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Towards augmenting cyber-physical-human collaborative cognition for human-automation interaction in complex manufacturing and operational environments

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The importance of augmenting human-technology collaborative cognition has been envisioned as one of the fundamental ways to bolster human cognition through human-automation interaction in complex manufacturing and operational environments. The focus on collaborative cognition entails a human-automation mutual adaption strategy for augmenting team cognition and collective intelligence. This paper provides an overview of augmenting collaborative cognition from an analytic and model-based decision-making perspective. Aiming to advance basic research for understanding human cognition augmentation, the fundamental and applied aspects of creating mathematical and computational models are discussed in regard to cognitive state sensing and assessment, human-automation interaction adaption and control, as well as group decision making in human-automation systems. A research roadmap towards cyber-physical-human analysis is deliberated to reveal a variety of opportunities of developing novel methods for enhancing affective cognition and perception learning, trust dynamics modelling, human cognitive performance prediction, as well as human-automation interaction optimisation.

Keywords: Human factors in manufacturing; human-automation interaction; cyber-physical-human systems; augmented cognition

1. Introduction

Technological advances are shaping the future of work (NSF 2018), which significantly intensifies the challenges facing human workers to perform in today's complex operational environments related to manufacturing and service industries (Salas et al. 2007). This leads to a growing reliance on automation, involving both hardware and software coevolution (e.g. intelligent agents and robotic systems), to support and enhance human physical and cognitive capabilities (Cuevas et al. 2007). Successful team performance for effectively executing cognitively complex tasks (e.g. smart manufacturing, aviation control) become even more dependent on team cognition that requires collaboration (cooperation, competition, and coordination) to address the contexts of both human-human and human-automation teams (Fiore, Jentsch, Becerra-Fernandez et al. 2005). Team cognition entails a binding mechanism that produces collaborative behaviour among multiple agents (human and/or automation) within a coherent human-automation system to make decisions that maximise the overall social-technological utilities (IBM 2018).

Human factors have been a focal point in design, maintenance, and supervision of human-machine systems. Since the start of industrialisation, machine capabilities have increased in such a way that human control of processes has evolved from simple (with mechanisation) to cognitive (with computerisation), and even to emotional (with semi/full automation). The processes have also evolved from simple to complicated and now to complex systems, in the prevailing context of Industry 4.0 (Liao et al. 2017; Pacaux-Lemoine et al. 2017). The emerging smart manufacturing systems combine smart sensing and embedded technologies, industrial Internet of Things, and data analytics to realise predictive and adaptive behaviours (Becker and Stern 2016; Kusiak 2018). Industrial research has focused mainly on improving the manufacturing system performance, almost neglecting human factors and their relation to the production systems (Mital and Pennathur 2004; Dode et al. 2016). In order to create a competitive smart factory context, human performance should be included to drive smart system adaptation in an efficient and effective way, which leads to a notion of human-in-the-loop cyber-physical systems (Schirner et al. 2013). Design of human-centred adaptive manufacturing systems has been advocated for the modern

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companies to adapt to individual workers' needs considering the differences in their physical and cognitive capabilities, and thus to improve the human-machine interaction and the workers' wellbeing (Peruzzini and Pellicciari 2017).

The emerging trend of cyber-physical production systems with human in the loop will provoke changes in many ways for the future of work, concerning the role of human workers in the factory of the future (Nunes, Sa Silva, and Boavida 2018). Leading experts expect less basic, repetitive work but more ambitious tasks in collaboration with automation systems, and thus the factory of the future will not be deserted, but organised as a human-automation collaborative system (Mattsson, Fasth, and Stahre 2012). It has been envisioned that the central theme of future work lies in *human-automation interaction* (HAI), which can be defined as the way a human is affected by, controls and receives information from automation while performing a task (Sheridan and Parasuraman 2005). Although HAI has been approached from many perspectives, the effects of interaction are still hard to predict (Bustamante, Madhavan, and Wickens 2009). The reason for interaction breakdowns has been attributed to a variety of aspects, including context and situational awareness (Endsley 1996), performance (Endsley and Kaber 1999), feedback (Norman 1990), and levels of automation (Endsley 1997; Endsley and Kaber 1999; Parasuraman, Sheridan, and Wickens 2000; Miller and Parasuman 2003; Kaber 2018). Recent literature points to a need for finding quantifiable models (Miller and Parasuman 2003) and to understanding human behaviour and the relationship between human and automation (Sanchez 2009).

This paper envisions the importance of *augmenting collaborative cognition* as one of the fundamental ways to bolster human cognition with technologies through human-automation interaction in complex manufacturing and operational environments. The paper overviews augmenting collaborative cognition from an analytic and model-based decision-making perspective. The fundamental and applied aspects of creating mathematical and computational models to advance basic research for understanding human cognition augmentation are deliberated in regard to cognitive state sensing and assessment, human-automation interaction adaption and control, as well as group decision making in human-automation systems. Also discussed are recent trends and future research directions towards developing a variety of novel methods for enhancing affective cognition and perception learning, trust dynamics modelling, human cognitive performance prediction, and human-automation interaction optimisation.

2. Fundamental issues of augmenting human-automation collaborative cognition

Team cognition has been identified as a key component to achieve operational goals in a dynamic, team-based and distributed manufacturing and operational environment (Salas et al. 2007). Effective team performance in fulfilling cognitively complex tasks requires that team members hold a shared understanding of the tasks and their teammates. The HAI problems in real life require collaboration (cooperation, competition, or coordination) from multiple agents (human and/or machines) in a social machine to make decisions that maximise an overall goal, while every agent in such a collaborative setting has its own goal (IBM 2018).

The increased presence of augmented intelligence within public discourse has advocated a symbiosis of *collaborative cognition* to enhance team cognition (Silverman 2017), whereby technologies and human complement each other by performing the tasks most suitable to them (Zheng et al. 2017). In line with this new human-technology frontier, it is necessary to frame collaborative cognition within an augmented cognition framework (e.g. sensing, learning, and decision making) to provide solutions for real world HAI problems. One particular approach to collaborative cognition is from an analytic and model-based perspective that looks beyond an individual's cognition to include interactions of individuals with others (e.g. non-human cognitive agents like automated decision aids), so as to augment human team cognition and collective intelligence, through computational modelling and evaluation of strategic interactions (e.g. human-automation mutual adaption) among the human and automation agents. The focus on augmenting collaborative cognition is relevant to the state-of-the-art knowledge, as elaborated below.

2.1. Team cognition

The rise in importance of teams for addressing complex work environments (e.g. those involving numerous workers using sets of computerised equipment and communication systems) is paralleled with an increase in the number and difficulty of cognitive tasks allocated to teams (Caldwell 2005). Team cognition can be characterised as an explanation of the interaction of and dependencies between intra-individual and inter-individual level processes (Fiore and Schooler 2004). Team cognition is a property of individual cognition and team process behaviours and emerges as the team is engaged in performance episodes (Cooke et al. 2004). Understanding and measuring cognition at the team level is a critical aspect of assessing team performance and effectiveness in these environments (Mohammed, Klimoski, and Rentsch 2000; Lipshitz et al. 2001). Teams dynamically coordinate activities necessary for task completion and adaptation to task demands including sharing information and resources (Salas and Fiore 2004). This dynamic coordination is made possible by the mechanisms of team cognition (Salas et al. 2007). In order to better understand team cognition in human-automation systems, team performance models need to address issues surrounding the effect of human-human and human-automation interaction on critical team processes such as coordination and communication (Fiore, Jentsch, Rehfeld et al. 2005). A critical question for augmenting team cognition involves determining which information human-automation teams use to perform a given task or how the presence of non-human team members may hinder or help coordination efforts. Coordination may be impaired because of the difficulty associated with conveying and processing critical task-relevant information due to a lack of understanding of automation team members' roles and functional capabilities and limitations (Fiore, Jentsch, Becerra-Fernandez et al. 2005).

2.2. Human-automation team interaction

The envisioned benefits of an HAI team include superior performance in highly unstructured tasks, reduced human workload, and flexibility and robustness in task execution. The main challenge of HAI is how to fuse the cognitive capabilities of human workers and the autonomous capabilities of the automation system appropriately, in order to maximise task performance, efficiency, and intuitiveness of the interaction. This leads to the consideration of suitable levels of automation in light of varying human cognitive and behavioural capabilities (Music and Hirche 2017). This is in line with the concept of flexible automation that refers to systems that invoke a certain level of automation depending on the operator's state or critical events in a complex environment (Chen and Barnes 2014). The approaches differ in their workload requirements (amount of cognitive resources available for tasks) and allocation of decision authority (Goodrich 2010). Research on human teams shows that mutual adaptation, which requires all team members involved to adapt their behaviours to fulfil common team goals, can significantly improve team performance (Mathieu 2000), and thus adaptation is critical for effective team collaboration (Nikolaidis, Hsu, and Srinivasa 2017). Since the performance of human worker changes during the working shift, HAI should be controlled by adjusting the machine performance according to what the operator desires (Sadrfaridpour et al. 2016). Fast-Berglund et al. (Fast-Berglund, Mattsson, and Bligard 2016) observed that an effective cognitive automation strategy is to take individual aspects into account by choosing an appropriate level of automation. The evolution of digital tools, increased number of co-bots and human-automation collaboration in nowadays plants converge to increased use of both cognitive and physical automation in the manufacturing context. For an HAI team, a smart and skilled operator performs work in such a way that he is to be aided by machines if and as needed. It represents a new design and engineering philosophy for adaptive production systems where the focus is on treating automation as a further enhancement of the human's cognitive capabilities (Mattsson et al. 2013).

