Antecedents and Outcomes of Artificial Intelligence Adoption and Application in the Workplace: the Socio-Technical System Theory Perspective

Abstract

Purpose – The use of artificial intelligence (AI) in the workplace is on the rise. To help advance research in this area, we synthesise the academic research and develop research propositions on the antecedents and consequences of AI adoption and application in the workplace to guide future research. We also present AI research in the socio-technical system context to provide a springboard for new research to fill the knowledge gap of the adoption and application of AI in the workplace.

Design/methodology/approach – This paper summarises the existing literature and builds a theoretically-grounded conceptual framework on the socio-technical system theory that captures the essence of the impact of AI in the workplace.

Findings – The antecedents of AI adoption and application include personnel subsystem, technical subsystem, organisational structure subsystem and environmental factors. The consequences of AI adoption and application include individual, organisational and employment related outcomes.

Theoretical and Practical implications – A research agenda is provided to identify and discuss future research that comprises not only insightful theoretical contributions but also practical implications. A greater understanding of AI adoption from socio-technical system perspective will enable managers and practitioners to develop effective AI adoption strategies, enhance employees' work experience and achieve competitive advantage for organisations.

Originality – Drawing on the socio-technical system theory, our proposed conceptual framework provides a comprehensive understanding of the antecedents and consequences of AI adoption and application in the work environment. We discuss the main contributions to theory and practice, along with potential future research directions of AI in the workplace related to three key themes at the individual, organisational and employment level.

Keywords: Artificial intelligence; Socio-technical system theory; Workplace

Paper type: Conceptual paper

1. Introduction

Artificial Intelligence (AI) is the key driver of the fourth industrial revolution that organisations are strategically implementing as essential functions to solve a variety of daily management challenges (Schwab, 2017; Syam and Sharma, 2018). AI refers to “machines performing cognitive functions usually associated with human minds, such as learning, interacting, and problem solving” (Raisch and Krakowski, 2021, p.192). The increasing use of computer systems with advanced AI is able to sense, reason, and respond to the dynamic work environment (Hughes *et al.*, 2019). AI has been developed beyond industrial automation and is now increasingly found to perform complex tasks for employees outside of highly regulated factory environments. The fast development of AI and the corresponding innovative technologies including robots, smart devices, and the Internet of Things (IoT) have been radically changing the interaction between employees and organisations (Larivière et al., 2017) as organisations are now adopting and applying AI to establish processes and expedite tasks that were conventionally conducted by human employees.

Ongoing technological development of AI will have notable impact on job categories, working hours, relationship between employers and employees, and remuneration models (Li *et al*., 2019). AI adoption may make employees feel insecure and employees are more likely to quit from their jobs (Brougham and Haar, 2018). Employees’ attitudes may significantly impact their technology acceptance decisions, which, in turn, influence organisation’s performance and innovation (Lichtenthaler, 2019). Comparably, some studies indicate that AI could help innovate the business value chain by automating manufacturing processes, exploring data value and optimising decisions and actions which help organisations enhance overall operational efficiency (Kim and Heo, 2021; Wright and Schultz, 2018). For example, healthcare robots can now monitor patient health and mood, as well as provide companionship (Broadbent *et al*., 2016). In the wholesale and retail industry, Analytical AI has been applied by Amazon to assist inventory management (Kaplan and Haenlein, 2019). In theme parks, AI tour-guide/tutor robots are being deployed to enhance guests' experience (Matsumoto, 2020). In the hotel industry, the introduction of AI-powered chatbot helps manage customer's stay and handle routine customer queries (Chung *et al*., 2020). In addition, AI is used in contact centres to enhance customer service experiences (Kirkpatrick, 2017). Companies can anticipate considerably high returns and business value from such investment in AI (Finch *et al*., 2018).

However, challenges emerged as a result of these applications that AI is not able to fully address. Ethical concerns have become important reasons to explain why some organisations are hesitant to adopt AI. Data privacy and network security could significantly influence AI adoption among users, and in turn impact organisational adoption decisions and outcomes (Chi *et al*., 2020). Poor network security could cause personal and sensitive data to be hacked and accessed remotely which may result in physical and psychological distress among users (Wirtz et al., 2018). The personal data breaches and incidents involved in AI applications may lead to loss of user trust and limit their willingness to adopt AI. Moreover, transparency and bias issues are still yet to be solved and remain as the ethical challenge for organisations (Zou and Schiebinger, 2018). Sophisticated AI technologies such as how AI makes decisions, what decisions are based on and how algorithms operate are still not transparent to users. One reason why people may reject AI could be linked to low perceived transparency of AI systems. Therefore, to achieve the best outcomes of AI adoption, leaders and practitioners need to understand the threats and opportunities that AI would bring. Toward this end, we seek to understand the antecedents and consequences of AI adoption and application in the workplace, based on the socio-technical system theory.

