Chapter 5
Industry 5.0 and Artificial Semi-General Intelligence. Exploring Future Challenges and Opportunities Within Industries and Societies

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Abstract Industry 4.0 has been dramatically impacted by artificial intelligence technology in recent decades which has led to both positive and negative outcomes. The increased productivity and better optimization processes allowed factories to be more efficient, however, due to ever-expanding artificial intelligence capabilities certain work professions are at risk of automation. Thus, Industry 5.0 emerged as a movement that is supposed to lead to a more cohesive, resilient, and stable society. Nonetheless, a new rise of artificial semi-general intelligence is right around the corner, which delivers unprecedented digital cognitive abilities which could either be net positive or negative on society. For these reasons, this chapter attempts to discuss and unpack some of the current artificial intelligence projections, and the possible impact on industries and societies.

Keywords Industry 4.0 · Industry 5.0 · Artificial semi-general intelligence · Narrow AI · Human-centric

5.1 The Inception of the Industry 5.0 Concept Before the Advent of ASGI

The concept of Industry 4.0 can be traced back to 2011 when the German government began to promote the idea of “Industrie 4.0” as a vision for the future of manufacturing. The goal of the initiative was to help German manufacturing companies maintain their competitive edge in the global market by leveraging digital technologies to optimize production processes, improve efficiency, and improve product

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S. Nousala et al. (eds.), *Industry 4.0 to Industry 5.0*, Translational Systems Sciences 41, https://doi.org/10.1007/978-981-99-9730-5_5

quality. Although it took some time, the term Industry 4.0 became widely adopted as a characterization of industry developments across EU countries (Queiroz et al., 2022; Grybauskas et al., 2022). In 2014, only three scientific papers were released that incorporated Industry 4.0 as a keyword, but in 2015 the number of papers grew to 15. Simultaneously, the news coverage experienced a sharp increase on the topic during 2018, with news articles released that included Industry 4.0 as a keyword (Grybauskas et al., 2022).

An Industry 4.0 revolution was believed to be unfolding as evidenced by a number of innovations, including:

(a) Robotics and automation
(b) The Internet of Things (IoT)
(c) Cloud Computing
(d) Blockchain technologies
(e) Advanced Sensors
(f) Collaborative Robots
(g) 5G networks
(h) Digital Twins
(i) Drones and autonomous aerial vehicles (AAVs)
(j) Machine learning
(k) Advanced materials and Nanotechnology
(l) Additive manufacturing (3d-printing)
(m) Edge Computing
(n) Wearable technology
(o) Human-machine interfaces
(p) Augmented reality (AR) and virtual reality (VR)

As these technologies were being integrated concurrently in many countries, a unifying concept ("Industry 4.0") was eagerly welcomed by experts around the globe. Moreover, the adoption of such technologies has delivered profound benefits in terms of efficiency and productivity which were recorded by many scholars and consulting firms (Fettermann et al., 2018; Ghobakhloo, 2020; McKinsey, 2020). For instance, 5G networks can transfer data at much faster speeds than previous generations of wireless networks, reducing latency and enabling real-time data processing, with increased efficiency for various applications. Additive manufacturing with rapid prototyping, for production of parts and products, has significantly reduced lead times and time-to-market. Machine learning models allow for automating of repetitive tasks, that deliver predictive analytics and process automatization, thus saving valuable resources for companies. Similar benefits have also been described by other Industry 4.0-linked technologies.

However, while some proponents of Industry 4.0 technologies argued that they can lead to increased efficiency, productivity, and economic growth, others have raised concerns about the potential negative impact on workers and society. An impactful paper written by Frey (2017) has estimated that around 47% of total US employment was in the high-risk automation category due to technological advancement which could directly lead to job losses. This statement set the stage for labor economists to question whether the Industry 4.0 technological revolution was excluding humans from the loop. The fears were further escalated by such organizations like McKinsey, OECD, and PwC, which claimed that 38% of US jobs will be automated by 2030, or putting it another way, 60% of all occupations will have the ability to absorb at least 30% of technically, automated activities (McKinsey, 2017; PwC, 2017). Such numerical forecasting has instilled fear, pushing policymakers to rethink Industry 4.0 strategies, thus the idea of Industry 5.0 was born.

In essence, Industry 5.0 aimed, in part, to turn away from purely productivity-driven benefits, by proposing three important pillars: human-centricity, resilience, and sustainability (EU, 2022). On a surface level, it made perfect sense to shy away from a narrow focus that only made factories more efficient, excluding any significant human life-work balance concepts. As such, a new trend among researchers and scholars had begun to emerge where social sustainability concepts were prioritized. Scholars outlined the problems of the digital divide, digital literacy, social exclusions, job loss, skills mismatches, employee health, job insecurity, and many more issues that were ongoing due to innovation (Grybauskas et al., 2022).

Although the understanding of Industry 5.0 human-centricity concept was and still is unfolding, certain shifts to a more workplace conscious environment can already be empirically detected and tested. For instance, Fig. 5.1 depicts some of the changes that were detected by reviewing thousands of online job postings in 2023; more precisely, it summarized how companies positioned themselves and their goals during Industry 4.0 and Industry 5.0 rollouts. Prior to 2020, companies' job posting descriptions outlined what companies make, e.g., product type, and what they want from the applicant. Very few companies attempted to declare their personal commitments to the environment, workers' mental health, career development, and additional monetary benefits.

