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## Grand challenges in industrial and systems engineering

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### ABSTRACT

Contemporary society faces a growing set of complex issues representing significant socioeconomic, health and well-being, environmental, and sustainability challenges. The discipline of industrial and systems engineering (ISE) can play an important role in addressing these issues. This paper identifies and discusses eight grand challenges for ISE. These grand challenges are (1) Artificial Intelligence (AI) For Business and Personal Use: Decision-Making and System Design and Operations, (2) Cyber-security and Resilience, (3) Sustainability: Environment, Energy and Infrastructure, (4) Health Issues, (5) Social Issues, (6) Logistics and Supply Chain, (7) System Integration and Operations: Humans, Automation, and AI, and (8) Industrial and Systems Engineering Education. The discussed grand challenges were derived by accomplished ISE professionals who are the authors of this paper. The implications of the ISE grand challenges for education, training, research, and implementation of ISE principles and methodologies for the benefit of global society are discussed.

### ARTICLE HISTORY

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Industrial engineering;  
systems engineering; global  
society; grand challenges;  
research needs

## 1. Introduction

### 1.1. Background

Industrial and systems engineering (ISE) is defined as a discipline concerned with the design, improvement and installation of integrated systems of people, materials, information, equipment and energy. It draws upon specialised knowledge and skill in the mathematical, physical, and social sciences together with the principles and methods of engineering analysis and design, to specify, predict, and evaluate the results to be obtained from such systems (IISE 2024). Furthermore, the main components of ISE knowledge that reflect a categorisation of pertinent industrial and systems engineering theories and models include (1) work design & measurement, (2) operations research & analysis, (3) engineering economic analysis, (4) facilities engineering & energy management, (5) quality & reliability engineering, (6) ergonomics & human

factors, (7) operations engineering & management, (8) supply chain management, (9) engineering management, (10) safety, (11) information engineering, (12) design and manufacturing engineering, (13) product design & development, and (14) system design & engineering. Given its broad knowledge base, the ISE discipline is well positioned to address and respond to the growing and highly complex set of interrelated socioeconomic, population growth, health and safety, and sustainability challenges that global society faces today. ISE professionals can also play an important role in accelerating the process of translating relevant ISE research output into practical solutions, desired tools, methods, systems, and applications to improve the lives of the billions of people on Earth.

The main goal of this paper was to define and discuss a set of grand challenges that represent the key and pressing areas of work for ISE discipline and profession. Our goal

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was not only to outline key grand challenges but also to propose a way forward to ensure that ISE can respond to each challenge, including how specific ISE methods can be applied. Furthermore, our intent was also to communicate to ISE researchers and practitioners the role of ISE in responding to major global issues and challenges. By articulating how ISE can assist in responding to key grand challenges, this position paper should facilitate further discussion and applications of ISE to large-scale global issues.

### 1.2. Grand challenges and their impact

The general idea of grand challenges in science, medicine, engineering, technology, and education, explored by individual scientists, research organisations, international non-profit entities, or national governments, has a long and rich history (Omenn 2006; Woolf et al. 2013; Hicks 2016; Lufkin 2017; Kaldewey 2018; Peña and Stokes 2019). The notion of ‘grand challenges’ has also recently been widely used in research and innovation policy, focusing on global societal problems such as energy, health, and the environment (Ulnicane (2016).

According to Kaldewey (2018), the concept of grand challenges and grand challenges discourse illustrates how scientists, policymakers, and the public have communicated their respective agendas in recent decades (see, for example, Peña and Stokes 2019). Furthermore, Bostic (2016) pointed out that today, ‘the humanities must engage global grand challenges’ since such challenges represent urgent and widely shared problems that require large-scale, long-term, coordinated responses. He et al. (2013) also underscored that the premise of grand challenges often constitutes ‘a call to action for investigators to develop the capabilities of our society for research, education, and translation . . . as well as for funding agencies to continue or expand their support of these highly important fields’.

Global challenges are highly complex, multifaceted, dynamic, heavily interrelated, and difficult to fully describe, understand, and manipulate successfully. This evolution in how society thinks about complex global risks is thus urgently needed (Arnold and Wade 2015). The World Economic Forum’s latest global risks report identifies climate action failure, extreme weather, social cohesion erosion, livelihood crises, infectious diseases, human environmental damage, natural resource crises, debt crises, and geo-economic confrontation as the most severe risks currently facing us (World Economic Forum 2022). By 2050, there will also be emergent global risks related to artificial general intelligence (AGI), automation replacing human workers, the genetic modification of humans, an aging population, and otherworld settling

(Hancock 2022; Salmon et al. 2021). A summary of the selected grand challenges related to the field of industrial and systems engineering is presented in Table 1. It should be noted that some of these grand challenges are already being addressed within the ISE profession, demonstrating the interdisciplinary nature and theoretical and practical overlaps of these challenges.

## 2. Methods

The development of this industrial and systems engineering (ISE) grand challenges position paper went through the following process. The Chairs have identified the potential coauthors based on the knowledge of their professional interests, published contributions to the wide spectrum of ISE discipline, and perceived reputation and potential value to the teamwork. Each team member was asked to propose up to five ISE Grand Challenges with a brief write-up of the rationale of the proposed grand challenges. Next, an extended virtual meeting was held during which all team members discussed and extensively deliberated the grouping of the originally submitted challenges and synthesised these into eight clusters. Such groupings of the proposed ISE grand challenges were conducted based on the similarity of the received ideas and concepts proposed by all team members. During the virtual meeting, the team members also determined their interest in specific grand challenges, and leaders were appointed for each of the eight grand challenges.

Each ISE grand challenge team had two members, one serving as team leader. Each team was requested first to prepare a Table of Contents, tables, figures, and a list of references that the members planned to include in their grand challenge. This information was then shared with all the members of all eight teams. The team leaders and members of each grand challenge team coordinated and developed the write-up for each ISE grand challenge. The chairs of the paper have integrated the write-ups for the eight ISE grand challenges into a unified paper, including an abstract, introduction, and conclusion. This complete paper was shared with all the members, and feedback was requested from all team leaders and members on how to improve the paper further. These inputs have been integrated into the final paper submitted to the journal for further review. All coauthors of the paper have reviewed and accepted the final draft manuscript.

## 3. Grand ISE challenges

The following ISE grand challenges have been identified: (1) Artificial Intelligence for Business and Personal Use: Decision-Making and System Design and Operations, (2) Cybersecurity and Resilience, (3) Sustainability:

**Table 1.** Selected grand challenges from domains related to industrial and systems engineering.

Domain	List of grand challenges
Human Factors and Ergonomics (Karwowski et al. 2025)	1) Evolution in Societal Thinking; 2) the Future of Human Activity; 3) Climate Change and Sustainability; 4) the Future of Education and Training; 5) the Future of Personalised Health, and 6) Life, Technology, and the Metaverse.
Human-Centric Manufacturing (Lu et al. 2022)	I) Social challenges: 1) Technology acceptance and trust; 2) Change of team dynamics; (3) Lifelong learning. II) Technical challenges: (4) Human-centric AI and Personalised AI; (5) Transparency and Explainability; (7) Performance measure; and 8) Manufacturing systems research.
Human-Centered Artificial Intelligence (Ozmen Garibay et al. 2023)	AI that: (1) is centred in human wellbeing, (2) is designed responsibly, (3) respects privacy, (4) follows human-centred design principles, (5) is subject to appropriate governance and oversight, and (6) interacts with individuals while respecting human's cognitive capacities.
Human-Computer Interaction (Stephanidis et al. 2019)	(1) Human-Technology Symbiosis; (2) Human-Environment Interactions; (3) Ethics Privacy and Security; (4) Well-being, Health and Eudaimonia; (5) Accessibility and Universal Access; Learning and Creativity; and (6) Social Organisation and Democracy.
Science Robotics (Yang et al. 2018)	(1) New materials and fabrication schemes; (2) Biohybrid and bioinspired robots; (3) New power sources, battery technologies, and energyharvesting schemes; (4) Robot swarms; (5) intelligence; (7) Brain-computer interfaces; (8) Social interaction and moral norms; (9) Medical robotics Navigation and exploration in extreme environments; (6) Fundamental aspects of artificial with increasing levels of autonomy; 10) Ethics and security for responsible innovation in robotics.
Grand Challenges for Engineering in the twenty-first century (NAE 2016)	(1) Advance personalised learning; (2) Make solar energy economical; (3) Enhance virtual reality; (4) Reverse-engineer the brain; (5) Engineer better medicines; (6) Advance health informatics; (7) Restore and improve urban infrastructure; (8) Secure cyberspace; (9) Provide access to clean water; (10) Provide energy from fusion; (11) Prevent nuclear terror; (12) Manage the nitrogen cycle; (13) Develop carbon sequestration methods; and (14) Engineer the tools of scientific discovery.
Modelling and Simulation (M&S) (Taylor et al. 2015)	(1) Big simulation: data, ontology and simulation modelling coordination for scalability; (2) Human behaviour and composability; (3) Cloud-based M&S and composability; (4) Reproducible M&S: engineering replicability into computational models; (5) The democratisation of modelling & simulation.
Operations Research and Engineering (Barnhart 2008).	(1) Developing a self-sufficient sustainable energy programme; (2) Using advanced sensor and telecommunication technologies to diagnose infrastructure faults; (3) Creating driverless highways and achieving congestion mitigation; (4) Improving healthcare in developing countries and in the United States; (5) Enhancing medical imaging and diagnostic capabilities; (6) Developing effective counter-terrorism strategies; and (7) Using the Internet to improve education in emerging countries.

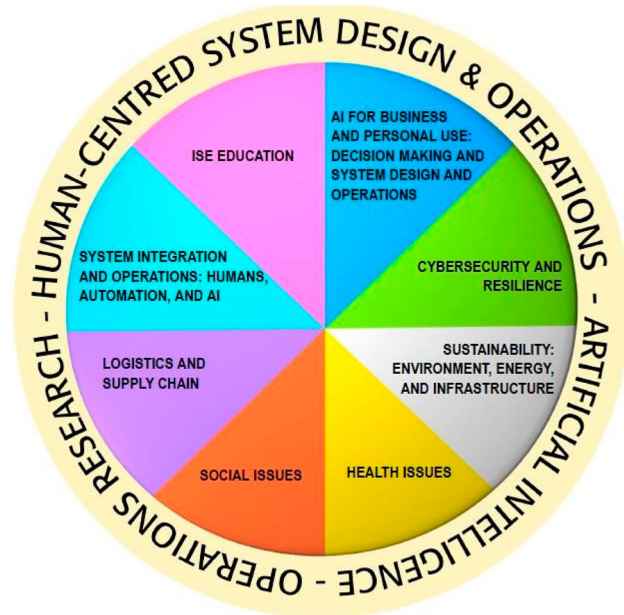
Environment, Energy and Infrastructure; (4) Health Issues, (5) Social Issues, (6) Logistics and Supply Chain, (7) System Integration and Operations: Humans, Automation, and AI, and (8) Industrial and Systems Engineering Education (see Figure 1). These challenges are discussed in detail below.

#### 4. Grand challenge of artificial intelligence for business and personal use: decision-making and system design and operations

Over the next 10–20 years, artificial intelligence (AI) will revolutionise industry, government, and society as profoundly as technologies such as industrial machines, computers, and the internet have done in the past. As a discipline focused on improving industry (and society) with engineering and related scientific methods, ISE has an enormous opportunity and responsibility to address grand challenges associated with artificial intelligence.

##### 4.1. Background and the impact of artificial intelligence

AI is a set of scientific approaches to train machines or systems to conduct tasks that normally require human

**Figure 1.** Industrial and Systems Engineering Grand Challenges.

intelligence. AI utilises algorithms, analytics, natural language processing, and other techniques to learn from data and the environment to solve problems, learn skills, or perform specific tasks. AI approaches build upon multiple disciplines such as computer science, mathematics,

statistics, and engineering. AI can have a strong relationship with areas such as operations research (OR), which has an explicit focus on optimising decision-making under uncertainty and with limited resources. The public may not necessarily distinguish between different types of algorithms (AI or not).

Interest in AI has existed since at least the 1940s, when Alan Turing described a machine that could read, learn, recall, solve problems, and more, usefulness for specific tasks (e.g. playing chess) or more general ones Turing (1950). A machine is considered 'intelligent' by the Turing test if an interrogator cannot distinguish the answers of the machine from those of a human being (Turing 2009). Over decades, advancements in methods and technology have led to AI programmes that can play chess, navigate mazes, devise mathematical proofs, simulate dialogue, recognise patterns, learn languages, navigate roads, and classify images. AI may encompass approaches such as machine learning, neural networks, deep learning, evolutionary heuristics, and natural language processing. Recent years have seen advances in generative large language models, which can learn to predict subsequent words from previous ones, resulting in programmes that appear to speak and synthesise knowledge. Already many companies say their organisations are using generative AI for at least one function.

There are many existing examples where AI has been deployed to generate functionality to industry or society. Current applications include smart assistants that understand language and personalise services, manufacturing robots that collaborate with humans, chatbots to engage customers and answer questions, smart devices to control home environments, tools to generate images based on language prompts, healthcare algorithms to predict high-risk patients, programmes that screen job applicants, facial-recognition systems, and social media algorithms to encourage engagement. One difference in recent AI applications is that some of the tasks mimic those of humans where creativity seems involved (e.g. such as generating new images or songs), although this is achieved by learning from past data (Anantrasirichai and Bull 2022).

Indeed, many uses of AI are not fully transparent, and people are often unaware of AI's role in decisions that affect them daily. Further, there are many examples where AI programmes are measuredly biased (e.g. towards hiring men for a job), which can be a function of the data used for training (Landers and Behrend 2023). A third challenge is that the results from AI may be inaccurate or unreliable, which can have significant consequences when decisions are being made in high-impact areas (Araujo et al. 2020). Fourth, it has been demonstrated

that there can be large computational, financial, and environmental costs of training and running AI programmes (Wu et al. 2022). These challenges and others help motivate the need for AI that is responsible, ethical, equitable, and effective.

In the next 10–20 years, more and more data will be digitised. AI will be deployed for tactical, operational, and strategic-level decisions across a broad set of domain areas. It is likely to touch every grand challenge outlined in this article and beyond, including ones such as sustainability, environment, and energy; health; social issues; logistics; system integration with automation; education; and cybersecurity and resilience. AI will help further the use of real-time decision making in complex systems. We can only begin to imagine the changes this will bring, and the potential for positive transformation to society if deployed well. Below we highlight four specific areas where ISE as a discipline and profession can contribute to this grand challenge, including (1) systems orientation, (2) integration of OR and AI, (3) people, and (4) education.

#### 4.2. Challenges related to AI

Artificial intelligence and similar methods integrate sophisticated algorithms with analysis of data that is deep and broad to enable decision making that can mimic (or exceed) that of humans. ISE, as a discipline and profession, should engage in understanding and improving the impact of AI within systems. The results can include improved outcomes across supply chains, health systems, transportation, military, and many other applications. In addition, by examining AI in the context of industrial and societal systems, Industrial and Systems Engineers will play an important role in understanding the current and future impacts of AI on equity, including related to the data sets that are curated or used, the cascading effects of one system element on another, the impact of AI on human decisions throughout enterprises, and ultimately on the responsible use of AI that is ethical, equitable, and effective.

However, along with its capabilities, there are grand challenges that must be addressed. Here are some of the key challenges associated with the use of AI, to ensure it will be Responsible, Ethical, Equitable, Effective AI, that can contribute positively impact industry and society.

##### 4.2.1. Challenge with AI #1: incorporating human factors through AI systems

The grand challenge of AI for business and personal use poses significant human factors challenges in decision-making and system design and operations. One of

the primary concerns is the need for effective human-machine interaction to ensure safe and efficient operation of AI systems. As AI becomes more autonomous, the need for human oversight and intervention increases, requiring a deep understanding of human factors principles to design effective interfaces and workflows. Another critical human factors aspect is the need for transparent and explainable AI decision-making processes to support human decision-making (Lasi et al. 2014). The increasing complexity of AI systems requires humans to understand and trust AI-driven decisions, which can be a significant challenge for humans without prior experience in these areas (Hermann, Pentek, and Otto 2016). Ultimately, the success of AI integration in business and personal use depends on the ability to design AI systems that are intuitive, transparent, and trustworthy, and that can effectively support human decision-making.

The importance of designing AI systems that are intuitive, transparent, and trustworthy is particularly relevant in advanced manufacturing, where AI systems have the potential to significantly impact productivity and efficiency (Jan et al. 2023). To realise these benefits, it is essential to ensure that AI systems are designed to support human decision-making and oversight, which requires a deep understanding of human factors principles and the ability to design effective interfaces and workflows. However, the integration of AI also raises significant challenges for advanced manufacturing, including the need for significant investment in infrastructure and training, as well as the potential for job displacement and changes to traditional workforce structures (Manyika et al. 2017). Moreover, as manufacturing systems become increasingly complex, interconnected, and automated, a systems perspective is essential for understanding and managing emerging risks and challenges. Applying systematic thinking approaches can help manufacturing organisations and policymakers anticipate and mitigate these risks.

#### **4.2.2. Challenge with AI #2: identifying and reducing bias in AI systems**

The second major challenge is the potential for bias in AI systems. AI systems are trained on data, and if that data is biased, the AI system can perpetuate and even amplify those biases, resulting in discriminatory outcomes or reinforcing existing societal biases. For example, a sentiment analysis tool that is trained on data from primarily English-speaking sources may have difficulty accurately analysing sentiment in non-English languages. This risk is particularly acute in sensitive applications such as criminal justice, where biased AI could potentially influence decisions on suspect identification, risk assessments, and sentencing (Angwin et al. 2022). This

type of bias not only undermines the reliability of AI applications but also raises serious ethical concerns about equity and inclusivity in AI-driven decision-making.

Overcoming this challenge requires careful data collection, unbiased model training, and ongoing evaluation to achieve fairness and mitigate bias in AI systems. Addressing AI bias necessitates a comprehensive approach in system design and operations that encompasses: (1) Ethical Data Collection: Ensuring diversity and representativeness in the datasets used for training AI systems to prevent the perpetuation of existing biases (Barocas and Selbst 2016). (2) Unbiased Model Training: Implementing methodologies that detect and neutralise bias in AI models during their training phase (Bellamy et al. 2018). (3) Ongoing Evaluation and Calibration: Continuously monitoring AI systems post-deployment to detect emergent biases and recalibrating the systems as necessary to maintain fairness over time. These measures are imperative to cultivate trust and reliability in AI applications, fostering their successful integration into both personal and business environments. The commitment to unbiased AI also aligns with broader regulatory and societal expectations for ethical AI use.