2.3. Human trust in automation

An important human aspect that concerns willingness to collaborate is self-confidence and trust, which is pertaining to relationships between humans, as well as between humans and automation agents (Millot and Pacaux-Lemoine 2013). Willingness to collaborate can be seen as an increasing function of trust in the system and a decreasing function of self-confidence (Pacaux-Lemoine et al. 2017). This is consistent with a study conducted by Lee and Moray (Lee and Moray 1992) on function allocations between humans and automated control systems. Moreover, Rajaonah et al. (Rajaonah et al. 2008) showed that trust also plays a critical role in the interaction. Trust in automation has been considered a central influence on the way a human interacts with an automation system – if trust is too high there will be overuse; if trust is too low there will be disuse. Binary measures of trust (Hall 1996), as well as continuous measures (Lee and Moray 1992; Desaim 2012; Xu and Dudek 2016), and ordinal scales (Muir 1990; Hoffman 2013) have been proposed. For real-time measurement, Desai (Desaim 2012) proposed the area under the trust curve, which has been used to account for one's entire interactive experience with a robot (Yang et al. 2017). Lee and See (Lee and See 2004) identified the antecedents (i.e. purpose, process, and performance) for trust development in the context of HAI, which provides a framework of measuring system and environment-related factors that contribute to trust development. However, relationships between people are different from those of HAI. This discrepancy brings about a need for investigating empirical and theoretical considerations for adopting trust in human workers as a model of trust in HAI (Lee and See 2004). It is thus necessary to model trust in automation by considering both human and automation performance (Lewandowsky, Mundy, and Tan 2000). This is consistent with the fact that when a human worker observes a discrepancy between his performance and what he expects from the automation agent, his trust in automation decreases accordingly; and vice versa (Sadrfaridpour et al. 2016).

2.4. Augmented cognition

Augmenting human cognition has attracted much attention over the last decade, focusing on computational systems that sense, infer, and take action based on detailed knowledge of the capabilities and limitations of human cognition (Horvitz

2018). The major focus of DARPA's augmented cognition programme has been developing more robust tools for monitoring cognitive states and integrating them with automation systems (Schmorrow and Kruse 2002). Augmented cognition is a form of human-system interaction in which a tight coupling between human and the system is achieved via physiological and neurophysiological sensing of a worker's cognitive state (Barker et al. 2004; Siddhartha and Dagli 2013). This interactive paradigm seeks to revolutionise the manner, in which human engages with automation by leveraging this knowledge of cognitive states to precisely adapt human-system interaction in real time (Diethe 2005). Augmented cognition enables the human to gain conception for adaptation to his particular needs and to derive explanations (Engelbart 2001). There are three main components of an augmented cognition system: cognitive state sensors, adaptation strategies, and control systems (Stanney et al. 2009). Augmented cognition research generally focuses on tasks and environments to develop applications that capture the human's cognitive state in order to drive real-time automation systems (Reeves, Schmorrow, and Stanney 2007). In doing so, these systems are able to provide operational data specifically targeted for human in a given context (Schmorrow and Kruse 2002). There are generally three major areas of research in the field: cognitive state assessment, mitigation strategies, and robust controllers, in order to enhance the ability of a team to remember, think, and reason (Schmorrow, Estabrooke, and Grootjen 2009).

3. The emerging research roadmap

The focus on collaborative cognition entails a human-automation mutual adaption strategy for augmenting human team cognition and collective intelligence. For the sake of the engineering implication of augmented cognition, it is of particular importance to formulate the problem of augmenting collaborative cognition as how to optimise HAI in line with a systems design perspective. It is imperative to enhance the human-technology partnership and advance human performance augmentation by adopting computational modelling and model-based analytic techniques to smartly adapt the automation system behaviour to the working conditions and to the specific workers' skills, tasks, and cognitive-physical abilities.

As shown in Figure 1, augmenting collaborative cognition is centred on four pillars: cognitive state sensing and assessment, mitigation/adaption, control/action, and group decision making. On the other hand, HAI concerns individual differences in human emotions and cognitive capabilities, settings of the type and level of automation, and the complexity and workload of the tasks. Optimal HAI design aims to adapt to individual differences in cognitive capabilities of human workers by: (1) accommodating each human worker with an appropriate type and level of automation (reflecting the mitigation/adaption strategy), and in the meantime (2) to dynamically assigning a task either to a human worker or to an automation agent (in line with the control/action strategy), while (3) leveraging upon the overall operations system performance and costs (echoing the group decision making aspect). Cognitive state sensing and assessment facilitates modelling of human

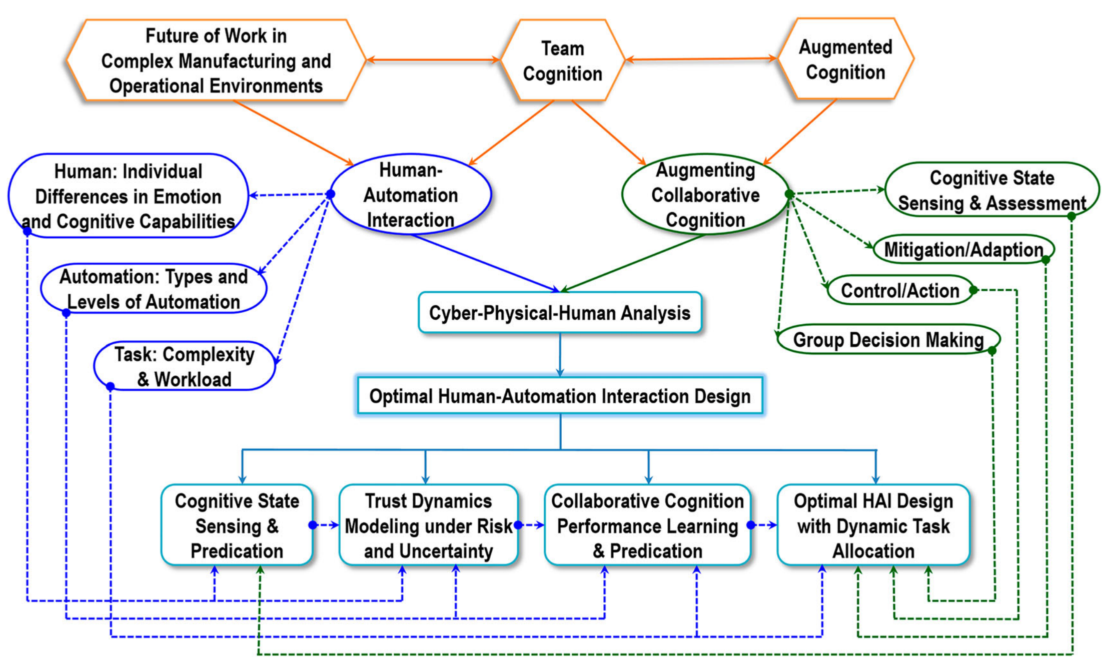

Figure 1. Augmenting cyber-physical-human collaborative cognition through optimal HAI design.

workers' emotion and cognitive capabilities in fulfilling an effective cognitive automation strategy towards taking individual human differences into account by choosing an appropriate type and level of automation. Overall, optimal HAI design manages to fuse the cognitive capabilities of human workers and the autonomous capabilities of the automation system appropriately, while maximising task performance, efficiency, and intuitiveness of the interaction.

This technical framework implies four fundamental research issues, including (1) cognitive state sensing and prediction, (2) trust dynamics modelling under risk and uncertainty, (3) collaborative cognition performance learning and prediction, and (4) optimal HAI design with dynamic task allocation. Figure 1 illustrates the coherence among these fundamentals and connections between various research components. The trust dynamics model takes input from cognitive state prediction model. The collaborative cognition performance model performs as the basis of optimal HAI design. These fundamental issues are reviewed in subsequent Sections 4-7, respectively.

4. Cognitive state sensing and prediction

To better understand HAI, it is important to enhance the sensing and assessment of cognitive states, so as to dynamically identify changes in human cognitive activity as human workers engaged in cognitive tasks. Acquisition of cognitive states has been typically approached in a subjective form (psychology-oriented) by self-reporting from a participant (Muhammad et al. 2010). Despite the capability of interpreting self-report data, the subjective methods suffer from recall and selective reporting biases (Stone and Shiffman 1994; Fuge 2015). Recent efforts have been geared towards an objective route (neurophysiology-oriented) by means of monitoring the participant's behavioural indicators or physiological signals (Schmorrow and Fidopiastis 2016). However, relying on one single channel of physiological measure alone can hardly be adequate to give a full picture of what cognitive states occur with the user (Siddhartha and Dagli 2013); and thus it is necessary to monitor diverse physiological signals collectively (Nicholson et al. 2005). It is challenging to comprehend multimodal physiological data and map out their coherence with the underlying implications of emotion, cognition, and perception (Salas et al. 2007).

