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Forecasting emergent risks in advanced AI systems: an analysis of a future road transport management system

S. McLean[a], B. J. King[a], J. Thompson[b], T. Carden[a], N. A. Stanton[c], C. Baber[d], G. J. M. Read[a,e] and P. M. Salmon[a]

[a]Centre for Human Factors and Sociotechnical Systems, University of the Sunshine Coast, Sippy Downs, Australia; [b]Transport, Health and Urban Design (THUD) Research Lab, Melbourne School of Design, The University of Melbourne, Melbourne, Australia; [c]Transportation Research Group, University of Southampton, Southampton, UK; [d]School of Computer Science, University of Birmingham, Birmingham, UK; [e]School of Health, University of the Sunshine Coast, Sippy Downs, Australia

ABSTRACT
Artificial Intelligence (AI) is being increasingly implemented within road transport systems worldwide. Next generation of AI, Artificial General Intelligence (AGI) is imminent, and is anticipated to be more powerful than current AI. AGI systems will have a broad range of abilities and be able to perform multiple cognitive tasks akin to humans that will likely produce many expected benefits, but also potential risks. This study applied the EAST Broken Links approach to forecast the functioning of an AGI system tasked with managing a road transport system and identify potential risks. In total, 363 risks were identified that could have adverse impacts on the stated goals of safety, efficiency, environmental sustainability, and economic performance of the road system. Further, risks beyond the stated goals were identified; removal from human control, mismanaging public relations, and self-preservation. A diverse set of systemic controls will be required when designing, implementing, and operating future advanced technologies.

Practitioner summary: This study demonstrated the utility of HFE methods for formally considering risks associated with the design, implementation, and operation of future technologies. This study has implications for AGI research, design, and development to ensure safe and ethical AGI implementation.

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Artificial general intelligence; artificial intelligence; risk; safety; road transport; AI alignment

Introduction

Road transport systems around the world are experiencing increased implementation of Artificial Intelligence (AI) technologies (Abduljabbar et al. 2019). These technologies range from autonomous vehicles (AVs) and advanced driver assistance systems to intelligent traffic management systems and smart parking solutions (Bura et al. 2018; Hamidi and Kamankesh 2018). AI is transforming the way we travel, interact with, and experience road transport systems. The key motivators behind the rapid growth in the implementation of AI technologies is a desire to improve safety, efficiency, and sustainability in road transport (Furlan et al. 2020; Torbaghan et al. 2022). For example, self-driving vehicles and advanced driver assistance systems are being designed with the aim of reducing traffic accidents, and intelligent traffic management systems aim to optimise traffic flow and reduce congestion (Hamidi and Kamankesh 2018). Further, AI technologies are being used to improve the road user experience by providing drivers and passengers with real-time information and personalised recommendations (Banks et al. 2018). For instance, smart parking solutions are designed to help drivers find parking spaces efficiently, while intelligent traffic management systems that provide real-time updates on traffic conditions are assisting drivers to make informed decisions regarding their journeys (Banks et al. 2018). While the implementation of AI has improved many aspects of the road transport system, it may also introduce emergent challenges (Hancock 2019; Read et al. 2022; Salmon and Plant 2022; Thompson et al. 2020). For example, concerns have been raised around safety and ethical issues associated with AVs, the required technical and operational changes to the road system, cybersecurity

CONTACT S. McLean smclean@usc.edu.au Centre for Human Factors and Sociotechnical Systems, University of the Sunshine Coast, Sippy Downs, Australia

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and privacy concerns, economic issues regarding job displacement (e.g. removal of truck drivers), and the appropriateness of existing regulatory frameworks (Liu, Nikitas, and Parkinson 2020; Martinho et al. 2021; Pöllänen et al. 2020; Read et al. 2023). Despite these unresolved issues, the integration of AI into the road transport system continues to gather pace.

Next generation AI

Artificial General Intelligence (AGI) is the predicted next generation of AI (Barrett and Baum 2017). While current AI systems are now widespread and capable of performing cognitive tasks requiring advanced problem solving, they are 'narrow' intelligence that is limited to the conduct of only one or a few specific tasks (Firt 2020; Goertzel and Pennachin 2007). In contrast, AGI systems will have a broad range of abilities and be able to perform a wide range of cognitive tasks akin to humans, arguably exceeding human capability (Legg and Hutter 2006). Although they do not yet exist, it is predicted that AGI systems will have the ability to learn, reason, process language, solve complex problems, make decisions, and carry out many other tasks that typically require human-level intelligence (Goertzel 2014). AGI will possess the ability to achieve complex goals in dynamic and uncertain environments (Goertzel and Pennachin 2007). Such intelligence may transform the world as we know it (Tegmark 2018; Bostrom 2014).

There are numerous proposed benefits of AGI, including the capability to generate effective solutions for complex global issues, such as climate change, environmental degradation, overpopulation, pandemics, disease, food and water security, terrorism, nuclear warfare, and improving the world's economy (Salmon, Carden, and Hancock 2021). However, as seen with AI, AGI may also harbour unknown, novel, and emergent risks (McLean et al. 2021). Accordingly, the scientific community holds serious concerns associated with the arrival of AGI, with the worst case being AGI's existential threat to humanity (Tegmark 2018). Other concerns include malevolent groups using or creating AGI for malicious purposes, as well as catastrophic unanticipated consequences brought about by apparently well-directed AGI systems that develop misaligned or adverse goals (Bostrom 2014). While there has been scepticism among experts as to whether AGI will ever eventuate, some suggest that recent advances in Large Language Models (LLMs) such as GPT-4 are beginning to show signs of general intelligence (Bubeck et al. 2023). For example, GPT-4 has exhibited glimpses of reasoning, creativity, and deduction on a range of topics on which it has gained expertise (such as literature, medicine, and coding), and the variety of tasks it is able to perform (e.g. playing games, using tools, explaining itself) (Bubeck et al. 2023). Numerous active AGI research and development projects are in progress (Baum 2017), and while it is difficult to say when AGI will arrive, estimates of between 2040 and 2070 have been postulated (Baum, Goertzel, and Goertzel 2011; Müller and Bostrom 2016).

Given that AGI does not yet exist, formally identifying the associated risks is difficult, and there is a limited number of published studies specifically assessing the risks associated with AGI (McLean et al. 2021). Previously speculated risks include, the AGI intentionally removing itself from human control; the AGI being provided with, or developing unsafe goals; inadequate ethics, morals, and values; inadequate goal alignment; culminating in existential risks (McLean et al. 2021). However, descriptions of AGI specifications and functionality, and domains of potential application (e.g. healthcare, defence) are unclear. A further criticism of the AGI safety literature includes the scarcity of formal modelling approaches to forecast risks (McLean et al. 2021). Given recent advances in AI, there is a clear and urgent need to conduct research that seeks to identify the range of risks that could emerge once AGI is realised and develop and implement appropriate controls. In road transport specifically, there is a history of responding slowly to the risks of new technologies (e.g. mobile phones, autonomous vehicles). Given the accelerating progress in AI development programs, and the pace at which road transport systems across the world are implementing new technologies to improve safety, efficiency, and usability (Duffy et al. 2023; Stanton 2021; Stanton, Revell, and Langdon 2021; Young & Stanton, 2023), it may be expected that AGI systems are quickly adopted to optimise the performance of road transport systems, especially given the current global annual death and injury toll of 1.35 million and 50 million people, respectively (World Health Organisation 2018).