#### **4.2.3. Challenge with AI #3: enhancing explainability of AI systems**

Many AI algorithms, particularly deep neural networks, are complex and difficult to understand or explain. This lack of transparency raises concerns about trust and accountability. For instance, if an AI system recommends a specific medical treatment for a patient, it is important that healthcare providers can understand and trust the reasoning behind that recommendation. Developing interpretable and explainable AI systems is crucial to address this challenge and ensure that users can comprehend the decision-making processes of AI systems.

Addressing the challenge of explainability in AI systems requires strategic modifications in system design and operations: (1) Development of Interpretable Models: It is crucial to focus on creating models that are easier to comprehend. Prioritising techniques that make complex models more interpretable or that approximate them with simpler explanations is essential. The work by Ribeiro, Singh, and Guestrin (2016) highlights methods for explaining the predictions of any classifier, which is a step forward in this direction. (2) Integration of Explainability Tools: Utilise tools and frameworks like LIME or SHAP to make the outputs of complex models more comprehensible. These tools, as discussed by Lundberg and Lee (2017), along with the methodologies described by Sun, Lin, and Shen (2022), can help bridge the gap between AI decisions and human understanding. (3) User-Centric Design: Designing AI systems with

the end-user in mind ensures that users can effectively understand and interact with the AI's decision-making processes.

#### **4.2.4. Challenge with AI #4: addressing data privacy, security, and ethical concerns**

As AI technology advances and becomes more integrated into daily activities, significant challenges related to data privacy, security, and ethics arise. These issues stem from AI characteristics such as data dependency, complexity, and autonomous decision-making. First, AI systems require vast amounts of data, often including sensitive personal information. Mishandling this data can lead to privacy violations. Second, the complexity and interconnected nature of AI systems make them targets for cyberattacks. Ziegeldorf, Morchon, and Wehrle (2014) highlighted increased risks in systems like the Internet of Things, where a breach in one part can compromise the entire network. An example is a hack into an AI-powered healthcare system, leading to stolen medical records. Third, AI's autonomous decision-making can lead to ethical challenges, especially when decisions impact human lives. Jobin, Ienca, and Vayena (2019) discussed concerns over AI systems in sensitive areas like law enforcement, where they might perpetuate biases and lead to unfair treatment. These challenges can undermine public trust, cause significant losses, and harm marginalised communities. Furthermore, the rapid pace of AI development can outstrip regulatory and ethical frameworks, leading to governance gaps.

When designing and operating AI systems, it is essential to prioritise privacy by collecting only necessary data and employing technologies that safeguard personal information. Security is equally crucial; regular testing and integrating security practices throughout the AI development process help address vulnerabilities. Moreover, ethical considerations should guide the operation of these systems, with clear guidelines and regular assessments to ensure fairness and accountability. Transparency is key to building trust, achieved by making the AI's decision-making processes understandable and involving diverse perspectives in the development process. Together, these measures ensure that AI systems are safe, ethical, and well-received by society.

#### **4.2.5. Challenge with AI #5: overcoming technical limitations with current AI methods**

AI faces several technical limitations that need to be overcome, including handling ambiguity, understanding context, common sense reasoning, and adapting to dynamic environments. Moreover, while AI systems excel in specific tasks, they often struggle to generalise their knowledge or skills to new or unfamiliar situations and lack

the broader adaptability and versatility of human intelligence. For example, autonomous vehicles sometimes struggle in unpredictable weather conditions or unexpected traffic scenarios because they are programmed for specific, predictable environments and lack the ability to adapt as quickly as a human driver might. Emulating human emotional intelligence, ensuring robustness against adversarial attacks, and addressing other limitations present additional challenges that need to be tackled. To successfully address these challenges, collaboration among researchers, policymakers, industry leaders, and society as a whole is crucial. By working together, we can ensure the responsible and beneficial development and deployment of AI technologies.

### **4.3. ISE opportunities to address challenges with AI**

There are enormous opportunities for ISE to address AI challenges, including across subdisciplines of ISE, in collaboration with computer science, and in partnership with industry. Below we identify several including some that relate to the challenges outlined above.

#### **4.3.1. Systems orientation**

The ISE discipline is at its core, a discipline that is focused on methods in the context of a facility, an organisation, a domain, or a system. AI has emerged as a powerful tool in addressing various challenges across industry and academia. In common applications, AI is designed to excel in specific areas such as speech recognition, image classification, recommendation systems, and data analysis. These task-specific AI systems rely on large datasets to learn patterns, recognise objects, and make predictions. Techniques such as machine learning (ML), deep learning, and statistical models are employed to process and analyse data, thereby informing decision-making processes. For instance, AI plays a crucial role in supporting decision-making in healthcare and Medicare (Vasey et al. 2022; Amann et al. 2022; Čartolovni, Tomičić, and Mosler 2022), enabling more accurate diagnoses, personalised treatments, and efficient patient care. ML algorithms can analyse vast volumes of medical data, including patient records and medical images, to identify patterns and assist in diagnosis. AI-powered systems can predict patient outcomes, optimise workflows, and support drug discovery.

AI can perform better than humans in situations where there are well defined rules and regulations, such as AlphaGo, and it can also learn huge amounts of data and make reasonable conclusions about certain things (e.g. chatbot responses) (Sarker 2021). However, AI, in its current stage, still struggles in making decisions in complex systems, where different stakeholders



and competing objectives have to be considered. Systems engineering seeks to understand the big picture and provide a structured approach to develop, implement, and manage complex systems (Hitchins 2008). ISE practitioners contribute by analysing requirements, designing system architecture, managing data, optimising performance, verifying, and validating systems, addressing safety and security, and supporting maintenance and upgrades. Their interdisciplinary knowledge ensures AI systems align with user needs, operate efficiently, and meet ethical and legal standards. They play a crucial role in integrating AI technologies across diverse domains and industries.

#### 4.3.2. Integration of OR and AI

Recent advances have demonstrated that there can be significant benefits from integrating techniques from OR with AI. AI and ML have been of particular interest to a vast number of researchers of various disciplines, offering solutions to specific problems, enhancing decision-making processes, and automating tasks to improve efficiency and performance. OR is one of the fields that has been impacted and shaped by AI and ML (Gupta et al. 2022). In fact, the fields of OR and ISE can also bring valuable expertise and perspectives to the development of AI and ML solutions. OR and ISE experts often possess strong analytical and optimisation skills. They specialise in mathematical modelling, optimisation techniques, and decision-making processes, and OR techniques often exploit the structure of complex problems. The OR and ISE skills can be valuable in designing efficient algorithms, developing optimisation models, and addressing complex problems in various domains. These are the complementary skill sets of OR and ISE experts as compared with the field of Computer Science (CS). Moreover, operations researchers often have domain-specific knowledge and expertise in particular industries or applications. This understanding allows them to identify critical factors, constraints, and objectives, which can inform the design and development of AI and ML solutions that are tailored to specific needs and challenges within those domains.

OR and ISE practitioners recognise the importance of considering human behaviour, societal infrastructure, and incentives when designing and implementing AI and ML solutions. They understand the broader systems and human elements that impact the effectiveness and acceptance of these technologies. It is also important to note that CS experts bring invaluable expertise to the development of AI and ML solutions, with specialisation in areas such as ML algorithms, deep learning, NLP, and data engineering. Their expertise in developing and implementing advanced algorithms and techniques

is critical for building sophisticated AI systems. Hence, collaboration among CS, ISE, and OR experts is crucial. By working together, their respective skills, knowledge, and perspectives can combine to build more comprehensive and robust AI and ML solutions. This collaborative effort ensures that technical aspects are balanced with practical considerations and real-world constraints.

A large number of ISE and OR scholars have been attempting to explore the interplay between OR and ML in distinct forms (Subramanian and Holger Teichgraber 2023). The combination of ML and optimisation has proven to be powerful in modern data-driven applications. The ‘predict-then-optimize’ paradigm involves using an ML model to predict outcomes, which are then fed into an optimisation model to make coordinated decisions. By leveraging the structure of the optimisation problem, better prediction models can be designed, resulting in improved decision outcomes (Elmachtoub and Grigas 2022). Alternatively, by integrating the prediction step and optimisation step, integrated data-driven methods can generate improved solutions and have shown applicability in many real-world decision-making situations (Qi and Shen 2022), including supply chain management, portfolio optimisation, and power system operations. In particular, ML tools have become an important technique for achieving integrated data-driven solutions. For instance, an end-to-end deep learning-based algorithm has been developed to solve the inventory replenishment problem (Qi et al.). Moreover, ML can also benefit from optimisation techniques, which can make ML methods more interpretable or better performing (Liu et al. 2024). Additionally, ML methods can be embedded into optimisation solvers, improving performance and decision-making capabilities. On the other hand, optimisation solvers can take advantage of ML methods internally, where many state-of-the-art solvers employ ML techniques. The development of surrogate ML models for optimisation problems has proven impactful, allowing for faster results and the development of more powerful optimisation models.

#### 4.3.3. People

ISE is a human-centred engineering discipline. Humans are both autonomous decision makers (e.g. engineers, designers, other workers), and receivers of products or services (customers, users, stockholders). ISE as a discipline necessitates considering how humans interact with technology and are affected by system changes. The domains in which ISE operates also directly impact humans and society, such as in healthcare, transportation, manufacturing, service centres, and more. We identify at least three thrusts where ISE should be involved with the AI Grand Challenge.

First, in every domain where AI is deployed, human-in-the-loop interactions are critical, and ISE can ensure humans are incorporated in the system, designs the system, curates the data, helps monitor the programme, analyses, and evaluates the system. Along with this aspect, human factors engineers bring added perspective on topics such as human-machine interactions, worker safety, and integration of technology like augmented reality or virtual reality for workplaces. The focus on human-in-the-loop is important for many systems, such as healthcare, where AI may play a role in diagnosing and treating, designing drugs or personalised treatments, monitoring patients, and recommending or performing interventions (Ahmed et al. 2020).

Second, AI (and associated areas such as automation) will have a significant impact on workers and on the overall job market, and ISE can help in understanding impacts and mitigating where possible. ISE may help determine what process steps are most appropriate for AI or automation tasks, and which require human creativity, complex thinking, or team approaches. In addition to deployment aspects, ISE should consider the impact that AI will have on workers, jobs, and industries, and look for opportunities where worker skills can be utilised, and industry can innovate to create new options.

Third, the evaluation of AI on systems and people aligns well with the focus of ISE on reliability, quality, and performance. ISE will be involved in ensuring AI systems are monitored for anomalies and drift. Perhaps the greater challenge will be in promoting quality of the system overall, with a broad lens on quality. Specifically, ISE can help translate concepts such as equity and effectiveness into measures that can be quantified and measured in a system where AI is deployed. This is especially important since AI and technology are known to have some challenges including the potential to ‘hallucinate’ and display biases associated with input data. ISE should also consider how to understand the potential gaps in AI when it is deployed in a system and the unintended consequences that can occur when one action has a cascading effect.

#### 4.3.4. Education

AI could have huge impacts on education, both within a discipline such as ISE or computer science, as well as in the broader sense in education across any field. There are already AI initiatives to enable personalised learning. In education, ISE has a critical role educating students within degree programmes on how they can integrate AI into problem solving, innovation, and deployment of solutions.

This may include specific skills (e.g. prompt engineering) as well as integration of technology throughout

a system (augmented reality, sensors with continuous data collection, or AI algorithms for learning). One challenge includes enabling this AI-oriented education while ensuring that students maintain the ability to think critically and are able to identify gaps in AI. Secondly, ISE has a role to play in re-educating and upskilling professional engineers, especially those who will work at the intersection of AI and associated technologies deployed in a system. In many cases, AI will be deployed to improve processes, learn from data in a system, recommend actions that achieve an organisation’s goals, and be evaluated for improvements. The intersection of the AI field with the focus on systems and process improvement will open new opportunities that ISE should address in the AI grand challenge.

#### 4.4. Conclusions and future steps

In summary, we are already seeing some of the impacts of AI on the world around us. In some domains, methods and techniques from ISE and OR are even considered part of the broader sphere of AI, in the context of helping computers learn and make complex decisions as humans do. However, AI in its current form has a number of limitations and challenges that need to be addressed. The ISE discipline and its associated community need to be proactive in addressing AI challenges. We need to be integrating AI into research, extending AI beyond its current methods and technical limitations, expanding the education of our students and practitioners, and showing what can be done if the ISE perspective is integrated with AI.

### 5. Grand challenge of cybersecurity and resilience

#### 5.1. Background

The infrastructure of our world is increasingly connected and composed of cyber components. The integration of systems creates opportunities for delivering good, services, and energy at scale and do so reliably. However, at the same time the interconnectedness of systems also introduces risk in the form of vulnerabilities to various hazards (e.g. cascading failures in connected systems (Dolgui, Ivanov, and Boris Sokolov 2018)). Identifying such vulnerabilities and protecting/securing systems is crucial for designing resilient infrastructure. However, knowledge gaps exist that must be addressed to ensure that as interconnected systems grow in complexity, vulnerabilities are identified so that infrastructure is protected and secured.

Key to enhancing resilience is acknowledging that it is impossible to fully protect these systems, and therefore,

some components will fail. Taking a system-level view is necessary for mitigating risks when failures occur and addressing knowledge gaps. There are five challenges within this topic :1) Protecting cyber-physical systems and software supply chains, 2) Enhancing resilience in connected infrastructure systems, 3) Resilience of systems in the context of shortage economy, and 4) Designing energy-resilient networks, and 5) Designing stress tests. These challenges lead to a wide range of opportunities for the ISE community.

The challenges outlined above rely on a definition of systems resilience. To this end, we define system resilience as the capability to withstand, adapt, and recover from disruptions to ensure the target performance. There are multiple essential perspectives of resilience (Woods 2015). *Performance-deviation based resilience captures* the ability of a system to absorb disruptions and recover to its original performance and structure after a disruption. *Adaptation-based resilience* reflects the ability of a system to maintain the persistence of system performance through adapt-ability while accepting oscillations and performance deviations (Hosseini, Ivanov, and Dolgui 2019). *Viability of systems* reflects the ability of a system to operate and continue to serve in the presence of disruptions and long-term crises (i.e. the ability to survive in the long-term) through adaptation and reconfiguration and changing states dynamically (Ivanov and Dolgui 2020). These perspectives of resilience map to the rebound, robustness, adaptability, and extensibility concepts of resilience from Woods (2015), and they guide the challenges in this section.

Next, we review opportunities for the ISE field by outlining the challenges across the five challenge areas outlined above. Then, we discuss the next steps to enable the next generation of engineers for addressing these challenges, focusing on securing software supply chains. Finally, we summarise this section.

## 5.2. Challenges in cybersecurity and resilience

In this subsection, we discuss each cybersecurity and resilience challenge, and we outline several opportunities for advancing resilience within each challenge area.

### 5.2.1. Challenge in cybersecurity and resilience #1: securing cyber-physical systems and software supply chains

Critical infrastructure has become increasingly reliant on cyber systems, which has highlighted the importance of protecting cyber-physical systems across all infrastructure sectors (Enayaty-Ahangar, Albert, and DuBois 2020). Cyber-physical systems encompass physical and cyber components as well as information flows, people,

and processes. Securing cyber-physical systems is challenging due to the ubiquity of cyber-systems, the increasing size of attack surfaces and number of attack vectors, and the dynamic, persistent nature of threats (Zheng et al. 2019). The National Academy of Engineering (NAE) 2008.

Grand Challenge of ‘Securing Cyberspace’ focuses on protecting cyber aspects of systems (National Academy of Engineering 2008). Moving beyond protecting cyberspace to adopt a systems approach including physical and human aspects of systems could yield a significant step forward in security.

The ISE community has historically created models to support security and protect critical infrastructure (Brown et al. 2006), however, nearly all of these models have focused on protecting physical systems and assets (Albert, Nikolaev, and Jacobson 2023). Several advances from the ISE community could advance the security of cyber-physical systems, and we list these as the grand challenges. First, new networks models that capture the operational aspects of cyber-physical systems (e.g. cloud computing networks (Dragotto et al. 2023)) would enable the identification and understanding of system vulnerabilities (Albert, Nikolaev, and Jacobson 2023). Connecting system dynamics to performance is crucial for allocating scarce resources to improve security. Models that capture the multifaceted aspects of system performance, including financial consequences, information theft, and deterrence, would add a layer of realism to the models that is informative for planning (John et al. 2024). Enhanced models would likely be even more difficult to solve than existing network models – which are generally NP-hard – which in turn may motivate algorithmic advances.

Capturing human factors is crucial for understanding and predicting the performance of cyber-physical systems and could uncover new insights for protection (Scala et al. 2019). This is crucial, since humans interact with cyber-physical systems, and the role of human behaviour has been linked to the most significant cybersecurity breaches. For example, human factors can address the challenge of misinformation by expanding our understanding of how users of cyber-physical systems perceive and process complex information – including misinformation propagating throughout such systems, thereby contributing to risk and security. Cybersecurity risks stem from many types of adversaries ranging from lone adversaries to nation-states, and adversary types have different levels of resources, sophistication, and goals. There is a need to gain insights when protecting against a range of adversarial sophistication and intent. Expanding modelling paradigms to consider the impact of multiple attackers with different goals, resource

levels, and levels of strategic sophistication could yield deeper insights (Zheng and Albert 2019; DuBois, Peper, and Albert 2023; Rios Insua et al. 2021).

Security data offers many opportunities for researchers interested in data science and machine learning. Security datasets often contain rare anomaly data and are incomplete, since ground truth is often not known, and breaches are generally not made public. Achieving unbiased insights with security datasets is a challenge for fundamental research (Albert, Nikolaev, and Jacobson 2023). Cybersecurity encompasses challenges such as misinformation that propagates through social networks, which represents a new application area amendable to ISE tools (Hunt, Agarwal, and Zhuang 2022; Paul and Nikolaev 2021) and can inform planning decisions (Allen, Sui, and Parker 2017). Layered networks that consider infrastructure along with information and processes could uncover deeper insights for protecting critical infrastructure. In addition to providing insight into protecting cyberinfrastructure, ISE tools could be applied to attribution and forensics to support recovery (Albert, Nikolaev, and Jacobson 2023). Finally, IISE should contribute to the convergence of industrial, systems, and software engineering theories and methods to ensure the highest levels of cybersecurity in the nation's software supply chains.