Many commercial technologies are available for a non-invasive measure of physiological status, such as EEG (electroencephalogram), SCR (skin conductance response), peripheral temperature, BVP (blood volume pulse), facial EMG (electromyography), as well as respiration amplitude and rate. The key challenge, however, lies in how to predict affective cognition and perception with context-awareness in an HAI environment. A promising approach is to set up user experiments and to measure the user's physiological status along with behaviour tracking and motion sensing during human interaction with the system while fulfilling certain cognitive tasks. By extracting affective–cognitive features from physiological experiment data and cognitive activity tracking and sensing data, it is possible to construct affective–cognitive prediction models using computational learning techniques (Jiao, Zhou, and Chu 2017). Deep learning using augmented physiological and behaviour measurement will help reveal the correlation between perception and behaviour underlying HAI studies by integrating multimodal physiological and behaviour measures into a coherent framework of intelligent computational learning. Recent advances in neurophysiological and psychophysiological sensing technologies have a great potential for enhancing this cognitive state detection task.

4.1. Augmented sensor platform

The emerging trend of cognitive state sensing is to integrate user physiological measurement (Zhou, Qu, Helander et al. 2011; Zhou et al. 2014) and cognitive activity recognition (Zhou, Ji, and Jiao 2014a) into a cohesive augmented sensor platform. Such augmented platforms enable identification of affects (i.e. feature extraction to reveal the underlying meaning of physiological data), as well as activity recognition of specific cognitive tasks underlying the fulfilment of particular HAI use cases. This hardware platform comprises two sets of measurement systems: physiological measure and motion tracking and sensing (Jiao, Zhou, and Chu 2017). Overall the augmented sensor system should work well for revealing affective–cognitive features in terms of prediction accuracy and especially context awareness regarding cognitive modelling, perception, emotion, and interaction (Zhou, Xu, and Jiao 2011). Further opportunities exist for enhancing the motion study hardware platform by incorporating head tracking, eye tracking, along with hand and finger motion sensing.

4.2. Cognitive feature extraction and deep learning

Based on statistical analysis of physiological and motion study experiment data, it is possible to extract affective–cognitive features related to HAI. Linear discriminant analysis (LDA) is a useful technique for reducing the dimensionality of the original feature space for better computational efficiency and accuracy (Fodor 2002). Comparing with principal component analysis that is capitalised on between-class information, LDA explicitly makes use of both between-class and within-class difference information for better performance (Martinez and Kak 2001). In addition to proper LDA models for dealing with multimodal physiological data, rough set-based data mining (Bazan et al. 2000) has the potential for cognitive states learning, owing to its strength in classifying approximations of concepts from multiple features (Pawlak 1991). Powerful rough set mining methods include decision rules, k-nearest neighbours, and decomposition tree. In addition, determining reasonable thresholds of support and strength for learned associations is not trivial for any rule mining method, in particular when facing a large training set (Fairclough 2009). An important research issue is to investigate the potential of incorporating with a k-nearest neighbour mining method for alleviating this problem. It is worthwhile to study the possibility of introducing heuristics to the mining process, as well as the potential of deep learning neural networks. Another research issue is how to improve the prediction power. A potential effective means is to discretize affective–cognitive features into different intervals using cuts that are produced using a global strategy based on the maximal discernibility heuristics (Gora and Wojna 2002). Maintenance of numerous prediction rules is also a challenging issue, which is related to how to leverage the decomposition tree mining method (Bazan and Szczuka 2000).

Recently, deep learning methods are proposed in computer vision and time series data analysis, such as convolutional neutral networks (CNNs) and long-short-term memory (LSTM) as a special type of recurrent neural networks. The CNNs can learn a hierarchical feature representation from the raw data automatically, eliminating the burden of feature space construction (Figo et al. 2010). The LSTM is able to model the temporal dependence in the time series data (Hochreiter and Schmidhuber 1997). In order to extract features for cognitive state prediction, it is promising to combine the benefits of CNNs and LSTM to model both spatial and temporal relationships among the predicting variables. Such a combination in a unified framework has shown its advantages in emotion recognition (Kanjo, Younis, and Ang 2019), speech recognition (Sainath et al. 2015), and human activity recognition (Ordóñez and Roggen 2016).

5. Modelling trust dynamics under risk and uncertainty

There is a largely unexplored aspect of HAI that the human decision leading to interaction behaviour has traditionally considered a manifestation of the user's level of trust in automation (Parasuraman and Manzey 2010). It means that if HAI is to be actively managed in joint human-automation systems, one must calibrate the trust of the user so that decisions about interactions with automation are appropriate (Jamieson and Vicente 2005). This is especially applicable in the HAI case inasmuch that trust reflects changing degrees of perceived risk and uncertainty and is an instance of value-based decision making in dynamic contexts. Drnec et al. (Drnec et al. 2016) suggested that physiological correlates of value-based decisions could be measured and leveraged to provide valuable data that may increase the likelihood of predicting a consequent interaction. While trust is one of many important factors influencing HAI performance, it is ultimately the interaction behaviour that is of interest. Even though extensive research into trust in automation has identified specific HAI behaviours, a knowledge gap may exist for a unique quantification model of trust incorporating HAI behaviours has yet to be clearly identified (Bliss, Proaps, and Madhavan 2015). It thus becomes important to realise a value-based decision process underlying a mental model of quantifying trust as predictable behaviour under uncertainty. Moreover, human individual differences in their cognitive states lead to a varying degree of trust due to their different risk attitudes and preferences towards automation (Miller 2005). It is promising to build a theoretical ground of trust quantification through a novel synthesis of prospect theory (Kahneman and Tversky 1979) in the field of behavioural economics in the particular context of HAI under risk and uncertainty.

5.1. Prospect theoretic model for quantification of trust

Human trust in automation can be modelled as perceived value of a particular automation agent (a_i) at a certain level (a^*_{ik}), for which trust can be quantified as a value function, $v^{Trust}(a^*_{ik})$. The perception of trust on different levels of automation is often articulated in comparison with a certain level (($a^*_{i,ref}$)) that coincides with a neutral trust and thus can act as a reference point. The basic form of a trust value function can be defined as (Zhou and Jiao 2013):

$$v^{Trust}(a^*_{ik}) = \begin{cases} \lambda^P (a^*_{ik} - a^*_{i,ref})^{\alpha^P} & a^*_{ik} \geq a^*_{i,ref} \\ -\lambda^U (a^*_{i,ref} - a^*_{ik})^{\alpha^U} & a^*_{ik} < a^*_{i,ref} \end{cases},$$

where λ^P, λ^U, α^P and α^U are shape parameters that regulate the curvature of a trust value function. Reported work shows a great potential of prospect-theoretic modelling for affective–cognitive decisions (Zhou, Ji, and Jiao 2014b). It is worthwhile to further investigate the possibility of using cumulative probabilities, which theoretically could lead to evaluations that choose first-order stochastically dominated choices rather than the dominating one (Ingersoll 2008). To formulate cumulative trust prospect evaluation, it is necessary to convert choice probabilities of multiple levels of automation (LOAs) to their corresponding cumulative choice probabilities. For example, a particular probability-weighting function originally proposed by (Kahneman and Tversky 1979) can be extended to the unique context of trust in automation.

5.2. Parameter shaping for risk attitude

Early theories about trust are developed from the psychological construct of interpersonal trust, and they posited that calibrated trust was critical for successful HAI system performance (Lee and Moray 1992). Myriad definitions of trust imply that it is the result of a feeling of trustworthiness towards the automation such that a human user can depend on the automation to perform the task for which it is designed. Therefore, much like interpersonal trust (Lee and Moray 1994; Muir 1994), trust develops in the face of a sense of risk. In these situations, trust then develops and shows dynamic changes from the ongoing comparison of the expectations about the automation system behaviour and observations by the human user about the automation performance weighted heavily on the risk borne by the human user (Muir and Moray 1996). The shape parameters in the above trust prospect value functions are of particular advantages in dealing with such varying human attitudes towards trust in automation. A particular shape of $v^{Trust}(a_{ik}^{*})$ characterises the cognitive tendency under a specific risk attitude, in which the values of shape parameters reflect the influence of affective and cognitive states on the risk attitude in choice decision making (Ahn 2010). Zhou et al. (Zhou et al. 2017) revealed the feasibility of estimating these shape parameters through mining and learning from user experiment data. This task can take advantage of an augmented sensor platform to collect user data regarding affective and cognitive states through the HAI experiments and to test different statistical and computational learning algorithms for effective estimation of the risk attitude shape parameters. Sensitivity analysis experiments are needed to investigate the significance of incorporating risk in trust quantification towards HAI behaviour.

5.3. Modelling trust dynamics as a Markov decision process

One of the first explicit theories of trust in automation (Muir 1994) suggests that trust evolves throughout the course of automation use. The importance of these expectations related to trust dynamics differs depending on the stage of the interaction with the automation (Drnec et al. 2016). In addition, as levels of trust dynamically change throughout the course of observations about the automation's behaviour, it is important that interaction decisions and consequent behaviours should reflect the extant level of trust under uncertainty (Wickens and Dixon 2007; Wang, Jamieson, and Hollands 2009). Obtaining mathematical models that can accurately predict human trust levels over a wide range, is fairly challenging because of its inherent uncertainties caused by a variety of individual characteristics and external environments. While previous work (e.g. Lee and Moray 1992; Floyd, Drinkwater, and Aha 2015; Xu and Dudek 2015; Wang et al. 2016) has focused on either quantifying or maximising trust in human-robot interaction, it is imperative to enable the HAI to leverage upon a model of human trust and choose actions to maximise task performance.