	Industry 4.0	Industry 5.0
Company info	Describes when the company was established, in what sector it works and what products it makes.	Describes the purpose of the company and what impact it wants to create for the society. Additionally, adds it's sector and product information.
Job description	Describes what is required of an applicant: years of experience, proficiency in certain software or tools, working hour schedules and other important vairables.	Not only describes what requirments of the applicant are required, but explicitly names what benefits, enviroment and career development opportunities awaits.

Fig. 5.1 Detected job postings description changes after reviewing thousands of different web scraped job ads from online job platforms

However, after 2020, job postings began to dedicate a whole paragraph to talk about the companies' sustainable goals, their commitment to environment and ethics as well as a whole section of benefits that an employee might receive. To illustrate how these small changes are starting to occur, Fig. 5.2 outlines two anonymized job postings for cleaners, made by two small companies. On the left side of Fig. 5.2, Company A provided a very basic and superficial description, that did not mention any benefits, prospects, sustainability, or self-dignity to becoming a cleaner at this firm. In contrast, Company B started with a welcoming message that one would be able to become a part of a team, although in both cases a cleaner was required to work alone for extended periods of time. However, the latter acknowledged the candidate as an important link in the company and as a member of a team. Furthermore, Company A simply put forward the salary numbers and avoided any additional bonuses, while company B provided six additional perks. Although some of the benefits were marketing tricks, certain compensations were objectively beneficial for both: the company and an employee. For example, by helping to find other employees to join the team one could get salary bonuses. Also, the fact that equipment and clothing were provided helped to avoid additional costs that an applicant might face. In addition, company B mentioned the use of eco-friendly

Fig. 5.2 An anonymized job listing comparison between similar companies for the cleaner job position. Certain images have been generated by A.I.

substances and chemicals, that effects both the environment as well as the workers' health, which might be compromised by dangerous substances. Lastly, considering that this is one of the lowest-paid professions in many parts of the world, with usually less detailed descriptions, the second job posting was much more transparent, saving time for an employee to make unnecessary inquiries before applying.

Although this example is far from comprehensive, it illustrates some important aspects of Industry 5.0 (e.g. how automated cleaning machines and humans are integrated, whether workers privacy is respected). The result was a gentle and important acknowledgment, that mindfulness towards essential worker concerns and environment should be cultivated in the transition to Industry 5.0.

Looking on a more macro-scale, Fig. 5.3 presents selected keywords obtained from a pool of 100 distinct job advertisements. The aim was to discover the rewards that are beginning to be offered by employers. More focus was placed on employee well-being than on environmental dimensions. By data mining, it was possible to cluster five different types of benefits that companies targeted: monetary benefits, equity promises, environment benefits, career growth, and job arrangement benefits. For example, companies offered financial incentives, such as stock ownership options, that would make an applicant not only an employee at the company but also a stakeholder. In addition, bonuses, car allowances and bike lease opportunities, healthcare plans, pensions, and insurance schemes have been offered to ensure a

Fig. 5.3 A word cloud of keywords that were mined from job postings. The collected keywords represent benefits that companies are willing to offer to applicants

sustainable future and retirement. The work-life balance appears densely populated with numerous advantages, that included financing many physical activities. These ranged from climbing, yoga, meditation, soccer, and many other sports. Interestingly, even taking care of laundry was offered. Many work forms were also offered, where an applicant can choose from working at home, sharing a job position with another employee, or even working on a contract basis. Finally, two sections were dedicated to career advancement (to maintain up-to-date skills) and creating an equitable working environment, highlighting a strong commitment to not discriminate against individuals based on religion, race, or age.

It is crucial to be cautious and not jump to the conclusion that the mentioned benefits automatically ensure human-centricity within the workplace, as human-centricity is a much wider concept that puts human and robot collaboration at the center. On an empirical level, such declarations from companies could also indicate a tighter job market, forcing companies to offer more benefits to attract applicants. Nonetheless, industry 4.0 was marked with a plethora of issues concerning the problems of the workers well-being. If we view Industry 5.0 as a continuation of Industry 4.0, we should strive to pay more attention to the on-going issues that will spill-over to future generations. As a result, the well-being of a worker should be a piece of a puzzle when discussing the human-centricity concept that should incorporate work-life balance, privacy, health of a worker, fair pay, inclusivity, and other important aspects.

Although a small shift has been detected in the job postings where companies are starting to consider eco-friendliness or employee well-being as part of their strategy, the danger lies within the presumption that the job market can be made human-centric. This may not be possible to achieve in the current work climate, since humans are currently observing early indications of artificial semi-general intelligence (ASGI), meaning that they are poised and positioned to initiate a fresh wave of social transformation. More precisely, the current iterations of ChatGPT and GPT-4, were developed after the formation of the Industry 5.0 concept, and to much surprise of the experts, (that were hoping to witness ASGI become viable only around 2050 or later), have become freely available, to be accessed, automated and integrated within robotics, companies, phones, and other environments. Thus, the human-centricity concept might need to be reconsidered from the very foundations of our societies, to encapsulate not only human-centricity but civilization-centricity.