### 5.2.2. Challenge in cybersecurity and resilience #2: enhance resilience/security in connected systems

Industrial engineering models have been used to model interconnected systems using network models, where they have been used to evaluate the performance of systems based on how their components operate and interact (Alderson, Brown, and Matthew Carlyle 2015). These modelling efforts have been valuable in the planning, design, and operations of infrastructure systems, where they are used to identify vulnerabilities and prescribe actions to mitigate the vulnerabilities (Brown et al. 2006). Network interdiction and game theory have emerged as important tools to address issues of resilience and security (Sharkey et al. 2021). Network interdiction models have studied the *vulnerability* and *security* of systems, where the goal is often to limit the scope of damage. Failure is often defined to capture worst-case component failures or international damage inflicted by adaptive adversaries (Smith and Song 2020). These models can be used to identify which components of a system require protection or fortification. Game theory models have generally been used to model more strategic issues involving resource allocation to counter terrorism (Bier, Oliveros, and Samuelson 2007) as well as natural disasters (Zhuang and Bier 2007). Adversarial risk analysis methods have sought to inform planning and

decision-making when facing intelligent adversaries and uncertain outcomes (Banks et al. 2022).

Many of the methodological and computational advances involving network interdiction models made by the ISE community have focused on stylised interdiction models that are address to treat using mathematical optimisation methodologies, e.g. by exploiting duality to solve large-scale problem instances (Smith and Song 2020). A challenge for the ISE community is to develop realistic models that provide deeper insights into how to protect critical infrastructure. There are several directions for future ISE research that would take a large step forward in enhancing resilience in connected infrastructure systems. First is the consideration of repeated games in consequential settings (Sefair and Cole Smith 2016). Existing game theory and network interdiction models typically consider a one-shot game played by two players, such as in Stackelberg models of a defender-attacker game. Defender-attacker network interdiction models are usually NP-hard, and extending these games to more than two turns is almost always more difficult (e.g. Defender-Attacker-Defender models) (Sefair and Cole Smith 2016). The consideration of more sophisticated player interaction through repeated turns presents a computational challenge for the ISE research communities (Smith and Song 2020). Fusing optimisation-based approaches – where ISE has excelled – with artificial intelligence approaches may lead to a breakthrough (Albert, Nikolaev, and Jacobson 2023).

Second, most of the mathematical optimisation approaches focus on optimality with well-defined objective functions (Smith and Song 2020). Emphasising resiliency rather than optimality may expand our understanding of how to protect complex systems. Resilience could, for example, encompass prolonged disruptions that occur over multiple time periods, human behaviour, and equity (Albert, Nikolaev, and Jacobson 2023). Additionally, past research on modelling adversarial objective functions (e.g. Wang and Bier 2011) have indicated that such functions reflect the adversarial organisation and goals that generally reflect multiple criteria and are dynamic. Adversarial risk analysis has introduced frameworks for planning in the presence of intelligent adversaries and outcomes that mitigates some of the drawbacks from game theory and can be informed by human factors research (Banks et al. 2022). Other structured approaches could overcome computational limitations to provide insight into resilience. Research that addresses this challenge may require interdisciplinary collaboration between applied researchers who are adept at creating models as well as computational researchers who can analyse model structures and identify algorithmic techniques for solving the resulting problems.

### 5.2.3. Challenge in cybersecurity and resilience #3: energy-resilient supply networks

Transformation of the energy sector along with increasingly volatile global and local environments, risks and instability put the questions of energy-efficiency and energy-resilience in the forefront of supply chain and operations management (Ekinici et al. 2022). Both proactive disruptive technologies based on renewable energies and reactive responses and prioritization for scarcity of energy resources caused by disruptions call for developing working methods and models to support supply chain managers. While the research on energy-efficient manufacturing and logistics has been flourishing in industrial engineering for the last two decades, the integrated supply chain perspective of energy-efficiency still needs to be developed. Energy-resilience of supply chains is a new and unexplored research domain while the large body of knowledge from supply chain resilience can be used to develop this exciting and practically important area.

There are several areas that could lead to breakthroughs in the area of supply chain design and management with consideration of energy-resilience aspects. Several possible research advances that could be transformative include modelling energy-efficient and energy-resilient supply chains with consideration of advanced energy-saving technologies in manufacturing, warehousing, and transportation; supply chain design, redesign, and replanning with renewable energy considerations (including the scarcity and volatility of energy resources); and energy-resilience in the context of supply chain viability, viable supply chain models, and reconfigurable supply networks. Models and empirical research from operations management, industrial engineering, and operations research communities are necessary to respond to these challenges at the interplay of supply chain energy-resilience and sustainability.

### 5.2.4. Challenge in cybersecurity and resilience #4: resilience in the conditions of shortage economy

A transition from an economy of scale via economies of scope, speed, and collaboration had been expected to develop toward a digital economy and global, green growth. However, we are now faced with what appears to be an economy marred by widespread shortages (Ivanov and Dolgui 2022b). Energy, workforce, and materials are becoming scarce, and supply chains are adapting to cope with resource shortages along with rapidly rising prices and associated risks of hyper-inflation. For example, semiconductor shortages have caused global ripple effects and tremendous problems in the supply chains of automotive and electronics industries, and power outages in Texas in February 2021 and several provinces in China

in 2021 led to severe consequences for societal viability and supply chain resilience. The global supply chains experienced an unprecedented shortage of transportation capacities in 2020–2022 caused by the imbalances in inter-continental logistics flows limiting the number of available containers and resulting in an increase in freight prices, product shortages, and overall destabilisation of supply chains. As a delayed effect of the COVID-19 pandemic, demand and markets have recovered much faster than expected, while the supply and production capacity ramp-up times were longer and resulted in a severe mismatch between demand and supply. Sometimes, managers refer to the shortage setting as chaos which results in global ripple effects (Hosseini, Ivanov, and Dolgui 2019).

This might be a temporary crisis or a long-term trend. Regardless of the duration, resource scarcity and risks of hyper-inflation pose novel and unexpected challenges to resilience analysis in industrial and systems engineering and operations management. Past research has contributed to the area of aggregate planning and has developed associated models designed for multiple future scenarios as well as dynamic and reactive re-scheduling. However, most of the existing methods and models consider disruptions and shortages from a short-term, temporary perspective. For example, design and planning methods generally presume resource availability and rational customer behaviours. These methods mostly utilise a top-down planning approach starting from the demand forecasts and assume availability of production capacities and materials, even if with some constraints, can be taken for granted. These assumptions require critical reconsideration in the setting of a shortage economy, and overcoming these limitations represents an opportunity for scientific breakthroughs. Thus, a major challenge is to build an understanding of the implications of a shortage economy on operations management and ISE and to motivate new research areas *instigated by its novel context* (Ivanov and Dolgui 2022b).

### 5.2.5. Challenge in cybersecurity and resilience #5: stress tests

The real-life stress-tests such as COVID-19 pandemic and geopolitical tensions have revealed new insights about resilience and viability of existing supply chains. In this setting, further research is needed for understanding resilience and viability and developing new methods for stress-tests of supply chains well before a real shock hits and disrupts structures and operations (Simchi-Levi and Simchi-Levi 2020). Topics suitable for research include identifying methods that can be used to stress-test a supply chain.

Expanding our understanding of the optimal design of a supply chain network – the most efficient, the most resilient, or the most adaptable and viable one – could uncover deep insights into designing resilient global supply chains. Methodologies for stress tests could inform how to design supply chains that are both adaptable and efficient as well as how to utilise digital technology and data analytics to enhance supply chain resilience and viability. Advances in the area of stress testing could shed light on the role of adaptability in the resilience and viability of value creation systems, as well as how inherent adaptability can be implemented while maintaining profitability (Ivanov and Dolgui 2022a).

### **5.3. ISE opportunities to address cybersecurity and resilience challenges: securing software supply chains**

The cybersecurity and resilience challenges described above provide a framework for the ISE community to improve resilience in the decades ahead. These challenges require a range of ISE tools that span operations research, human factors, and advanced manufacturing. Interdisciplinary research and coordination across research teams. In this section, we discuss an example to illustrate the multifaceted aspect of the resilience challenges we introduced. This example regards securing software supply chains, which aligns with the first challenge.

Cybercrime, encompassing recovery costs and remediation efforts, inflicted more than \$3 trillion US on the US economy 2015 and \$6 trillion US in 2021. Understanding the interconnected aspects of security software supply chains is essential, since these can be the source of breakthroughs. Considerations include system integration, feasibility, reliability, human error, development and deployment costs, and alignment with regulatory and social acceptance.

The President's Executive Order (EO) 14028 (2021) on Improving the Nation's Cybersecurity (The White House 2021) mandates enhancing cybersecurity through various initiatives related to the security and integrity of software supply chains. There are opportunities to secure software supply chains that leverage the breadth of ISE. Advances in risk analysis can ensure the integrity of software supply chains by balancing multiple objectives, including cost, quality, reliability and robustness. Industrial engineers can contribute to the development of standards, tools, and guidelines, which includes introducing criteria for evaluating software security, assessing developers' and suppliers' security practices, and auditing compliance with security policies. New methods drawing on manufacturing methodologies could establish traceability mechanisms throughout the supply chain

to enhance forensics as well as optimised processing for conducting audits to verify compliance with standards. Recognising that human components are integral to cyber-physical systems, ISE can improve next-generation software supply chain security by centring human factors within software supply chains. Enhancing interfaces and training programmes reduces accidental misuse and fosters compliance with policies.

In summary, industrial engineering, with its holistic approach and multidisciplinary toolkit, plays a pivotal role in fortifying software supply chains against cyber threats.

### **5.4. Conclusions and future steps**

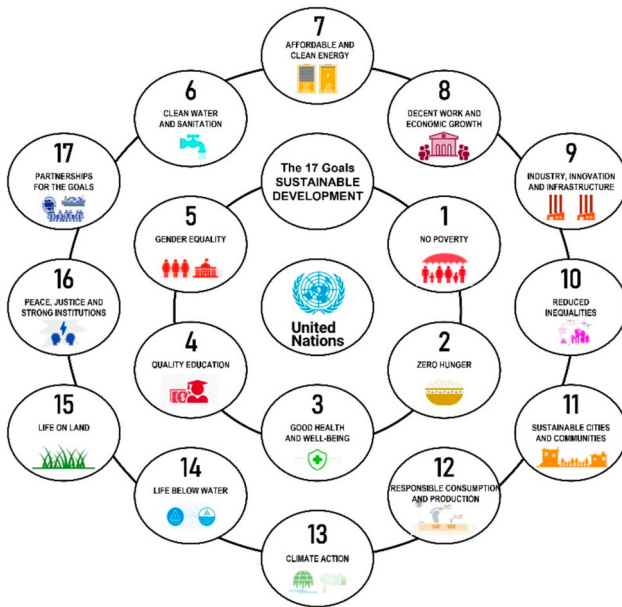
The ISE toolkit provides many opportunities to positively impact resilience. A common theme of the challenges in this section is that they seek to leverage ISE knowledge of interconnected system to identify and mitigate vulnerabilities in complex systems in new and impactful ways. To achieve breakthroughs in this area, it will be necessary to leverage knowledge across ISE. Increased training in networks, data analytics, and supply chains need to be emphasised in undergraduate and graduate curricula to enable progress on these challenges. Additionally, the role of human factors is critical to these issues due to its historical focus on improving people's ability to perceive and process complex information in various contexts.

## **6. Grand challenge of sustainability: environment, energy and infrastructure**

### **6.1. Background**

In September 2015, the 193 UN Member States approved the Sustainable Development Goals (SDGs), also known as Agenda 2030 (Gigliotti, Schmidt-Traub, and Bastianoni 2019). Together there are 17 goals addressing the three pillars of sustainability: economic development, social inclusion, and environmental sustainability, as well as peace, justice, good governance, and partnership, within the SDG framework (see Figure 2). To achieve these goals, complex challenges exist in sustainability, involving numerous factors with significant impact on the climate, environment, health, and quality of life among many others (Chester 2019).

Particularly, maintaining ecosystem services and promoting human well-being should be prioritised (Henderson and Loreau 2023). Responding to these challenges, industrial and systems engineering (ISE) needs to study the complex relationships between humans, their organisations, surroundings, and communities, and the natural environment from a system perspective, and investigate



**Figure 2.** The framework of the 17 Sustainable Development Goals (Gigliotti, Schmidt-Traub, and Bastianoni 2019).

the factors that affect the environmental, social and economic goals of the society.

Numerous innovations have been developed using a multidisciplinary, pragmatic, and systems-oriented approach to improve the environment, such as delivering clean water, reducing air, water, and soil pollution, and processing waste, as well as recycling, remanufacturing, and reusing. From an environmental perspective, providing a sustainable food, water, and energy supply, curbing climate change and adapting to its impacts, designing a future without pollution and waste, creating efficient, healthy, and resilient cities, and fostering informed decisions and actions are significant challenges (Wang 2021), where industrial and systems engineering can contribute in responding and solving through systems thinking and management.

The significant increase of renewable energy generation (wind, solar, biomass, etc.) has created a number of grand challenges to the manufacturers, power grid, and end users. One such challenge is that renewable energy exhibits substantial fluctuations in availability, making it difficult to sustain a stable supply. This has made consumption forecasting, power grid stabilising, and energy management extremely complex and has presented substantial difficulty when integrating renewable energy to the power network.

Infrastructure can be viewed as a set of technological systems consisting of humans, their communities, and the broader environment, as well as the interactions among them (Thacker et al. 2019). From a physical perspective, it can be defined as the physical structures and

the associated equipment and arrangements to enable and enhance human activities. From a broader point of view, it may include all the physical assets and the services they can enable and provide, including power generation and information network facilities, water treatment plants, roads, etc. The rapid development in digital technology has created a new sector, which transforms the sustainability infrastructure but also has substantial impact on energy and environment (Wei et al. 2023). The relationship among the infrastructures, and how humans interact with the infrastructure and the natural environment have been the subject of a substantial amount of work. However, how to quantify them is still challenging, because the corresponding systems have become more and more complex. Physical infrastructures are increasingly interdependent, since both scale and functions have been growing over time, by incorporating more and more components, as well as various new technologies. Thus, when infrastructure is impacted by, for example, a natural hazard, or has experienced a component breakdown due to aging, the resulting losses in services are difficult, or, impossible to predict.

Industrial and systems engineers with their unique training in decision-making and design methods for complex and uncertain environments are uniquely qualified to address the grand challenges in developing sustainable systems. Specifically, challenges that ISE can address and make a significant impact in improving sustainability include: (1) environment, (2) energy and (3) infrastructure.

## 6.2. Environment

- (1) Studying complex issues in multiple scales over time and space.

Extreme complexities exist in human-nature interactions across multiple spatial and temporal scales. The environmental challenges usually are not limited by local or regional boundaries but are global issues. To respond, incorporating the spatial externalisation and the temporal lagging effect of environmental issues into the analysis framework with higher resolution and across larger spatial-temporal scales becomes inevitable.

- (2) Integrating analysis various frameworks and methods across disciplines.

The multi-disciplinary nature of all environmental issues is a fundamental grand challenge. Integrating the knowledge, methods and ideas from different subjects is necessary at four levels: integration of professional knowledge, theories and methods; incorporation of the

interaction and feedback dynamics of all kinds of systems into the analysis framework; recognition and appreciation of diverse ideologies in different subjects; and finally, dissemination and application of integration of the results in multiple fields.

- (3) Addressing broad and deep uncertainties from systematic changes.

Most of the changes are non-linear and time-varying, especially when the system undergoes sudden, substantial, and irreversible transitions. Thus, acquiring larger-scale and higher resolution socioeconomic and natural system observation data becomes a necessity, in order to investigate the dominating driving factors and influencing mechanisms of the non-linear and time-varying changes in the system, and finally, to develop exploratory modelling, simulation, and analysis based on extensive settings of future scenarios and adaptive feedback dynamics.

- (4) Virtual modelling for life cycle assessment (LCA).

The environment impacts of sustainable systems can be analysed using virtual models based on life cycle assessment to identify environmental impact indicators and their metrics (Shao, Kibira, and Lyons 2010).

### 6.3. Energy

- (1) Energy efficiency and management.

Improving energy efficiency and managing demand to reduce energy cost while shaping the load profiles of electricity consumption under demand changes and supply variations are critical in generating mixed supplies to achieve this goal.

- (2) Scheduling

Effective scheduling with strong optimisation capabilities in real time can lead to significant savings and benefits through better capacity utilisation, which not only can result in substantial economic benefits but can also help reduce the environmental load through decreased or better controlled energy demand.

- (3) Reduction of energy consumption with better coordination

Reducing overall energy consumption without sacrificing the production and logistics through sufficient coordination of production plans of up- and downstream

production stages, particularly in the short term, is of significant importance.

- (4) Digital technology for energy transition

Using digital technology such as AI-based optimisation tool, block chain, and open data platforms, as well as generative AI models, to track emission and energy consumption in a value chain to speed up the energy transition to a deep decarbonisation future. A database on sustainability development in renewable energy system can speed up the studies (Abdolmaleki and Bugallo 2021).

- (5) Transportation system

Clean mobile technology and electrical vehicles offer a crucial and viable option for the decarbonisation process, which relies on battery development and their utilisation, as well as electricity generation, transmission and distribution planning to ensure genuine benefits from the decarbonisation of the energy system.

### 6.4. Infrastructure

- (1) Network analysis

Studying the causality working in both directions, such as the gap between inputs, outputs and outcomes, the complex interdependencies between individual components of the systems and between the networks.

- (2) Data acquisition

Integrating data in different silos which requires standardisation of data with different types, volumes and features, and the consolidation of datasets in different contexts and the transfer across the contexts. In addition, developing methods to handle small data sets is critical to response to rare events.

- (3) Digital communication

Providing information and communication as well as the necessary channels, including hazard warnings, financial transactions, carbon footprint, and transportation (access and safety), etc.

- (4) Deployment

Investigating the conditions, applicable contents, variations, and social dimensions of the infrastructure and



deploying the structure in reality, and adapting the structure to accommodate the responses from feedback.