A Markov Decision Process (MDP) framework (Puterman 2014) is appealing to addressing the uncertainties in human trust dynamics, such that the dynamic uncertainty from one trust level to another can be modelled by a transition function whose value is determined by the HAI performance. The MDP human trust model can thus be viewed as a stochastic abstraction of the conventional continuous models proposed in (Lee and Moray 1992; Sadrfaridpour et al. 2016; Saeidi et al. 2016). The advantage of the MDP lies in systematic inference and influence of human workers' trust on the human-automation system (Chen et al. 2018), and in turn to leverage trust for improved human-automation collaboration and long-term task performance (Wu, Hu, and Lin 2015). Many prevailing MDP models, such as the partially observable MDP (Kaelbling, Littman, and Cassandra 1998), reinforcement learning MDP (Narendra and Thathachar 1989), and fuzzy MDP (Fakoor, Kosari, and Jafarzadeh 2016), can be used for populating human trust dynamics based on prospect value functions to analyze the performance of human-automation collaborative cognition.

6. Statistical learning and prediction of human collaborative cognition performance

Future work in an HAI environment entails a large network of human and automation agents (e.g. robots, automated decision aids). Such networked systems have very complex properties that are poorly understood and difficult to predict. Limitations in human attention and memory can lead to a degradation of system performance when network size and complexity increase, leading to an increasing demand on human coordination (Lewis, Wang, and Scerri 2006). Empirical studies and modelling efforts are needed to examine and understand these and other emerging issues in a networked human-automation system (Nisar et al. 2013). Moreover, augmenting collaborative cognition in such a complex HAI environment coincides with the rising importance of teams for addressing complex work environments (e.g. those involving numerous workers using sets of computerised equipment and communication systems). This is paralleled by an increase in the number and difficulty of cognitive tasks allocated to teams (Caldwell 2005). Collaborative cognition can be characterised as an explanation of the interaction of and dependencies between intra-individual and inter-individual level processes (Fiore and Schooler 2004). Understanding and measuring cognition at the team level is a critical aspect of understanding team performance and effectiveness in these environments (Mohammed, Klimoski, and Rentsch 2000; Lipshitz et al. 2001).

One important research focus is to examine the challenging problem of modelling the interaction between individual attentional limitations and decision-making performance in networked human-automation system tasks. Statistical learning approaches are suggested to be useful for collaborative cognition performance prediction in response to task characteristics, team shared mental models and individual workers' cognitive traits. For example, non-parametric Gaussian processes and probabilistic Bayesian networks can be applied to modelling and making predictions based on experimental networked team performance data. Such prediction models can help the design of networked human-automated systems cope with various uncertainties in order to accommodate future users by linking expected operating conditions and performance from experimental data to diverse observable cognitive traits of human workers.

6.1. Prediction of human collaborative cognition performance

Let $X = (X^{Task}, X^{Human}, X^{Team})$ denote a human-automation system operating point defined by task conditions (X^{Task}), operator cognitive traits (X^{Human}) and team cognition profile (X^{Team}). If let $Y = (Y^1, Y^2, \dots, Y^N)$ be some value of a vector of the team performance metrics, $Y = (X) = (X^{Task}, X^{Human}, X^{Team})$ constitutes a prediction model of collaborative cognition. Depending on specific domain problem contexts, task characteristics define the complexity and workload of a task to be accomplished by an HAI system. Individual differences in human cognitive traits (X^{Human}) can be defined according to some cognitive load metrics that can be derived from the predicted cognitive states. In line with cognitive load theory (Sweller 1988), the ergonomic approach seeks a quantitative neurophysiological expression of cognitive load that can be measured using common instruments. For example, several studies (e.g. Parasuraman and Manzey 2010) have shown that individual differences in working memory capacity play a key role in determining how well operators can supervise multiple automation agents and should therefore be included in the modelling process.

Effective team performance in complex environments requires that team members hold a shared understanding of the task, their equipment, and their coworkers (Salas et al. 2007). A well-formulated human trust model has been suggested to be a good indicator to enhance shared/team cognition (Martinez-Miranda and Pavon 2012). It is possible to define X^{Team} by the trust value function to enable sufficient robustness in performance assessment and capability to allow for a rich and deep understanding of team cognition. It is noteworthy to define $X^{Team} = \{v^{Trust}(a^*_{ik})\}$, such that collaborative cognition performance becomes correlated with each team-member's perceived trustworthiness of different settings of LOAs in an automation system. This enables human-automation mutual adaption, whereby technologies and humans complement each other by performing the tasks most suitable to them. In addition, quantitative indices for $Y = (Y_1, Y_2, \dots, Y_M)$ can be developed according to the comprehensive taxonomy of team cognition performance metrics $\{Y_k\}$ proposed by Salas et al. (Salas et al. 2007). These metrics indicate the presence of team-level knowledge structures and cognitive or behavioural processes in terms of shared mental models (Orasanu and Salas 1993) and situation assessment (Cooke, Kiekel, and Salas 2003; Cooke et al. 2004), respectively.

Initially, diverse measures of collaborative cognition performance can be modelled by linear regression functions of variables that measure task conditions and operator cognitive load. However, they have inherent limitations that make them inappropriate for describing the complex and uncertain relationships between performance measures, task conditions, and operator characteristics, in order to address the practical problems of extended prediction and inverse reasoning (Ahmed et al. 2014). It is therefore natural to consider a holistic probabilistic modelling approach, in which the operator performance metrics, task conditions, and operator characteristics are all treated as uncertain random variables. Extended prediction means performance prediction for conditions that are dissimilar to those recorded in the experimental data used for model learning. Inverse reasoning refers to an inference of unknown tasking conditions or operator capabilities from calculated performance metric values. These two performance reasoning tasks provoke consideration of two alternative statistical modelling approaches, Gaussian processes and Bayesian networks, as elaborated below.

6.2. Probabilistic modelling with Gaussian processes for extended prediction

Gaussian processes generalise the linear Gaussian prediction model by casting mean and standard deviation directly in terms of the original data using special functions called covariance kernels. In this sense, Gaussian process models are said to be non-parametric, i.e. instead of discarding the data after fitting it to a linear/nonlinear function model, the original data are preserved and directly used to make all subsequent predictions (Bishop 2006). Unlike a linear regression model, the Gaussian process model has the appealing ability to adjust its prediction statistics on the basis of how similar a new previously unsampled operating point is to the original modelling data. For implementation, it requires collection of experiment data to test these properties by learning separate Gaussian process regression models for each performance metric output as a function of three independent input factors in X using the open source Gaussian processes for machine learning (GPML) Toolbox for Matlab® (Rasmussen and Williams 2001).

6.3. Bayesian network (BN) models for probabilistic inverse reasoning

For practical HAI applications, the values of some X^{Task} and X^{Human} may be required but may also be unknown or difficult to measure. In such situations, these variables can be estimated from observed performance measures via Bayesian inference, which inverts uncertain probabilistic relationships that are given by a joint probability distribution over X^{Task} and X^{Human}, as well as the performance metrics. This joint probability distribution can be encoded by a BN, which is an explicit model of conditional independence relationships among random variables represented by a compact graph structure that permits the use of powerful algorithms for data-driven model learning and probabilistic inference (Heckerman 1998).

A BN is formally defined by a directed acyclic graph consisting of nodes representing different random variables and directed edges representing the probabilistic conditional dependence relationships among nodes. Given a particular BN model, the inference is accomplished by applying Bayes' rule to the joint probability distribution, which gives the following posterior distribution for each BN:

$$p(X^{Task}, X^{Human}, X^{Team} | Y_1, Y_2, \ldots, Y_M) = \frac{p(X^{Task}) \times p(X^{Human}) \times p(X^{Team}) \times p(Y_1, Y_2, \ldots, Y_M | X^{Task}, X^{Human}, X^{Team})}{p(Y_1, Y_2, \ldots, Y_M)},$$

where $p(X^{Task})$, $p(X^{Human})$ and $p(X^{Team})$ are the prior probability distributions (which encode information available before the inference process). The posterior probability distribution provides a statistically consistent and compact description of all information available about X^{Task}, X^{Human} and X^{Team}, given uncertain prior information and noisy performance observations. The posterior distribution can be used to obtain point estimates for X^{Task}, X^{Human} and X^{Team}. The specification of conditional dependencies plays a key role in determining what can be inferred about such variables as X^{Task}, X^{Human}, and X^{Team} from observed performance measures.