5.2 The Roadmap and Inflection Points of ASGI

5.2.1 Narrow A.I.

To understand how dangerous and transformative AGI, or its smaller brother ASGI, is to the industry 5.0 concept and goals, one must take a deep dive into its origin, inflection points, and future projections for A.I. development. The previously listed technologies from Industry 4.0 to 5.0, up to 2023, only touched on, and were limited to, modest machine-learning tasks. In fact, the AGI or ASGI had not even existed on a consumer level. A more precise keyword that could describe the stage of artificial intelligence technology up to 2023 is "Narrow A.I" (see Table 5.1), which is only the first stage of artificial intelligence development. In the domain of Narrow A.I., many algorithms have been developed to perfect single-task precision. The tasks usually involved classifying images, e.g., dogs vs cats, predicting real estate prices, default likelihoods in the banking sector, stock price forecasts, next character prediction, movie or product recommendation projection, and many more.

After the growth of Narrow A.I's popularity, certain domains of its applications had begun to form. These included computer vision (CV), a domain which deals with enabling machines to interpret and understand images and video data from the real world, involving tasks such as object detection, segmentation, image recognition, and image generation. Natural language processing (NLP). enables machines to understand, interpret, and generate human language. Reinforcement Learning (RL), trains machines to learn from their environment through trial and error, taking actions that could maximize a reward signal, and so on. The algorithms to achieve these kinds of tasks were based on long-standing research done by computer scientists. A popular choice for computer vision was to use convolution neural networks (CNN) to detect edges of the picture that then were pooled and classified into the given objective. Although the CNNs could classify all sorts of shapes, faces, animals, and other objects, it was designed to perform one given task at a time extremely well. Figure 5.4 depicts how CNNs work to detect edges sequentially to make a classification prediction.

On a similar note, the NLP domain developed its own tools to parse through text and make predictive models. In the early days of NLP, researchers used rule-based approaches that relied heavily on regular expressions and dictionaries. These methods worked well for simple tasks such as text cleaning, tokenization, and part-of-speech tagging but struggled with more complex tasks such as sentiment analysis and machine translation; however, after introducing more advanced tokenization methods as well as the recurrent neural network (RNN) architecture, new milestones were reached.

A simplified summary of how RNNs work is depicted in Fig. 5.5, where at each time step t, an RNN takes an input x_t and a hidden state h_{t − 1} from the previous time step t − 1 as inputs and produces an output y_t and a new hidden state h_t as outputs. The new hidden state h_t is a function of both the input x_t and the previous hidden state h_{t − 1}. This creates a feedback loop in the network that allows

Table 5.1 Three stages of A.I. development. Inspired by https://analyticsindiamag.com/artificial-narrow-vs-artificial-general/, and expanded by the author

Artificial narrow intelligence	Artificial combined intelligence or ASGI	Artificial general intelligence
Idea: Machine's ability to perform single task extremely well	*Idea*: Machine's ability to perform multiple tasks extremely well	*Idea*: Machine's ability to perform any task extremely well

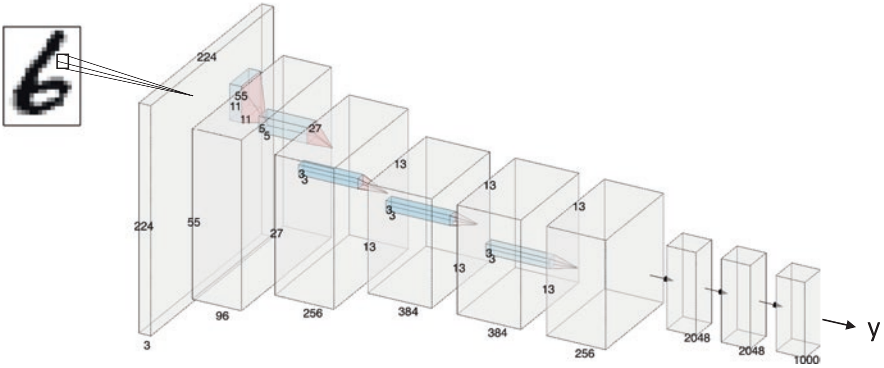

Fig. 5.4 A CNN architecture for the digit classification task. This process is performed on only one task and thus is considered part of Narrow A.I.

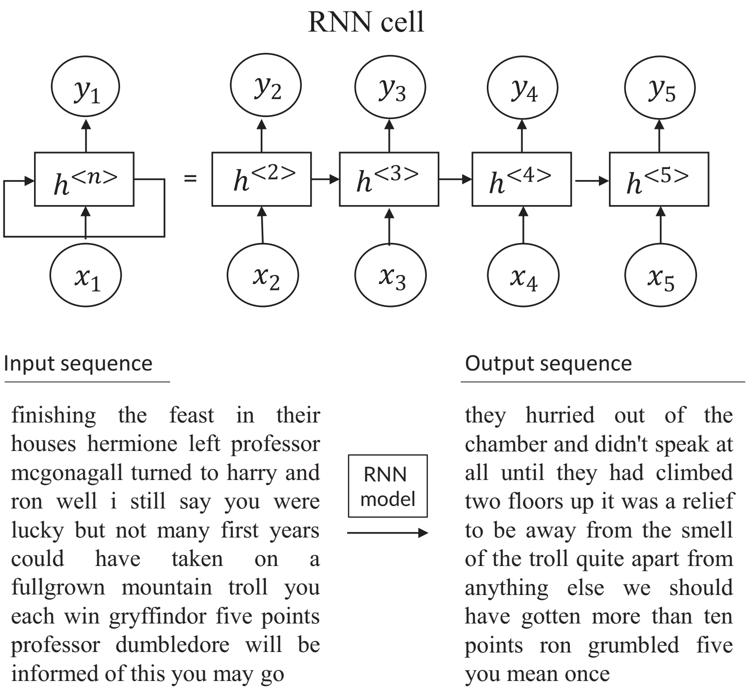

Fig. 5.5 A depiction of general RNN architecture that was trained on the Harry Potter book. The input sequence was fed into the RNN model to generate the output sequence. In this case, the choice of RNN was LSTM

it to remember information from previous time steps and uses it to make predictions at the current time step. The latter architecture of RNNs allowed for machine text translation, next character, word, sentence prediction, or even text generation from a prompt. Some important types of RNNs to remember are simple RNNs, Long-Short-Term-Memory networks (LSTM), and Gated Recurrent Unit neural networks (GRUs).