### 6.5. Methodology integration

It is important to integrate the diverse array of methodologies and models, from qualitative and experimental methods in the social sciences, to quantitative approaches in optimisation, econometrics and computer simulations. Understanding of these methodologies, including their strengths, weaknesses and complementarities, is essential for the development of a more integrative perspective on infrastructure systems and services. In addition, resilience and sustainability for civil infrastructure are complementary and should be used in an integrated perspective with a unified approach (Bocchini et al. 2014). We next illustrate these challenges and the role that ISE can address them in context of a transportation system example. The increasing demand on the transportation infrastructure has caused significant social issues such as traffic congestion and air pollution. For example, due to continuous urbanisation and growth in the population, traffic congestion has become an important issue worldwide, especially in large cities. According to the Urban Mobility Report, an average commuter had about 54 hours of annual delay due to traffic congestion, which in monetary terms amount to 1170 USD. Nationally, the total travel delay was about 8.7 billion hours and congestion costs were 160 billion USD (Lasley 2021). Meanwhile, there is no public support for increased taxation to finance infrastructure capacity expansion and in many cases land use issues restrict further infrastructure expansion.

Therefore, transit agencies and cities need innovative system level solutions that make use of advanced algorithms as well as taking into consideration human behaviour.

Significant advances have been made in the procurement and provision of real-time information required for the effective control of a transportation system and transit operations. For instance, transportation infrastructure and vehicles are now equipped with sensors, interconnected data systems, multi-way communication devices, and onboard computers. These efforts have made available a wealth of real time and dynamic data about traffic conditions that was not previously available. These technologies have primarily been used for Automated Traveller Information Systems (ATIS) to provide real-time arrival time status at some stations to passengers or congestion pricing on roads. However, these technologies have not led to a fundamental shift in the way that transportation services are provided to the public. That is, transit solutions in most urban areas are still

based on centralised system design primarily operating on fixed lines. A centralised system may be suitable for large cities such as New York City and some European cities, but is not effective for satisfying the transportation needs of many cities due to a lack of a single high density business and residential centre. A centralised system lacks the flexibility required to meet the dispersed demand and may be less effective than a dynamically adaptable solution in very random or dynamic traffic conditions.

The information technologies (such as GPS systems both in vehicles and rider's cell phones) can form the basis for a new type of decentralised transportation system for real-time allocation of resources, hence potentially increasing service in a cost-efficient manner. Transportation capacity is a valuable resource which needs to be fully utilised and market-based mechanisms can often achieve an efficient allocation of resources. Auction mechanisms and game theoretic models can exploit the wealth of available traffic data and can be automated to allow services and pricing to respond directly to consumer demand. The development of such a distributed transportation system that matches services to demand in real-time will require the development of fundamentally new methods in distributed optimisation, mechanism design, machine learning, agents and user-interfaces, computation of large-scale equilibria, and planning under uncertainty.

In addition to increased passenger demand, freight shipments are increasing throughout the world as a result of globalisation, rising incomes, and shifting patterns of production and consumption. At the national scale freight demand is largely a function of GDP per capita. Given expected economic growth, it is estimated that the global heavy-duty truck fleet will increase by a factor of 2.6–64 million by 2050 (Mulholland et al. 2018). Trucks generate a disproportionate share of greenhouse gases (GHGs), The transport sector in the US accounts for 28% of greenhouse gases, second only to industry According to the U.S. Environmental Protection Agency (USEPA 2018a), trucks account for 23% of the transport sector share (USEPA 2018b). Trucks also contribute disproportionately to air toxics. The US transport sector accounts for nearly 56% of nitrogen oxides (NOX) and 22% of volatile organic compound emissions (VOCs), the precursors to smog and ozone (USEPA 2018a). The transport sector also accounts for almost 20% of particulates. Trucks account for about one third of NOX and 30% of particulates from the transport sector.<sup>1</sup> One of the most promising directions for reducing GHG emissions in the trucking industry is adopting zero-emission trucks such as electric trucks in freight operations. However, the limited charging infrastructure and long charging times limit

the wide-scale adoption of these trucks, which are natural research problems for ISE to address.

In summary, significant changes and rapid development in environment, energy and infrastructure have created opportunities for ISE to contribute to addressing these grand challenges through systematic methods and approaches to develop sustainable systems and societies.

## 7. Challenge of health issues

### 7.1. Background

Recent decades have seen extraordinary advances in data collection in medicine, including the implementation of electronic medical records, the creation of new devices and wearable sensors for health monitoring, rapid gene sequencing and editing technologies, and disease surveillance and tracking systems, to name a few examples. Ultimately, these advances, and their resulting data collection and storage, have surpassed the ability of industrial and systems engineering methods to use these data to improve medical decision-making and healthcare delivery. As a result, there is a knowledge gap that, until addressed, will limit the effectiveness and adoption of these new technologies to improve health and human safety. There are two fundamental and equally important technical challenges to address. The first challenge concerns quantitative methods for harnessing data to transform it into information and subsequently to recommendations (alternative decisions) for whether and when to intervene to achieve health and safety goals in a way that is consistent with patient preferences. The second challenge is to overcome barriers to implementation that result from a combination of constraints imposed by human behaviour, policies, and processes resulting from the fragmented nature of health systems that limit information sharing and coordination across medical disciplines and healthcare providers. These challenges exist in most health systems around the world, and some of these challenges are particularly pronounced in the United States, which serves as the primary reference point for this article.

The challenges outlined above exist within the confines of exogenously defined complexities, including multiple and often competing criteria among stakeholders (e.g. patients, physicians, third party payers), latent health factors that may not be directly observable to decision makers (e.g. undiagnosed cancer, asymptomatic infections), and a dynamically and unpredictably changing health system that results in shifting stakeholder needs and goals over time (e.g. the discovery of new health interventions, the surge in demand due to a natural

disaster, spread of a novel virus). We consider these complexities to be immutable, but nevertheless, important considerations frame the feasibility of approaches to address the above challenges.

Collectively, the above challenges and their attendant exogenous complexities lead to a wide range of important opportunities for ISE to play a role in affecting positive improvements to healthcare systems. In the next section, we begin by summarising each of the challenges and subsequently discuss some of the root causes of these challenges. Next, we summarise opportunities for the ISE field by using specific examples to illustrate the nature of the problems. Finally, we discuss the important next steps to facilitate the development of the next generation of engineers positioned to address the challenges.

### 7.2. Challenges in healthcare

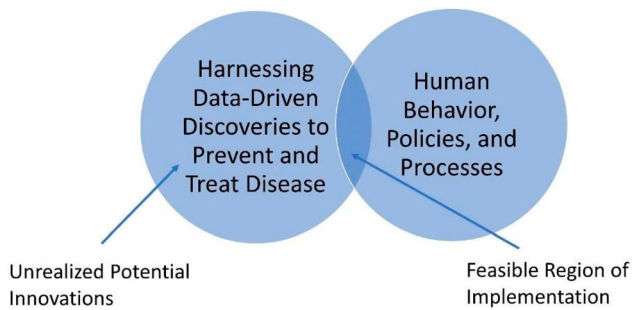
To begin, we describe each health challenge independently, followed by a discussion of how they interact and the exogenous factors that contribute to the complexity of addressing them.

#### 7.2.1. Challenge in healthcare #1: harnessing data-driven discoveries to prevent, treat, and manage diseases.

New technologies, such as sensors for remote monitoring, real-time DNA sequencing devices, molecular biomarkers, and advances in information technology (IT) infrastructure, are continuously adding to the possibility of real-time situational awareness about individual patients and the health systems where they seek treatment. However, the sheer size of the resulting datasets and the vast number of signals that can be monitored overwhelm clinical decision-makers, insurers, and policymakers, who must balance the potential benefits and harms of using these data to guide decision-making. Approaches for addressing confounding, missing data, and other sources of bias inherent to observational data are not keeping pace with the opportunity for improving the selection and execution of recommended courses of action. Moreover, many advances are specific to an isolated part of complex interconnected health systems. As a result, the pace of medical discoveries and other technical innovations to acquire data has surpassed the speed of the data analytic innovations needed to use the data to optimise healthcare delivery and improve the prevention, treatment, and management of diseases.

#### 7.2.2. Challenge in healthcare #2: enhancing human behaviour, policies, and processes

New technologies for furthering the understanding of patient health at home, work, or clinics and hospitals



**Figure 3.** Interaction between healthcare challenges #1 and #2 illustrating the role of healthcare challenge #2 in constraining potential future data-driven discoveries related to healthcare challenge #1.

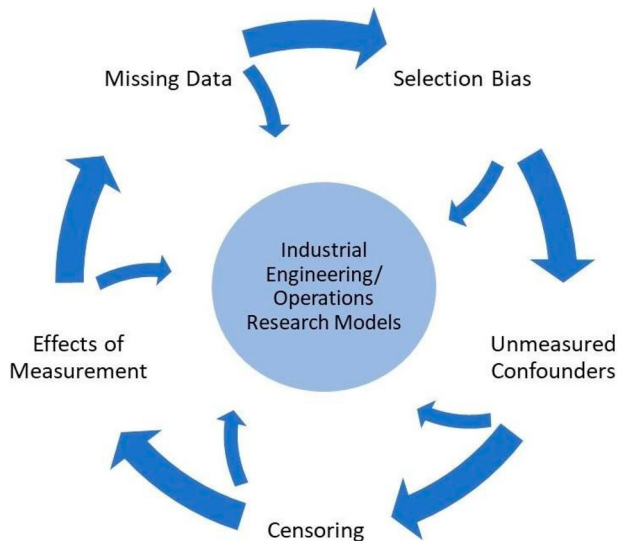
are rapidly emerging. Still, these advances are only as valuable as individuals and organisations enable them to be. All health systems in developed countries operate within a microcosm of government regulations, laws, and internal standard operating policies and processes that define whether and when new innovations may be used, subject to safety, cost, and privacy restrictions. Moreover, individual human behaviour and the propensity for mistrust in new technologies and processes significantly affect decision-making at the point of care between a clinician and a patient. This often leads to inefficiencies in the delivery of care, such as redundancy in diagnostic evaluations, fragmentation among healthcare providers, and over-treatment that burdens patients unnecessarily and contributes negatively to their overall well-being. Furthermore, many healthcare delivery systems that comply with their policies and regulations ultimately marginalise vulnerable populations, increasing risk and widening the disparity gap.

These two health challenges interact to create barriers to improving healthcare delivery. Figure 3 illustrates this interdependence as a Venn diagram. From the perspective of healthcare challenge #1, technologies in the form of medical devices, such as patient sensors, imaging technologies, and new diagnostic tests, are now able to amass extraordinary amounts of data for individual patients, which, if aggregated, can serve as a resource to optimise decision-making for the prevention, treatment, and management of diseases. These data present a resource that, when collected over time, can be used for a wide range of purposes, including understanding a patient's current health condition, predicting future health outcomes, identifying possible health interventions, monitoring the effects of interventions, and using these data to improve decision-making through a continuous feedback loop over time.

In practice, the various data sources needed to enhance decision-making are challenging to aggregate

for several reasons, including patient privacy, healthcare provider policies and processes arising from proprietary and liability concerns, and general fragmentation of healthcare delivery systems, resulting in challenges in collecting and linking data across different organisations. Nevertheless, the emergence of data aggregators such as MarketScan, and Optum, as well as health system initiatives, are contributing to the ability of individuals and organisations to access increasingly detailed data on large populations, including demographic data, environmental exposures, past medical history, claims, lab results, genetics, and the results of diagnostic tests (Blewett et al. 2018). As a result, researchers have access to an extraordinary breadth of population data, and advances in data collection and storage continue to accelerate. However, the availability of data alone is not sufficient because observational data, while abundant, is rife with challenges resulting from a wide range of complexities, as illustrated in Figure 4, adapted from Denton (2023), which summarises some of the sources of bias that limit how such data can be used to aid decision making. Emerging research in data analytics and artificial intelligence is opening doors for addressing some of these challenges. Still, ultimately, such methods require a deep understanding of the context in which the data is collected. Otherwise, serious problems can arise, introducing inequities and unethical recommendations (Panch, Mattie, and Atun 2019). Thus, a necessary condition for success in this area is to combine methodological developments with a big-picture contextual understanding of the underlying health system, including socioeconomic considerations, stakeholder performance measures, processes, and constraints. Many aspects of human factors, such as human-centred design, human-computer interaction, and user trust in data analytics and artificial intelligence will play important roles in the successful implementation of decision support systems; This multidisciplinary endeavour is something the field of ISE is ideally suited to address with its long history of combining expert knowledge of industrial systems with methodological advances in problem-solving, and the study of human-technology interfaces and user trust.

Historically, much of the progress in the ISE community has been focused on isolated challenges, such as a single disease or condition in the case of medical decision-making (e.g. cancer, diabetes, heart disease, HIV), or a particular part of the health system in isolation (surgical suites, outpatient clinic, laboratory operations). The wide availability of data and data analytic methods to address the challenges of using observational data will open the door for the creation of more comprehensive computational models that consider the complexity of multiple comorbid conditions and diseases and linking

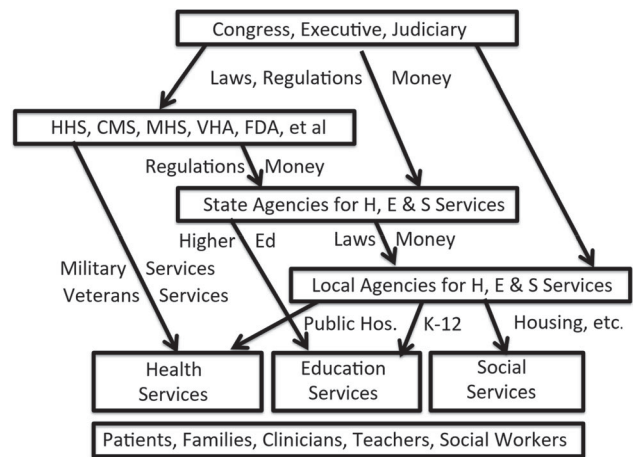


**Figure 4.** Sources of systematic bias interact to cause errors in industrial engineering and operations research models estimated using observational data.

of interdependent networks of healthcare operations in a way that avoid locally optimal solutions that do little to improve the overall system of care.

From the perspective of healthcare challenge 7.2, there are numerous constraints imposed by human behaviour, policies, and processes, which limit potential opportunities to improve healthcare. The constraints arise from a complex interaction of the overall population ecosystem, driven by political pressures, population dynamics, and economic objectives, forcing healthcare organisations, clinicians, and patients to work within the prescribed constraints. This further creates incentives that drive healthcare organisation's investments and subsequent processes. Ultimately, this determines feasible courses of action and system capabilities, which govern the potential options for physician and patient stakeholders. Thus, healthcare challenge #2 imposes constraints on physicians' possible actions and recommendations. Ultimately, this puts limits on the available capacity for further probing of healthcare concerns identified by monitoring patients (e.g. MRI, CT scan, biopsy, endoscopy) and creates financial incentives that lead providers to invest in the capacity that is feasible with respect to third-party payer requirements, and regulations imposed by government agencies.

Some of the constraints related to healthcare challenge #2 are well-founded and intended to act in patients' best interests. For example, regulations around the use of new drugs and medical devices, which most developed countries impose, provide a process for a thorough evaluation of the risk versus return tradeoff before allowing widespread use, which could lead to unintended

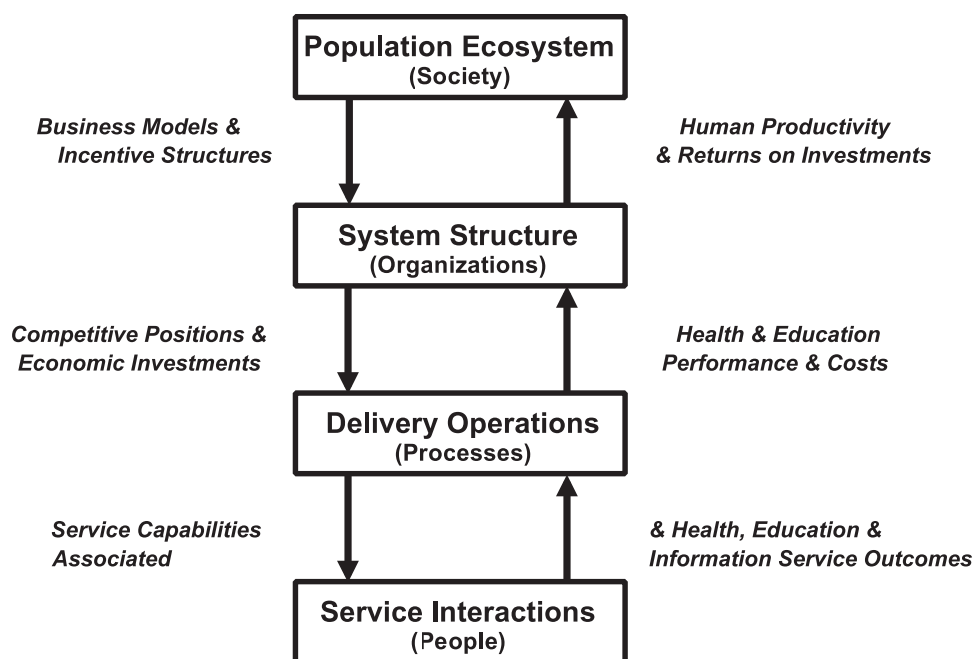


**Figure 5.** Relationships among organisations and services (Rouse, Johns, and Pepe 2019).

public health concerns. A recent case in point is the opioid crisis, which started with the approval of a purportedly non-addictive treatment that ultimately caused hundreds of thousands of deaths and costs measured in trillions of dollars (Maclean et al. 2022). Consequently, the time it takes to achieve adequate assurances to enable widespread use is, in part, a matter of process, which falls squarely in the purview of the field of ISE. Thus, as this example illustrates, the constraints related to healthcare challenge #2 can be complex, involving multiple criteria (e.g. risk vs return). Furthermore, the relative benefits of modifying these constraints depend on many factors, including the cost of such efforts, monetary and implied human effort, and potential rewards, such as quality and length of life.

Healthcare system design and operation constraints arise from a complex interaction between policymakers and health, education, and social services (Rouse, Johns, and Pepe 2019). Figure 5 portrays who is involved in providing health, education, and social services in the United States and the inherent complexity of interactions. The complex organisational ecosystem is highly fragmented, often resulting in low-quality, expensive services and inequity in access to healthcare. (Rouse 2015) outlines a framework for modelling complex social enterprises, which can be applied to healthcare delivery (Rouse and Cortese 2010; Rouse and Serban 2014) and other domains such as higher education (Rouse 2016). This framework addresses the physical, human, economic, and social phenomena underlying complex ecosystems. A population health version of this framework is shown in Figure 6.

