work, and in particular, work performed on a computer indicates that this will result in faster and more comprehensive automation of knowledge work, and therefore the net job loss will not be equally distributed across all industries, but in fact is weighted towards work that does not require mechanical robots, at least over the next twenty years.

The journey of towards automation is in early stages, so we started with a total Proportion of Automation of 1% in 2024. As milestones, we set our model to 30% by 2030, which is consistent with McKinsey's Ellingrud, K., et al.[13] and to 90% by 2044 (see figure 4), which is also within the range allowed by McKinsey, although on the more aggressive end of their scale. We explain why below, under "Forced Adoption."

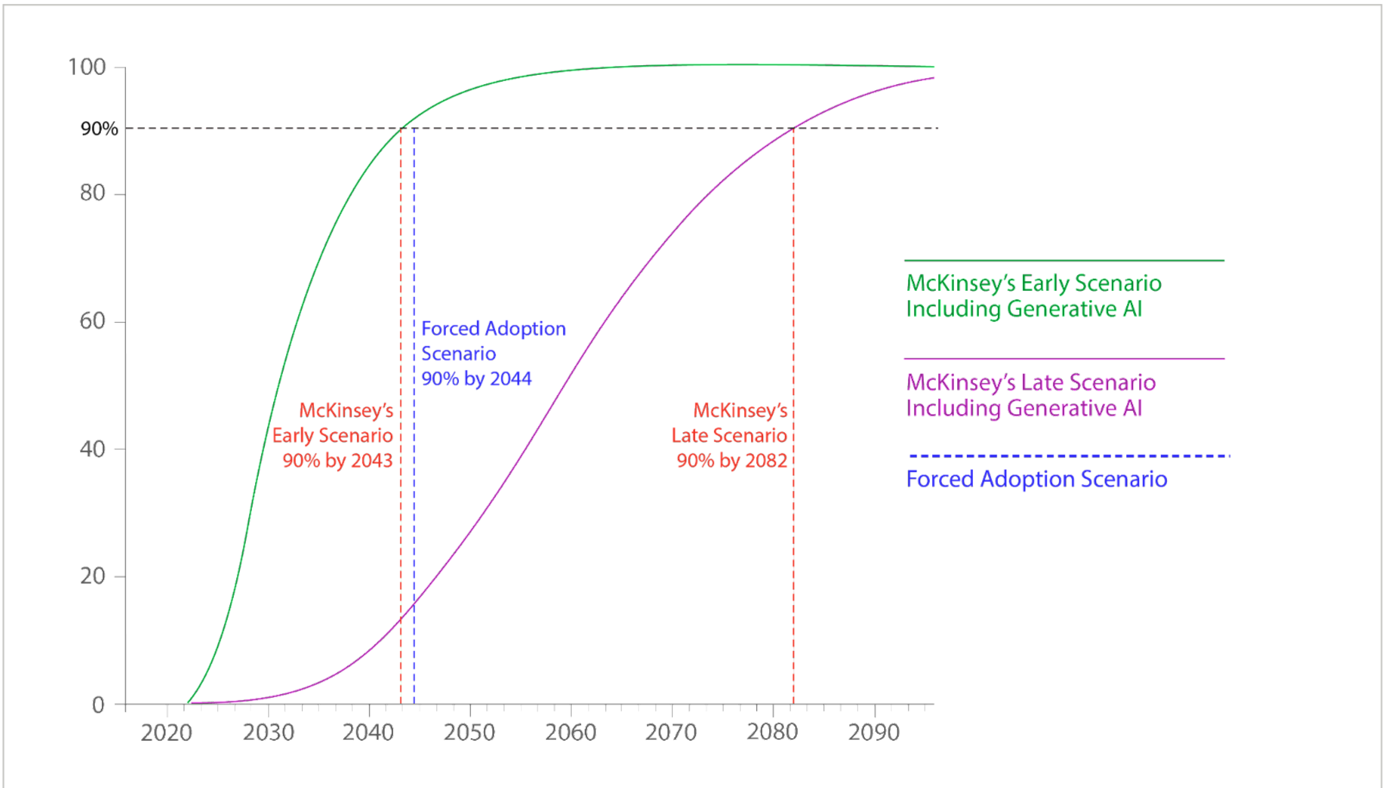

Figure 4: % of Automation of Current Work Activities. Adapted from McKinsey[14e]