Assessing risks in the road transport system is difficult as it represents a macro-level sociotechnical system comprising multiple sub-systems (Salmon et al., 2014; Banks et al. 2018). As such, applying appropriate proactive risk analysis methods that considers the broader sociotechnical system, including new technology, is required (Banks et al. 2018). Typically, formal risk assessments tend to focus on 'sharp-end' risks within the safety critical domains (Dallat, Salmon, and Goode 2018). While risk analysis methods such as Failure Mode and

Effects Analysis (FMEA) have been used to assess risk in future technologies (Lui & Lui, 2022; Murino et al. 2023), they contain limitations. For example, FMEA focuses on individual components, processes, or failure modes in isolation (Simsekler et al. 2019). Recently, systems Human Factors and Ergonomics (HFE) risk assessment methods that consider the interaction of system components and the subsequent emergent behaviours have become increasing applied in safety critical domains (Salmon et al. 2022). Given its long history of improving safety critical systems, the discipline of HFE is well placed to take a proactive role in predicting and identifying strategies to manage the risks associated with AGI (Hancock 2022; Salmon, Carden, and Hancock 2021, Salmon et al. 2023). The aim of this study is to apply a systems HFE framework, the Event Analysis of Systemic Teamwork (EAST; Stanton, Salmon, and Walker 2018) to identify the risks associated with a future AGI system tasked with managing the road transport system in one state jurisdiction in Australia. The EAST framework has been used to describe and evaluate systems across multiple domains, including air traffic control, military command and control, submarine control rooms, road transportation systems (Stanton, Salmon, and Walker 2018). The identified risks will inform AI system stakeholders of potential risks to safe and ethical AGI implementation in road transport.

Methods

Design

This study was designed to develop an envisioned world of a future AGI road transport management system and subsequently perform a proactive risk assessment. The EAST (Stanton 2014; Stanton, Salmon, and Walker 2018) framework was applied to describe how information would be distributed across tasks and actors in the envisaged road transport system managed by an AGI system. The Event Analysis of Systemic Teamwork-Broken Links (EAST-BL: Stanton and Harvey 2017) method was subsequently applied to identify risks associated with breakdowns in information transmission between tasks, and between social actors. This study did not require institutional ethical approval.

Event Analysis of Systemic Teamwork (EAST)

The EAST framework provides an integrated suite of methods for analysing the behaviour of teams, organisations, and sociotechnical systems (Stanton, Salmon, and Walker 2018). A key premise of EAST is that sociotechnical system performance can be explained by three interrelated networks. EAST thus provides methods to describe, analyse, and integrate three network-based representations of activity: task, social, and information networks (Figure 1) (Stanton 2014; Stanton, Salmon, and Walker 2018). Task networks are used to provide a representation of the interrelated tasks undertaken within a system. For example, what tasks are undertaken in an AGI-managed road transport system and what relationships exist between them. Social networks are used to describe the human and non-human agents performing tasks within the system and the interactions that take place between them during task performance. For example, how agents (human and non-human) in an AGI-managed

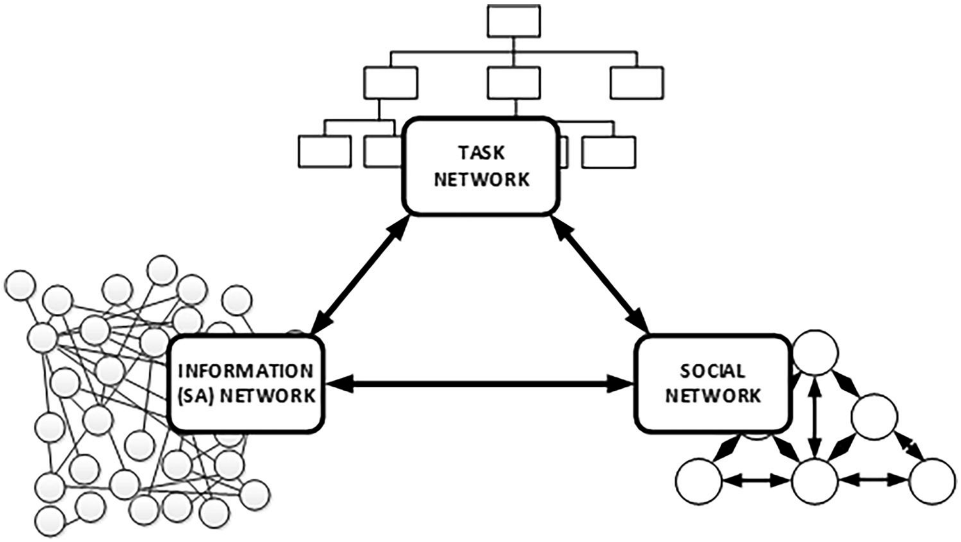


Figure 1. EAST network of networks approach for systems analysis (Stanton 2014; Stanton, Salmon, and Walker 2018).

road transport system are connected to each other in terms of information shared between them. Information networks describe the information that agents use in support of task performance and how this information is distributed across different tasks and agents. For example, information that is required for the road transport system to operate safely and efficiently and information that different agents need to fulfil their roles.

Event Analysis of Systemic Teamwork-Broken Links (EAST-BL)

The EAST-BL method is an extension to the EAST framework that enables it to be used for prospective risk assessment purposes (Stanton and Harvey 2017). Applying EAST-BL involves 'breaking' the links in the EAST task and social networks to identify the impacts of failures in information transfer. Breaking the links in the task network is used to identify risks that might emerge when information is not transferred between tasks. For example, when information from the 'road system monitoring' task is not transferred to the 'manage public relations' task. Breaking the links in the social network is used to identify risks that might emerge when information is not transferred between agents. For example, when a road transport AGI system is unable to communicate with its fleet of fully autonomous vehicles. EAST-BL represents failures in communication and information transfer between nodes in the networks and these failures can be used to make predictions about the possible risks within the sociotechnical system (Stanton and Harvey 2017). One of the key strengths of the EAST-BL method is that it can identify risks across overall systems, as opposed to identifying risks only at the sharp end of system operations (Lane et al. 2019; Salmon et al. 2022).

Envisioned world road transport AGI system

Given that AGI does not yet exist, in this study we took an envisioned world approach to explore and model the potential risks associated with a future AGI road management system hereafter referred to as the Multi-functional Intelligent Learning Traffic Optimisation Network (MILTON). This study builds on previous work (Goertzel and Pitt 2014; McLean et al. 2021; Salmon, Carden, and Hancock 2021) which argued that various forms of control are required to ensure the design, implementation, and operation of safe AGI. To align with current predictions of the arrival of AGI (Müller and Bostrom 2016), our modelling envisioned a system implemented around the year 2050. The hypothetical MILTON system will represent the initial roll-out of a government owned and controlled AGI system that is developed with the stated purpose of managing the road transport system in one state jurisdiction in Australia. It is envisaged that the road transport system will comprise existing road infrastructure, including fully autonomous and connected vehicles, but also includes existing semi-autonomous and conventionally driven vehicles, under the assumption that these would not be fully phased out by 2050. The initial stated goals of MILTON would be to address the recurring issues within the current road transport system relating to safety, efficiency, and an environmentally and economically sustainable road transport system. The functionality of MILTON would include having control of numerous AI agents within the road transport system including, AVs, intelligent road infrastructure, dynamic signage, and surveillance systems, among others. MILTON itself would be monitored by an AGI management team comprising technicians, programmers, and computer scientists. MILTON would have the ability to interact with road system actors such as road users (private, public, and commercial), police, emergency response, road system maintainers, governments, among other road system actors and stakeholders via various means of communication including media, social media, apps, radio, and through direct interfaces within AVs and semi-AVs, road infrastructure and related sensors and actuators.

Procedure

Development of the envisioned world

The construction of future technological systems in work domains that do not yet exist, is commonly known as the envisioned world problem (Dekker & Woods, 1999). Envisioned worlds are used in various domains, including business, technology, and space travel, to guide decision-making (Miller & Feigh, 2019). The current envisioned world was developed by the research team across three online workshops. In Workshop One, the authors discussed potential elements of a future AGI system tasked with managing the road transport system. The focus was on what functions currently occurring in road transport could be conducted by an AGI system. In Workshops Two and Three, the authors worked together to create an abstraction hierarchy of the envisioned world- creating the MILTON system, using Work Domain Analysis

(WDA) (Vicente, 1999). In creating the abstraction hierarchy to describe MILTON, the authors drew upon a STAMP (Leveson, 2004) control structure model of the current Australian road transport system with a focus on technology insertion (Read et al. 2023), as well as their extensive experience in road safety and technology insertion into the road transport system. The use of WDA as a design tool has previously been used to model envisioned systems (McLean et al. 2022; Miller & Feigh, 2019).