This multi-level framework provides the basis for integrating different types of computational models to explore policy alternatives. The People level is usually



**Figure 6.** Population health enterprise.

agent-based, raising fundamental challenges in decision theory, behavioural economics, and human system integration. The Process level is often represented as networks of flows, resources, and resulting queues, often modelled using descriptive and predictive models. The Organisational level involves the microeconomics of resource allocation and resulting decisions, often modelled using prescriptive models to optimise resource allocation. The Society level consists of the macroeconomics of policy, which has a wide-ranging impact on all the levels below. The resulting multi-level framework describes a highly complex interaction that is difficult to change and costly to experiment with.

At the People level, central phenomena include establishing a route through the many needed health services; however, behaviourally, people may balk (not become patients) or renege (drop out of treatment) along the route due to delay times, and other factors. Process level phenomena include getting appointments for each service in the route in a way that considers overall delays to patient care. Delays between services can be measured in weeks or months. Often, delays are highly affected by capacity constraints. At the Organisational level, capacity constraints are due to investment policies, as well as the availability of personnel. Organisations, not surprisingly, tend to invest in capacities needed to provide services that are highly reimbursed. Thus, cancer, cardiology, and orthopaedic surgery services are typically better provisioned than routine chronic disease management. At the Society level, investment policies are related to payer reimbursement policies for different services.

This level also relates to how value is defined. Healthy people have lower healthcare costs and typically work, earn incomes, pay taxes, etc. Thus, society benefits from a healthy population far more than the lower healthcare costs.

### 7.3. ISE opportunities to address healthcare challenges

The healthcare challenges described above provide a high-level framework for thinking about the wide range of opportunities for the field of ISE to participate in improving healthcare over the decades ahead. Ultimately, the challenges described are too complex to be addressed directly through single initiatives or by any one organisation. Instead, what is needed is coordinated efforts and a philosophy of continuous experimentation and improvement that considers the complex sociotechnical challenges of healthcare delivery. In this section, we provide motivating examples of such challenges, focusing on the interdependency between the two grand challenges.

The first example is based on the predominant fee-for-services payment scheme in the United States, which discourages adopting technologies that reduce the need for reimbursable services. In contrast, capitated payment schemes, like Medicare Advantage (MA), incentivise adoption of such technologies. Kaiser Permanente's MA offers a case in point (Inovalon 2023). This illustrates how phenomena underlying Challenge 2 can undermine success in addressing Challenge 1. Fee for service reimbursements drives providers to invest in capacities whose

use is highly reimbursed. Technologies such as remote patient monitoring that reduce demands for highly compensated services undermine the economic objectives associated with these investments. However, fully taking advantage of remote patient monitoring requires investing in analytic capabilities to monitor and interpret the, often 24×7, flow of patient data, typically from thousands of patients within a particular catchment region. Clinician decision support systems are needed, and time must be allocated to learn how to use the new systems. Thus, providers must invest in new systems, compounding the problem of reduced revenue and profits. This is fundamentally at odds with the sustainable economic viability of healthcare providers unless a capitated payment scheme incentivises keeping people healthy at a lower cost, as with MA.

The second example is coordinating care for patients with multiple chronic diseases and conditions. The average person in the United States has three or more chronic conditions by the time they are 65 years of age (AHRQ 2014). Consider a patient who has a pacemaker due to cardiovascular complications, chronic obstructive pulmonary disease, type 2 diabetes, and suffers from depression. New technologies make it possible to conduct real-time surveillance of risk factors in the home, such as monitoring electromagnetic signals from the heart, pulse, oxygen, blood pressure, lung congestion based on thoracic impedance, blood sugar, sleep patterns, and many other relevant signals that could help predict the need for a patient intervention. While technologies in the form of sensors exist for remote monitoring of these factors in real-time, there is little understanding of how to use multiple streams of data, considering various comorbidities, and a large number of potential alerts – each subject to false positives and false negatives for their respective outcomes – to make well-intended decisions that seek to meet patient preferences for safety, the burden of care, and risk attitude, and which may differ significantly from one patient to the next. Additionally, the data streams may be convoluted by hidden environmental factors or other confounding variables that are not observed, leading to a wide range of open questions from a predictive and prescriptive modelling perspective. Technical challenges notwithstanding, there are ethical and liability concerns for providers in the event of a false negative. This will necessitate AI insurance policies (Bertsimas and Orfanoudaki 2021) to mitigate risk exposure. There are also privacy concerns to be addressed and questions of whether and how insurers would pay for the devices, how they are priced, and whether they are cost-effective.

To inform and support the range of stakeholders in the decisions associated with adopting new policies and practices, computational models need to be highly

interactive and support complete immersion in interactive representations. Clinician decision-makers will not accept third-party analysts' assertions of treatment recommendations. They will want to be involved in the search for the best answer, laced with much discussion and debate, and the need to be able to interpret how and why algorithms arrived at a specific recommendation and how to mitigate various sources of bias and other unintended consequences of using observational data to aid decision making. Human Factors approaches will be critical to understanding factors that influence clinicians' trust in the computational models and the resulting AI-enabled software systems that support user-friendly immersive interaction with data and recommendations. New approaches for human-centred design to optimise user experiences for clinicians, patients, policymakers, and other stakeholders will be necessary for the successful implementation of these discoveries in an already complex healthcare delivery environment.

The above examples illustrate the complexities of the healthcare challenges we laid out. A unifying construct is the notion of human well-being, which includes physical, mental, social, and economic health (Rouse, Johns, and Curran 2024). The pursuit of this construct in the United States involves a variety of performance challenges. The inherent complexity of the highly fragmented US system underlies these challenges. Numerous behavioural and social phenomena must be addressed, and various interventions developed. Digital technologies and algorithmic advances can enable these interventions, and the field of ISE can contribute to addressing the management implications of developing and deploying these interventions.

#### 7.4. Conclusions and future steps

Healthcare has been described as a class of production system called a *complex service system* (Maglio et al. 2019) owing to the complicated interaction of numerous resources, people, and processes. There are many areas in the scope of the grand challenges where the field of ISE, drawing on its history of innovation in production systems, can positively influence healthcare. To overcome the multi-level impediments of challenge #2 that are undermining success in addressing challenge #1, ISE education and research must address the economic, behavioural, and social phenomena across multiple levels, in addition to data analytics and related methods for responsible data-driven decision-making. Increased training in statistics, causal inference, machine learning, and related data analytic methods need to be emphasised in undergraduate and graduate curricula to enable progress on challenge #1. Further, increased training and experiential learning opportunities related to public

health, economics, public policy, law, and other relevant aspects of behavioural and social sciences are critical skills needed to position future engineers to affect positive change in healthcare.

## 8. Grand challenge of social issues

### 8.1. Background: technology and culture

In this section, we discuss two main topics related to the grand challenge of social issues that the ISE community can potentially tackle, namely 1) technology and culture and 2) re-engineering welfare states: ISE for social welfare delivery system.

Conversational agents provide opportunity for users to use natural language to communicate with an automated system. Ruane, Birhane, and Ventresque (2019) suggest ways for agent designers, developers and owners to approach conversational agents with the goal of responsible development. These agents can have a direct effect on everyday life and even behavioural change. It is noted that conversational agents and bots are developed by teams that can influence social, political, economic and culture. Social and ethical issues include trust and transparency, privacy, agent persona and anthropomorphism (Ruane, Birhane, and Ventresque 2019).

Increased interest in artificial intelligence (AI) has contributed to recent discussions about augmentation versus automation by machine intelligence. Augmentation of intelligence can provide industrial and systems engineering-related challenges for design, use and impact of AI on professionals, organisations and the future of work (Paul et al. 2022). In order to improve the intelligence, there needs to be some collaboration between the human and the AI. The impact can of AI on jobs is a subject of debate. The nature of the effect may depend on how and where the technology is implemented, and its cost for the use context. Future research directions include human-automation interaction (HAI) and human factors (Paul et al. 2022). Key elements of the research include dimensions of HAI trust such as expected performance, the process by which the AI is working, and the purpose. Additional detail about trust elements is shown in Table 2.

### 8.2. AI and automation for the future of work

Modern workplaces are changing. Additionally, modern work necessitates the continued attention to occupational safety and health on behalf of the workforce. The National Institute for Occupational Safety and Health (NIOSH) of the Center for Disease Control in the U.S. has developed priority topics and subtopics for future research in support of the future of work.

**Table 2.** Dimensions of Human-Automation Interaction (HAI) and Trust (adapted from Paul et al. 2022).

HAI trust dimensions	Trust elements
Performance	<ul style="list-style-type: none"> <li>● Competence of HAI               <ul style="list-style-type: none"> <li>○ Functional</li> <li>○ Human-AI interaction</li> </ul> </li> <li>● Timeliness of solution in real-time HAI</li> <li>● Reliability               <ul style="list-style-type: none"> <li>○ Context-specific reliability</li> </ul> </li> </ul>
Process	<ul style="list-style-type: none"> <li>● Openness</li> <li>● Consistency</li> <li>● Understandability</li> <li>● Predictability</li> <li>● Data integrity</li> <li>● Accessibility</li> </ul>
Purpose	<ul style="list-style-type: none"> <li>● Authorised responsibility for administering and using HAI</li> <li>● Intention of machines and users in HAI</li> <li>● Faith in HAI</li> </ul>

Those are shown in more detail in Table 3. Priority topics in the Future of Work initiative at NIOSH include: organisational design, technological job displacement, work arrangements, artificial intelligence, robotics, smart technologies, sensors and surveillance, demographics, economic security and skills (Tamers et al. 2020).

The use of AI has potential for improving the well-being social good. As a research theme, AI for Social Good (AI4SG) has shown trends in terms of application domains and AI techniques used. According to Shi, Wang, and Fang (2020), eight application areas can provide conceptual groupings. These are listed in order of the greatest number of research articles to least include healthcare (344), transportation (253), environmental sustainability (225), public safety (177), combating information manipulation (155), social care and urban planning (90), education (78), agriculture (40). The top ten techniques used include: machine learning (460), planning, routing and scheduling (210), constraint satisfaction and optimisation (173), multiagent systems (122), human computation and crowd sourcing (98), computer vision (79), reasoning under uncertainty (78), game theory and economic paradigms (78), human-AI collaboration (69), heuristic search and optimisation (69) (Shi, Wang, and Fang 2020).

West (2018) explains that his assistant emailed Amy, the personal assistant of the individual with whom he was to meet. Amy was prompt in her follow-up and emailed West's assistant multiple times over the weekend trying to find a date that would work. Amy performed the tasks of a human assistant who read emails, discerned intent, and came up with a relevant response. The clue to discovering that the respondent was virtual was the incredible persistence over a weekend, West explained. The digital assistant performed quite well according to West and is no longer a futuristic vision.

**Table 3.** Priorities topics in future of work initiative as CDC/NIOSH (adapted from Tamers et al. 2020).

<b>ISSUES THAT IMPACT WORKPLACE, WORK AND WORKFORCE</b>	
Emergency and Disaster Preparedness and Response * Exposures and Hazards * Extreme Weather Conditions * Globalization * Industry 4.0 * OSH 4.0 * Policies * Politics * Resources * Social Disruption	
<b>WORKPLACE</b>	
<b>ORGANIZATIONAL DESIGN</b>	Autonomy * Burnout and Stress Prevention * Healthy Leadership * Job Flexibility * Leave Systems * Scheduling * Social and Corporate Responsibility * Workplace Built Environment * Workspace * Work Life Fit
<b>TECHNOLOGICAL JOB DISPLACEMENT</b>	Automation * Digitalization * Job Quantity and Quality * Occupational Polarization * Productivity Enhancement and Quality Improvement through Automated Manufacturing * Stable, New and Redundant Work
<b>WORK ARRANGEMENTS</b>	Alternative * App-based * Contingent * Contractual * Direct Hire * Distributed * Free Lancer * Job Sharing * Non Standard * On-Call * On Demand * Part-Time * Platform * Precarious * Seasonal vs Multi-Employers * Temporary
<b>WORK</b>	
<b>ARTIFICIAL INTELLIGENCE</b>	Deep Learning * Machine Learning * Neural Networks
<b>ROBOTICS</b>	Autonomous, Collaborative, Industrial, Managerial, Service, and Social Robots * Autonomous Vehicles * Human Machine Interaction * Unmanned Aerial Systems * Wearable Exoskeletons and Exosuits
<b>TECHNOLOGIES</b>	Additive and Smart Manufacturing and #3D Printing * Advanced Cloud and Quantum Computing * Bio-Manufacturing * Bio-Technology * Clean and Green Technologies * Digitalization * Information and Communication Technologies * Internet-of-Things * Nanotechnology and Advanced Materials * Sensors * Sensor Surveillance * Smart Personal Protective Equipment
<b>WORKFORCE</b>	
<b>DEMOGRAPHICS</b>	Diversity and Inclusivity * Multi-Generational * Productive Aging * Vulnerable
<b>ECONOMIC SECURITY</b>	Adequate Wages * Equitable and Commensurate Compensation and Benefits * Minimum Guaranteed Hours
<b>SKILLS</b>	Continual Education, Learning and Training * Re-Skilling and Up-Skilling

Robots, AI, virtual reality, autonomous vehicles, facial recognition, drones, and mobile sensors are altering numerous sectors and leading us to an automated society (West 2018). The impact of these emerging technologies is considered in the context of work, education, politics, and public policy (West 2018). West wonders, 'If companies need fewer workers as a result of automation and robotics, how are people outside the workforce for a lengthy period of time going to get income, health care, and retirement pensions?' West suggests that it is important to rethink work and move toward lifetime learning.

### 8.3. Data analytics for quality management and industry 4.0

Recent research has explored how big data analytics can facilitate effective decision making in different quality management problems of small and medium-sized enterprises. Smart technologies have been shown to assist managers to control quality in manufacturing using sophisticated data-driven techniques (Sariyer et al. 2001). A proposed 3-stage model and algorithm that uses main features of the data set, product, customer, country, production line, production volume, sample quantity and defect code can support product quality level classification with 96% accuracy (Sariyer et al. 2001).

Data analytics is the set of techniques that focus on gaining actionable insight to make smart decisions from a massive amount of data (Duan and Xu 2021). As performance is improved by smart decisions and smart

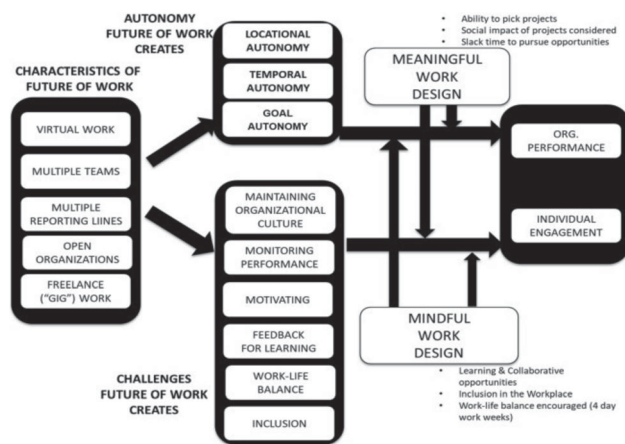
decisions need support from operations to collect relevant data, there has been an increase in research efforts in support the synergistic efforts of data analytics and Industry 4.0 together. Industry 4.0 is the considered the fourth industrial revolution for decentralised production through shared facilities to achieve on-demand manufacturing and resource efficiency (Duan and Xu 2021). Three elements of overlapping interest between Industry 4.0 and data analytics include: the industry sector, cyber-physical systems and analytical methods. Interdisciplinary research areas of interest for ISE that have social implications include 5G network, big data, blockchain, cloud computing, deep learning, IoT and quantum computing (Duan and Xu 2021).

### 8.4. Job design and organisational culture

Job design has potential to impact psychological state of motivation. Ho and Wu (2019) report that perceived social impact can effect motivation to benefit others' lives and further improve service quality. The results have practical implications for ISEs through consideration of appropriate job design to support employee's ability to perceive their job impact on customers as well as have a connection with them (Ho and Wu 2019).

Additionally, organisations are concerned with developing leadership from employees that can lead from a distance (Bagga, Gera, and Haque 2023). Organisations rely more on virtual teams now to accomplish their work and goals. Given the pace of change in the work environment and organisational culture, leaders need to be





**Figure 7.** A conceptual model of the characteristics, challenges and suggested design in the future of work (adapted from Malhotra 2021).

proactive in their approach as all organisations are working more in virtual teams connected by information and communication technologies (Bagga, Gera, and Haque 2023).

A conceptual model of the characteristics, challenges and suggested design in the future of work include: virtual work, multiple teams, location autonomy, goal autonomy, maintaining organisational culture, monitoring performance, meaningful work design and mindful work design (Malhotra 2021) (see also Figure 7). Malhotra (2021) suggests that as individuals realise new ways of accomplishing their tasks using technology and as they adapt to new ways of working, organisations will need to rethink how they structure themselves for the future of work.

### 8.5. Re-engineering welfare states: ISE for social welfare delivery system

Another direction that the broad ISE community can potentially make a significant contribution toward addressing social issues is to improve and enhance the formal societal system itself. A good example is welfare state and social welfare delivery system. A welfare state is a type of government in which the government is responsible for providing basic economic security and social well-being for its citizens (Weir 2001). Originated from the German term 'sozialstaat (social state)' which refers to the reform by Otto von Bismarck, the first chancellor of the German Empire, the notion of welfare state in the modern sense has become a critical part of government functionalities after World War II, especially in the USA and some of Western European countries (Skocpol 1995).

While the specific ways of implementation vary substantially across different countries (Alesina, Glaeser, and Sacerdote 2021) as its evolution has been highly dependent upon the historical trajectories, its domain has grown enormously since WW2. The definition of a welfare state is still equivocal, its purpose is well established and widely understood (Barr 2018) – 1) to assist the poor, and more importantly, 2) to address market failure. The main areas covered by welfare state include: pensions, healthcare, disabilities, family, unemployment, housing benefits, etc. As of 2022, the average public social expenditure-to-GDP among OECD countries is 21% (OECD 2023). In many parts of the world, it is unimaginable for the government to fully neglect such responsibilities. Consequently, it has long been a very active research topic in social science, especially in political science, economics, social welfare, and public administration.

### 8.6. Unexplored territory: how to deliver social welfare efficiently and effectively 'in ISE Sense'

There is a vast amount of literature spending including multiple Nobel Prize winning works (Sen 1982) related to welfare states and social. Nevertheless, despite the colossal size and impact that social welfare has to the society, there seems to be a lack of studies specialising in making it more efficient and effective from engineering – to be exact, industrial and systems engineering – perspective, with the exception of healthcare (Choi 2021). A prominent example is the social welfare service delivery system. Its objective is to deliver the social welfare services to those who are in need in the most efficient and effective manner. It has been studied within the fields of social welfare and public administration disciplines almost exclusively, but the line of research does not address such aspects much.