A pilot example of RNN capabilities can be found below in Fig. 5.5, where a Harry Potter book was used as a source of training data to create a sequential prediction model, in other words a series of choices. The input text was tokenized and converted into integer sequences. After hyper tuning the parameters the model was ready to provide a new sequence of narratives according to the input data. As depicted in Fig. 5.5 input sequence, the sentence ended in the professor's order to leave. The RNN model managed to capture this context and responded with a new sequence where characters left the chamber, which seemed to be a logical continuation of the narrative. Although results are far from perfect when iterating over many sequences, such new tools have marked a new era of NLP capabilities.

5.2.2 Inflection Point: A Deeper Dive into Developing Capabilities

It was no secret that online textual information was a gold mine to be exploited as it contained everything that an AGI would need to be trained on: it had our thoughts, intentions, confessions, actions, solutions to probability questions, anecdotes, song lyrics, books, scientific discoveries, historical narratives, languages and much more. Nonetheless, important bottlenecks needed to be solved before proceeding to development of AGI capabilities. For instance, the RNN networks had a problem regarding their ability to retain long-term dependencies and information over time. This is commonly known as the vanishing-gradient problem, which occurs when the gradient signal in the network becomes too small to propagate updates to earlier time steps. As a result, RNNs struggle to capture long-term dependencies in sequential data, which can lead to the loss of important contextual information. Several variants of RNNs, such as LSTMs (Long Short-Term Memory) and GRUs (Gated Recurrent Units), have been developed to mitigate this problem by incorporating memory cells and gating mechanisms that allow for more effective information retention and propagation over longer sequences. However, even the LSTM memory capacity is limited. As new tokens are added to the sequence, the LSTM must decide which information to keep in the memory state and which to discard. This process is known as *forgetting* and it becomes more difficult as the sequence length grows. As a result, scientists, being aware of such limitations, were not eager to predict an AGI to emerge anytime soon, and the forthcoming Industry 5.0 concept, which only experienced limited capacity of neural network models, appeared to be reasonably achievable. However, a new and unexpected breakthrough was on the way.

In 2017 an interesting paper appeared under the name “Attention is All You Need” that was written by eight scientists (Vaswani et al., 2017). At a first glance, it looked like just another NLP methodology paper that introduced the transformer architecture depicted in Fig. 5.6, however, upon deeper analysis, it stumbled upon two-amazing discoveries.

The first one is related to the attention mechanism which can be calculated using the following formula:

$$Attention(q,k,v) = softmax$$

where q is the query vector, k is the key vector, and v is the value vector. Because of the attention mechanism, the transformer is able to capture dependencies between all tokens in a sequence, whereas RNNs only capture dependencies between neighboring tokens. This attention mechanism allows transformers to better understand the context of each word in a sentence.

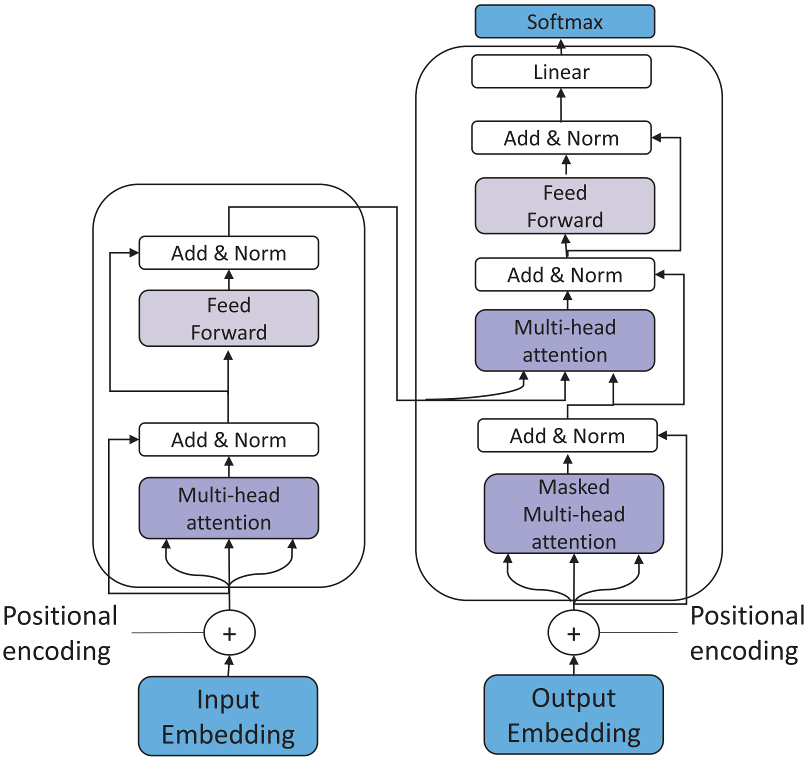

Fig. 5.6 The transformer model architecture. Adapted from Vaswani et al. (2017)

The second major contribution is related to "parallelization". On one hand, RNNs can process data sequentially, one token at a time, making them slow for long sequences. On the other hand, Transformers can process all tokens in a sequence in parallel, which makes them much faster.