In this study, we synthesise the academic research input and classify the antecedents of using AI in the literature as personnel, organisational, technical and environmental related factors, and we categorise the consequences of AI adoption into three types in terms of focus of reaction: individual, organisational and employment. We used the major databases such as Business Source Complete (*EBSCO) and Science Direct* (Hewett et al., 2018) to examine top-tier journals published in business management and technology advancement fields. We also examined databases of *Emerald, Elsevier, ProQuest* and searched Google Scholar to ensure that we covered a wide range of literature in this conceptual paper. The search keywords performed were “artificial intelligence” or “AI” or “technology” or “automation” or “robot” or “algorithm” or “smart device” or “chatbot” as well as “organisation” or “organization” or “employee” or “employment” or “workplace”. The search might not cover all articles relevant to this study, but we are confident the selected articles in this conceptual paper identifies a comprehensive range of literature in business management and human resource management fields in the last 20 years to guide the direction for the theory development and future research from the socio-technical system theory perspective.

The socio-technical system theory can be applied as the theoretical foundation to analyse how AI in the work environment integratively contributes to work outcomes. This theory examines “both *the technical system* and *the social system* and their *interrelations on the work group level*” (Ehn, 1988, p.261). The principle of the socio-technical system theory is exploring learning and behaviours regarding the resources and interactions of the system that involves current technology, interpersonal interactions, language, and external environment (Kull *et al*., 2013). The idea of the socio-technical system has been created to emphasise the reciprocal relationship between human and technology and to promote the programme of framing both the technical and the social sides of job, in a way that productivity and humanness do not negate each other (Jones *et al*., 2013). Although much research has been conducted on socio-technical system in the fields of science, innovation and technology, there's limited attention given to the business management and human resource management fields (Loureiro, Guerreiro, & Tussyadiah, 2021; Wilkens, 2020). Research on AI has primarily concentrated on functionality and technical efficiency (Prentice *et al*., 2020) and as such, we shed light on the impact of AI adoption and application on the individual, organisational and employment outcomes from the socio-technical system theory perspective.

Drawing on the socio-technical system theory, this paper seeks to identify how AI influences employees and organisations. Specifically, our paper contributes to existing AI literature in threefold. First, we summarise the current literature of antecedents and consequences of AI adoption and application in the workplace and identify research gaps in the literature. Second, we build a theoretically-grounded conceptual framework capturing the essence of the impact of AI in the workplace from the socio-technical system theory perspective. This integrated model presents the inter-connection of the subsystems which conjointly influence the transforming process from antecedents to outcomes. In doing so, we aim to promote theory and research development in this area. Third, by proposing the socio-technical system theory in the business management context, we hope this article provides a theoretical view on the value of AI in the work environment and stimulates new research to fill knowledge gaps in this field. The propositions on antecedents and consequences of AI adoption and application in the workplace are developed to guide the future research.

2. Socio-Technical System Theory

The socio-technical system as coined by Trist and his colleague in the 1950s in the UK (Trist and Bamforth, 1951) aimed at improving the performance of work system by examining how employees deal with technological difficulty and uncertainty effectively. Accordingly, the socio-technical system has produced a ‘win-win’ situation that employees were more productive and committed, technology was adapted successfully and organisations achieved better performance overall. However, the approach failed to spread widely due to the resistance of leaders to share operational control with employees. Managers complained that workers were not complying with their directions on how the technology was to be operated, while workers insisted that operating the technology directed by engineers was impossible in their working conditions. By the 1970s, Davis and Cherns (1975) incorporated the socio-technical system in various organisations in the US and supported the idea of ‘Quality of Work life’. It was adopted to create meaningful work for employees, but failed to diffuse further again due to traditional leaders who concerned giving workers greater control over the design and operation of work systems. In the early 2000s, researchers (e.g., Hammer and Champy, 2001) redesigned the system by offering firm control for leaders and constructed the lean six-sigma approach to enhance performance by focusing on efficiency and cost saving. In recent years, the burgeoning of digitisation, AI, and machine learning has significantly changed the interaction between employees and technologies in the work system, and socio-technical system has become more relevant than ever before (Pasmore *et al*., 2019). Sirianni and Zuboff (1989) argued that in the era of smart machines, individuals would face great challenges of either becoming masters of technology or its slaves, and there is a need to design work systems that could fit either of these situations. The socio-technical system developed a hope that organisations could achieve joint optimisation from both technological development and human aspirations.

With the entrance into the era of automation, organisations have employed new ways of working by incorporating AI to enhance organisation-related outcomes, and AI is developed to either make decisions or guide the future decisions (Kaplan and Haenlein, 2019). However, organisations are struggling to keep their social systems in the pace of technology advancement, and they are facing the challenges of navigating high caliber talent, engaging the workforces, developing effective work design and enhancing organisational capabilities (Pasmore *et al*., 2019). With these considerations, the socio-technical system theory is adopted as the theoretical foundation to analyse how multiple components jointly contribute to the work outcomes. The better fit between social and technical subsystems, the more desired individual and organisational outcomes will be achieved through AI adoption and application.