While anecdotal, the child abuse prevention system of South Korea exemplifies this well. After a series of unfortunate events, South Korean government implemented a machine learning based child abuse identification and prevention system, called 'eChild' in 2018. Albeit not a crystal ball, by leveraging the sensitive social welfare data of every single child of the nation collected and managed by Social Security Information Services (SSIS), it is designed to provide useful information as to whom is likely to be a next victim.

Disappointedly, it did not serve its purpose to the degree that was initially anticipated. While the system has a room for an improvement for its accuracy, it is not the main cause. Rather, it is due to the fact that the eChild system has not been properly integrated with the existing child abuse prevention network consisting of social

workers, police, and local communities at the operation level, which ultimately made the people in charge not to use it as designed (Han 2022). Loosely translating it to ISE terms, it is as if the sensor network is introduced without carefully designing operations within the existing quality management and preventive maintenance system, thus leading to confusion and unnecessary overhead costs.

As the case of eChild system illustrates, many unaddressed issues in the welfare state and its delivery system resemble what the ISE community has been studying for a long time. At the micro level, such matters as identifying the children in danger, lonely death, etc., share similar features as quality management, preventive maintenance, etc. The key challenge in providing care for those in need such as the disabled and the elderly at the state level is essentially a large-scale supply chain management problem. From this perspective, many members of the ISE community will agree that addressing operational issues with welfare state and its delivery system could be a great application field for ISE to make a great social impact, in addition to academic and industrial implications. It is quite obvious that the quantitative and technical tools that the ISE schools have been adopting as the core curriculum such as optimisation, simulation, statistics, human factors, ML and AI that ISE will be of great use for tackling relevant problems. This implies that, the ISE community can make an immediate and sizable impact in making the social welfare delivery system more efficient and effective.

### 8.7. Huddles and challenges

Those who are trained in the ISE community might feel that one can simply plug in the quantitative models to the welfare delivery system related issues to get the right answers. However, the reality is more complicated than one can imagine, as the subject matters are not commercial products. They are human beings. For instance, there are two possible errors regarding the child abuse case – type I and II. Upon the occurrence of a type II error, a child who could have saved may face an unspeakable event. As any statistics textbook states, a type II error should be reduced to a certain degree. In turn, it tends to increase the chances of a type I error. Under the typical preventive maintenance scenario, it is no big deal as the consequence is some loss in monetary value. However, a type I error in child abuse prevention means stigmatising a happy and innocent family by falsely accusing them. The typical quantitative approach that minimises an objective function consisting of reward and penalty does not fit the bill anymore.

Putting the ethical and philosophical dilemmas aside, there is another huddle for ISE methodologies to be

employed at the quantitative modelling level – data. It is obvious that quality research requires a good amount of real data desirably along with a platform to test hypotheses. Unfortunately, it is not so easy to have access to such a data set as it contains very sensitive personal information. The eChild system uses extremely private data sets such as the income level of the parents, daycare/school attendance, missing vaccination, missing utility bills, etc., which should not be publicly disclosed under any circumstance. In many cases, it is illegal, or at least unethical to get a hold of such data. This makes it practically impossible to initiate any type of research, not to speak of publishing the results to academic forum.

There seems to be one remedy, though. If one can generate synthetic data by AI trained on real world samples with sensitive information, and if the generative AI has enough representation power, the data related issues could be much relieved. In this regard, KAIST and SSIS has taken an initiative toward such a direction with the financial support from National Research Foundation. While it is hard to tell how long it will take, once successful, it will allow the members of the broad ISE community to have a free access to the synthetic data without violating privacy for academic purposes, which will certainly make the ISE community the first and only discipline to deliver a social value to a greater public by reengineering welfare state and improving social welfare service delivery system around to world.

## 9. Grand challenge of logistics and supply chain

### 9.1. Background

In today's era, the logistics industry plays a pivotal role in the global economy. They are the backbone of modern commerce, facilitating the movement of goods from manufacturers to consumers.

Hence, the challenges supply chain and logistics companies facing are diverse and complex.

Organisations can use specific strategies and a commitment to adaptability to overcome the challenges, contributing to the smooth flow of goods and global economic services. Supply chain resilience has recently become vital for businesses (Chen and Miller-Hooks 2021). Cyclone Debbie (March 2017) caused damage in Australia and disrupted Indian steel mills by disrupting coal imports and impacting supply chains. The Russia-Ukraine conflict disrupted oil, gas, and wheat supplies, raising prices. Therefore, understanding and measuring resilience is essential, especially with the increasing complexity of expanding supply chains. Significant work has been done to quantify and define resilience (Gao et al.

2019), especially in the manufacturing sector (Ergun et al. 2022; Waseem and Chang 2023).

## **9.2. Challenges in logistics and supply chain**

The logistics and supply chain industry are currently facing a range of challenges that stem from global economic shifts, technological advancements, and evolving consumer demands. The challenge of enhancing supply chain resilience and efficiency in logistics and supply chain management is multifaceted and encompasses various interconnected factors.

### **9.2.1. Sustainable transportation**

While facilitating the movement of goods, rising transportation costs become the grand challenge in logistics and supply chains. It is a significant expense for the logistics companies as the transportation costs continue to increase. The expenses of transporting goods from one location to another are influenced significantly by fuel prices, labour costs, and regulatory changes. These increasing costs make it challenging to remain competitive. Rising transportation costs increase overall expenditure on supplied products, negatively influencing market demand. Using eco-friendly transportation like electric vehicles to optimise logistics for fuel efficiency will help reduce the environmental impact of the supply chain. Incorporating renewable, reusable, recyclable materials in the process is needed to minimise waste and promote a more sustainable approach to management. Integrating supply chain and sustainability helps avoid the risks associated with damage, resource scarcity, and regulatory changes. The major challenge for logistics and supply chain sustainability is balancing the economic objective with the environmental responsibility. This requires investment in technology, materials and processes. In the era of e-commerce, customers expect quick and reliable delivery. To meet ever-increasing customer expectations and service quality while maintaining profitability is a significant logistics and supply chain challenge. With technological advancements, as the industry continues to evolve, the growing skills gap must be filled. Finding and retaining skilled workers in the industries can be a significant challenge. Consequently, the logistics industry faces operational difficulties due to the increasing demand for skilled workforce.

### **9.2.2. Competitive pressure and global trade wars**

The intense competition in the world within the logistics industry can lay down the profit margins. The logistics and supply chain industries encounter the challenge of competitive pressure in the fiercely competitive global environment. The presence of numerous players in the

same industry intensifies competition within the logistics sector, potentially triggering price wars and inevitably compressing profit margins. Companies engaged in international trade face a challenging environment due to the global trade wars. Uncertainties stemming from geopolitical tensions and tariff fluctuations directly impact shipping costs, causing a ripple effect throughout the entire supply chain. To manage and mitigate risks effectively, companies can employ logistics strategies encompassing potential modifications to shipping routes and implementing advanced inventory management practices.

### **9.2.3. Effective warehouse management**

Striking the required or right inventory balance in the logistics and supply chain companies is a constant challenge. Effective inventory management is crucial for logistics companies, but it's difficult, and hence companies often struggle with managing inventory effectively. Missed opportunities and dissatisfied customers are the result of understocking, whereas overstocking leads to high storage costs. The holiday seasons and special sales events typically witness a spike in demand, creating challenges for logistics capacities to cope with the increased workload. Meeting these peak demands and capacity constraints while maintaining the service quality can be a logistical challenge. In the order fulfilment processes of a customer, the lack of adequate space for storage leads to inefficiencies, causing customer dissatisfaction. To maintain order fulfilment capabilities, warehouse space constraints are the challenges faced by many logistics' companies, especially in urban areas where real estate costs are high.

### **9.2.4. Supply chain disruptions**

Logistics heavily relies on smooth supply chains. Disruptions in supply chains can have repercussions for logistics companies, causing delays and escalating costs, ultimately resulting in customer dissatisfaction. The disruptions include natural disasters, political instability and global health crises. Supply chain disruptions are a significant challenge to businesses, creating obstacles to solving this issue. Some measures should be taken, such as strategic planning and the integration of technology to enhance visibility in the logistics and supply chain. Due to the interdependency and interconnectedness of all companies, even a small problem in a particular region can impact the entire global supply chain. So, the massive change in trends and events can affect supply chain disruption enormously. During the Covid-19 pandemic, around 75% of U.S. companies witnessed a supply chain disruption. According to the World Trade Organization report, more than 44% of companies still need a strategy to manage the disruption in the supply

chain during the pandemic. Pierre Haren and SimchiLevi published a paper in Harvard Business Review (Haren and Simchi-Levi 2020) that predicted the peak impact of Covid-19 on global supply chains would happen in mid-March. Every element of the manufacturing supply chain, spanning vendor operations and the availability of packaging to the logistics of transportation across land, sea, and air, has been significantly shaped by the imposition of lockdowns and social distancing measures during the Covid-19 pandemic.

The ongoing conflict between Russia and Ukraine led to an increase in the prices of several commodities, encompassing nickel, neon, fertilisers, wheat, corn, oil and natural gas. As a consequential outcome, warehousing space availability has dwindled, increased freight charges, created container shortages, and forced companies to grapple with heightened storage constraints. The impact extends to port operations, with several ports forced to close due to the tumultuous situation. The worldwide impact of a power surge-initiated fire at the Renesas Electronics factory in Naka, Japan, in March 2021, damaging 23 machines, resonated strongly in the automotive industry. Renesas, a major supplier, provides nearly a third of the world's microcontroller chips, significantly affecting the global production of vehicles by renowned brands, including Ford, Hyundai, and Toyota. The global supply chain encountered a severe setback when the Ever Given container ship became lodged in the Suez Canal, disrupting trade networks far and wide. While the vessel's extraction took only six days, the ensuing traffic backlog cast a long shadow, causing a substantial 60-day disruption to supply chains worldwide. The Ever Given's blockade affected a total of 62 container ships, boasting a combined capacity exceeding 727,000 TEUs (Leonard 2021). The ripple effect extended further as alternative routes around South Africa and the Cape of Good Hope led to additional delays for various vessels. With the Suez Canal being a critical conduit for approximately 12 per cent of global trade, Ever Given's obstruction triggered a shortage of containers, resulting in elevated prices for these essential shipping units. Additionally, the disruption caused numerous missed handovers to freight transport, compounding the challenges faced by the global supply chain.

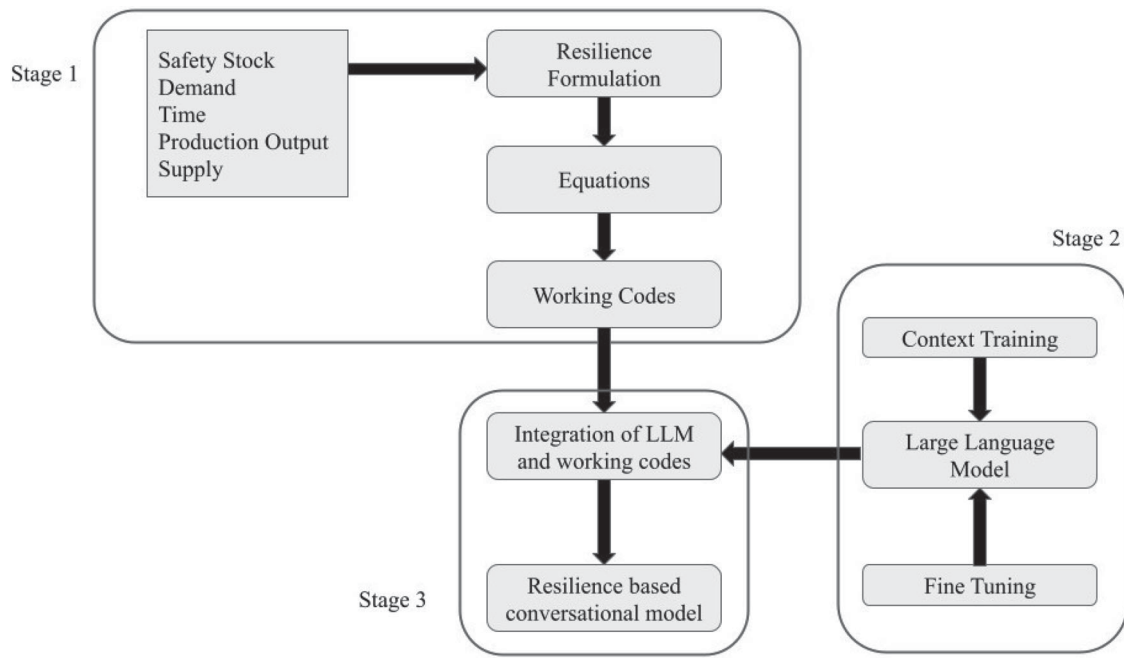
Hence the challenges of logistics and supply chain are diverse ranging from rising transportation costs, sustainability, competitive pressure, global trade wars, effective inventory management, peak demand and capacity constraints, customer expectations and service quality, shortage of skilled labour to supply chain disruption. Resilience becomes strategically imperative when the disruption is more complex for the various industries. To

adhere to resilience needs robust risk management strategies, clear communication or visibility and leveraging technology for monitoring and support for decision.

### 9.3. Enhancing supply chain resilience and integration of language models

In this technological era, all industries are moving towards advanced technologies to build human-friendly models so users can use them conveniently. The supply chain management and logistics field has witnessed a paradigm shift towards data-driven decision-making, playing a pivotal role in providing valuable insights into the supply chain performance of companies. Advanced technologies (Yan et al. 2023) such as knowledge graphs (Mitra, Wongpiromsarn, and Murray 2013), transformers (Vaswani et al. 2017, Reimers and Gurevych 2020), large language models (LLM) (Li, Mellou et al. 2023; Li, Yu, et al. 2023), and versatile tools where a transformer encodes and decodes the natural language text. A significant challenge lies in developing a robust resilience metric that is both comprehensive and accurate. Resilience is often interconnected with various factors, so capturing the interdependencies accurately in a metric can be complex. A crucial aspect of our work involves crafting a dynamic resilience metric that comprehensively considers almost every important scenario in its calculation. Therefore, we are developing a resilience metric and integrating it with an LLM to utilise it conveniently. By quantifying these factors, the company can use these as leverage to gain meaningful advantage. For example, an eligibility indicator for banks to assess loan qualifications of organisations. LLM integration empowers diverse industries, enabling automation, insights, and innovation across sectors, driving progress and efficiency.

We introduced a framework (Figure 1) that uses the concepts of Time-to-Survive (TTS) and Time-to-Recover (TTR) to estimate the resilience of a supply chain. Various factors that influence TTS and TTR have been identified, and a mathematical approach is provided to measure TTS and TTR. We identified different scenarios that can occur during disruption and devised a pseudo code to determine a component of TTR. Further, an approach to integrate the LLM into the framework of resilience calculations is introduced. We trained this LLM according to our use cases and linked it with the resilience equation, enabling us to measure various resilience-related metrics. A generative question-and-answer conversation model is developed to facilitate engaging and informative interactions, providing answers to our inquiries. We trained our language model to calculate resilience by natural text, facilitating generative conversations for problem-solving and explanations.



**Figure 8.** The conceptual framework with stages.

This framework (Figure 8) is segmented into three distinct stages:

- Stage 1: Involves the establishment and computation of the resilience equation.
- Stage 2: Configuring a LLM for our specific use case.
- Stage 3: Incorporating LLM into the resilience equation and generating question-and-answer conversational model.

### 9.3.1. Stage 1: resilience metric

Prior efforts by Simchi-Levi et al. (2015) on TTR and TTS, provided a solid foundation to delve into the critical concepts of supply chain resilience and risk management. TTR refers to the time taken for a supply chain to recover and return to normal state after a disruption. On the other hand, TTS is the maximum duration that the supply chain can match supply with demand after a node disruption.

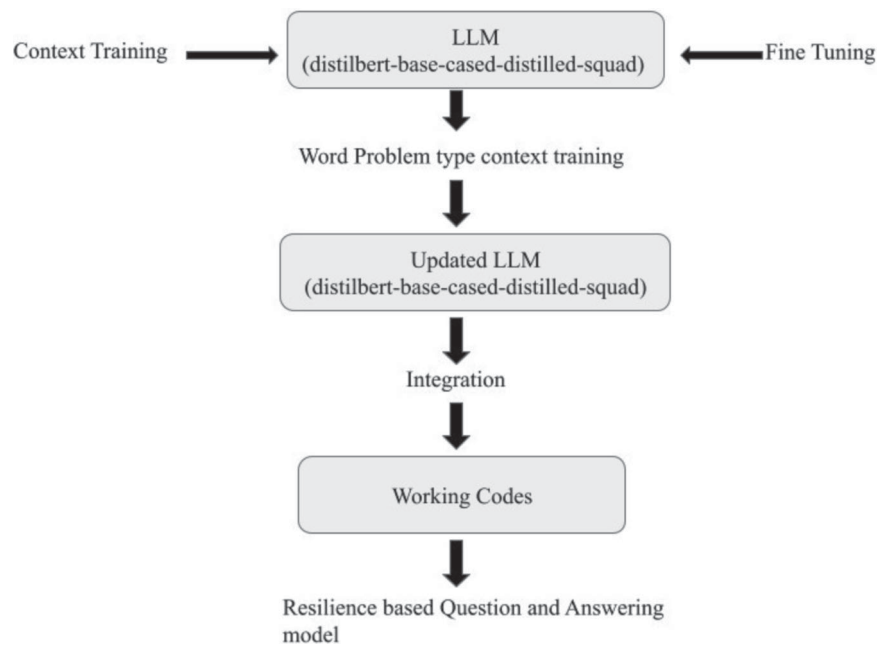
### 9.3.2. Stage 2: large language model (LLM)

To improve supply chain resilience, we utilise an innovative method using DistilBERT (Sanh et al. 2019), a well-regarded language model. DistilBERT-base-cased-distilled-squad offers advantages over other LLMs. It balances model size and performance well, providing a smaller, faster alternative. It's also proficient in handling question-answering tasks due to specialised training on the SQuAD dataset. Moreover, its accessibility via the Hugging Face Transformers library, including

pre-trained models and user-friendly APIs, streamlines integration and deployment. We took a strategic approach to empower DistilBERT with domain-specific knowledge by intricately curating and fine-tuning custom datasets crafted to measure supply chain management resilience precisely. These datasets encompass a diverse array of scenarios. We trained the model using a unique prompt for resilience-based word problem-type questions, thus imbuing it with an innate understanding of supply chain resilience (Figure 9).