Forced Adoption

Adoption of customized AI and automation solutions by organizations is underway. If it appears there is a slow start, this may be partially due to general lack of awareness by some, of the current capabilities of AI, at least with regards to use cases within organizations (automatic writing of articles is one of the few widely known use cases). It may also partially be due to the current lack of publicly advertised, off-the-shelf automations that might benefit an organization. Chatter in the development world indicates that many customized solutions are under development, but have not yet hit the market.

If organizations are hesitating or reluctant to aggressively automate their operations, this could also be due to the fact that competitors have yet to begin producing goods and services at vastly lower costs. Adoption is currently optional. But if the trajectory holds, this optional state of affairs will not last, especially as the labor market acquires considerable skills and know-how related to leveraging AI applications. There will come a tipping point in pricing where certain companies utilize automation to the extent that their operational costs fall low enough to make a noticeable difference in their pricing strategies.

The tipping point of pricing will be different for every industry, but if a competitor automates and can thereby lower its price significantly yet still make the same profit, this could make competition untenable. In this scenario, every company will be forced to adopt or die. Under this scenario, adoption will not be optional. Indeed, early adoption by some could create a waterfall effect where adoption becomes a forced race (even a stampede), and those who get started early enough may get such a lead that they cannot be overtaken.

McKinsey's assessment is that automating 90% of work may happen as soon as 2043 or as late as 2080. The model in this paper leans towards the early date, as it is highly plausible that forced adoption becomes the norm, leaving companies with no choice but to automate.

As yet we have few public examples of dramatic price decreases, but they appear to be on the horizon. It is our hypothesis that competitive price cuts will upend operational priorities with a sense of urgency that will dramatically speed up adoption, and that there may be significant opportunity for market leadership for those companies who are first to automate at scale.

6 - Input Minutes

The parameter *Input Minutes* refers to the amount of time a human is providing input to AI systems each day. This is the time that would have previously been worked by a human to directly produce value. In this model, the human input minutes are instead used to steer and/or provide feedback to AI systems, which can presumably produce more value in less time than it would have taken the human.

While there are a great many definitions of productivity, and a great many ways of measuring it, for the purpose of this paper, productive work is herein defined as work that directly or indirectly produces the goods and services that might be consumed by others. It does not include time wasted, nor time spent on maintaining, such as cleaning one's desk. The values provided are based on the assumption that a typical human productively creates value for only about half of the time they are working in average 8-hour workday. There are currently no generally accepted productivity statistics for work of this definition, so we applied a measure of just over four hours per day to allow for a modicum of loss due to inefficiency or tasks which do not contribute directly or indirectly to the production of value. It is important to note that whether the actual number is 2 hours, 4 hours or even 8 hours, the outcome of abundance is only by a matter of degree. Extreme levels of abundance are still inevitable.

The input minutes are calculated by multiplying the Rate of Automation by the assumed number of minutes per day that a human typically works productively. As a starting place, we used 262 productive minutes per day and a 1% Rate of Automation, resulting in an initial parameter value of 2.62 minutes per day where humans are steering AI systems to produce value.

7 - Output

Output refers to how many units of human-equivalent output is produced by automation. This is the product of the *HAILR* multiplier by the *Input Minutes*. At the initial parameter values, a HAILR multiplier of 100 produces 262 Human Equivalent Output minutes. This is based on 2.62 minutes of human input. The output column of the model provides the Human Equivalent Output in weeks, months or years to better make sense of the data as time goes by and as production scales. Note that we assumed a work-week of 40 hours when calculating output in weeks, and a year of work at 50 weeks to allow for two weeks of holiday.