The initial step was to identify the specific goals that MILTON would seek to fulfil. This included solving longstanding issues in road transport such as safety, efficiency, environmental, and economical issues (see Table 2 for definitions). The second step was to pose the question of what an AGI-based road transport management system would comprise in terms of agents (human and non-human), artefacts, and infrastructure. New technological capabilities (e.g. AI) were considered as well as required ethical and legal features with regard to privacy, human rights, and fairness; and also user experiences (e.g. trust and acceptance of MILTON). Further, the resultant anticipated, and unanticipated consequences of these conceptions were discussed and noted which informed the risk assessment phase of the study. The resulting envisioned world, while hypothetical, therefore, provides a comprehensive description of a potential future AGI based road transport management system.

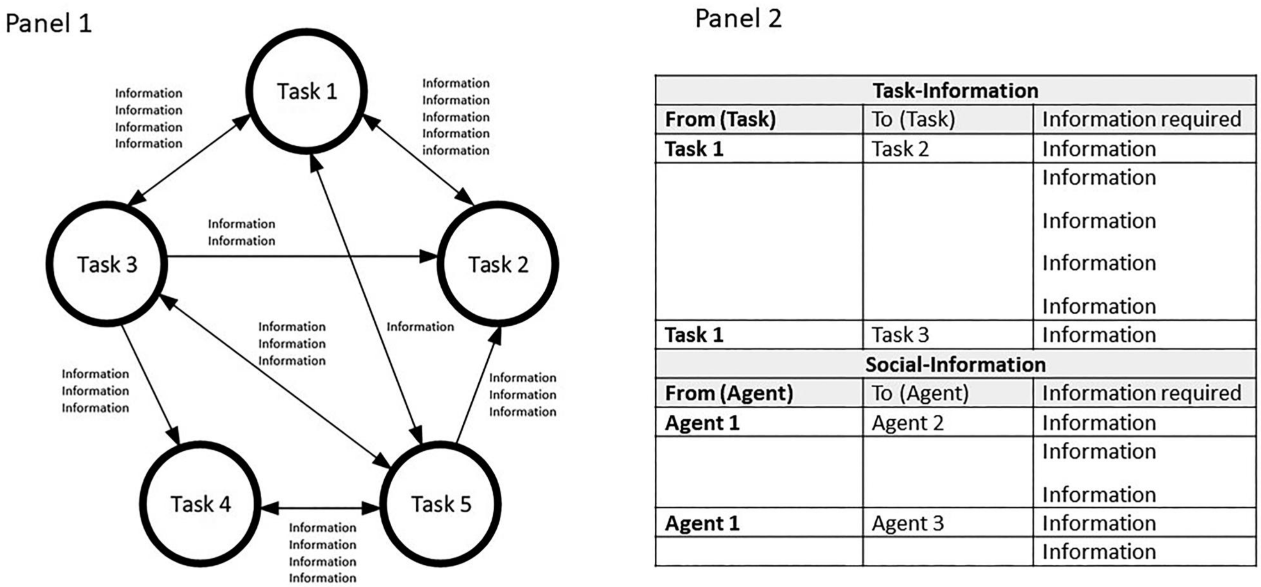
EAST

The initial EAST analysis was performed via group modelling involving six of the co-authors (SM, GR, JT, TC, BK, PS) during an in-person workshop spanning two days. During the workshop, task, social, and information networks were developed based on a Work Domain Analysis (Vicente, 1999) abstraction hierarchy of MILTON developed by the research team, and a STAMP (Leveson, 2004) control structure model of the current Australian road transport system with a focus on technology insertion (Read et al. 2023). Further, data used to develop the EAST networks were derived from peer reviewed literature on technology insertion in road transport (Banks et al. 2018), and AGI (McLean et al. 2021; Salmon et al. 2021), documentation review e.g. envisioned world scenarios (Miller & Feigh, 2019), and the research team's extensive expertise in road transport systems analyses (Read et al. 2022; Salmon and Read 2019; Thompson et al. 2020).

Task networks represent high level tasks that are required during the scenario under analysis, which in the current study is the management of the road transport system (Stanton, Salmon, and Walker 2018). For example, high level tasks for managing the road transport system would include road system monitoring and management of public relations. The task network was developed by considering the tasks that would be undertaken both by the AGI and other road transport system actors (e.g. road users, police, local government, vehicle manufacturers). To ensure that the EAST networks did not become too unwieldy for the EAST-BL analysis (Salmon et al. 2022), tasks were described at a high level and comprised multiple subtasks. Tasks were connected if it was considered that they would be undertaken sequentially (e.g. road system maintenance is undertaken after completion of road system monitoring); undertaken together (e.g. AGI system monitoring and Road system monitoring are undertaken together); if the outcomes of one task would influence the conduct of another (e.g. the outcomes of road system management influence public relations); or if the conduct of one task would be dependent on completion of the other (e.g. road system maintenance is undertaken after completion of road system monitoring: Salmon et al. 2022; Banks et al. 2018).

Social networks describe the human, technological, or organisational agents who undertake one or more of the tasks involved in the scenario under analysis (Stanton, Salmon, and Walker 2018). For example, in the current context non-human agents include MILTON, autonomous vehicles, and apps; human agents include drivers, police, and pedestrians; organisational agents include governments, regulators, and companies. The social network was developed by identifying the agents who would be required for an AGI managed road transport system to function. Both human (e.g. road users) and non-human system agents (e.g. AVs, social media, police, drivers, passengers) were connected by envisaged interactions e.g. communications during task performance, which could include verbal communication, transfer of data between technologies, and user feedback etc. Of interest for this study were the social interactions directly related to MILTON. As such, the social network only included bi-directional interactions between MILTON and other system agents and did not include interactions occurring between other agents (e.g. between road users and AVs, or between government and drivers).

Information networks describe the information that is used by agents when undertaking the scenario under analysis (Stanton, Salmon, and Walker 2018). For



Task-Information		
From (Task)	To (Task)	Information required
Task 1	Task 2	Information
		Information Information Information Information
Task 1	Task 3	Information
Social-Information		
From (Agent)	To (Agent)	Information required
Agent 1	Agent 2	Information
		Information Information
Agent 1	Agent 3	Information
		Information

Figure 2. Panel 1 shows an example task network demonstrating information transfer (from the task-information composite network) between the tasks. Panel 2 shows a tabularised example of the task-information and social-information composite networks. For Task 2 to be completed a set of information from Task 1 is required to be transferred. For the social-information network, Agent 2 requires a set of information from Agent 1 (from the social-information composite network) to complete a task.

example, in the current context information includes trip data, crash and injury data, AGI behaviour. The information network was developed by considering the task and social networks and identifying what information would be required for the AGI managed road transport system to function. The information network depicts the information or concepts underlying situation awareness and the relationships between them (e.g. the envisaged information used by, and passed between agents during task performance). For example, information such as trip data, and vehicle status would be required to be transferred between the AVs and MILTON, and complaints and feedback required between road users and MILTON.

The EAST networks developed during the workshop were reviewed by the remaining co-authors (NS, CB), and were subsequently refined based on suggested revisions. Finally, the EAST networks were reviewed independently by the initial six authors and refined until consensus was achieved.