From the socio-technical system perspective, effective implementation of AI into organisations requires an integrated approach in which development in both social and technical systems is considered (Bélanger *et al*., 2013). This theory incorporates components from four elements that transform work system inputs to desired outputs, including the *personnel subsystem* in regard to social and people-related factors, the *technical subsystem* in regard to technology-related factors, the *organisational structure or work/job design subsystem* in terms of organisational structure and work process, and *environmental* factors external to the work system

(Bélanger *et al*., 2013; Høyland *et al*., 2019). As indicated in Figure 1, these subsystems identify the internal and external contexts in the workplace.

Insert Figure 1 about here
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3. Antecedents of AI Adoption and Application

3.1 Personnel Subsystem

In the examination of social and people related factors, Bélanger *et al.* (2013) identified three elements including demographic characteristics of employees (e.g., gender, culture), psychosocial aspects of employees (e.g., personality, attitudes) and employees' degree of professionalism (e.g., self-efficacy, skills).

Demographic characteristics. Brown *et al*. (1998) have compared different cultures and argued that employees in Japan may not fear AI and robotics as they would in the US, as employees may not be treated as disposable assets in Japan as they were viewed in the US. Rosen and Weil (1995) studied computer anxiety in ten countries and found that males and White participants often disclose higher level of self-efficacy and less fear in adopting new technology than females and non-White minorities. Gender difference has confirmed in various studies (McClure, 2018) that females generally exhibited greater technology anxiety than males. In fact, previous research indicated that females are restricted by their own beliefs that they are not suitable for traditional male occupations due to lack of the ability to master core skills, including technology (Bandura, 1977; Talukder and Quazi, 2011).

Psychosocial aspects. Lichtenthaler (2019) suggested that employee attitudes (both optimistic and pessimistic) are crucial for organisations to benefit from AI adoption. The optimistic view believes that AI will augment human capabilities, thus, labour is upgraded, from unskilled to indispensable, and from mechanical to thinking

(Huang *et al*., 2019), and AI can liberate manual labour and provide new business opportunities (Wilson and Daugherty, 2018). On the contrary, the pessimistic perspective considers that AI will eventually replace human jobs, making human employees obsolete in a fully robotised society, resulting in job insecurity (Wirtz *et al*., 2018). When employees expressed negative attitudes towards interaction with AI, it often resulted in limited openness to adopt AI solutions, as they focused more on emotional intelligence and empathy and preferred personal interactions with humans (Lichtenthaler, 2019). In comparison, when employees exhibited positive intelligent automation attitudes, they were more likely to adopt a pragmatic approach to AI solutions and emphasised more on rational decisions, efficiency and optimisation. We cannot make generalising statements from a work science point of view, however, it is important that "soft" aspects of jobs (e.g., thinking, creative, empathetic and intuitive skills) are becoming more important, and pairing AI and human employees to complement each other can make job more effective and engaging (Xu *et al*., 2020).

Moreover, trust is seen as the critical reason for employees to adopt AI; the level of trust employees have in AI systems could determine their behaviour to accept, progress and develop AI in the workplace (Siau and Wang, 2017). Building initial trust and facilitating continuous trust development could foster employees' strong relationship with AI (Siau and Wang, 2017). In addition, Anthony, Clarke, and Anderson (2000) studied the relationship between personality types and the adoption of technology and identified that neuroticism was positively correlated with the level of fear to adopt technology. Adding on to this, Korukonda (2005) suggested that apart from stable and enduring personality correlates, individuals are more likely to trust technology when equipped with better maths and logic skills.

Professionalism. Self-efficacy could serve as a significant predictor of AI adoption, which refers to perceptions of self-confidence in one's abilities or skills to perform a task (Bandura, 1977) and specifically a judgment of one's capability to use technology (Compeau and Higgins, 1995). Previous research reported a significant relationship between self-efficacy and the acceptance of technology and innovation (Hayashi *et al*., 2004; Lai, Wang, and Lei, 2012). High or low levels of self-efficacy could trigger positive or negative attitudes towards technology, which in turn results in AI adoption or rejection (Duane et al., 2014). Vargas, Yurova, Ruppel, Tworoger, and Greenwood (2018) demonstrated that low levels of technology and quantitative self-efficacy in terms of fear of math and statistics and low analytics awareness acted as a barrier for employees to adopt innovation. Furthermore, according to Rogers (2003), individuals' beliefs about innovation's suitability and applicability to their previous experiences, existing values and current needs significantly impact technology adoption. The greater compatibility the innovation is with individuals' experiences and values, the higher the opportunity of acceptance (Chung, 2014).