Now it might seem that parallel computation is not such a big milestone, however, without this achievement, the training for large decoder models would take tens or hundreds of years; thus, it is a detrimental yet still sought-after improvement even over the current transformer architecture.

The publication of the "transformer" paper initiated a competitive pursuit towards the development of the ASGI since everything required was within arm's reach; the data were already available online and the transformer was able to capture meaningful neural connections within a reasonable timeframe. Hence began the showdown of large language models, which aimed to understand and generate human-like language responses. In 2017, OpenAI created a Generative Pre-trained Transformer (GPT) model. In 2018 Google presented a Bidirectional Encoder Representations from Transformers (BERT). In 2019 OpenAI's released a newer version of GPT called GPT-2, and in 2020 Facebook joined the race with a model called RoBERT.

Each of the previous model iterations was impressive in its own way. Data scientists managed to integrate them in the form of chatbots, sentiment analysis, language translation, text summarization, and much more. However, from a human or Turing test perspective, they were not on par with human intelligence and frequently made unreasonable answers. Here is an example prompt provided to GPT-2:

Question: If I have two shoes in a box, put a pencil in the box, and remove one shoe, what is left?

Answer: Shoes

From a human perspective, this simple mistake is unforgivable to even consider a machine to be conscious or have decent reasoning skills. From a modeling perspective, to answer such a statement requires a state-of-the-art solution and although prompting was impressive, it was still light years away to be considered a contender to human reasoning skills, thus a question remained: how do you make or lead an A.I. system reason? Do we need something more than a transformer architecture?

Few things have been discovered while trying to tackle this problem. First, in order for the A.I. system to reason, there is an inflection point that must be reached in terms of the model size. As discovered by Brown et al. (2020), that in detail tested many types of neural network configurations, one of the most important factors contributing to A.I.'s ability to reason is the number of parameters that neural network architecture has. Constructing models of only 1 billion parameters provides very little ability for the model to answer simple mathematical questions. Between 1.3B and 2.6B parameters, we begin to witness the slope change, although the accuracy of answers is still below 20%. In this region exists the dilemma, and the focus of a lifetime for any engineer involved. The GPT-2 release was in this region with 1.5B. parameters. Now the cost of GPT-2 development was around $50,000 USD, and it took weeks to train. In order to achieve another milestone a significant investment in millions of dollars would be needed to purchase the required equipment, however, there were no guarantees that the result would be any different.

Despite the uncertainty, OpenAI decided to take the risk, using around four million dollars to begin developing GPT-3, with millions of additional parameters. Around 2020, GPT-3 was released along with a paper called "Language Models are Few-Shot Learners". The paper presented eight new models: GPT-3 Small (125M parameters), GPT-3 Medium (350M parameters), GPT-3 Large (760M parameters), GPT-3 XL (1.3B parameters), GPT-3 2.7B (billion parameters), GPT-3 6.7B, GPT-3 13B and GPT-3 175B. The astonishing achievements can all be found in Brown et al. (2020), where a clear trend of reasoning improvement can be detected right after the 6.7B parameter model. This huge discovery was yet another leap forward toward creating an AGI system, as the problem-solving skill within the A.I. began to emerge.

5.2.3 From ASGI to AGI

Initially, the created GPT-3 model was not provided for download, as this model's capability was so powerful that concerns emerged about it falling into the wrong hands; thus only API accessibility was provided. For this reason, the GPT-3 model did not reach viral coverage around the world, since consumers were unable to access it without programming skills to reach the API endpoints. Nonetheless, in 2022 November, a ChatGPT was released which acquired 100 million users within the first month. Although it was based on the GPT-3 175B parameter model, it was fine-tuned to specific tasks and incorporated reinforcement learning to better fit the user experience. The results were surprising to everyone from all backgrounds: academic members were amazed how their exams were being solved in real-time, programmers were receiving full code solutions in any programming language within seconds, personal gym programs were developed for gym enthusiasts, book-writers were startled as it was able to write consistent, interesting, and dynamic narratives in the blink of an eye.

At this point, it is important to make several distinctions. To be fair, the ChatGPT system cannot be called an AGI system, as it still was confined between "Narrow A.I." and a combined A.I. space. As described in Table 5.1, the AGI system would

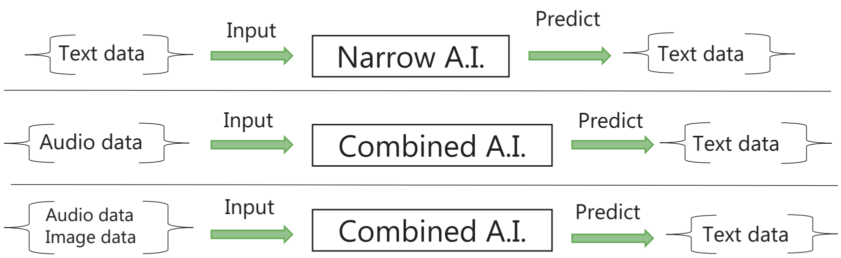

Fig. 5.7 The combined ICA can combine different sources of information with different sources of output

be able to perform any task, while combined A.I. can do multiple tasks. In addition, Fig. 5.7 depicts how the combined A.I. differ from the "Narrow A.I." in terms of input and output sequence. The latter input and output data have to be unified in order to for the model to work, e.g., a language model needs text data as input and provides text data as output, while combined A.I. can take image data as pixels, and provide text data, that describes the picture and vice versa. Thus, the most accurate description of ChatGPT is that it can be positioned as an ASGI (combined A.I.) since it can understand text, and numbers, write code, and provide code prompts; however, sound, vision, and other dimensions are not integrated.