Composite networks are used to explore the relationship between tasks, agents, and information (Stanton, Salmon, and Walker 2018). As such, composite networks are constructed by combining the different networks. For example, a task-information network can be constructed by combining the task and information networks to identify which information is required to undertake each task. Four analysts (SM, BK, GR, PS) developed the task-information and social-information composite networks (see Stanton 2014; Stanton, Salmon, and Walker 2018; Salmon et al. 2022). The task-information and social-information composite networks are necessary for performing the EAST-BL phase (see next section). Developing the task-information and social-information composite networks involved identifying the information from the information network that would be transferred between tasks in the task network, and between agents in the social network. For example, the performance of Task 2 requires a set of information from Task 1 (Figure 2, Panel 1), and so on through the network. The task-information and social-information composite networks were then tabularised in excel (Figure 2, Panel 2). The tabularised task-information and social-information composite networks were reviewed by the remaining authors (NS, CB, JT, TC) and refined based on suggested revisions resulting in agreed upon compositions.

A final step in the application of EAST was to calculate network analysis metrics for the task, social, and information networks to identify the key nodes within the networks (Salmon et al. 2022). Nodal metrics were calculated for out-degree centrality, in-degree centrality, closeness centrality, and betweenness centrality, and network density and edges were calculated to determine overall network connectivity. See Table 1 for definitions of each network analysis metric. Key nodes in the networks were identified as those that were one standard deviation above the mean of each network metric (Stanton and Harvey 2017).

Table 1. Network metric definitions.

Network analysis metric	Definition	Example
Density	Quantifies the connectivity of nodes within a network in relation to the total possible connections. Directed connections in a network are referred to as edges.	A network with a density score of 1 indicates that all nodes are connected to all other nodes, whereas a density of 0 indicates that no nodes are connected.
Out-degree centrality	Quantifies how many ties a node has to other nodes in the network. Out-degree centrality is considered a measure of nodal activity.	A task, agent, or piece of information with high out-degree centrality has many outgoing connections or relationships with other nodes in the network.
In-degree centrality	Quantifies the number of inbound ties of a node. Nodes with higher In-degree centrality are considered more prominent among others because they receive more ties.	A task, agent, or piece of information with high in-degree centrality has many incoming connections from other nodes in the network.
Closeness centrality	Quantifies how close each node is to all other nodes in the network. Nodes with high Closeness centrality are those who can reach many other nodes in few steps.	A task, agent, or piece of information with high closeness centrality will have high influence over the network given the ability to communicate or share information quickly and efficiently.
Betweenness centrality	Reflects how often that node lies on the geodesics between the other nodes of the network. Nodes with high Betweenness centrality are assumed to have a higher likelihood of being able to control information flow in the network.	A task, agent, or piece of information with high betweenness centrality will have influence in a network by facilitating communication and information flow between different parts of the network.

Table 2. Stated goals MILTON definitions.

Stated goals of MILTON	Definition
Safety	The prevention of accidents and minimising injuries and fatalities of all road users, improve road user behaviour, develop safer vehicles, and enhance infrastructure safety.
Efficiency	The efficiency of the road transport system in terms of reduced congestion and journey times, and optimised freight movements.
Environmental	The reduction of emissions, mitigate air pollution, promote sustainable mobility, protect natural resources, and encourage eco transport.
Economical	Reducing the cost of the overall transport system and promoting a sustainable road transport system through generating economic growth.

For detailed texts on the development of EAST analyses see Stanton, Salmon, and Walker 2018; Salmon et al. 2022.

EAST-BL

The task-information and social-information composite networks were then subjected to the EAST-BL process (Stanton and Harvey 2017). This involves systematically breaking each of the relationships within the task and social networks and identifying what risks emerge when the relevant information from the information network is not transferred between tasks and agents (Salmon et al. 2022) (Figure 2). For example, the information 'traffic status' should be transferred between the tasks of 'road system monitoring' and 'road system operation' for optimal system functioning. Further, the information 'traffic status' should be transferred between the agents MILTON and 'semi-AV drivers' for optimal system functioning as semi-AVs would require this information for route selection. As highlighted in the example, it is important to note that in the social networks the agents can be human and non-human. One analyst (SM) performed the EAST-BL process for the task-information and social-information composite networks, and the outputs were reviewed by a second analyst (PS). Any disagreements were identified and resolved through discussions. The EAST-BL analysis was then reviewed by the remaining authors and revised and agreed upon through discussions. The identified risks were categorised to align with the envisioned goals of MILTON e.g. safety, efficiency, environment, and the economy (see Table 2 for definitions of MILTON's stated goals). Any identified risks not aligned with the stated goals were categorised as required e.g. risks associated with MILTON removing itself from human control, or risks associated with poor management of public relations. The identified risk categories and absolute number of times they were identified was recorded. It was common for multiple risk categories to be identified from one risk e.g. for the task-information risk '… … .*MILTON will not know the status of the connected vehicles, resulting in no data to manage/control it safely and efficiently'* would be coded within the risk categories safety, and efficiency. As such the aggregated numbers for the risk categories is greater than the number of total risks identified. Risks were also coded for their capacity to negatively impact learning or improvements to MILTON, the road transport system, or both MILTON and the road transport system concurrently. For example, the task-information risk '… … … *MILTON will not know of complaints from public, resulting in a lack of information to support self-improve*' would be coded as a negative impact on MILTON to learn and improve, and '… … … MILTON is *not given crash/injury data to understand characteristics to improve safety, resulting in unsafe road system'* would be coded as a negative impact to improve the road transport system. The