Proposition 1. The personnel subsystem in relation to social and people-related factors contributes to the AI adoption and application in the workplace.

3.2 Organisational Structure Subsystem

The organisational structure factors could be summarised as business strategy and operations, top management support, organisational culture and organisation size. These features are generally unique resources and embedded to organisations that contribute to the adoption of AI associated practices and processes. According to Awalegaonkar *et al*., (2019), the majority of C-suite executives believe that appropriate organisational structure and governance need to be in place to achieve the pervasive use of AI , and organisations widely adopting AI have clearly linked AI strategy and operating model to organisation objectives, fostered data-driven AI culture, secured appropriate funding, clearly defined responsibilities and formulated leadership support for such AI application.

Business strategy and operation. AI adoption associated with complex technology innovation leads to significant organisational change of business process and organisational practices, which require top management support and alignment with overall organisational strategic goals. Successful AI transformations need a solid AI business case and should align with existing business strategies; a lack of strategic vision and plan could hinder IT innovations (Armstrong and Sambamurthy, 1999). Organisations are more likely to implement new technology if they embrace new ideas and face the prospect of change in improving business operations and creating strategic effectiveness (Greenhalgh *et al*., 2004). The easier the technology is integrated into business operations, the greater the chance it could be adopted (Oliveira *et al*., 2014).

Top management support serves as a key factor in new technology adoption (Chong *et al*., 2009) in terms of providing sufficient funds, developing strategic vision and allocating appropriate resources (Yang *et al*., 2015). Capable managers could have intuitive understanding of new technologies and leverage them effectively to align business processes with organisational goals (Garrison *et al*., 2015). Once leaders determine AI application as a top business priority, they tend to be engaged and willing to allocate resources for AI implementation (Nah *et al*., 2001). A lack of management support could impede the adoption of innovation and fail to improve organisation's competitiveness in the market (Wade and Hulland, 2004).

Organisational culture has been reviewed frequently in the literature as an important factor in the adoption of technology (Davenport, 2013; LaValle *et al*., 2011). Cultural challenges could be as critical as technology and business challenges, as it takes a long time to create a culture to adapt to innovative technology (Halper, 2014). The technological culture could dramatically influence employee's innovation decision process, but such culture can only be developed once the innovation has been adopted in the organisation (Vargas *et al.,* 2018). It is essential for top managers to create a strong creative and innovative workplace culture and establish leadership support with dedicated AI champions, where AI adoption experience is shared across the organisation.

Organisation size. Previous studies identified that company size positively affects the adoption of new technology and innovation (Rogers, 2003). Larger organisations are more likely to innovate and benefit from it because they possess more technical and financial resources (Aboelmaged, 2014; Wright and Schultz, 2018), encounter greater competitive challenges, have higher capacity and can take greater risks than smaller companies (AlSheibani, 2018).

Proposition 2. Organisational structure or work/job design subsystem in terms of organisational design and work process contributes to the AI adoption and application in the workplace.

3.3 Technical Subsystem

The technology-related factors could be summarised as physical assets of technology that are essential to adopt AI, such as IT infrastructure, technology complexity, trialability and IT maturity; and intangible assets of best practices applied in AI adoption, such as training, communication, collaboration, and reward. This could also be described as technical capabilities that promote the integration of AI technologies and business processes. The more capable organisations are to leverage relevant resources and address the complexities and challenges, the faster AI could be adopted to the existing IT infrastructure.

Technology readiness provides a clear way to predict the advantages gained from technological implementation (Richey *et al*., 2007) and it shows how well an organisation prepared for AI adoption. Technological resources such as computer software and hardware, data and networking are critical for new technology adoption (Aboelmaged, 2014). The existing standard machine learning algorithms and data analytics in organisations are likely to contribute to further development of intelligence (AlSheibani, 2018). Notably, the complexity of AI could be the obstacle for adoption, as employees may perceive it as difficult to understand and operate. In this way, trialability related opportunities to try or experiment the innovation could positively influence users' attitudes towards adoption (Chung, 2014). Moreover, IT maturity significantly influences organisation's adoption decisions. The more mature of the technology, the better knowledge about the implementation, the more likely organisations are willing to adopt it (Huang and Palvia, 2001).

Practices. Many organisations struggle to adopt AI due to their emphasis on technology rather than technical skills and practices for application (Gartner, 2017). AI implementation involves significant changes in business processes and requires organisations to design best practices to facilitate it. Previous studies indicated that technical capability including a dedicated IT team, technical knowledge, IT development and effective communication and collaboration within organisations serves as a key factor for IT adoption (Garrison et al., 2015; Nakayama, 2003). Formal training and new skillsets are critical for successfully scaling AI, as employees understand better on how AI can be applied to their job roles and how they can implement AI responsibly (Awalegaonkar *et al*., 2019). Managers could encourage excellent internal communication and interactions in the workplace to reduce employees' perception of potential threats caused by AI (Ivanov and Webster, 2017). Leaders could expand and embed best practices and resources at the organisational level and potentially change the business operation and decision-making process (Kor and Mesko, 2013). Once organisations have adequate technical knowledge and expertise in AI implementation, they are able to integrate AI into existing IT infrastructure more efficiently to achieve organisational goals.