The Model

This model is intended to reveal the inevitability of the reduction in cost of goods and services, as human work is automated. While the authors consider the projected dates plausible, the model is not intended as a prediction of precise dates. We invite researchers to manipulate the variables and add their own refinements, with confidence that similarly remarkable outcomes will result.

Year	Computing cost	Computing units	AI Model efficiency	HAILR Multiple	PoA	Input Minutes	Output minutes	Output years
2024	1.00	1.00	1.00	100	1%	2.62	262	0.002
2025	0.85	1.15	1.30	150	3%	7.8	1,173	0.010
2026	0.72	1.32	1.69	224	7%	18	4,093	0.036
2027	0.61	1.52	2.20	334	12%	31	10,489	0.091
2028	0.52	1.75	2.86	500	18%	47	23,522	0.20
2029	0.44	2.01	3.71	747	25%	65	48,841	0.42
2030	0.38	2.31	4.83	1116	30%	78	87,621	0.76
2031	0.32	2.66	6.27	1669	35%	92	152,825	1.3
2032	0.27	3.06	8.16	2495	40%	105	261,112	2.3
2033	0.232	3.52	10.60	3731	45%	118	439,158	3.8
2034	0.197	4.05	13.79	5577	50%	131	729,491	6.3
2035	0.167	4.65	17.92	8338	55%	144	1,199,647	10
2036	0.142	5.35	23.30	12465	59%	154	1,923,907	17
2037	0.121	6.15	30.29	18635	63%	165	3,071,240	27
2038	0.103	7.08	39.37	27860	67%	175	4,883,028	42
2039	0.087	8.14	51.19	41650	71%	186	7,735,956	67
2040	0.074	9.36	66.54	62267	75%	196	12,216,817	106
2041	0.063	10.76	86.50	93089	79%	207	19,238,230	167
2042	0.054	12.38	112.46	139169	83%	217	30,217,414	262
2043	0.046	14.23	146.19	208057	87%	228	47,352,145	411
2044	0.039	16.37	190.05	311045	90%	235	73,232,541	636

Primary Findings

By 2044…

- One minute of human labor could produce 311,045 minutes (2.7 work-years) of productive output.
- One person, with four hours of productive work, could produce 636 years of productive output.
- Nine out of ten knowledge workers will be permanently displaced from employment.

These projections provide some sense of how disruptive these AI-driven changes in production may be. Rather than demeaning human knowledge workers, the results show how productive the remaining workers will be with the assistance of AI automation. Their efforts will be leveraged with the capabilities of AI technologies.

Discussion

This paper has focused on the transfer of knowledge work from humans to machines. If, as we suggest, most knowledge workers will eventually lose jobs without new jobs to replace them, then additional research must be done to find those people meaningful purpose and livelihood. The new human-AI collaborations may indeed be satisfying and enriching to the knowledge workers who obtain them(15).

It has been suggested UBI (universal basic income) be given to displaced workers, but this may be problematic. Companies will not willingly give up profits to feed people who are not contributing, thus taxation must be enforced. However, this has not consistently worked in the past with large corporations so alternative ideas must be generated. For example, perhaps the government could allocate land in rural areas to people who would like to return to a self-sustaining, husbandry way of life. It would be an ironic outcome if the high tech movement resulted in many of us living a more low tech lifestyle!

We acknowledge that in addition to automating tasks, AI may also be applied to aiding humans in being more productive by helping them focus longer on higher value tasks, thus increasing the time worked each day on tasks that produce real value. It is anticipated that were this to happen, that it may give companies a significant competitive advantage, as each incremental minute rescued could mean weeks, months or even years of additional productive output. For as long as automated activities require the input of a human, the variable of rescued minutes could bring about dramatically improved efficiency of output. On the level of human emotion, having one's time be productive to its maximum level could result in increased job satisfaction and even self-actualization, thus both the employer and employee will likely benefit from aggressive adoption of solutions that increase human productivity, not necessarily enjoined to the automation process, but in and of itself.