**Context Training:** Research has demonstrated that LLMs use context learning for tasks like solving math problems and answering questions. It offers a clear way to interact with LLMs using examples, making it easier to incorporate human knowledge. In-Context Learning (ICL) resembles human decision-making and is training-free compared to supervised training. During ICL, LLMs learn tasks like question answering with task descriptions and examples. Then this knowledge is applied to new examples and undergo evaluation.

**Fine Tuning:** Commenced the fine-tuning process by initialising the LLM with pre-trained weights and subsequently augmented it with specialised layers tailored to the Question-and-Answer task, encompassing start and end token classifiers. The model has been trained with a dataset and is experiencing iterative refinement through supervised learning. During fine-tuning, constant validation dataset monitoring ensured halting training at optimal convergence, observing performance plateau.



**Figure 9.** Integration of LLM (Distilbert-base-cased-distilled-squad).

### 9.3.3. Stage 3: integration of LLM with working codes

Combining LLMs with code can greatly enhance their capabilities. This integration improves natural language understanding, content generation, task automation, problem-solving, and rapid prototyping. LLMs are adaptable and scalable, providing versatile tools to enhance user experiences and application functionality like chatbots, virtual assistants, and interactive applications. LLMs face difficulties with recursive operations like TTR calculations and also to overcome the limitations of LLMs in code execution accuracy, we used them to extract values from natural language text. These values were then incorporated into another set of code for calculating TTS, TTR, and resilience metrics.

### 9.4. Human aspects of logistics and supply chain operations

Logistics plays a pivotal role in a country's economy by facilitating the efficient movement of goods, services, and information throughout the supply chain. The global logistics market size was approximately 10.71 trillion USD in 2023 and expected to reach 14.08 trillion USD in 2028 (Makedon, Mykhailenko, and Vazov 2021). The logistics industry creates employment opportunities across a wide range of sectors, including transportation, warehousing, distribution, and freight forwarding. By employing a diverse workforce, logistics contributes to reducing unemployment rates and improving living standards in communities. From workforce shortages and skill gaps to employee safety and well-being, these human

aspects profoundly impact the efficiency and effectiveness of supply chain management.

With the increasing complexity of operations and the adoption of advanced technologies like automation, cobot (Faccio et al. 2023) and generative AI (GenAI), there is a growing demand for skilled workers who can adapt to new tools and processes. The adoption of platforms provides substantial advantages for organisations, businesses, and customers alike, enabling seamless information sharing, fostering collaboration, and unlocking both individual and collective benefits (Sun et al., 2022). Additionally, human-centric considerations such as ergonomics, workplace culture, and training programmes are essential for ensuring employee satisfaction, reducing turnover, and enhancing overall productivity. Furthermore, effective communication and collaboration among team members, both within organisations and across supply chain partners, are critical for overcoming logistical challenges and improving operational resilience. By taking into account these human factors, companies can create more agile and adaptable supply chains capable of navigating evolving market dynamics and meeting customer expectations.

#### 9.4.1. Human factor implications in advanced manufacturing and logistics

Human factors play a critical role in advanced manufacturing supply chains, influencing efficiency, quality, and innovation. The implications of human factors, combined with GenAI, LLM, transformer, knowledge graph (Mitra, Wongpiromsarn, and Murray 2013),

and geo-spatial technologies in logistics and supply chain management for advanced manufacturing are profound. Human factors, such as workforce skill sets and behaviour, directly impact the adoption and effectiveness of AI-driven technologies. LLM offers transformative capabilities, enabling predictive analytics, real-time decision-making, and autonomous systems. However, successful integration requires addressing human-centred challenges, such as workforce training, change management, and trust-building with AI systems. By leveraging LLM, supply chain managers can optimise production processes, predict demand fluctuations, and enhance supply chain visibility. This convergence of human factors and advanced technologies promises to drive efficiency, innovation, and competitiveness in advanced manufacturing environments.

Skilled workers are needed to operate complex machinery, manage automated processes, and interpret real-time data analytics. Workforce diversity and training become essential as technologies evolve, requiring adaptable teams capable of effectively learning and leveraging new tools. Workplace ergonomics and safety are paramount, especially in robotic systems and heavy machinery environments. Additionally, addressing the implications of human factors involves promoting a culture of innovation and fostering employee engagement to embrace technological advancements and optimise supply chain performance. By recognising and addressing these implications, organisations can enhance their competitive edge and achieve sustainable growth in advanced manufacturing supply chains.

### 9.5. Conclusion and future steps

Global interactions between companies have made the business landscape more interconnected and interdependent than ever before. While these connections are good, they also increase the vulnerabilities of the companies against any disasters. This introduces a framework for resilience, using TTS and TTR to assess and understand resilience more comprehensively. Resilience can demonstrate the strength of a company, risk management, and adaptability. Our conversational LLM enhances result acquisition and can be integrated into various applications, including chatbots. By integrating cost considerations, we can gain a holistic view of a company's ability to manage disruptions cost effectively. As LLMs evolve, we can enhance the framework further, incorporating factors like demand fluctuations, supplier availability, lead time, and financial ability to delve deeper into resilience mathematically.

## 10. Grand challenge of system integration and operations: humans, automation, and AI

### 10.1. Background

Technological innovation in computing, sensing, communications, and robotics is creating opportunities to give both decision-making capabilities and physical autonomy to systems that are, or could be ubiquitous, and that directly engage humans on a large scale (Annaswamy et al. 2023).

Examples range from systems that are locally deployed to systems that span the globe:

- Collaborative robots (Cobots) in manufacturing (Liu et al. 2024)
- Assistive robotics in healthcare (Christoforou et al. 2020)
- Self-driving vehicles (Baldwin 2020)
- Personalised commerce (Brown and MacKay 2022)
- Battlefield autonomy (Knight 2023)
- Smart grid (Omitaomu and Niu 2021)
- Air traffic control (Gopalakrishnan and Balakrishnan 2021)

Expansive computational capabilities and sensing devices are also behind emergent technologies such as digital-twins (Jones et al. 2020; Srai et al. 2019) which blend the physical and digital world for improved monitoring, predictive analysis, and optimised data-driven decision. The promise of advanced autonomous technologies is further amplified by recent advances in AI and machine learning that demonstrate 'super-human' performance in settings ranging from drone racing (Ackerman 2023; Song et al. 2023) to highly complex strategy games such as poker (Brown and Sandholm 2019), StarCraft II (Simonite 2019), and Diplomacy (Meta Fundamental AI Research Diplomacy Team (FAIR) 2022).

For these kinds of systems, it is easy to speculate on the benefits of faster and better decision-making and physical autonomy. It is much more difficult to assess potential risks, especially those that might lead to catastrophic failures, or to identify and implement mitigations. Technological progress brings with it great promise, but as we have learned from past experiences that promise must be vetted against potential risks and the ability to mitigate unforeseen bad outcomes. The pharmaceuticals industry is one good example. The development of a single new drug will consume upwards of US\$1 billion and require a decade or more, yet 90% of new drugs fail in clinical trials despite having passed a pre-clinical test. Failure can result from lack of efficacy or unacceptable side effects (Sun et al., 2022). What seemed like a promising idea 15 years ago turns out to be a very expensive

mistake. The failure rate is so high because experiences like Thalidomide (Kim and Scialli 2011) showed us the societal consequences of not being careful with pharmaceutical technology.

Robots in the factory may allow removing people from hazardous jobs, 'lights out' operations, and more. When used for very simple, though physically demanding, tasks in highly structured environments, robot adoption has been enormously successful. As more sophisticated applications are tried, especially those requiring human-robot collaboration, results have not always been so good (Gihleb et al. 2023). It should be noted that several of the examples were the result of people not fully understanding their role in the collaboration. Automated driver assistance systems (ADAS) are a form of robotics that can drive our vehicles for us and offers great promise in areas of logistics and urban traffic management. On the other hand, despite upwards of US\$40 billion in development, reliable and more importantly, safe, self-driving vehicles are still 'on the horizon' (Baldwin 2020). According to reports (Lauge 2023) both the US and China are pursuing the development of battlefield robots, while at the same time, international efforts seek to ban certain capabilities, such as autonomous targeting and firing.

Another example is smart infrastructure. As such systems become increasingly sophisticated, they also become increasingly interconnected. This interconnectivity offers opportunities for increased performance while simultaneously introducing fragility through the possibility of cascading failure because of newly introduced interdependencies (Kilmek et al. 2018). A hypothetical example is physical damage to commuter rail, e.g. because of a storm, can lead to utilisation of an electric vehicle fleet that was providing power during an hour where there is typically high demand, thereby impacting electricity supply.

## 10.2. System integration and operations

Technological innovations allow us to do something that in the past was not possible. That is the promise. Where we face challenges is in understanding and mitigating the risks of technological innovations. Consider self-driving vehicles. Unless their deployment is accompanied by a massive make-over of the existing vehicle transportation infrastructure, they will operate in an environment that is not tightly controlled. In other words, the developers of these systems will not have a precise definition of the domain of application, and thus cannot predict with perfect certainty how the systems will perform once 'in the wild'. Such a consideration is magnified many times for systems like the electric power grid (EPG), which actually

is the aggregation and integration of many unique and somewhat independent systems. Historical experience demonstrates that local contingencies can lead to system failure on a larger scale. Because of the size and complexity of the EPG it is simply impossible to test all possible contingency scenarios. So how do we 'qualify' a new technology that promises better control of a nation-wide EPG?

From a societal perspective, the grand challenge of physically autonomous, AI-enabled systems is *guaranteeing safety with regard to humans and efficacy with regard to the domain of application*. The requirements for achieving this grand challenge are formidable. Below, we briefly describe some of the most critical topics that are current areas of active research.

### 10.2.1. Open decision architectures

As autonomous systems become more sophisticated, they may learn from past experiences to improve performance or adapt to evolving environmental conditions for increased resilience (cf., deep learning [LeCun, Bengio, and Hinton 2015]). Such open decision architectures present unprecedented challenges in the certification of safe operations. This issue may be the most formidable concern in the deployment of increasingly advanced autonomous systems. Existing approaches to system certification (Mitra, Wongpiromsarn, and Murray 2013) incorporate tools such as formal methods (Pola and Di Benedetto 2019) to assure that a process complies with all requirements and specifications under a presumed range of operating environments. A complementary approach is to incorporate validation in the design process, rather than after the fact, to derive systems that are 'correct by construction' (Tabuada 2021). The main challenge is one of computational feasibility. These methods rely on models derived from a blend of first principles and increasingly available data (Rai and Sahu 2020). As systems are more complex, the problem of certification may be computationally intractable, leading to simplifying assumptions and approximations that either dilute the certification or are overly conservative. Setting aside these issues, an implication of open decision architectures is that it becomes difficult *a priori* to foresee the outcome of adaptation, since adaptation depends on the order in which operating environments are encountered, i.e. path dependencies. Accordingly, although the original system may meet a set of prescribed specifications, its evolved version need not.

### 10.3. Strategic environments

Another complication is that one does not have an *a priori* characterisation of the range of operating



environments. A major contributing factor is that adaptive systems will be deployed in the presence of other adaptive systems, and these ‘systems’ may be other machines/algorithms or may be humans. Accordingly, systems will be evolving/learning in a non-stationary environment. Even in highly stylised settings, learning in the presence of other learners can lead to chaotic behaviour (Piliouras and Shamma 2014). In the case of interacting machines/algorithms interacting with other such systems in a particular domain, each system may be developed and deployed by different entities, perhaps even competitors. That is, there most likely will not be a central entity in charge of system planning in that particular domain. Accordingly, there may be unintended emergent behaviours in the long run. A representative illustration is work that demonstrates how profit maximising algorithms with independent adaptation can learn to collude (Calvano et al. 2021). The problem is magnified by the potential interactions between autonomous systems across domains.

There are similar concerns in the case of adaptive systems interacting with humans, as humans also exhibit adaptive behaviour. A representative instance is the case of driver collusion in rideshare platforms (Tripathy, Bai, and Hesse 2022). Such platforms deploy pricing strategies in response to customer demand and driver availability. It has been reported (Hamilton 2019) that drivers will collude to create an artificial shortage to trigger the activation of surge pricing for the collective benefit of drivers. As with the previous case of machine-to-machine collusion, intelligent agents adapted to exploit other intelligent agents, except now on one side are ‘machines’ and on the other side ‘humans.’ This phenomenon is a form of decision-dependent distributions (Dong, Zhang, and Ratliff 2023), where data characteristics that were gathered prior to the deployment of a decision system shift in reaction to the specific decisions of the deployed system. Research includes the design of systems that are robust to distribution changes (Delage and Ye 2010; Kuhn et al. 2019) or anticipate strategic reactions (Zrnic et al. 2021)

#### 10.4. Online vs offline learning

Many of the successes of learning systems employ extensive simulations of realistic environments for which there are computational models of sufficient fidelity. This approach, called simto-real transfer (Zhao, Queralt, and Westerlund 2020), is motivated by two main considerations. First, it bypasses the need of gathering real-world data sets. Second, it allows for experiential learning that balances exploitation versus exploration without real-world consequences. An active area of research is how to design the simulation environment in such a way

to maximise the likelihood that the autonomous system will be successful, or at least require minor adjustment, when deployed. Major concepts, among others, are domain randomisation (Tobin et al. 2017), so that the learning system is insensitive to environmental variations, and meta-learning, which is training a system to best adapt/learn to unseen environments (Finn et al. 2019), and variable domain fidelity, which challenges the notion that higher fidelity is necessarily better for training (Truong et al. 2023). It is noted that the theory of reinforcement learning does admit a middle ground, known as off-policy learning, where real-world data is used to train an autonomous system offline (Di-Castro, Di-Castro, and Mannor 2021).

An obvious challenge in this framework is the availability of a simulation environment that enables the transfer from simulation to real-world. In the absence of such an environment, one must gather real-world data and experience simultaneously. This requirement presents a major limitation of applying learning methods to safety-critical systems, where there may be costly or even tragic consequences to a failed experiment, e.g. large-scale infrastructure or small-scale operation near humans. To address this concern, there is extensive interest in the concept of ‘safe learning’ (Hewing et al. 2020; Brunke et al. 2022). In this setting, there are internally imposed limiters in the learning algorithm that inhibit exploration until sufficient data has been gathered so that a performance improvement can be realised through a cautious learning step. Data may be learning about the autonomous system (e.g. robot or vehicle dynamics) or the environment (e.g. the behaviours of other actors). As mentioned previously, learning in the presence of other learners, be they machines or people, presents a significant challenge to safe learning.

#### 10.5. Technology acceptance and adoption

Advanced autonomous systems cannot be deployed without a societal acceptance of their presence and adoption of the technology. Emerging themes related to this topic are trusted autonomy (Hoff and Bashir 2015) and explainable/interpretable AI (Dosiilovic, Brcic, and Hlupic 2018). As discussed in (Hoff and Bashir 2015), accidents can occur because of both under-trusting autonomy and over-trusting autonomy. Opposing examples are overriding an autopilot in favour of manual control or continued usage of an autopilot after sensor failure warnings (see also (Dingus et al. 1998) for historical perspectives). Furthermore, once trust is diminished, perhaps because of a system failure, an autonomous system must somehow regain the trust of a human user (de Visser, Pak, and Shaw 2018). This is where the notion

of explainable or interpretable AI may come into play. As decisions are handed off from humans to algorithms, there is a desire to understand the reasoning behind algorithmic decisions.

A complicating factor in all the above discussion is that these issues depend on the perception of the human user. For example, to be trustworthy, motion planning of mobile autonomous vehicles in close proximity to humans must not only assure collision avoidance but also must also maintain such a distance where the human feels safe, even when closer trajectories still avoid collisions (Yoon et al. 2019). Such issues are compounded by variabilities in human behaviours and attitudes that occur from person to person, or over time for the same person, and depend on the underlying context of the environmental setting (Hoffman and Stawski 2009). Another complicating factor, which is by now a recurring theme, is that trust in adaptive autonomous systems is much more challenging because of temporally longitudinal changes in behaviours stemming from learning and adaptation.

### 10.6. Closing (by ChatGPT<sup>2</sup>)

In conclusion, the rapid evolution of computing, sensing, communications, and robotics has ushered in a new era of advanced autonomous technologies with the potential to revolutionise various aspects of our daily lives, from manufacturing to healthcare, transportation to infrastructure. The examples provided, ranging from collaborative robots in manufacturing to self-driving vehicles and smart infrastructure, illustrate the breadth of possibilities that these technologies offer. However, as we venture into this era of unprecedented innovation, it becomes increasingly clear that along with the promise of enhanced efficiency and autonomy comes the critical responsibility of managing and mitigating potential risks. The pharmaceutical industry's costly lessons serve as a poignant reminder that technological advancements must be rigorously vetted to avoid unforeseen and undesirable outcomes.

The grand challenge we face is not only to guarantee the safety and efficacy of physically autonomous, AI-enabled systems but also to navigate the complexities of open decision architectures, strategic environments, online vs. offline learning, and societal acceptance. Addressing these challenges requires continuous research and development, a commitment to safe learning methodologies, and an understanding of the intricate interplay between technology and human perception. As we pursue the promises of technological innovation, it is imperative that we tread carefully, ensuring that the benefits realised are not overshadowed by the risks encountered on this transformative journey into the future.

## 11. Grand Challenge of industrial and systems engineering education

This section discusses the grand challenge in Industrial and Systems Engineering education, including background, motivation, and recommendations. We have identified the following five main challenges relevant to Industrial and Systems Engineering Education:

- (1) What new and different subject matter needs to be taught? How best to maximise the learning of the new subject matter on the part of students?
- (2) What research is needed to harmonise and exploit synergy between Industrial Engineering (IE), Systems Engineering (SE), and Artificial Intelligence (AI)?
- (3) What new methods need to be included in practice based on lessons learned especially from transportation and aerospace domains?
- (4) What domain-specific knowledge needs to be imparted to students in different domains (e.g. healthcare, manufacturing, finance)?
- (5) How can Large Language Models (LLM) be exploited in IE/SE education and research while recognising the bounds of competence of LLMs and chatbots?