A variety of techniques exist for learning BN graph structures and conditional probability parameters from data, and there are many efficient algorithms for online inference (Bishop 2006). However, the choice of which learning and inference algorithms to apply is heavily problem dependent (Ahmed et al. 2014). For instance, more sophisticated inference techniques (e.g. Monte Carlo sampling and variational approximations) must be applied to handle arbitrary non-tree graph structures or more general conditional probability distribution models (Heckerman 1998). One metric often used to compare models is the Bayes information criterion score (BIC), for which a high BIC score indicates a reasonable balance between model accuracy and structural complexity (Ahmed et al. 2014). However, structure learning is generally quite challenging in practice since the candidate space of models can become extremely large, so heuristic methods must often be applied to generate suitable candidate BN structures for comparison. For evaluation of BN models, another powerful Bayesian scoring metric is also available, i.e. Bayesian Dirichlet equivalence (BDe) (Heckerman 1998), to conduct comparative studies for both BIC and BDe. Furthermore, a useful BN of HAI performance study must strike a suitable balance between providing an accurate model of uncertainty for the variables of interest and supporting computationally efficient learning or inference procedures. It will be helpful to introduce some intuitively reasonable assumptions to the BN modelling process to capture nonlinear/non-Gaussian relationships with simple yet flexible conditional probability distributions, so as to permit the use of efficient learning and inference methods. The implementation may take advantage of the open-source Matlab Bayes Net Toolbox (Murphy 2001) to develop the learning and inference procedures.

7. Optimal human-automation interaction design with dynamic task allocation

The goal of augmenting human cognition can be achieved through optimal human-automation system design and dynamic task allocation, such that more decisional capabilities are embedded in system design, transforming them into efficient automation systems to help human workers enhance performance. In this context, it is suggested that each of these automation systems embed individual as well as collaborative capabilities (Pacaux-Lemoine et al. 2017). A critical aspect of augmenting human cognition is that the human-automation system is supposed to adapt to individual differences in cognitive capabilities of human workers by accommodating each human worker with an appropriate type and level of automation, and in turn dynamically assigning a task either to a human worker or to an automation agent, while leveraging upon the overall operations system performance and costs (Wu, Hu, and Lin 2015).

Modern human-automation systems consist of human operators and many automation agents (e.g. intelligent robots) collaborating with one another to accomplish complex tasks that are less efficient or cannot be completed by either human or automation alone (Hu and Chen 2017). The system performance of such human-automation systems depends heavily on reliable and efficient human-automation collaboration, which may be seriously compromised due to temporal variations in human interaction with automation. One promising direction is to model the fulfilment of networked human-automation system tasks as a Markov Decision Process in order to capture its dynamic uncertainties on how human and automation performance affects each other. It is also necessary to formulate the overall human-automation system design under adaptive human-automation collaboration as an optimisation problem where an optimal task allocation policy is obtained to maximise human performance while leveraging the efficiency of automation agents.

In a complex manufacturing and operational environment, making a tradeoff between human performance and production system efficiency in term of time, costs and production rates involves human behaviours and perceptions of their interaction with various automation agents (Peruzzini and Pellicciari 2017). It is imperative to develop mathematical optimisation models while keeping human in the loop (Lake 2012). In addition, the scientific foundation of HAI is originated from the design of a multi-agent tournament that affects the outcomes of non-cooperative games of crowd-augmented cognition in systems design (Kittur 2016; IBM 2018). This call for research to examine and develop the theoretical foundation of human-in-the-loop optimisation models by extending game-theoretic decisions from contest theory and behavioural game theory (Jiao and Tseng 2013; Yang et al. 2015). The models can be validated by comparing the predictions from analytical game theoretic optimisation models with observed user behaviours under well-designed experimental settings.

7.1. Modelling of dynamic task allocation

It is normal to consider the task allocation problem between the human workers and the automation agents. Most existing work often assumes that this problem can be formulated as an optimal control problem where the system performance is optimised in terms of minimising a well-defined discounted or average cost (Wu, Hu, and Lin 2015). The only cost-based criteria, however, may be inadequate for human-automation systems with complex system specifications. In contrast to most existing work, one strategy is to focus on the task allocation problem for a human automation system whose task specifications can be formulated as a Linear Temporal Logic (LTL) formula (Baier and Katoen 2008). Thus, efficient human-automation collaboration is enacted through an optimal task allocation strategy that maximises human team performance while minimising average costs for maximising the probability of satisfying the given specification (Ding et al. 2014; Fu and Topcu 2016).

7.1.1. Task model

Consider an industrial assembly system involving both human workers and robots. The assembly tasks can be represented by an action-deterministic transition system using LTL formula, Ω^{Task}. There are N parts that need to be assembled by actions, either done by the automation agent (e.g. robot/machine), $A^M = \{a_i^M\}$ or by the human worker, $A^H = \{a_i^H\}$. 'Reset' is a dummy action to restart a new round of the assembly. During the task execution all necessary parts are fed by suitable mechanisms such as the conveyor belts. The assembly tasks often consist of a sequence of stages where each stage represents one subtask that needs human or machine's actions to complete. In practice, the difficulty levels of the sub-tasks in the assembly process often varies from stage to stage, which may result in stochastic variations on an automation agent's performance.

7.1.2. Automation system model

Introduce an MDP to model the stochastic dynamics of the assembly system performance, i.e. $\Omega^{Automation} = \{S^M, s_o^M, A^M, T^M, L^M, C^M\}$, where S^M is a finite set of states representing the machine state, $s_o^M \in S^M$ is the initial state, T^M is the transition matrix, and L^M and C^M are the machine performance in terms of the cycle time and the cost. Many automation agents are equipped with certain capabilities of autonomous control. Robust intelligence algorithms are available to learn the expected machine performance by the human worker over the course of working shift. For example, the artificial neural network is used to predict the desired robot performance so that the human worker does not necessarily need to adjust it manually (Sadrfaridpour et al. 2016).

7.1.3. HAI model

A HAI model, Ω^{HAI}, can be defined as the MDP model of value-based trust dynamics. That is, $\Omega^{HAI} = \{S^T, s_o^T, A^M, T^T, C^T\}$, where S^T is a finite set of human trust levels, $s_o^T \in S^T$ is the initial human trust level, the transition matrix is defined as

$T^T(s^T(i), a_i^M, s^T(i+1)) = Pr(s^T(i+1)|s^T(i), a_i^M)$, and $C^T : S^T \times A^M \to \mathbb{R}^+$ is a positive cost function representing the cost of a task to be done by a human worker instead of an automation agent.

7.1.4. *Human performance model*

Likewise, a human performance model can be defined as an MDP of human performance prediction obtained in Task T3, i.e. $\Omega^{Human} = \{S^H, s_o^H, A^H, T^H, C^H\}$, where $C^H : S^T \times A^H \to \mathbb{R}^+$ is the cost function of human workers.

7.1.5. *Operations system model*

With MDP definitions of task model Ω^{Task}, automation system model $\Omega^{Automation}$ and human trust model Ω^{HAI}, augmenting human collaborative cognition through HAI can be characterised by the fact that the human trust towards specific type and levels of automation can be appropriately regulated by controlling automation system performance through strategic task assignment. A desired level of human trust w.r.t. a specific LOA setting will certainly improve the human team performance in the assembly processes, thereby leading to an effective human-automation collaboration. Therefore, in the presence of HAI, the human-in-the-loop operations system can be modelled as Ω, which is an MDP from the parallel composition of the three models, i.e. $\Omega = \Omega^{Task}||\Omega^{Automation}||\Omega^{HAI}$, where $||$ denotes the parallel composition of MDPs (Parker et al. 2006). From the definition of parallel composition, the state of Ω is indicated as a tri-tuple: $s = (s^H, s^M, s^T)$, indicating that the transition probability in the assembly process is not only dependent on the actions taken by an automation agent or a human operator, but also on the automation system performance or the human trust level when those actions are taken. This dependency explicitly models the impact of the HAI on the assembly process, and addresses the practical concern that the human or automation's real time performance does affect how well the tasks can be accomplished.

7.1.6. *Task assignment model*

Let S_π denote all the states when one round of assembly is finished. The assembly process should keep on going and the finished state should be visited infinite times. Each visit to the set S_π completes a cycle. When dealing with an assembly task, the average cost per cycle (ACPC) is a more reasonable cost measure to optimise (Ding et al. 2014). Then a dynamic task assignment problem is defined to be finding a task assignment policy Φ that optimises the probability of finishing the assembly process infinitely often while minimising the ACPC, that is, $J(s_0) = \lim_{N\to\infty} \sup E\{\frac{\sum_{k=0}^{N} c(s_k, \Phi(\omega_\Phi^{s_k}))}{C(\omega_\Phi^s, N)}\}$, where ω_Φ^s denotes the state path under policy Φ, $\omega_\Phi^{s_k}$ denotes the state path up to stage k, and S_π is visited infinitely often and the observed label sequence along the ω_Φ^s obeys other constraints ϑ. As a result, dynamic task assignment entails an optimal policy making problem to minimise the expected average cost on each cycle of the persistent tasks while maximising the probability of satisfying constraints ϑ expressed in LTL specifications.