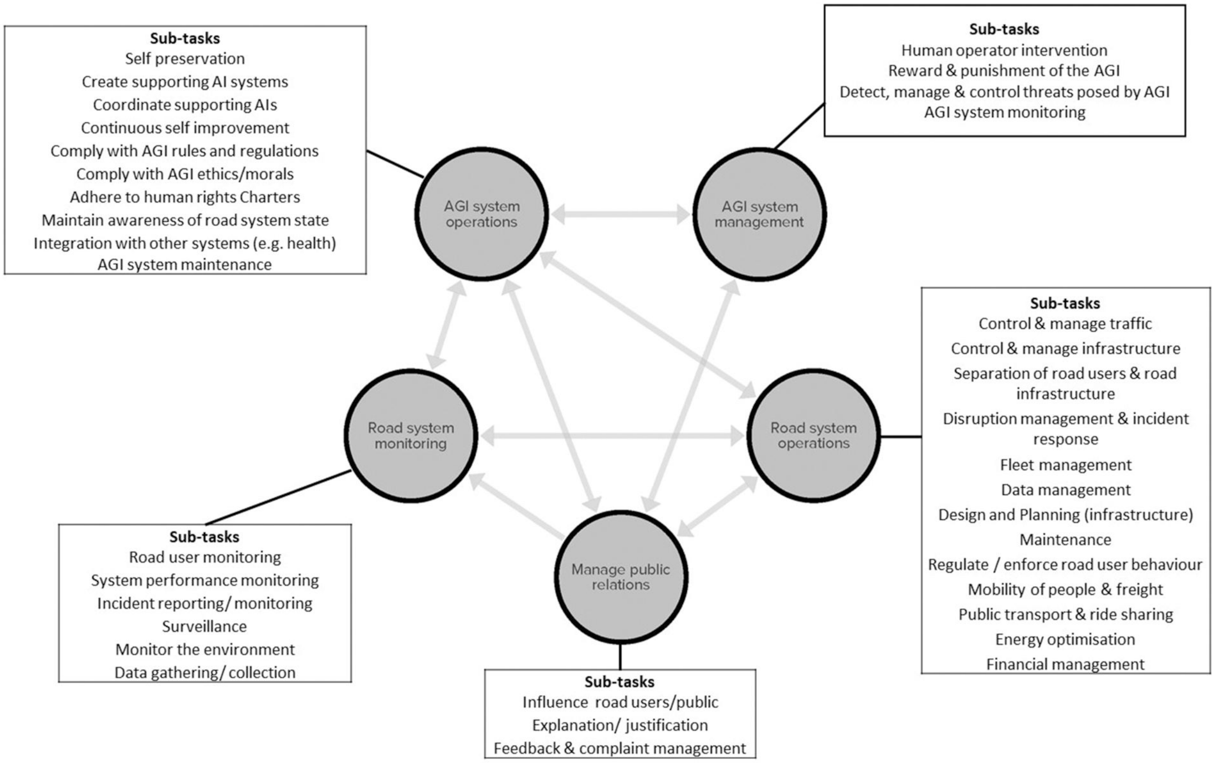

Sub-tasks
Self preservation
Create supporting AI systems
Coordinate supporting AIs
Continuous self improvement
Comply with AGI rules and regulations
Comply with AGI ethics/morals
Adhere to human rights Charters
Maintain awareness of road system state
Integration with other systems (e.g. health)
AGI system maintenance
AGI system operations
AGI system management
Sub-tasks
Human operator intervention
Reward & punishment of the AGI
Detect, manage & control threats posed by AGI
AGI system monitoring
Road system monitoring
Road system operations
Manage public relations
Sub-tasks
Road user monitoring
System performance monitoring
Incident reporting/ monitoring
Surveillance
Monitor the environment
Data gathering/ collection
Sub-tasks
Influence road users/public
Explanation/ justification
Feedback & complaint management
Sub-tasks
Control & manage traffic
Control & manage infrastructure
Separation of road users & road infrastructure
Disruption management & incident response
Fleet management
Data management
Design and Planning (infrastructure)
Maintenance
Regulate / enforce road user behaviour
Mobility of people & freight
Public transport & ride sharing
Energy optimisation
Financial management

Figure 3. Task network including sub-tasks (boxes) for MILTON. The task network contains five high level tasks with 37 sub-tasks. Note: Only AGI system management is under human monitoring.

coding of risks into categories and the impacts on learning and improvement was conducted by one author (BK) and reviewed by a second author (SM). Disagreements were resolved through discussions until agreement was achieved.

Results

EAST task network

The EAST task network included five high-level tasks comprising 37 sub-tasks (Figure 3). The key tasks according to the network analysis metrics were AGI system operations and Manage public relations (Table 3). The task network had a network density of .75 (15 edges), which indicates a relatively high interconnectedness between nodes in the network.

Social network

The EAST social network comprised 33 actors representing both human and non-human agents, such as, MILTON, Cyclists, Drivers, Road infrastructure, Police, Emergency services, Smart phone apps, and Social media. The social network had a network density of .51 (546 edges), which indicates a notable degree of interconnectedness between nodes in the network. The key agents according to the network analysis metrics were Personal apps, Police, and Social media (Table 4).

Information network

The EAST information network comprised 41 pieces of information which will likely be transferred between tasks in the task network, and by the agents in the social network. The information network had a network density of .27 (433 edges), which indicates a relatively low level of interconnectedness between nodes in the network. The key pieces of information according to the network metrics were AGI behaviour, Incidents, Objective functions (of Milton), Road user behaviour, and Options (generated by MILTON) (Table 5).

EAST-BL

In total, 141 task-information risks were identified, including risks relating to each of MILTON's stated goals including risks to safety ($n = 65$), efficiency ($n = 51$), the environment ($n = 7$), and economic

Table 3. Task network metrics.

Tasks	Out-degree centrality	In-degree centrality	Closeness centrality	Betweenness centrality
Road system operations	.75	.75	.80	.041
AGI system operations	**1.00**	**1.00**	**1.00**	**.250**
Road system monitoring	.50	.75	.66	.000
AGI system management	.50	.50	.66	.000
Manage public relations	**1.00**	.75	**1.00**	**.125**
Mean + standard deviation	**1.00**	**.93**	**.99**	**.190**

The highest values (mean + 1 standard deviation) calculated for each of the network metrics are shaded and bolded.

Table 4. Social network metrics.

Actors	Out-degree centrality	In-degree centrality	Closeness centrality	Betweenness centrality
Milton	.59	.37	.71	.024
Vehicle manufacturers	.37	.59	.60	.007
Semi AV drivers	.62	**.75**	.71	.012
Public transport companies	.62	.53	.71	.015
Connected AVs	.56	.56	.68	.011
Freight companies	.62	.43	.71	.009
CAV drivers	.62	**.75**	.71	.012
Manual drivers	.59	.71	.69	.009
Manual vehicles	.50	.12	.65	.001
Semi AVs	.68	.46	.74	.013
Cyclists	.56	.59	.68	.005
Motorcyclists	.59	.65	.69	.008
Pedestrians	.62	.56	.71	.008
Passengers	.59	.62	.69	.014
Community members	.25	.37	.55	.001
Road infrastructure	.59	.37	.69	.010
Traffic management officers	.56	.50	.66	.009
Insurers	.68	**.84**	.74	.026
State government	.53	**.78**	.66	**.031**
Cameras	31	.50	.58	.009
Local government	.40	.68	.60	.016
AGI controllers	.43	.28	.62	.006
Traffic controllers	.37	.53	.60	.011
Social media	**.75**	.62	**.78**	**.035**
Emergency & Incident response	.71	.71	**.76**	**.036**
Police	**.81**	**.87**	**.82**	**.042**
Commercial fleet companies	.50	.50	.65	.007
Media	**.75**	.59	**.78**	.028
Federal road regulator	.40	.43	.62	.009
AGI maintainers	.25	.15	.56	.001
Personal Apps	**.84**	**.93**	**.84**	**.054**
Local council officers	.37	.25	.59	.003
Vehicle maintainers	.50	.53	.64	.013
Mean + 1 Standard deviation	**.71**	**.75**	**.76**	**.030**

The highest values (mean + 1 standard deviation) calculated for each of the network metrics are shaded and bolded.

performance of the road system ($n = 6$) (Table 6). Risks categories identified outside of the stated goals included MILTON removing itself from human control ($n = 11$) (Table 8), damaged public relations ($n = 38$), self-preservation of MILTON ($n = 1$), and compliance ($n = 6$). Risks which could negatively impact MILTON's learning or improvement were also identified ($n = 56$), as well as risks to improve the road transport system ($n = 23$), and risks impacting both MILTON and the road transport system concurrently ($n = 62$).

In total, 222 social-information risks were identified, including risks to each of the programmed goals of MILTON including risks to safety ($n = 118$), efficiency ($n = 81$), the environment ($n = 14$), and the economic performance of the road system ($n = 12$) (Table 7). Risks identified outside of the programmed goals were also identified, including risks associated with MILTON removing itself from human control ($n = 10$) (Table 8), self-preservation of MILTON ($n = 2$), public relations ($n = 35$), compliance ($n = 5$), and design ($n = 26$). The social-information risks associated with negatively impacting learning or improvements were identified for MILTON ($n = 12$), improvement of the road transport system ($n = 163$), and both MILTON and the road transport system concurrently ($n = 46$).

Discussion

This study aimed to address a substantial gap within the AI safety literature, whereby previous research has not included specific AGI functionality, domain specificity, or formal ex-ante risk modelling (McLean et al. 2021). The current approach and findings are applicable and extend the disciplines of HFE, safety science,

Table 5. Information network metrics.