Clearly, these challenges are not independent and will have to be addressed accordingly. In the following sections, we undertake a broader explanation and foundations of how and why of these challenges. We discuss why addressing these challenges is important to ensure the sustainability of IE education in the long-term.

### 11.1. Background: complexity growth

Complex socio-technical systems are characterised by dynamic interactions which are multi-directional, often within networked systems, and frequently leading to emergent properties. Consequently, education and research cannot be independent of societal factors, technological advancements, and infrastructure-related issues. Complexity in such systems primarily results from an increase in the number of interacting independent entities in the system. The global community itself is a complex sociotechnical system, an amalgamation of systems comprising natural and human-made entities. Interconnectivity in these systems is characterised by the ability of these entities to communicate with each other. According to Statista (URL 1) there are currently 6.92 billion smart phone users, which translates to 85.88% of the world's population. In the limiting case, a fully interconnected network of humans is estimated to have 6.92

billion nodes. An undirected network of this magnitude will have approximately 23.95 quintillion edges. While not everyone will be connected to everyone else, this number is an upper bound which indicates the potential growth in complexity of the world we inhabit.

Today with multiple means and modes of information dissemination, such ultra-large networks in the absence of dissemination policies and controls, will manifest not only in instantaneous diffusion of relevant information but also unverified information. The opportunity for industrial and systems engineering as a profession is how best to address this challenge from educational, research, and training perspectives.

### **11.2. Opportunities for IE discipline resulting from disruptive AI technologies**

Nowadays, we also must contend with disruptive technologies such as Large Language Models (LLMs) and chatbots based on LLMs such as ChatGPT. As educators, we have come to realise that both our instructional content and modes of delivery must be critically reviewed as students now have all the requisite information at their fingertips because of technologies such as ChatGPT. Having an LLM available to students in the class is akin to each student having a personalised teaching assistant or tutor. While current LLMs do hallucinate (i.e. generate incorrect or nonsensical text and hence irrelevant context), it is a matter of time before their responses markedly improve. Therefore, the bigger question for academia is how to teach foundational disciplines with ubiquitous availability of technologies, and growing number of excellent online courses. Are traditional ways of teaching and existing instructional content in IE still relevant? If not, what needs to change and how?

The most important dynamic change is the explosion of data, and the growing interest in of a unified integrated data repository (a one-stop shop). While feasible, the latter still poses a formidable challenge when it comes to maintenance, update, and sustainment. In our lifetimes, we have seen simple IBM SQL databases of the 1970s that focused primarily on financial (payroll) applications transition to data warehouses (1980), to data lakes (2011), to lake houses (2020). This progression has made real-time streaming data analysis through AI models and data science approaches (which will be the future of training of industrial engineers) a non-trivial task. Against this backdrop, systems modelling, and optimisation need to consider the dynamism and heterogeneity of data to develop meaningful methodologies and sustainable applications. We have to ask ourselves ‘Is our profession prepared to tackle this problem?’ If not, what steps do we need to take to ensure that we can?

Below, we do not attempt to answer such questions. Rather, we focus on identifying fundamental changes needed in IE education, research, and training given the disruptive advances in AI and Systems Engineering (SE). Specifically, we posit that the future of IE lies in exploiting the potential synergy of Systems Engineering (SE) with Industrial Engineering (IE), and in fully utilising the recent developments in AI to enhance engineering productivity. We note that even though IE has changed its name to ISE, thus far this is a change in name only with little progress made in understanding the points of synergy between these two potentially complementary disciplines.

The past decade has witnessed an ongoing transformation of systems engineering to address the ever-growing complexity of sociotechnical systems. It has also seen dramatic advances in AI with the advent of deep learning and Large Language Models. The new slogan, AI4YOU, which implies personalised AI, is not a mere buzzword, but a slowly but surely evolving reality. Not only will we be dealing with systems interacting with individuals, but individuals also be modelled as digital twin systems. We include both individual and collective entities such as person, enterprises, and governments (local to state to federal) in this definition. The question then is how do we introduce such sophistication and complexity of thought process into IE education? The IE imperative today is to begin to explore how SE and AI advances can be harnessed to increase IE’s regime of applicability, core competencies, and assure continued relevance in the twenty-first century. With these concerns in mind, we review the evolution of these fields, and suggest promising directions for IE to pursue in education to assure its continued relevance in the twenty-first century.

### **11.3. Evolution of IE, SE, and AI**

Disciplines continue to evolve with new research findings and emergence of new technologies.

IE, SE, and AI have also evolved especially in the past decade.

#### **11.3.1. IE evolution.**

IE has been historically concerned with the design, improvement, and optimisation of complex systems, processes, and organisations. The first IE department, at Penn State was founded in 1908 focused primarily on the foundational works of Hugo Diemer (Diemer 2012) and Frederick Winslow Taylor (Taylor 1919). In the 1970s, it became Industrial and Management Systems Engineering, and then changed again. Despite several name changes, the emphasis on systems remained constant, even as the very concept of systems expanded to ‘an

interconnected network of people, devices, and tools.’ The above definition captures what is taught in IE today. Manufacturing, optimisation, human factors, and data analytics (or data science) are the basic silos that we have created. While ISE students are well trained in these disciplines and 321,400 industrial engineers are gainfully employed in the US (Bureau of Labour Statistics 2022) it is unclear to what extent these students understand and can apply ISE principles when pursuing IE approaches to solving problems. Understanding complexity, interactions, dependencies, and life cycles from a systems perspective has become vitally important for industrial engineers today.

### 11.3.2. SE evolution

SE is an interdisciplinary field of engineering focusing on design, development, and management of complex systems, with emphasis on quality attributes such as usability, safety, availability, and resilience. SE emerged as a distinct, recognised discipline in the 1940s with the term first employed by Bell Labs. Despite its initial lack of formal underpinnings, SE played a vital role in the 1969 Moon landing and the safe return of astronauts to earth. A perfunctory review of early SE applications suggests a few recurring themes: systems engineers tend to be domain experts; their analysis relied on domain specific engineering; their work cuts across multiple technical and non-technical disciplines. Over the past two decades, SE has focused on increasing its structure and rigour by exploiting concepts from computer science, biology, and software engineering. The emphasis today is on transdisciplinary systems engineering (Madni 2018), Model Based Systems Engineering (Madni and Sievers 2018), Trade-offs Analyses (Bahill and Madni 2016), design elegance (Madni 2018), and quality attributes such as cyber-resilience and agility.

### 11.3.3. AI evolution.

In the past five years there has been a surge in interest in AI for systems engineering and systems engineering for AI led by organisations such as the DoD Systems Engineering Research Center (sercuarc.org). With recent advances in LLMs and the advent of ChatGPT and its variants, systems engineers and industrial engineers have begun to explore ways to leverage the capabilities of LLMs as a means to automate routine tasks and serve as intelligence augmentation on cognitive and decision-making tasks. It is important to realise that LLM is a data association model that is capable of exhibiting competence within limited domains but is inappropriate for problems that require common sense and causal reasoning. Considering these findings, Madni (2020) has suggested the role of Augmented Intelligence for all AI

based systems. The key idea is to exploit AI as a performance enhancer or capability amplifier in cognitive tasks such as problem-solving and decision-making (Madni 2020).

From the initial coining of the term, ‘AI’ at the Dartmouth conference in 1956, AI has progressed from Knowledge-Based Systems to the more recent Attention-Based deep learning (Vaswani et al. 2017). AI has also progressed from foundational AI (Nilsson 1982; Gene-sereth & Nilsson 2012; Russell and Norvig 2010) to AI applications in medicine (Hamet and Tremblay 2017; Topol 2019) and manufacturing (Kumara, Kashyap, and Soyster 1989; Davies 2023). It is safe to say that AI is here to stay; however, its form can be expected to evolve. Looking back, AI has evolved from its initial prominence in the 1980s to a prolonged lull in the 2000s, to its re-emergence with machine learning as a ‘hot’ technology. Today AI is becoming increasingly an integral part of modern society.

## 11.4. Evolving world contexts

In *The Future of Work* (West 2018), the author states that the future is one in which there will be lifelong learning needed for every worker. The commercial stream of thought is that college degrees will no longer be necessary because it will be ‘gig economy,’ in which people with specific skills will drive the economy. In this regard, platform-based work has become critical (Taylor et al. 2017). This shift in the future of work implies that existing college education will need to change. We are already seeing the impact of this shift through online platforms such as EdX, Coursera, and others. We have a choice. We can continue with business as usual, doing what we have always done, or find alternate, robust means to train the future workforce. The key question here is how do we train the future workforce without adversely affecting the basic skillset that future industrial engineers would need?

## 11.5. New paradigm and key questions

Considering the foregoing, domains such as transportation (Malandraki et al. 2007), healthcare (Topol 2019), manufacturing (Balakrishnan, Kumara, and Sundaresan 1999), human systems (Karwowski 2005), cyber physical systems (Monostori et al. 2016) and social systems (Barabasi and Albert 1999), must be studied and understood from a more encompassing systems perspective. To this end, we propose two fundamental premises: the structure and behaviour of a complex system can be modelled as a network of interactions among its constituents; and complex sociotechnical problems need to exploit the convergence of engineering with other disciplines, i.e. Transdisciplinary Systems Engineering (Madni 2018).

It is worth recalling that many baby boomer generation industrial engineers were in fact exposed to systems theory not that long ago. They studied the works of Bertalanffy, Simon, and Wiener as graduate students. Unfortunately, today only a few schools still teach systems theory. Perhaps it is timely for IE to re-introduce the foundations of systems theory and SE in this age of exponentially growing system complexity and instantaneous feedback.

### 11.6. Human factors aspects

Industrial Engineering discipline focused on time and motion study, expending human effort, and efficiency improvement from human factors viewpoint most of the past 6 decades. In the last decade human computer interface has become important. Only recently with the proliferation of research as well as widespread usage of Robotics and AI human-machine collaboration has become critical. We address this in grand challenge 5, especially when we are dealing with this aspect from an education perspective. The future of IE from a SE point of view need to consider the complex issues that arise (see discussions earlier in this section) due to human-machine collaboration, and the emergent behaviours manifest from such complex interactions. IE discipline as mentioned before need to consider education its next generation using the extensive body of knowledge originated from Santa Fe Institute (Gellman

### 11.7. Implications for advanced manufacturing

AI and other related technologies are becoming an integral part of society. From healthcare to manufacturing AI is already seen as a driving force. This implies that the next generation Industrial Engineers must have a good background in AI, which we propose (see our discussion) to be an integral part of IE/SE education. Next generation systems (not only manufacturing but almost all including service systems) will have to address complexity in the context of technology as well as society. Let us for the sake of explanation hypothesise that future manufacturing will be using GenAI extensively. This leads to different human-machine (computer) and manufacturing machines interaction. Which will result in an exponential usage of energy which in turn will affect the socio-economic systems. Decisions in the future cannot be made in isolation (profit maximisation), independent of all these interconnected and interactive factors. Our discussion therefore emphasises that next generation engineers need to have a good understanding of systems, and networks besides other topics mentioned in this section. Manufacturing related decisions cannot be made in isolation but should be made considering value addition in

the context of climate, social wellness, and long-term sustainability. The current day Industrial Engineers are not equipped to address these.

### 11.8. Recommendations

Going forward, IE needs to re-introduce systems thinking and SE into the IE curricula. It needs to exploit AI not just for automating routine or repetitive tasks, but as a means for enhancing human performance and amplifying human capabilities in problem-solving and decision-making tasks (Madni 2020) It needs to address large scale systems, complexity, and data interconnectivity, intelligent decision making, augmented AI, systems theory, human-AI teaming, and sustainability. Of course, IE needs to continue to advance statistics, optimisation, simulation, and stochastic modelling. An interesting observation is that medical education in universities is always connected with hospitals. Medical students get real-world experience through their integral immersion with university attached hospitals. However, though engineering discipline is towards designing, building, analysing, and improving systems, they are not connected with enterprises in problem solving on a continual basis. Though some universities have real-world problem solving through a course using the capstone ‘Learning Factory Model’, real world problem solving is not an integral part of engineering education. Going into the future, the greatest challenge for industrial engineering profession is to work with enterprises (manufacturing, service, government, and NGO) and integrate real world problem solving in its education, research, and training.

This would make ISE relevant in the changing futuristic landscape of ISE workforce. The easiest course of action is to follow the adage of old wine in new bottle by repackaging existing courses with new names and await the demise of ISE or commit to a grass roots change. It is imperative that the ISE schools form an extended arm of individuals (individuals, enterprises, and governments) and to be in continuous engagement in training the next generation ISE workforce. A simple yet challenging advancement can be to define a case study that can be used in all the courses taught in an ISE school, in the new integrated ISE curriculum. From optimisation to machine learning to human centred analysis, a single case can be considered through different courses to get real-world problem-solving experience embedded into education. Such a case study possibly will pave the way to a future where teachers and students think seriously about how to effectively use a technique in real world problem solving than simply learning the technique by solving textbook examples. NSF has embarked on the new model of use-inspired research, and comprehensive

case studies that can effectively address various aspects of ISE learning may truly fit that model.

ISE needs a foundational change – one that exploits SE methods in IE problem formulations, and leverages IE methods in SE problem-solving with both being informed by advances in technologies such as AI, machine learning, and augmented intelligence. We are entering an unprecedented era of extended exponential technology growth in which bold action is called for within IE. It begins with exploring how complex systems thinking, SE, and AI can be harmonised with IE to assure continued relevance of ISE education and research in the twenty-first century.

## 12. ISE perspective on grand challenges

This paper identified eight grand challenges for industrial and systems engineering (ISE), including (1) artificial intelligence (AI) for decision-making and system design and operations, (2) cybersecurity and resilience, (3) sustainability: environment, energy, and infrastructure, (4) health issues, (5) social issues, (6) logistics and supply chain, (7) system integration and operations and (8) industrial and systems engineering education. We also want to point out that ISE is uniquely positioned to address many of contemporary society's multifaceted and interconnected global problems. By leveraging its comprehensive knowledge and systems approach, ISE can provide holistic solutions to complex socioeconomic, health, education, environmental, and sustainability issues. The discussed ISE grand challenges point out the need to understand better how the current ISE principles and methodologies can be applied and what new body of knowledge will be needed for ISE to make impactful advancements to improve the human condition worldwide.

First, ISE can enhance complex decision-making and system design by integrating applications of artificial intelligence technologies for business and personal use. By optimising processes, improving operational efficiencies, and enabling data-driven insights, ISE professionals can ensure that AI is effectively utilised to meet industry and societal needs. The focus on human-centred design should ensure that the integration of AI systems into all aspects of human life is safe, transparent, ethical, and user-friendly,

Second, protecting and sustaining critical systems against cyber threats is paramount in today's digital age. ISE can contribute to achieving socially desired levels of cybersecurity by facilitating the development of resilient system architectures, implementing robust security measures, and designing processes that can quickly recover from disruptions. The above should ensure the

continuous and secure operation of essential services and infrastructures globally.

Third, ISE can play a critical role in promoting environmental sustainability by optimising natural resource utilisation, reducing waste, and improving energy efficiency. By designing and managing sustainable systems and infrastructures, ISE can help organisations minimise their environmental footprint and contribute to global sustainability goals.

Fourth, addressing health challenges requires the efficient design and management of healthcare systems. ISE methodologies, such as process optimisation and systems integration, can improve healthcare delivery, enhance patient outcomes, and reduce costs. By focusing on system efficiency and effectiveness, ISE can improve the health and well-being of populations worldwide.

Fifth, tackling societal challenges involves understanding and solving complex social problems. ISE can contribute to the above quest by designing systems and processes that promote social equity, improve access to essential services, and enhance community resilience. By integrating social considerations into system design, ISE can ensure that all future technological advancements benefit all segments of the global society.

Sixth, improving the efficiency and resilience of logistics and supply chains is essential for socioeconomic and political stability and growth worldwide. ISE can optimise supply chain operations, enhance logistics management, and ensure the smooth flow of goods and services. Such efforts can reduce costs, increase reliability, and improve business responsiveness to market demands.

Seventh, harmonising the interactions between people, automation, and AI is crucial for modern system integration and operations. ISE can provide the framework for designing integrated systems that leverage the strengths of both human operators and automated technologies. The above should ensure that all technological systems are efficient, adaptable, and resilient to changes and disruptions.

Eight, advancing education and training in ISE is fundamental to preparing the next generation of engineers to successfully address the needs and aspirations of the global society. ISE education should equip students with the skills and knowledge needed to address complex global issues by updating curricula, incorporating new technologies, and emphasising interdisciplinary and systems approaches.

In summary, by integrating scientific and engineering expertise with a deep understanding of human and social factors, ISE professionals can design and implement systems that improve efficiency, enhance resilience, and promote sustainability across various domains of modern life. The ISE discipline and profession can lead

and significantly contribute to addressing the pressing socioeconomic issues facing our world today.

### 13. Conclusions

The outlined eight grand challenges of ISE should support more effective design and operation of integrated systems of people, materials, information, equipment, and energy. These challenges also underscore the increasing importance of the need for effective system integration of complex technological systems at all levels. To date, ISE practice has been mainly based on twentieth-century knowledge. The development of new knowledge, identification, and adoption of recently developed twenty-first models, theories, and strategies in the related fields of science, engineering, and medicine should help address the identified grand ISE challenges. The above discussion points out the need to significantly expand the current knowledge content of the ISE domain. Such a need is primarily driven by the rapid development of intelligent technologies, the evolving global economy, the sustainability of life on Earth, and many emerging socio-economic trends that will likely transform and shape modern societies. Finally, we hope that this paper will contribute to the current discussion about the future of ISE, stimulate much-needed reflections on ISE challenges, and facilitate developments in ISE theory and practice for the benefit of humankind.

### 14. Study limitations

The current study has several limitations. The discussed ISE Grand Challenges reflect the joint views and vision of co-authors from 3 continents and five countries, including China, France, India, S. Korea, and the United States. Future studies should address and discuss the implications of the above concerns and limitations.

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### Data availability statement

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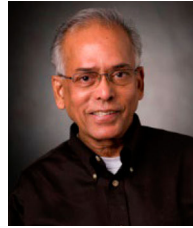
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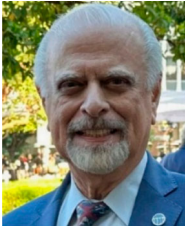
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## Notes

1. Calculated by authors from USEPA Air Pollution Emissions Trend Data, 2018a.
2. In the spirit of the topic of this subsection, the closing paragraphs are written by ChatGPT prompted by a draft of the section.

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