Proposition 3. Technical subsystem in regard to technology-related factors contributes to the AI adoption and application in the workplace.

3.4 Environmental Factors

The environmental factors refer to the related characteristics of the context where the socio-technical system operates. Organisations conduct business activities to respond to the external environment, meanwhile, this environment affects the business operations and decision-making (Høyland *et al*., 2019). Environmental factors are the driving forces for organisations to adopt new technology and negatively or positively influence the operating system (Bélanger *et al*., 2013). In regard to AI application, competitor pressures, customer responses, social and ethical challenges and government regulations are recognised as critical factors in shaping organisational actions.

Competitive pressure is considered as a significant factor for diffusions of innovation (Yang *et al*., 2015) and drives organisations to develop relevant strategies for AI adoption and application. Organisations may face the threat of losing competitiveness in the marketplace, if their competitors adopt innovative technology. They are more likely to speed up the process of adoption to maintain the competitive advantage (Oliveira and Martins, 2011). AI applications could potentially change the business process, enhance the operational efficiency and leverage the new routes to outperform the competitors.

Customer responses. High customer expectations of service quality and timely delivery are likely to trigger AI application. AI can operate 24/7, serve multiple customers simultaneously, deliver the service in a timely manner and generate higher revenue for organiations (Ivanov and Webster, 2017). Likewise, AI creates value for customers and improves their experience by providing interesting and entertaining services and communicating in an attractive and interactive manner (Kuo *et al*., 2017). However, customers may reject the interaction with AI and robotics due to the perception of dehumanised and devalued products or services provided by the company. For example, in the healthcare context, patients could lose social contact and emotional attachment with carers and act with anger and frustration towards robotic care (Veruggio *et al*., 2016). In the hospitality industry, customers may potentially feel that services are devalued by robotics due to lack of enjoyment or social interaction (Lin *et al*., 2020).

Social and ethical challenges can increase the cost and slow the process of AI adoption. Ethical issues such as privacy intrusiveness, algorithmic transparency, skill-bias remain unsettled, which could restrict users' AI acceptance. Societal issues of technological unemployment may create unequal income distribution and limit economic growth (Frey and Osborne, 2017; Nam, 2019). Braun *et al*. (2016) argued that technological changes in future industrialisation would accelerate social and economic revolution that could lead to world-wide revolution with dramatic social consequences. According to Langer and Söffker (2015), to achieve the best result on human-automation interaction, key priorities including trust, bias, cost, safety, responsibility and social issues in automation need to be fully addressed. Thus, it is critical for organisations to develop the code of ethics for responsible use of AI to achieve highest potential benefits and shield people from risks.

Government regulations involving the policies and rules set by the government authority could influence organizations' decisions on AI adoption. The government can influence IT innovation by setting or removing the challenges faced by organisations (Huang and Palvia, 2001). Notably, many governments (such as US, UK, China and Japan) have formulated strategic plans and allocated adequate resources to motivate AI development in recent years (Dutton, 2018). These supportive policies create a favourable environment for AI application and encourage its diffusion (Agrawal *et al*., 2018). Moreover, AI involves complicated technology with a broad range of influences in different industries, government regulations could monitor AI-related security, ethics, bias and privacy more closely to avoid negative social impact and promote benign AI development.

Proposition 4. Environmental factors external to the work system contribute to the AI adoption and application in the workplace.

3.5 Joint Optimisation

Joint optimisation refers to the inter-connection of the subsystems in the socio-technical approach conjointly influencing the transforming process from antecedents to outcomes (Bélanger *et al*., 2013). In general, the internal subsystems of personnel, technical and organisational structure are affected by the external environmental subsystem, and they jointly produce the outcomes in the operating system (Hendrick and Kleiner, 2002).

In the AI application process, employees need to continuously interact with new technology to perform tasks and develop outcomes within organisational structures. AI associated business activity and process change can significantly influence the way employees conduct their jobs and impact on their psychological perception. Notably, an appropriate organisational structure in terms of top management support can create a favourable AI culture, improve employees' attitude to interact with AI, facilitate trust development, promote workplace communication and enhance the delivery of technical solutions for AI adoption. Likewise, adequate technical facilities and knowledge in AI application could promote AI integration into organisational structure more efficiently to achieve organisational goals. Therefore, we propose that interactions between personnel, organisational structure, technical, and external environment subsystems in the socio-technical approach will impact AI adoption and application, and ultimately lead to better individual, organisational and employment outcomes.