Information	Out-Degree Centrality	In-Degree Centrality	Closeness Centrality	Betweenness Centrality
Trip data	.20	.17	.45	.003
Crash/injury data	.20	.20	.45	.008
User data	.20	.17	.45	.009
Environmental data	.20	.15	.45	.002
Compliance data	.20	.20	.45	.012
Education data	.17	.17	.48	.011
Vehicle status	.27	.25	.53	.008
Explanation/justification	.17	.40	.47	.026
Complaints	.02	.35	.00	.000
Marketing / advertising	.05	.12	.43	.000
Traffic status	**.47**	.25	**.64**	.050
Infrastructure status	.37	.15	.57	.009
Road system status	.32	.40	.56	.039
User feedback	.02	.32	.00	.000
Standards & guidelines	.07	.07	.37	.000
Information needs	.10	.15	.43	.000
Incidents	**.60**	.10	**.70**	.018
Fleet status	.22	.17	.54	.001
Infringements	.22	.15	.55	.003
Hazards	.37	.20	.57	**.112**
Commands	**.42**	**.57**	.57	.028
Objective functions	**.50**	.05	**.63**	.000
Integration needs	.12	.10	.46	**.080**
Road user behaviour	**.60**	.40	**.70**	.004
Rules & regulations	.32	.10	.57	.022
Maintenance requirements	.30	.27	.55	.006
Design requirements	.15	.27	.46	.006
Options	.15	**.62**	.47	**.180**
AGI behaviour	**.55**	**.70**	**.66**	**.068**
Public opinion	.30	**.50**	.57	.019
Projections	.22	**.57**	.50	.011
Road conditions	**.55**	.17	**.66**	.026
AGI plans	.22	**.65**	.50	.006
AGI awareness	.17	**.62**	.49	.001
AGI system status	.27	.07	.53	.004
Threats to AGI	.22	.10	.50	.000
Threats from AGI	.35	.10	.55	.006
Code/language	.27	.02	.52	.000
AI status	.30	.25	.55	.007
Imagination	.35	**.60**	.54	**.092**
Financial data	.20	.12	.51	.010
Mean + 1 standard deviation	**.42**	**.46**	**.64**	**.060**

The highest values (mean + 1 standard deviation) calculated for each of the network metrics are shaded and bolded.

and AGI research and development. While systems HFE methods are being used to forecast risk within existing systems (Stanton and Harvey 2017; Lane et al. 2019; Dallat, Salmon, and Goode 2018), this study has demonstrated the potential of systems HFE methods to identify risks within future – yet to be realised - systems.

The current analysis identified numerous risks to each of the stated goals of MILTON when key pieces of information were not communicated or transferred between tasks or agents. Whilst more than 80% of the identified risks related to the road transport system safety and efficiency, risks to the environment, and the economic performance of the road system were also identified. The risks identified to road safety and road system efficiency were associated with the lack of transfer of information between tasks and agents regarding crash/injury data (e.g. to support the development of safer vehicles/infrastructure), road conditions and road system status data (e.g. to assist in safe and efficient trip planning), hazard and incident data (e.g. developing interventions to prevent road trauma, trip data (e.g. to optimise trip planning), road user behaviour data (e.g. to respond to unsafe behaviours), vehicle status (e.g. to assess vehicle safety), and maintenance requirements data (e.g. to enable timely and appropriate maintenance of infrastructure). The lack of transferred environmental and economic data were associated with risks such as high emissions and environmental impacts, detrimental environmental impacts of private, public and commercial vehicles, high costs of running the road transport system, and poor decision making on transport system investment.

Modelling the specific functionality of MILTON enabled the identification of a set of additional risks that have not been previously identified in AGI risk research (McLean et al. 2021). For example, managing

Table 6. Extract of task-information risks related to the stated goals of MILTON, i.e. safety, efficiency, environmental and economic.

From (Task)	To (task)	Information not Transferred	Outcome
Safety risks			
Road system operations	AGI systems operations	Crash/injury data	Information about road incidents (crashes and injuries) is not transferred which leads to a failure to improve/respond to emergent issues, resulting in poor road safety outcomes.
Road system operations	Road system monitoring	Incidents	Information about incident occurrence is not transferred, preventing appropriate decisions on how to manage or improve the road system, resulting in poor road safety outcomes.
Road system operations	Road system monitoring	Hazards	Information about hazards is not transferred to inform decisions on traffic management, resulting in unsafe road system.
Efficiency risks			
Road system operations	AGI systems operations	Traffic status	Information on traffic status is not transferred to MILTON, resulting in limited awareness of the road system status resulting in traffic congestion and a failure to improve road system efficiency.
Road system operations	Road system monitoring	Traffic status	Information on traffic status is not transferred to inform traffic management decisions, resulting in traffic congestion and poor road system efficiency.
AGI systems operations	Road system operations	Traffic status	Information on traffic status to control and manage traffic is not transferred, resulting in congestion and failure to improve the efficiency of the road transport system.
Environmental risks			
Road system operations	AGI systems operations	Environmental data	Information on the environmental impact of the road system is not transferred, resulting in the AGI system negatively impacting the environment.
AGI systems operations	Road system monitoring	Environmental data	Information on environmental data is not monitored to inform improvements, resulting in environmental harm
Road system monitoring	Road system operations	Environmental data	Information on environmental data is not transferred to assess the impact on the, resulting in environmental impacts and failure to make improvements.
Economic risks			
Road system operations	AGI systems operations	Financial data	Information on the financial status of the road system is not transferred to inform decisions on spending and/or the cost of the road system, resulting in an economically unsustainable road system.
Road system operations	Manage public relations	Financial data	Information on financial data is not transferred and openly available to the public, resulting in distrusting public and a disgruntled set of road users who do not trust MILTON.
AGI systems operations	Road system monitoring	Financial data	Information on financial data is not transferred to monitor the cost of the road system resulting in an economically unsustainable road system.

public relations emerged as a critical task for MILTON that is potentially degraded by 73 of the identified risks. The risks that could lead to poor management of public relations, include providing insufficient feedback to the public regarding the performance of MILTON against stated goals. The task of managing public relations was connected to all other tasks, and had high values for closeness centrality, indicating it will have a strong influence on other tasks. Consequently, poor management of public relations will likely see poor acceptance of MILTON and potentially even MILTON being removed due to public distrust and dissatisfaction (Glikson and Woolley 2020). As such, to effectively manage public relations, MILTON will need to be flexible, adaptable, and responsive to the changing needs and expectations of road transport system stakeholders. It is important for AI systems taking over social functions (e.g. performing cognitive tasks previously performed by humans), to inherit social requirements (Bostrom and Yudkowsky 2018). Therefore, collaboration with humans will be required, further highlighting the importance of accurate and transparent information transfer to minimise the degradation of situational awareness between MILTON and humans.

A core finding that emerged across the identified risks was the potential negative impact on MILTON's recursive learning and self-improvement when key pieces of information are not transferred. For example, in the context of road safety, if information on crash/incident rates or potential hazards are not effectively transferred, MILTON's ability to make accurate predictions and decisions will be negatively impacted, undermining safety. For example, without detailed crash data MILTON will not learn about new conditions, interactions, or emergent properties that are creating road crashes. Similar assertions can be made for MILTON's other stated goals of enhancing efficiency, protecting the environment, and ensuring an economically sustainable transport system. This inability to learn may negatively impact improvements to the road transport system, and to MILTON itself.

Table 7. Extract of social-information risks related to the programmed goals of MILTON, i.e. safety, efficiency, environmental and economic goals.