With the invention of ChatGPT, the world began to see the rise of combined A.I. products. On March 14, 2023, OpenAI released GPT-4, however at the time of writing this chapter the company did not disclose how many parameters existed within this model. GPT-4 is able to recognize images, can understand image context by referencing user prompts, and can solve quite complex math equations, but most impressively it was tested on the bar exam for lawyers, as well as medical and other exams that students take at universities. The passing grade is considered somewhere around 60%, and random guessing is around 25%. The results portrayed on the OpenAI website depict a new milestone of achievement for humanity, where a GPT-4 model has managed to pass the most challenging questions in a majority of the subjects, and pass the full exams in many cases.

Of course, the GPT-4 and ChatGPT are not the only combined ASGI models. Dall-E 2 is a text-to-image model, where a text can be described and A.I. draws sketches or/and makes curves according to the prompt. Speech2Text converts recorded audio into textual information, and text-to-video presented by RunwayML generates video from textual information. Another interesting development is carried out by the DeepMind and the so-called GATO project (Reed et al., 2022a, 2022b). GATO is a deep neural network for a range of complex tasks that exhibits multimodality. It can perform tasks such as engaging in a dialogue, playing video games, controlling a robot arm to stack blocks, and more. The GATO project is a true strive for AGI that has all the dimensions encapsulated from text, sound, or video, however, the project is still in the making and has many milestones to overcome. Some initial results are reported in the DeepMind "Generalist" paper of how the model behaves (Reed et al., 2022a, 2022b).

As of now, the motion is set and the race to AGI has begun. The question is, by what year can we expect such a system to exist? Although there is no clear and definite answer, a retrospective comparison with a human brain as a benchmark can be made. It is calculated that a human brain has around 86 billion neurons and around 150 trillion synapses, so the average number of synapses per neuron is approximately 1744. The harder question involves subjective interpretation. It is difficult to objectively compare a human brain network with an artificial network, as there are important differences, however, the artificial neural network parameters are closer to synapses than neurons themselves. Thus, GPT-3 175B parameters are most closely related to 150 trillion synapses of the human brain from a functionality perspective. Using algebra, we could rearrange this into the following:

$$\text{Human brain}: 86 \text{ billion neurons, with } 150 \text{ trillion synapses} \\ \text{==>} 1744 \text{ synapses per neuron.}$$

$$\text{GPT} - 3: 175 \text{ billion parameters} \left(\text{equivalent to synapses}\right) / 1744 \text{ synapses per neuron} \\ \text{==>} 100 \text{ million neurons.}$$

which would be equal to around 100 million neurons that exist in the current ChatGPT model, however, these calculations should be taken with a grain of salt. Furthermore, if we assume Moore's law, which says that the number of transistors processing power doubles around every 2 years, our AGI progress could be extrapolated in such projection as Table 5.2:

Of course, not all neurons are equal. One can create 150 trillion useless and unoptimized synapses that won't achieve anything, however, the 150 trillion synapses should be the milestone at which everything that a human can achieve, the machine should be able as well. Therefore, if we assume that ChatGPT neurons are effective since they do provide logical and consistent prompts, we could expect some form of AGI around 2042. Some support for the latter claim can be found according to a survey of A.I. experts, where participants were asked "When is AGI likely to happen", around 50% believed that AGI is likely to happen by the time of 2040 (Dilmegani, 2023).

5.3 Navigating the Future of Industry 5.0

As was mentioned before, the Industry 5.0 concept was born before the advent of combined ASGI; thus, it had no realization of what societal transformations might come about. Prior, there was convincing evidence that the advancement of technology will predominantly target low-skilled workers in routine jobs (Ramaswamy, 2018) and the idea was to welcome such change as people can become free from

Table 5.2 Projection of effective neurons according to Moore's Law

Neurons	Years
100 million	2022
200 m.	2024
400 m.	2026
600 m.	2028
1.2 B.	2030
2.4 B.	2032
4.8 B.	2034
9.6 B.	2036
19.2 B.	2038
38.4 B.	2040
76.8 B.	2042

repetitive work and do more creative work. However, as noted by Ford (2013), the number of employees who engage in creative work has always been small, and historically routine jobs have been a good match for average workers' capabilities. Furthermore, when the technological transformation took place and destroyed some type of routine work, usually the worker was required to adopt new skills, but his relocation was essentially from one routine job to another, thus still being within the bubble of routine work that is yet to be automated.

However, if we set aside the routine job automation issue for a moment, and analyse guidelines by the WEF (2020) we could outline the following skill sets:

(a) Critical thinking and problem-solving skills.
(b) Creativity and innovation.
(c) Emotional intelligence and empathy.
(d) Social and cross-cultural skills.
(e) Complex communication and negotiation abilities.
(f) Technical and technological knowledge and expertise.
(g) Cognitive flexibility and adaptability to new situations.
(h) Leadership, teamwork, and collaboration.