Proposition 5. Internal subsystems of personnel, technical and organisational structure interact with external environment subsystem and they are jointly associated with AI adoption and application in the workplace.

4. Outcomes of AI Adoption and Application

In the preceding section, we have argued that personnel, organisational, technical and environmental related factors are the antecedents of AI adoption and application according to the socio-technical system theory. Below we propose important outcomes of AI adoption and application. We focus on three categories: individual, organisational and employment related outcomes.

4.1 Individual Outcomes

AI applications in the organisation could potentially send the signal to employees that their jobs are at risk and will be replaced by AI in the future, which may arouse their motivation to find alternative employment. Notably, turnover intention could be a critical variable in the job-related outcome category. More specifically, Brougham and Haar (2018) examined the impact of STARA (i.e., smart technology, AI, robotics, and algorithms) awareness on key job-related outcomes and concluded that the intention to replace employees with AI could cause employees to feel undervalued and unappreciated by their organisation and be losing control over their work environment, and contribute to diminished career satisfaction, organisational commitment and increased turnover intentions. Chui *et al*. (2015) indicated that the continuous automation of work activities and redefinition of job roles and processes by using AI in the workplace may potentially result in low job performance and high turnover rate in various occupations and industries. Li *et al*. (2019) also revealed that AI and robotics adoption has a significant positive effect on turnover intention especially when employees perceive lack of organisational support and high competitive psychological climate.

In contrast, previous studies (Kirkpatrick, 2017; Prentice *et al*., 2020) identified some positive outcomes and demonstrated that high quality AI application enhances employees' job performance by their perceptions of responding quickly to customer enquiries, conducting business knowledge search, and providing human-friendly services. This could also lead to employees' positive attitude towards technology and will likely influence their job retention.

AI applications in the workplace not only affect job-related outcomes, but also well-being outcomes. Recent research indicates that automation and AI reduce the frequency and quality of individuals' interaction, which may significantly influence their sense of belonging and emotional well-being, such as a feeling of isolation and disconnection (Wright and Schultz, 2018). It is difficult for employees to feel a high sense of workplace belonging or feel like they are part of the family if the organisation intends to adopt AI and replace some positions (Li *et al*., 2019). Job insecurity could be a salient predictor of psychological stress and burnout during a time of large-scale organisational change (Dekker and Schaufeli, 1995). Empirical evidence (e.g., Bommer *et al*., 2005) showed that organisational change or business environmental factors that are out of control by employees significantly lead to employee burnout. Long-term uncertainty of the job was more detrimental than knowing whether one was going to lose the job (Dekker and Schaufeli, 1995). It could be argued that AI application processes involving exploring and trailing new technology could lead to a constantly changing work environment and create significant uncertainty for employees. As such, employees' well-being will suffer due to the unforeseen future prospects. Employees would have an increased demand to perceive that organisations should offer adequate support if needed, provide accurate and constructive feedback, and appreciate their input during times of uncertainty. When employees' needs are not met during the change process, it could be expected that AI adoption may result in a development of nervousness and stress (Brougham and Haar, 2018). Nevertheless, scholars argued that some employees may show indifferent or distant attitudes (i.e., Cynicism) in the workplace which could serve as a critical coping and defensive mechanism in stressful and uncertain situations, and may cope better than those who know their jobs could be at risk (Cartwright and Holmes, 2006).

Proposition 6. AI adoption and application contributes to individuals' job-related and well-being related outcomes.

4.2 Organisational Outcomes

AI is innovating the entire business value chain by automating business processes, exploring data value and optimising human decisions and actions. AI application helps organisations boost profits by achieving the following outcomes.

First, researchers expected that AI could improve labour effectiveness. AI could augment labour productivity and optimise labour supply adjustments through taking on low-skilled routine jobs or supporting tasks and thus allowing employees to concentrate on high-skilled professional work (Arntz *et al*., 2017). At the same time, AI could save labour costs (e.g., operating 24/7 and serving numerous customers simultaneously) and solve HR problems (e.g., reducing potential lawsuits aroused from terminating an employment contract), which lead to visible productivity and financial advantages for organisations (Ivanov and Wester, 2017). Second, AI and automation was posited to achieve enhanced operational efficiency in organisations in regard to reduced cost and production time and improved production, safety and quality (Wright and Schultz, 2018). Third, AI is adopted to drive innovation by speeding up the development of new products and reducing research and development cost. Such an increase in innovation will not only accelerate new revenue generation but minimise redundant cost in organisations, thus, resulting in a profitability boost (Plastino and Purdy, 2018). Innovative products or services could also promote positive brand image by positive word-of-mouth among customers. Moreover, AI applications could improve customer service quality by understanding customer behaviour and providing innovative ways of service delivery to communicate and engage with them more effectively (Kuo *et al*., 2017). Additionally, AI could optimise decision making in organisations, particularly in addressing complexities. With superior computational and algorithmic thinking, AI is able to process huge amount of information or data at a speed in complex situations beyond the cognitive capabilities of human decision makers (Jarrahi, 2018). AI has opened up new opportunities for handling complexity and provided quicker and higher quality decisions through comprehensive data analytics (Jarrahi, 2018).