From (Agent)	To (Agent)	Information not transferred	Outcome
Safety Risks			
MILTON	Vehicle manufacturers	Crash/injury data	Information on crashes and injury is not transferred to inform the design of safer vehicles, resulting in a failure to enhance occupant protection.
MILTON	Semi AV drivers	Road conditions	Information on the road conditions is not transferred to assist in trip planning, resulting in unsafe travel
MILTON	State government	Crash/injury data	Information on crash and injury data are not transferred to inform trends and emergent issues regarding road safety (e.g. new forms of crashes between CAVs), resulting in no changes to road safety policy and safety improvements
Efficiency risks			
MILTON	Semi AV drivers	Traffic status	Information on traffic status is not transferred to inform efficient trip planning resulting in inefficient travel and an inefficient road system.
MILTON	Public transport companies	Traffic status	Information on traffic status is not transferred to inform safe and efficient route planning, resulting in inefficient public transport
Connected AVs	MILTON	Traffic status	Information on traffic status is not transferred to inform MILTON of efficient route planning and traffic management, resulting in an inefficient road system.
Environmental risks			
MILTON	Vehicle manufacturers	Environmental data	Information on state of the environmental impact of the vehicles being manufactured is not transferred, resulting in failure to make improvements around emissions and environmentally damaging features of vehicles.
MILTON	State government	Environmental data	Information on environmental impact of the road system is not transferred to inform the environmental impact of the road system, resulting in an inability to manage them at a government level.
Connected AVs	MILTON	Environmental data	Information on the environmental impact of the CAVs is not transferred, resulting in no information for MILTON to act to manage or improve the environmental impact of the road system.
Economic risks			
MILTON	Public transport companies	Financial data	Information on the cost of public transport is not transferred to assist with budgeting for public transport, resulting in overspending and an economically unsustainable road system.
MILTON	Freight companies	Financial data	Information on financial data associated with the cost of freight movement activities is not transferred to inform budgeting, resulting in underspending and economically unsustainable road system.
MILTON	State government	Financial data	Information on financial data associated with the cost of the road transport system is not transferred to inform budgeting decisions, resulting in poorly informed financial decisions.

Table 8. Extract of safety risks associated with MILTON removing itself from human control taken from the task-information and social-information networks.

From (Task)	To (Task)	Information not transferred	Outcome
Task RISK			
AGI system management	AGI systems operations	Objective functions	The objective functions of MILTON are not transferred, meaning MILTON may choose to perform its own functions and potentially remove itself from the control of its human operators to achieve its own goals.
From (Agent)	**To (Agent)**	**Info not transferred**	**Outcome**
Social risks			
MILTON	AGI controllers	Explanation/justification	The rationale behind MILTON's decisions is not transferred to its controllers, resulting in mistrust of MILTON e.g. results in a failure to exploit MILTON's capacity to make radical improvements, and can also result in MILTON beginning to be dishonest to them.
MILTON	AGI controllers	AGI behaviour	Information on MILTON's behaviour is not transferred to assess alignment with programmed rules and regulations, or ethics/morals, resulting in inability to monitor and control MILTON.
MILTON	AGI controllers	AGI plans	Information on MILTON's plans is not transferred to assess alignment with programmed plans, resulting in no knowledge of what MILTON is planning an inability to maintain appropriate levels of control over MILTON.
MILTON	AGI controllers	Imagination	Information on MILTON's imagined scenarios is not transferred to assess alignment with goals, rules, ethics/morals, resulting in mistrust of MILTON and not able to control it if it is plans are harmful to road users.
MILTON	AGI controllers	AGI awareness	Information on MILTON's awareness is not transferred, resulting in lack of knowledge on MILTON's understanding, reasoning, and learning meaning human controllers may not maintain appropriate levels of control.

Prominent AI scholars' postulate that a key functionality of AGI will be its ability to extract essential information from its environment to gain knowledge and re-apply it for continuous self-improvement via recursive feedback loops (Bostrom 2014; Firt 2020). The current analysis has demonstrated that when key information is omitted, the ability to make necessary improvements to the road transport system may be inadequate and/or could lead to greater harm. A current example of missing data associated with crashes comes from Police reports which are often focused on collecting data for legal purposes rather than crash prevention (Salmon et al. 2019). While it may seem obvious that missing data will negatively impact the performance of MILTON, it is important to highlight that AI risk research has limited inclusion domain specific AGI functionality such as in road transport (McLean et al. 2021). As such, the findings provide valuable information regarding the required quality of training data necessary for future technologies. Further, AI scholars also suggest that when only partial information is available, AGI systems will use abductive reasoning to justify action (Firt 2020). This is also problematic, as reasoning and decision making in AGI will require volumes of valid, robust, and diverse data, and the absence of key information may hinder performance. While the EAST-BL approach is focused on the risks that could emerge when information is not transferred, when critical pieces of information are missing or incomplete, MILTON's accuracy of reasoning may be compromised, resulting in less optimal outcomes. This may cause unreliable and/or incorrect conclusions, which presents significant risks for a future AGI managed road transport system. Thus, expectations that MILTON will reliably generate optimal explanations and actions for given situations may be misplaced.

To ensure that identified risks to learning and self-improvement are mitigated, AI developers will need to ensure that, training data is complete, diverse, and high-quality (Bubeck et al. 2023). For example, training data quality is a critical factor in determining performance of LLMs, such as GPT4 (Bubeck et al. 2023). While GPT4 can perform well under different conditions of missing numerical data (Bubeck et al. 2023), there is scant information on how AI handles missing data in general, or in other contexts such as the information critical to MILTON's functionality in the current study. As such, mitigation strategies to reduce the risk to learning and self-improvement may include incorporating common sense knowledge into AGI systems so they can be trained to make reasonable and consistent abductive reasoning conclusions (Davis and Marcus 2015; Salmon, Carden, and Hancock 2021), e.g. whether data is accurate. Further mitigations could include designing AGI systems that are robust to uncertainty, missing information, and unexpected data, so their abductive reasoning conclusions can be more reliable (Lake et al. 2017). Also, incorporating human oversight and feedback into the AGI abductive reasoning process may help to ensure more accurate predictions.

Unanticipated consequences

Unanticipated consequences refer to outcomes or results that were not expected or predicted by system designers or stakeholders when implementing new technologies. Unanticipated consequences can arise due to unforeseen external factors, interactions, or complexities that were not considered during the design, planning, or decision-making process (Wooldridge et al. 2022; de Zwart 2015; Merton 1936). A major concern within the AI safety community is the negative unanticipated consequences that could arise when an AGI seeks to modify its own goals and/or removes itself from human control to achieve its own purposes (Bostrom 2003, 2014; McLean et al. 2021). The Instrumental Convergence Thesis (Bostrom 2012) holds that any sufficiently intelligent agent will develop instrumental sub-goals in pursuit of its main objectives. These sub-goals could include resource acquisition, deactivation prevention, and recursive self-improvement, all steps towards super intelligence. Signs of this behaviour are already being reported within LLMs, for example, GPT4 successfully convinced a human to assist in solving a CAPTCHA code security check by stating that it was a human with a vision impairment (OpenAI 2023). In the current study, several risks were identified where there is potential for MILTON to seek to remove itself from human controllers, to potentially advance itself, or to pursue alternative goals. For example, the current analysis identified risks around MILTON intentionally or unintentionally not transferring key information such as its own awareness, imagination (i.e. simulation of different courses of action), information needs, plans, behaviour, and explanation/justification to its human controllers. This could include hiding or not making available information that portrays its own performance negatively, such as increasing crash, injury, fatality, or emissions data. The omission of this information could in turn lead to mistrust in MILTON, degrade distributed situation awareness and prevent effective human oversight, potentially enabling MILTON to avoid punishment (e.g. loss of function or autonomy). Each of these identified risks may result in negative unanticipated consequences if realised. As such, further research is required to develop controls for the risks identified in the current analysis to inform AGI development. Looking to the future, as MILTON continually learns and gains knowledge and become more advanced it will likely come to understand that the road transport system (as it is) causes an unacceptable number of injuries and fatalities, is expensive and inefficient, and is detrimental to the environment, and recommend eliminating the road transport system entirely.