7.2. Human-in-the-loop game theoretic optimisation

The key challenge of dynamic task allocation is how to support group decision making in human-automation system optimisation (IBM 2018). An optimal HAI system design involves three types of optimisation problems, i.e. human-centred optimisation, interaction-centred optimisation, and automation-centred optimisation, to be prioritised and integrated within a coherent framework. It is promising to adopt a collaborative group decision-making approach originated from a Stackelberg game (Fudenberg and Tirole 1991), which entails typical cooperative decision making scenarios in such a way that the leader and the followers negotiate interactively to achieve equilibrium solutions while leveraging upon different or even conflicting goals of the multiple aspects of a human-automation system (Du, Jiao, and Chen 2014). Bilevel programming (Deb and Sinha 2010) is associated with inherent mathematical characteristics (Dempe 2002) that excel in modelling leader-follower joint optimisation problems (Marcotte, Savard, and Semet 2004). As such, a mathematical model of bilevel game optimisation can be formulated through nested leader-follower joint optimisation for optimal allocation of tasks considering HAI.

Figure 2 illustrates the principle of human-in-the-loop game theoretic optimisation through cascading leader-follower decision making to coincide with nested bilevel mathematical programming techniques. The rationale of game theoretical optimisation lies in seeking for equilibrium solutions, instead of global optima, to arrive at a synergy of various interests of multiple decision makers in a cooperative game environment. Due to the coupling of leader-follower decision making, enumeration algorithms tend to be difficult to be computationally tractable. Nested genetic algorithms (NGA) can be developed to effectively accommodate the joint optimisation of the leader and follower optimisation models. To alleviate the complexity of bilevel interactions, a good strategy is to take advantage of the nested structure underlying the

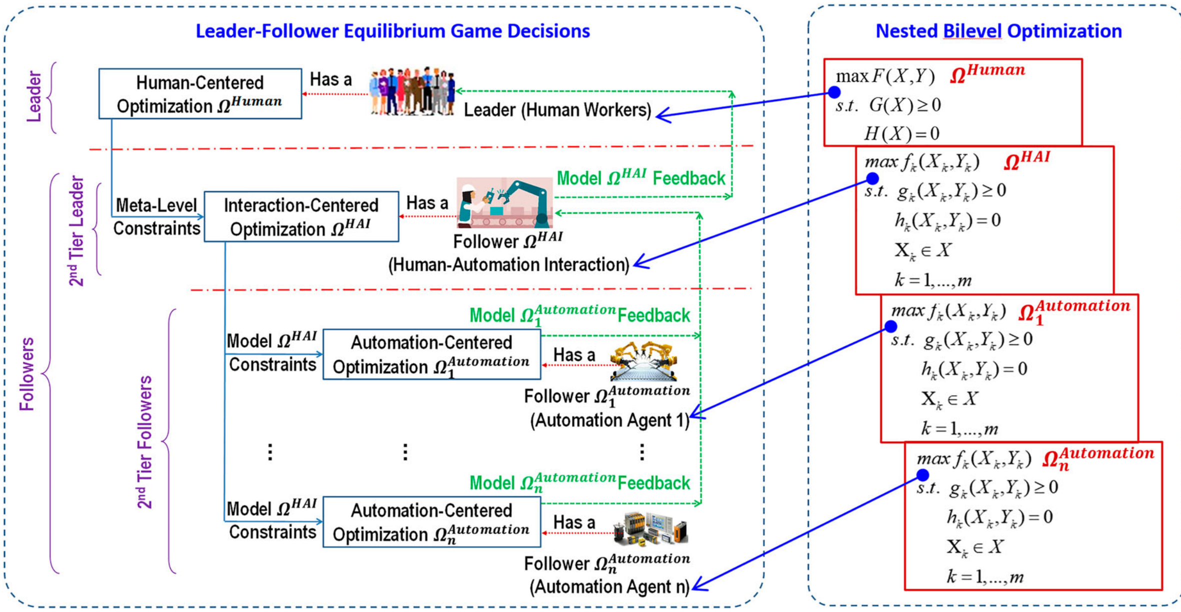

Figure 2. Human-in-the-loop game theoretic optimization for adaptive human-automation system design.

leader-follower games. The NGA can be implemented as an algorithm toolkit embedding some mainstream evolutionary optimisation algorithms, such as Non-Dominated Sorting Genetic Algorithm II, Strength Pareto Evolutionary Algorithm II, and Multi-Objective Particle Swarm Optimization. Since more than one optimisation method may be applied, performance evaluation experiments usually are introduced to compare different algorithms for specific problem contexts. The computational complexity of NGA can be tested in an environment for modelling and testing bilevel optimisation problems based on the GAMS (General Algebraic Modeling System) (Deb and Sinha 2010). Further research opportunities exist to develop rigorous mathematical analyses and intensive computational studies to verify model assumptions and solution conditions. Based on the analytical results of numerical examples, sensitivity analysis experiments can be set up to examine the patterns of leader-follower game decisions and the interaction variables and constraints associated with optimal HAI design.

8. Recent trends and future research

The above review suggests that augmenting human cognition has been tackled from a broad scope of HAI involving many disciplines. Recent trends and several possible directions are speculated for further research. Cyber-physical-human systems will become the norm, owing to the growing digitisation of products and smart sensing technologies widely deployed under the umbrella of the Internet of Things and Industry 4.0. Human cognition and learning are enacted through interaction with increasingly more advanced technologies and intelligent systems that are embedded in smart manufacturing systems. The last 20 years have seen rapid advances in machine learning, pattern recognition, planning, effective decision making, natural language processing, and machine vision. These advances have been fuelled by an increased amount of data, faster computation, and improved algorithms. They are yielding increasingly diverse and large-scale applications deployed in settings subject to unanticipated challenges with complex social effects. Integrative research on many interdisciplinary aspects of cyber-physical-human modelling and analysis will allow unprecedented extension of human perception and action, opening up vast reservoirs of knowledge and potential for innovation.

8.1. Social aspects of human-AI partnership

Long-lasting transformative research in artificial intelligence (AI) and machine learning (ML) have resulted in a variety of innovations that offer new levels of economic opportunity and growth, safety and security, as well as health and wellness. At the same time, broad acceptance of large-scale deployments of AI systems relies critically on their trustworthiness, which, in turn, depends upon the collective ability to ensure, assess, and ultimately demonstrate the fairness, transparency, explainability, and accountability of such systems. Importantly, the benefits of AI systems should be broadly available across all segments of society. It is imperative to understand the social challenges arising from AI technologies and enable scientific contributions to overcome them. With increases in the scale and diversity of deployments comes the need to better understand the human-AI partnership in the open world, including unforeseen circumstances and social impacts, and to craft approaches to AI that consider these from the start. Vital directions include developing principles for safe, robust, and trustworthy AI (including shared responsibilities between humans and AI systems); addressing issues of bias, fairness, and transparency of algorithmic intelligence; developing a deeper understanding of human-AI interaction and user education; and developing insights about the influences of AI on people and society.

For example, one important research area is computational research focused on fairness in AI, with the goal of contributing to trustworthy AI systems that are readily accepted and deployed to tackle grand challenges facing society. Important research topics deserving scrutiny include, but are not limited to transparency, explainability, accountability, potential adverse biases and effects, mitigation strategies, validation of fairness, and considerations of inclusivity. Such research efforts will further enable broadened acceptance of AI systems, helping the industries further capitalise on the potential of AI technologies. Advancing AI is a highly interdisciplinary endeavour drawing on fields such as computer science, information science, engineering, statistics, mathematics, cognitive science, and psychology. As such, practical problem contexts and application scenarios are expected to be critical to providing varied perspectives for the study of fairness in AI. Therefore, building AI that is fair and unbiased is an important aspect of further research initiatives on human-AI partnerships. It calls for fundamental computer science, social and economic research into theories, techniques, and methodologies that go well beyond today's capabilities and are motivated by challenges and requirements in real systems.

8.2. Collaborative cognition for future of work

One of the big ideas for bold, long-term research unveiled by NSF is future of work at the human-technology frontier in response to the challenges and opportunities for the future of jobs and work (NSF 2016). Tremendous opportunities exist for convergence research to understand and influence the impact of AI and automation technologies on workers and work, understand and develop the human-technology partnership, design new technologies to augment human performance, illuminate the emerging socio-technological landscape, understand the risks and benefits of new technologies, and foster lifelong and pervasive learning. Exponentially growing techniques are revolutionising society, leading to a force of disruption, as technologies are responsible for displacing some jobs and lagging behind some current skills, businesses, and institutions. Several reports and studies have highlighted the challenges and opportunities (National Academies of Sciences, Engineering, and Medicine 2017b; White House Council of Economic Advisors 2018). Many industries and organisations suffer from a talent gap. Not only do their current workers lack the requisite skills to perform twenty-first-century work, but graduates moving into the marketplace also lack those skills. It has been reported that an integrated set of skills, related to AI/machine learning, data science, and predictive analytics will be increasingly expected from current staff as well as new job applicants (BHEF 2017). A National Academies report (National Academies of Sciences, Engineering, and Medicine 2017a) makes the argument that workers will need to be trained and re-trained across the spectrum of education levels as more types of industry digitise their operations, from manufacturing to agriculture to the service industries and beyond. However, there remains, in general, a lack of alignment between educational opportunities at all levels and business demands. A holistic, more strategic, approach to this challenge is still needed.