Proposition 7. AI adoption and application contributes to improvement and optimisation of organisational outcomes.

4.3 Employment Outcomes

The development of AI and automation has raised great concerns on technological induced unemployment and employment structure, as well as their effects on the economy and society (Hughes, 2014). A number of studies on human capital emphasised the massive job losses and unemployment caused by the growing use of AI and robotics. For example, a McKinsey report in 2017 confirmed 5% of job losses were due to the application of AI (Manyika *et al*., 2017) and an Oxford University research estimated that 47% of jobs could be automated by 2033 (Ramaswamy, 2017). It has been proved that AI and robotics are capable of handling complicated tasks, do some jobs better than humans and reduce employment in different professions (Danaher, 2014). In the Fourth Industrial Revolution, technology may continuously put skilled jobs at risk and accelerate technological induced unemployment that is regarded as one of the most challenging societal issues for the future (Nam, 2019).

Apart from technological unemployment, the employment structure is changing due to the adoption of AI, which leads to job polarisation. The research evidence demonstrated that technology advancement has a dramatic influence on the landscape of the labour market in Europe, mainly on middle skill level jobs while the top and bottom skill level jobs are complemented (Fernández-Macías, 2012). Moreover, the polarised US employment structure indicated a great shift to growing focus on high skill and low skill level jobs – also known as skill polarisation (Vardi, 2015). Notably, technology innovations are more likely to automate middle skilled jobs in manufacturing and services, and raise the demand for highly skilled managerial jobs, while leaving untouched the demand for non-routine manual tasks such as personal services provided by low skilled employees (Accetturo *et al*., 2014).

In addition, the literature revealed the disruption of technology innovation (such as AI, robotics, big data and flying drones) on occupation and employment – known as endangered jobs (Frey, 2015). AI and big data are diminishing many jobs in writing, medical, financial and legal services, and robotics are taking jobs from services and manufacturing sectors for decades and will continue to spread the threat of automation to almost every occupation (Frey, 2015). By applying the Gaussian process classifier approach, Bowles (2014) estimated that 54% of European occupations could be automated by technology change, and Frey and Osborne (2017) predicted that 47% of total US jobs are in the high risk category and associated occupations could be replaced by AI and robotics in the coming decade or two. Similarly, Lee (2017) transferred this approach to Asia and identified that around 25% of employment in Singapore could be computerised by automation. Chui *et al.* (2015) argued that most occupations will be affected by automation to some degree, which will transform business processes and redefine job roles and responsibilities.

However, some scholars have been optimistic about technology innovation and expressed different views of technological related unemployment. Walker (2014) suggested that automation contributed to enhanced productivity for two centuries and did not lead to long-term structural unemployment. The study argued that AI and robotics could improve the work efficiency and create new job opportunities for workers rather than replace their jobs. Kolbjørnsrud *et al*. (2016) acknowledged AI as a colleague rather than competitor. They argued that human judgment is unlikely to be computerised by automation, and AI can add great value to managers' work by providing support in decision-making via big data analysis and search and discovery activities. Comparably, Li *et al*. (2019) recognised that AI could only diminish low skilled manual positions and most of the jobs involving human interaction are difficult to be automated and employees in the relevant positions face low threat of replacement. Organisations are more motivated to adopt AI and automation in terms of boosting economic growth by improving workplace productivity and optimising the deployment system. There is no doubt that technology innovation is affecting almost all workforces and human-automation-interaction is inevitable, so future work will require employees to work alongside technology to achieve competitive advantage in the marketplace.

Proposition 8. AI adoption and application contributes to employment outcomes in terms of technologically induced unemployment, job/skill polarisation, endangered jobs and human-automation interaction.

Based on the above discussion, a conceptual framework is proposed by summarizing the current literature to explain how the socio-technical system theory helps us understand the antecedents and consequences of AI adoption and application in the workplace. The framework is outlined in Figure 2.

Insert Figure 2 about here
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5. Research Agenda and Implications

In this paper, we display a theoretical framework that depicts the role of AI in the workplace. The conceptual model depicted in Figure 2 presents a basis in providing a theoretically-based framework to stimulate future research on how AI is influenced by the antecedents and influences various outcomes. This paper serves as the first step to an integrated view of AI in the workplace, however, many things remain to be explained in the future. We therefore highlight a research agenda to identify and discuss several areas for future research that comprises not only insightful theoretical contributions but also practical implications. Inspired by the three sets of outcomes – individual, organisational, and employment outcomes – as discussed above, this section is organised around three key themes at the individual level, organisational level, and employment level that can inform and be informed by the adoption and application of AI, with a summary of the specific research questions provided in Table 1.