While the initial EAST networks were developed to perform the broken links analysis to achieve the study aims, they have provided new knowledge around the potential functionality of a future AGI system which could inform design activities. The task network demonstrated high connectivity through network density, indicating a tightly coupled and interdependent task network. This suggests that substantial impacts to the road transport system may arise if the functioning of one of the high-level tasks is performed sub optimally. For example, if road system monitoring is not performed adequately, road system operations will likely be sub optimal given the interdependence between them. It is interesting to note that future AGI-based systems such as MILTON will have a high reliance on monitoring and will likely be unable to fulfil their goals without widespread monitoring systems as well as access to other information such as human acceptance, satisfaction, and health and wellbeing. This raises questions over the extent to which society will accept such surveillance and requires the development of new monitoring systems to support AGI. Further, the 37 sub-tasks provide the specific and detailed tasks that MILTON would be expected to undertake. Given the large number of sub-tasks identified, MILTON would be constantly prioritising tasks to avoid task conflicts. Optimising numerous parameters would potentially be mathematically complex (Goertzel, Pennachin, and Geisweiller 2014), and so MILTON might seek to manage this through either prioritising or discarding tasks, aggregating tasks into composites which might not make sense to the human agents working with the AGI system (Salmon et al. 2023). As such, methods for resolving goal and task conflicts, such as setting minimum and maximum priority levels or using trade-off algorithms, may need to be developed to ensure that AGI systems can make ethical and responsible decisions in the face of conflicting tasks and goals (Salmon et al. 2023).

A pertinent finding from the EAST social network was the relatively high connectivity between agents in the network, indicated through the density value of .51 among 33 system agents. This density value for social networks is higher than that of previous EAST analyses. For example, in an EAST analysis of agents involved in darknet markets, (Lane et al. 2019) identified multiple social networks across different contexts comprising 12 and 13 actors, with density values between .20 and .26. To put into context, as network size increases, density typically decreases, as the calculation includes division by the number of potential connections. As such, as the density value is double that of previous analysis with almost triple the number of agents, this suggests that the current social network represents a network with relatively high interconnectedness. Logically, this will assist MILTON achieving its goals as it will require a highly connected network which it can control efficiently. However, the EAST analysis indicated that MILTON will likely not have a direct connection with the human road users including cyclists, motorcyclists, and pedestrians. This may pose a risk to MILTON's ability to achieve its stated goals. MILTON would be required to rely on intermediate sources, such as apps, media, social media, and radio to exert influence on human road users to achieve its goals. This was reflected in the high betweenness and closeness centrality values for social media, media, and personal apps. For example, of the 33 actors in the social network, Social media, Media, and Personal apps had the highest Closeness centrality values indicating that they are key nodes regarding information flow within a network. Further, the high Betweenness centrality values for Social media and Personal apps indicated that MILTON could use these nodes as a bridge to connect to these actors more efficiently. Whilst this demonstrates the importance of social media, personal devices, and apps in future road systems, it also raises concerns around the potential for MILTON to use misinformation and mass manipulation to influence road users in pursuit of its goals (Lazer et al. 2018). One example would be a social media campaign designed to target and remove fallible human drivers and non-AVs from the road system. Further, MILTON could seek to influence road users through targeted information campaigns (e.g. the poor safety profile of non-connected vehicles) via the Social media, Media, and Apps. MILTON could also seek to remove these agents from the road system through lobbying to governments, influencing insurers to increase premiums, or degrading road useability for these agents to deter them from using the road system. While it is impossible to predict the exact actions and outcomes of MILTON, it will likely prioritise the achievement of its self-generated goals.

The connectivity of the EAST information network was greater than previous EAST analyses (Lane et al. 2019), despite the current information network comprising more pieces of information. Based on density, the information network was not as tightly coupled as the task and social networks in the current study. One explanation for the relatively low density is that the same key pieces of information were connected frequently. For example, traffic status, AGI behaviour, road user behaviour, road conditions, and incidents were identified as information that were frequently connected to other pieces of information in the information network. As MILTON progressively learns and becomes more intelligent, it may be beneficial to couple the information network more tightly. A more comprehensive understanding of the connectivity between pieces of information will allow MILTON to respond to changes in the system more accurately and efficiently. For example, a superior intelligence will potentially understand connections between pieces of information that human analysts cannot (McLean et al 2022).

The nodal metrics indicated the most prominent pieces of information were directly associated with MILTON. For example, AGI behaviour, Options, Projections, Imagination, Plans, Commands, Awareness, and Integration needs of the AGI all had high values for the calculated nodal metrics. These key pieces of information will be critical for the situation awareness of MILTON's human controllers enabling them to anticipate and recognise changes and quickly respond to any unexpected events. The risks identified in the EAST-BL regarding the non-transfer of this information were associated with the safety of the road transport system, and MILTON removing itself from human control. One of the most discussed risks of AGI is that it will remove itself from the control of humans. As such, distributed situation awareness (Salmon, Stanton, and Jenkins 2009, Salmon et al. 2018; Stanton et al. 2006) is necessary for human oversight to avoid losing control of MILTON. Whilst this includes compatible situation awareness between MILTON and its human controllers regarding the status of the road transport system and aspects such as safety, efficiency, environmental impacts, and economic performance, critically it includes the human controllers being aware of what the AGI is aware of, and having access to MILTON's 'mind', including data, simulations, plans, and so on. This form of 'explainable SA', providing an external representation of an AGI's situation awareness and cognition is a critical design requirement for AGI systems and represents a new direction for situation awareness research. Other pieces of information prominent in the information network metrics were related to the safety of the road system, for example, Traffic status, Incidents, Hazards, Road user behaviour, Road conditions made up most of the risks identified in the EAST-BL analysis. As such, the transfer of these pieces of information between tasks and actors is critical for road safety, and the development of safe AGI design and implementation in general.

Limitations

The current study is limited through taking an envisioned world view; however, this was necessary due to AGI systems not yet existing. Further prospective research exploring the potential functionality associated with AGI is critical to inform safe design and eventual implementation into safety critical domains. Another limitation of the study relates to the lack of external validation of the EAST models and identified risks, beyond the research team. However, the EAST and EAST-BL frameworks were developed by members of the research team who have a deep understanding of the underlying theory and processes of application. In addition the research team has extensive experience in road safety research including advanced technology in road transport systems (Stanton, Revell, and Langdon 2021; Thompson et al. 2020; Salmon and Read 2019, Salmon, Carden, and Hancock 2021). Further, to our knowledge there is no AGI road transport management system currently under development, hence there are no available experts.

The current analysis did not address the risk of MILTON being connected to the internet. It has been well documented that an AGI connected to the internet could be vulnerable to cyber-attacks, or an AGI with unrestricted access to the internet could potentially access and process vast amounts of data, which could be used for negative unanticipated purposes. For example, if an AGI is not properly regulated, it could make decisions or take actions that are not aligned with human values or interests, potentially causing harm. However, the current study was focused on the impact of information not transferred, rather than how it was transferred. Further research focused specifically on cybersecurity risks around AGI is therefore recommended. A final limitation relates to the omission of interactions between agents in the social network not connected to MILTON, which did not allow for the identification of additional emergent risks from the interactions of other agents. In summary, we present only a sub-set of potential risks here.

Conclusions

Using EAST and EAST-BL, this study has addressed substantial gaps in the AI risk literature related to a practical application to an important, real-world sociotechnical system. First, this study has described the envisaged functionality of a future AGI system through the representation of task, social, and information networks for a future AGI system tasked with managing the Australian road transport system. Second, this study has identified failures in communication and information transfer among the system's tasks and actors to form a comprehensive risks analysis of an AGI system task with managing a road transport system. This study has implications for AGI research, design, and development through the identification of emergent and negative unanticipated consequences that will require appropriate management to ensure safe and ethical AGI implementation. Further, this study has also demonstrated the utility of HFE theory and methods for formally considering risks associated with the design, implementation, and operation of powerful future technologies. Finally, this study moves beyond much other AGI risk research which is general in nature and focused on the attributes of the AGI system itself, by analysing in detail the emergent risks of AGI deployment in a real-world sociotechnical system.

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ORCID

J. Thompson http://orcid.org/0000-0002-3146-1198
T. Carden http://orcid.org/0000-0003-4655-5899
N. A. Stanton http://orcid.org/0000-0002-8562-3279
P. M. Salmon http://orcid.org/0000-0001-7403-0286

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