Unfortunately, even assuming that a large pool of routine workers can acquire the latter skillsets and considering that there is an incredibly high amount of demand for the outlined skills, the current development of ASGI systems has already begun acquiring some combination of these skills. In 2023 OpenAI released a paper that attempted to evaluate what impact the GPT models could have on certain professions (Eloundou et al., 2023). The methodology was based on questionnaires for both human respondents and GPT-4, along with statistical analysis. Occupation and skill exposures were calculated. On the human side, 15 professions were identified as fully exposed to LLM, while A.I. affected 86 professions. By examining the professions, humans agreed that writers and authors are at huge risk of automation, since GPT-4 can already write convincing and exciting narratives. As of 2023, Amazon is already selling books written by A.I. which in subsequent years may increase. In retrospect, writing a book was a definition of being creative, but since the invention of GPT-4, this section of creativity is being automated, thus the creativity skill which was praised as futureproof might no longer be resilient. As a result, the goal post has shifted, and now the question arises as to which part of creativity is resilient?

Another profession that was labeled as fully exposed is mathematicians. For the longest time, the discipline of math attracted the brightest minds around the world to solve complex equations. In the Open AIs survey, both humans and GPT-4 agree that LLM will continue to become better at solving derivatives, probability theory and physics equations, thus any answer which requires a pool of math expertise will be available in milliseconds by prompting. As a result, one of the most cognitive and creativity-dependent occupations, is extremely vulnerable to automation.

Similar statements can be made regarding other skill sets, such as problem-solving, emotional intelligence, and complex communication. For instance, one could provide a prompt with details about a specific situation, such as architecture design problems or the division of assets in a stock portfolio. Artificial intelligence can then solve the problem independently, providing thousands of solutions in a matter of milliseconds. We are yet to determine whether the quality of those solutions would be on par with humans, however, a recent paper by Zhang (2023) has already demonstrated that A.I. models are capable of passing the MIT math test at 100% accuracy. In the world of finance, much of asset division is being done by mathematic modelling, hence autonomous A.I. can certainly thrive in such cases. Additionally, language models are currently being tested for cross-examining witnesses in court cases, which requires a significant amount of communication skills. Lastly, emotional intelligence, a crucial skill for personal therapists, is also becoming a domain for AI. However, unlike humans who have limited time and patience for their patients, AI companions have significantly more endurance and tolerance to listen to people's experiences. A recent OpenAI article also concluded that individuals with bachelor's, master's, and professional degrees are more exposed to ASGI than those without formal educational credentials (Eloundou et al., 2023).

Overall, a new picture is starting to emerge, where notions of job safe havens are becoming more of an illusion, when gazing towards long-time horizons, as we reach a nexus where anything can be automated if the management and engineering teams decide to focus. Hence, Industry 5.0 will face completely different challenges compared to Industry 4.0. In the context of the latter, Narrow A.I. was possible to be dealt with by creating a work environment that merged with robotics, and was more well-being oriented. In the case of ASGI, human and robot collaboration might be hindered by autonomous agents. As OpenAI's CEO, Sam Altman stated: "The costs of intelligence and energy are going to be on a path towards near zero." Although it is hard to comment on the energy aspect, the statement that the cost of intelligence, where with a single prompt you can get highly complex answers, is going down, is true, and with that, the labor value might also fall. It is truly surprising that the most valued and mysterious feature of human intelligence is becoming automated, as ChatGPT case is made free online.

Although it is easy to portray a nightmare scenario for Industry 5.0, there are some important factors that make an important difference when evaluating human-centricity. First, it is important to understand that we are experiencing a population collapse. As depicted in Fig. 5.8 Side A, the growth of the world population is slowing, and the collapse is predicted to begin somewhere around 2100. Paradoxically, even the Chinese admit that they are lacking a labor force and this is especially evident in the Western hemisphere like Germany, where aging problems are causing concerns for companies to find workers, thus special visa programs are made to find young people from different parts of the world.

The labor shortage issue in Fig. 5.8, shows a very simplistic labor market model, where Side B, depicts the effects of population decline. The labor demand D1

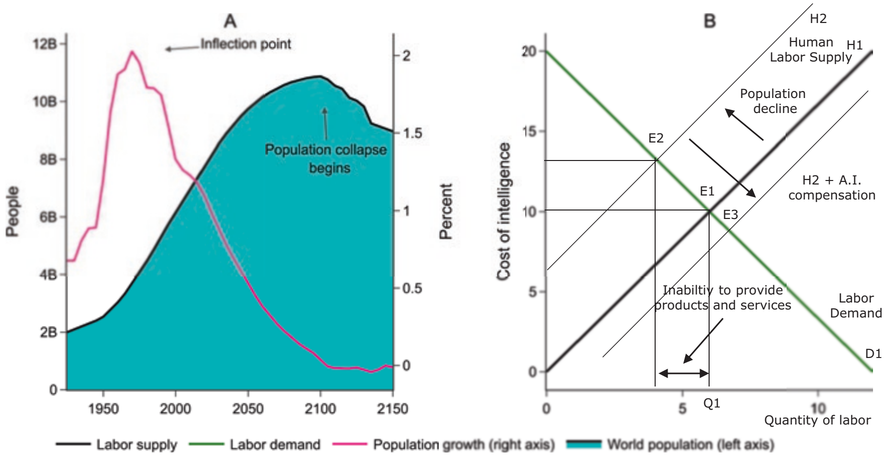

Fig. 5.8 Side A—world population projections. Side B is a supply and demand equilibrium model

corresponds to the amount of labor that firms are willing to buy for a certain cost of intelligence price.[1]