Limitations

There may be unforeseeable barriers and frictions to furthering automation potential, or adoption of automation even if full automation potential is achieved(16, 17). Barriers could prevent the world from achieving automation at the levels shown in the model and frictives could slow the trajectory towards mass automation. As just one example, some kinds of complex non-repetitive work will be automated only when more self-managing AI exists, which we have referred to in this paper as 'auto-automation'. Today it is just too expensive to engineer automations for most workflows that are less repetitive. If AI does not develop to the extent that automation of low-repetition tasks can be economically automated, that would be a barrier.

Other barriers and obstacles could include government-imposed or union-negotiated restrictions on the use of AI.

A limitation of the model itself is the proportion of automation. While automation of 90% of work suggests the loss of 90% of jobs, in fact it could be far more severe. Consider that if 90% of human labor is replaced, but the AI-enabled output produces years worth of equivalent work in a matter of hours, then it is not necessary for 10% of the people to remain employed. Just 1% of the current workforce, or even a small fraction of that, could conceivably meet all global demand.

Another limitation to consider regarding the model is that rather than laying off 90% or more of the workforce, employers may keep more people employed, but reduce their required hours or give them sinecure responsibilities. Thus fewer people become unemployed. However, if the stigma of being "unemployed" is removed, changes in society that lead to more meaningful and fulfilling lives for everyone can be wrought[18].

The definition of "knowledge work" is a limitation, in that there is no single definition and the scope of what can be characterized within its boundaries is expanding. But generally, cognitive work that is performed on a computer is ripe for automation, because anything that we can perform on a computer, can theoretically be replicated by a computer.

Conclusions

The world is heading towards a seismic shift that will have unprecedented impact on the way we live, not just work. Modeling this shift provides corporate leaders, policy makers, and community participants with insights as to the economic and social changes the shift will make on society. HAILR (Human to AI Leverage Ratio) enables modelers to explore the impacts of AI on production with some level of specificity, unlike many of the narrative-style projections. The accuracy of the model depends on factors that have not yet clearly emerged, such as the scope of the regulation of AI by nations. Model building efforts such as the one in this paper can equip communities, states, and nations to understand trends in productivity and ensure that the increased output produces true "abundance."

Further Research

The HAILR multiple presented has been generalized across all knowledge work. It is anticipated that some tasks and even entire job roles will be entirely automated, with zero human involvement. Further research could explore granular calculations for specific industries, job classes and tasks.

The measurement of true human productivity deserves additional research, as currently there is no single, widely accepted method for creating a generalized metric that might be equally applied across job functions. Sickles & Zelenyuk[19] made a great effort, but their methodology is apparently not convenient enough to use in production to the extent that it is widely used to compare the productivity of jobs where the duties are vastly different, such as salespeople vs. engineers. More development could result in a workable solution for production environments, such that all employees could equitably be compared with a single metric.

This model is a starting point, to provide scientists with some basic, yet plausible math that demonstrates how high levels of automation will result in an Age of Abundance. This isn't just a talking point, it is real. Yet we acknowledge the model could be improved by considering additional variables. For example, humans require breaks from work because of fatigue and illness so a model with this additional variable, and others, may improve the precision. In addition, the ratio of less repetitive tasks to highly repetitive tasks might be considered, which could give greater insight into the frictions that could slow the rate of transformation.

As AI may also be applied to aiding humans in being more productive by helping them focus longer on higher value tasks, additional research should be conducted into the precise application of AI to this problem.

Auto-automation is a topic for additional research. What can AI currently self-automate? How far out on the horizon is auto-automation at scale? A more precise prediction regarding the year-over-year Rate of Automation could benefit from this data.

The authors acknowledge that the content in this paper will benefit from updates, which are not possible to make after publishing. For this reason, updated versions may be found here: https://inspira.ai/science/hailr-and-the-age-of-abundance/

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