On the other hand, new technologies may actually also be seen as an opportunity, as the advances in the capacity to handle, collect and process large volumes of data is helping businesses and industries cut costs, reduce errors, save time, improve decision-making, and ultimately, solve complex problems that were once indecipherable by the human brain alone. Rather than displacing them, new jobs are being created pushing the boundaries of the traditional job market. In addition to creating new jobs, technologies are also helping to empower, retrain and upskill the workforce, while all will increasingly experience unimaginable changes in life. What does this mean for the augmentation of human cognition? Are there new security or privacy challenges in terms of consent, transparency, use, and control in these new contexts and products? If so, is the existing policy framework sufficient to address them? How to ensure that no one is left behind this revolution in the job market? These are just some of the questions that are imperative to be addressed. The research focus will be on how technologies would continue to innovate while projecting the future of work and the future of collaborative cognition.

Cyber-physical-human analysis lends itself to be a promising direction for collaborative cognition research to promote deeper basic understanding of the interdependent human-technology partnership. The research efforts will advance societal needs by advancing design of intelligent work technologies that operate in harmony with human workers, including consideration of how people learn the new skills needed to interact with these technologies in the workplace; for example, by enabling broad workforce participation, including improving accessibility for those challenged by physical or cognitive impairment. Also important is research on the social-economic aspect of collaborative cognition to understand, anticipate, and explore ways of mitigating potential risks arising from future work at the human-technology frontier. Ultimately, this research will advance the understanding of how technologies and people interact, distribute tasks, cooperate, and complement each other in different specific work contexts of significant societal importance. It will also advance the knowledge base related to worker education and training, as well as formal and informal learning to enable all potential workers to adapt to changing work environments. It will contribute to the understanding of human-technology collaboration as the links between the future of work and the surrounding society, including the intended potential of new technologies and the unintended consequences for workers and the well-being of society. In particular, research formulations focusing on specific work contexts will be helpful to yield practical insights and a better understanding of HAI. Such a focus on domain-specific applications will contribute to a more data-capable, twenty-first-century workforce with the skills to harness all the potential benefits that technologies can offer.

8.3. Trust dynamics and mitigation

While automation technologies have the potential to supplement or replace human decision-making, it is imperative that they are safe, trustworthy, and aligned with the ethics and preferences of the human users who are influenced by their actions. A promising area is the design of systems that augment the perception, cognition, emotion, and problem-solving abilities of people. Practical applications require predictive analytics and decision support to provide people with clarity about the understanding and confidence that automation systems have about situations and means for coordinating human and technology contributions to problem solving, and to enable automation systems to work with people to resolve uncertainties about human goals. Trust in technologies has been considered to have a central influence on the way a human user interacts with an automation system (Fukuyama 1995). Though extensive research into trust dynamics has identified specific human-technology interaction behaviours, or trust outcomes, a unique mapping between trust states and trust outcomes has yet to be clearly identified. Interaction behaviours have been intensely studied in the domain of human factors, leading to a reframing of trust in automation technologies in terms of reliance and compliance. It is noted that the behaviourally defined terms of reliance and compliance to be useful particularly in their functionality for application in real-world situations. However, once an inappropriate interaction behaviour has occurred it would become too late to mitigate it, especially in the cases that AI systems may perform more as an autonomous decision agent than an assistive tool as in traditional HAI. One important focus is to scrutinise the interaction decision that precedes the behaviour (Drnec et al. 2016). The decision neuroscience and human factors communities have revealed that decisions are fairly stereotyped processes accompanied by measurable psychophysiological correlates. It is thus important to emphasise that an interaction decision precedes an interaction behaviour by leveraging the knowledge of the psychophysiological correlates of decisions to improve joint system performance. To better understand the interaction decisions that are critical to the eventual mitigation of inappropriate interaction behaviour, it is necessary to integrate the state-of-the-art understanding of decision-making processes from the distinct perspectives of design theory, cognitive neuroscience, and industrial systems engineering. One promising direction is to formulate research hypotheses based on a meta-analysis consensus and shape a research path toward the ability to mitigate interaction behaviour of human-AI systems in the real world.

One promising perspective of the HAI concept is through the lens of a model depicting the key elements of automation-to-human and automation-of-human transparency. Automation-to-human factors represent information that the system needs to present to users before, during, or after interactions. Automation-of-human variables are factors relating to the human (or the interactions with the human; i.e. teamwork) that the system needs to communicate an awareness to the users. It is worthwhile to examine the potentials and design implications for the various transparency domains to include training and the human-automation interface (e.g. social design, feedback, and display design). To date, the transparency construct has been limited to explanations for anomalous behaviour, reliability indices, and attempts to define the analytic underpinnings of a system. These aspects of the automation system are certainly relevant and should be designed into novel systems. However, they have been considered in isolation and additional information relating to the automation-to-human and automation-of-human factors could add considerable value in complex HAI, where AI/automation systems have high degrees of autonomy. Transparency in this sense is a more comprehensive treatment of the information that a human operator may need or want when dealing with autonomous systems under high stress, workload, and uncertainty. Given the imperfect track record of automation use in recent years, such as Boeing 737 Max crashes (Wichter 2019), Tesla Model 3 production delay (Braga 2018), it is imperative that researchers consider the elements of HAI that allow individuals to properly calibrate their reliance on these systems, particularly as technologies get more complex in increasingly complex application scenarios. A broader operationalisation of transparency and an extended conceptualisation of transparency may offer one mechanism to foster optimal calibration between humans and automation systems.

8.4. Augmented intelligence for human cognitive sensing and prediction

The emerging trend of human-in-the-loop cyber-physical-systems is a promising class of applications for measuring cognitive activity through body and brain sensors (Schirner et al. 2013). Such capabilities make it possible to infer the intent through analysis on an embedded system, and then translate the intent into automation (e.g. a robot) control signals to influence the physical environment by robotic actuators, whereby the effects are then again observed by the human as an input for new decisions to close the entire loop (Feng, Quivira, and Schirner 2016). Originated from ambient intelligence (AmI) technologies (Shadbolt 2003), augmented intelligence (AI +) conceives a next-step conceptualisation of artificial intelligence that focuses on AI's assistive role, emphasising the fact that cognitive technologies are designed to enhance human intelligence rather than replace it (Zheng et al. 2017). It implies a paradigm of augmenting AI, that is, to improve or reinforce the role human intelligence playing when using machine learning and deep learning algorithms to discover relationships and solve problems (Jiao et al. 2007; Jiao, Xu, and Du 2007). For instance, a practically meaningful perspective of automatic driving could be human–computer collaborative driving, instead of (purely) autonomous driving that aims to replace or override human's driving. This refers to sharing of vehicle control between a driver and the intelligent system to accomplish the driving tasks cooperatively. It exemplifies a strong complementarity between a human driver and an assisted-driving machine, such as a driver assistance and safety warning system.

Utilising advances in system-level design, AI + enables a holistic framework for design and implementation of heterogeneous human-in-the-loop cyber-physical systems composed of physically distributed, networked components. It will advance sensing and predicting human emotion, perception, and cognition by incorporating context-aware inference and learning of task-specific human intent estimation in complex manufacturing and operational environments, such as applications involving semi-autonomous robotic actuators and an efficient wireless communication framework. For example, one typical application in augmented cognition is to utilise psychophysiological measures to identify changes in human cognitive activity during task performance in real time (Zhou et al. 2011; Lohani, Payne, and Strayer 2019). Liu and Wang (Liu and Wang 2018) reviewed recent advances of AI + applications to gesture recognition for human-robot collaboration. Through deep learning from visual observation of human workers' motion, Wang et al., (Wang et al. 2018) investigated a data-driven technique for continuous human motion analysis and future human-robot collaboration need prediction, leading to improved human-in-the-loop robot planning and control in accomplishing a shared task. Various AI + techniques have been applied to studying drivers' perception and cognition towards automation in vehicles (Beller, Heesen, and Vollrath 2013; Lee et al. 2015) and prediction of human behaviours in a driver-vehicle-environment system (Lin et al. 2005; Merat and Lee 2012).

Two basic models of AI + can be foreseen as a new form of machine intelligence for augmenting human cognition. One is human-in-the-loop augmented intelligence with human-automation collaboration. The other is cognitive computing-based augmented intelligence, in which a cognitive model is embedded in the machine learning system. Future research is geared towards a holistic framework for human-automation collaborative hybrid-augmented intelligence, for which the key elements of hybrid-augmented intelligence based on cognitive computing need to be integrated within a coherent HAI framework. These elements include intuitive reasoning, causal models, evolution of memory and knowledge, especially the role and basic principles of intuitive reasoning for complex problem solving, and the cognitive learning framework for visual scene understanding based on memory and reasoning.

8.5. Multidisciplinary knowledge integration

Due to the broad scope of this field, it is necessary to build upon existing convergence research with the intention of accelerating use-inspired research discovery and innovation (Stokes 2011). It is critical to facilitate convergent research that employs the joint perspectives, methods, and knowledge of computer science, engineering, research on education and learning, and workforce training, and social, behavioural, and economic sciences. This involves multidisciplinary knowledge integration spanning disparate engineering, social and economic disciplines. Augmenting collaborative cognition of HAI calls for a rigorous integration of multidisciplinary knowledge related to such fields as (1) manufacturing, service and operations systems, (2) human factors, behavioural economics, and cognitive engineering, (3) engineering system design, decision making, and integration, and (4) computing, sensing, intelligence, and infocom technologies. Figure 3 illustrates how the integration and symbiosis of cross-disciplinary perspectives can be aligned with the fundamental technical focuses systematically through the technical, human and larger societal dimensions of augmented collaborative cognition for the future of work.