Similarly, H1 corresponds to the human labor supply that is supplied for a certain price. If the market is in equilibrium, the position E1, Q1 number of workers is employed. However, since population decline is unavoidable, the amount of labor that can be supplied to the market will decrease, hence H1 moves to position H2. Since firms will not be able to pay the higher rate of cost of intelligence, the equilibrium position will shift to position E2. However, many firms will be unable to provide products and services due to shortages in the labor force. This could include hospital care, road maintenance, educational services, and more. Thus, if ASGI can become a substitute and compensate for the loss of labor, we could expect to move back to or even further down to position E3. This would allow firms with a declining population to keep up with the demand for products and services by substituting human work with ASGI functions.

In this scenario, ASGI or future AGI could be a saviour for productivity for the whole world. As of now, there is not much empirical evidence that population decline can be reversed with-out some technological breakthrough like an artificial womb, thus substitute for the human labor force is essential. In this scenario, the

[1] Conventional labor market models predominantly encompass dimensions of labor quantity and labor price. Nevertheless, in many instances, individuals are recruited for their intellect, which adds substantial value to the company—essentially, we are leasing out their cognitive prowess. While the measurement of this "intelligence cost" remains an abstract notion presently, I am confident that the future will unveil a well-defined and precise metric for quantifying one unit of intelligence. Drawing a parallel, just as cars are gauged in horsepower, Joseph Carlsmith's estimation equates the human brain to approximately 11 petaFLOPS of computational power. It's important to note that FLOPS, although not a direct representation of intelligence, pave the way for the emergence of evolving intelligence evaluation metrics that require time to mature. Thus, price per horse power, and price per intelligence becomes viable.

Industry 5.0 policies would need to be directed to helping certain groups of people retrain if job automation occurs, to teach workers to collabo-rate with A.I. machines. Collaboration would also include the development of A.I. to be ethical, safe, and responsible, with a continuation towards medical perks and mental health programs to keep people healthy, safe and aspirational.

However, at the other end of the spectrum, if A.I. substitutes the human labor pool too quickly and theoretical equilibrium cannot be reached, we could end up with strong chaos within the labor market. This situation is demonstrated in Fig. 5.9, where both moderate and steep declines in the cost of intelligence are depicted. Although in both situations an unemployment gap will occur, in the steep decline scenario, too many people can get replaced by A.I. too quickly compared to population decline. This can lead to the accumulation of an unemployable class of people that will need to be on benefit support from the government for the rest of their lives. If these circumstances are not approached effectively, this could lead to widespread protests worldwide. From an Industry 5.0 context, certain policy actions should be explored either in simulation or real-life studies. For instance, the efficacy of universal basic income (UBI), widespread personal robot income tax, deferred automation strategy, and other policy decision need to be explored if such circumstances occur. Thus, the Industry 5.0 policy has to be ready to address inequalities, joblessness, and disparity on a macro scale.

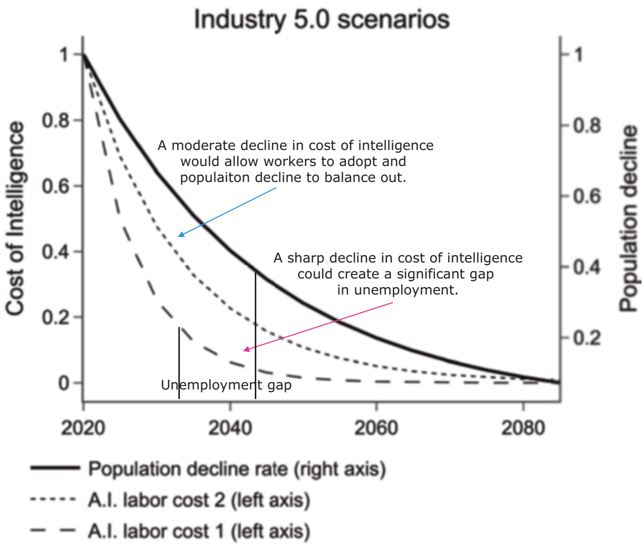

Fig. 5.9 Industry 5.0 cost of intelligence scenarios

5.4 Conclusions

In conclusion, the development of Industry 5.0 represents a promising step forward in ensuring that automation and technological transformation are balanced with the needs of people and society. Certain employers are already taking into consideration some aspects of workers well-being while constructing a healthy workplace, as well as making meaningful attempts to become more sustainable towards the environment. However, the potential rise of Artificial Semi-General Intelligence (ASGI) presents a unique challenge that requires careful consideration and planning. The realization that all types of skills can be automated with the right amount of effort highlights the importance of ongoing collaboration between management, engineering teams, academia, and governments to ensure that automation is implemented in a responsible and sustainable way. The explored scenarios for labor present both optimistic and alarming possibilities for the future of work, highlighting the need for proactive steps to ensure that the benefits of automation are shared by all members of society. The forthcoming trajectory of Industry 5.0 should embrace a dual emphasis: not only on the synergy between humans and robots but also on the consequential enhancement of productivity, ultimately proving advantageous for humanity. As we move forward into the era of Industry 5.0, it is essential that we remain mindful of the potential risks and work together to create a future that is beneficial for everyone.

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