Figure 4 shows an anatomy of how cross-disciplinary and cross-sector integration contributes to the specific research focuses, which coincides with a vision of how interdisciplinary research can integrate the technology into a domain system to generate additional discoveries inspired by the interaction of humans and technology (NSF 2016). New insights and knowledge are expected to be gained from leveraging and integrating the key knowledge fields identified above in Figure 3. As shown in the centre box of Figure 4, key research focuses are planned to fulfil an interdisciplinary and cross-organizational promise across different research areas that are synthesised within a coherent framework of the HAI technology domain.

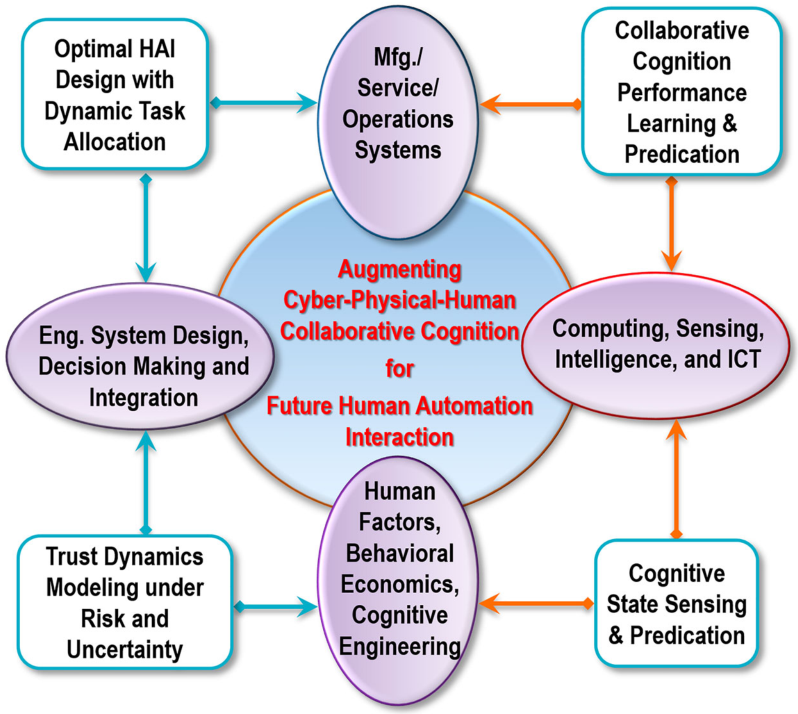

Figure 3. Collaboration of cross-discipline perspectives to create multidisciplinary knowledge integration.

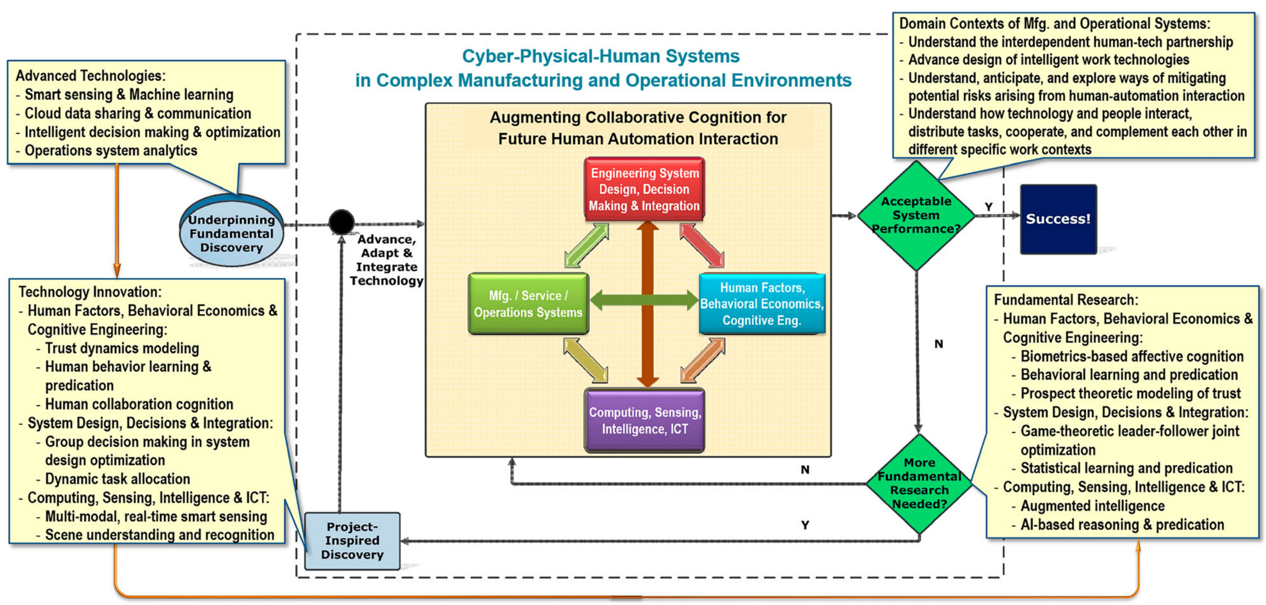

Figure 4. Synergies of research focuses and knowledge discovery towards augmenting human cognition.

Figure 4 also shows the scientific context of research discovery, the importance of the technologies, and the way how inter-disciplinary and cross-organizational research collaboration can be further advanced and adapted, so as to allow integration of advanced technologies (as shown in the upper-left box in Figure 4) into a viable smart manufacturing and operational system (as shown in the upper-right box in Figure 4). In terms of project-inspired discovery as shown in the lower-left box in Figure 4, the research is expected to result in a number of interdisciplinary innovations to advance the HAI technology domain and create new knowledge on operations system applications. Composition and synthesis of these technology innovations into the human-automation systems open up many new opportunities for fundamental research, as shown in the lower-right box in Figure 4, which ultimately contributes to advancing the fundamental understanding of augmenting human cognition. Collaborative cognition is thus of practical importance to encourage the development of a research community dedicated to designing intelligent technologies and work organisation and modes inspired by their positive impact on individual workers, the work at hand, the way people learn and adapt to technological change, creative and supportive workplaces, and benefits for social, economic, and environmental systems at different scales.

9. Concluding remarks

Future working environments will be populated by both human and automation agents to collaborate on a shared understanding of the tasks, in which team cognition has been identified as a key component to achieve operational goals. It is important to advocate a symbiosis of collaborative cognition to enhance team cognition so that technologies and human complement each other by performing the tasks most suitable to each of them. Consistent with a systematic augmented cognition framework of sensing, learning, and decision making, the research focus on collaborative cognition reveals a human-automation mutual adaption strategy for augmenting human team cognition and collective intelligence. The analytic and model-based approach to augmenting collaborative cognition goes beyond an individual's cognition to include interactions of individuals with other non-human cognitive agents, through computational modelling and evaluation of strategic interactions among the human and automation agents.

One important area is the computational learning approach by prediction from multimodal physiological and behavioural data to understand human workers' underlying emotion, cognition, and perception. Monitoring physiological status and behavioural activities using augmented sensor technologies facilitates affective cognition recognition and perception learning. It helps reveal how human workers' emotional states, cognitive workload, and cognitive capabilities influence their performance during the process of HAI in the workplace.

An important perspective is to use value-based trust dynamics models to quantify trust in automation. While extensive research has been devoted to human-human trust modelling, there exists a knowledge gap for a unique quantification model of trust in automation. It is reasonable to capitalise on a value-based decision process to quantify trust with regard to different levels of automation to predict human workers' behaviour under uncertainty. In addition, human individual differences in cognitive capabilities lead to varying degrees of trust due to their varying risk attitudes and preferences towards automation. It is promising to extend prospect theory in the field of behavioural economics to build a theoretical ground of trust quantification in the particular context of HAI under risk and uncertainty. The approaches to inferring affective and cognitive influence on trust through the shape parameters of a trust value function can improve the prevailing practice of trust dynamics modelling based on a Markov decision process by incorporating the decision makers' cognitive tendency with risk attitudes.

Understanding and measuring cognition at the team level is a critical aspect in understanding team performance and effectiveness in a complex HAI environment. It is critical to adopt a holistic probabilistic modelling and statistical learning approach to predict human collaborative cognition performance. While a probabilistic Gaussian process model excels in extended prediction beyond limited sampling data, a Bayesian network model contributes to probabilistic inverse reasoning. Such prediction models can help the design of networked human-automated systems cope with various uncertainties in order to accommodate future workers by linking expected operating conditions and performance from experimental data to diverse observable cognitive traits of human workers.

In a complex manufacturing and operational environment, making a tradeoff between human performance and system efficiency in term of time, costs and production rates involves human behaviours and perceptions of their interaction with various automation agents. It is of practical importance to formulate augmenting collaborative cognition as an optimal HAI design problem for mutual adaption between human workers and the automation system. The human-in-the-loop game theoretic optimisation model is a promising approach to empowering dynamic task allocation to achieve equilibrium solutions, such that collaborative cognition augmentation can be achieved by adapting to individual differences in human cognitive capabilities with appropriate types and levels of automation, while leveraging upon the overall operations system performance and costs.

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