Insert Table 1 about here

5.1 Theme 1 Individual Level: AI and Training, Performance, Feedback and Employee Experience

To ensure that employees keep pace and progress, organisations should educate and train them. Employees need to develop core skills and abilities to perform their roles in their job, e.g., competencies such as technology readiness, digital literacy and interpersonal skills. However, much remains unknown about what specific skills and abilities underlie each distinct role. Yet, this knowledge is very important for developing efficient training practices. Training entails conventional (e.g., in person) and inventive (e.g., computer-based, gamification) tools (Hamari and Koivisto, 2015). Training can be useful to overcome employees' resistance against using AI. It is also important to ensure effective internal communication and collaboration among employees to maintain effective training. However, not each employee is keen to work with AI and technology and they may experience distrust, stress and anxiety, which may lead to counterproductive workplace behaviours such as service sabotage (Naseer *et al*., 2020). Meanwhile, research on employees' experiences when working with AI is currently lacking, and this topic deserves much more attention and research. Structured analyses of the employees' experiences working with AI, the specific conceptualisation and measurement would significantly advance the knowledge of this field. Organisations dedicated to enhancing employees' experience will gain a sustainable competitive advantage.

Furthermore, researchers and practitioners should design new metrics to track employee performance and their experience thereof. For instance, employees can be judged on their actual contribution to the task improvement processes working with AI. Those adapted metrics can provide relevant information on employee evaluation and help the development of novel incentive schemes. Thus, an important question is how to establish appropriate reward and incentive systems to promote employee engagement in innovation. AI can also be adopted to achieve customer evaluation. Evaluating customer's performance as well as providing feedback on how well customers perform their roles can help to boost future organisational performance. For example, Uber, authorises their drivers to rate riders in aggregate scores from one to five. Being relatively new in concept and practice, the rating system is designed to give mutual feedback and fosters mutual respect between riders and drivers, which builds and develops employees and customers trust (Moriuchi, 2020).

5.2 Theme 2 Organisational Level: AI Integrated with Organisational Design

We suggest that employers explore ways to embrace AI and at the same time minimise potential disruptions for their employees. AI, if designed and applied appropriately in the workplace, can bring about many advantages for organisations and employees such as enhanced efficiency, reduced capital investment, as well as overall improvement in employee well-being (Wright and Schultz, 2018). To gain full value from AI, C-suite executives are recommended to be the primary AI champions (Plastino and Purdy, 2018). It is thus critical for top management to support employees in the AI adoption process, build an effective internal management mechanism for AI implementation and create an effective talent mechanism to build a great project team for AI adoption.

Organisations need to be at the fore-front of the dynamic forces that are radically changing the workplace environment. Thus, organisations should develop adaptive competencies which allow them to evaluate changes in the market, experiment with multiple setups and develop good connections with technology-creation parties (Larivière et al., 2017). Organisational culture should be adapted to the presence of the new AI "employees." Organisations need to embrace AI as a powerful resource of competitive advantage. Moreover, companies need to continuously evaluate their existing business models (e.g., capability mix, stakeholders, mission, vision, and strategy), and examine how the characteristics of other models could complement the existing ones to improve employee experiences. The goal here should be set to build an optimised and hybrid model emerging from a mixture of business models, which build values via a blend of physical, human (employee), intellectual (technology creator), as well as social network capital. Effective leadership is vital to such changes (Xu *et al*., 2020). Scholarship should attend to how humans and automation can collaborate and co-create value for organisations.

5.3 Theme 3 Employment Level: AI and Employment issues

Organisational change because of AI has not only been transforming employee roles, but also resulting in the disappearance of numerous conventional jobs. Apparently, such changes represent a critical event for any involved party, which will typically result in a growth in employees' feeling of uncertainty, anxiety, psychological stress and resistance (Larivière *et al*., 2017), especially under the challenges of COVID-19. Therefore, more empirical studies are needed to uncover how AI affects employees' experience. Furthermore, the displacement of work through AI might eliminate some people's predominant source of self-worth in the modern society (Wright and Schultz, 2018). As AI is continuing to replace low-skilled labour, policy makers and organisations should create initiatives encouraging people to pursue advanced education and training. AI should be seen as a tool for technical advancement instead of human replacement. It is critical for scholars and policy makers to evaluate what skills and abilities are crucial for employees to survive in this rapidly-changing business environment, and how education and training programmes can be adapted to prepare the young to enter the workforce and protect job sustainability in the future. Organisations should also set up upskilling and reskilling mechanisms to get employees ready for AI application, and create initiatives of corporate social responsibility to create employment opportunities keeping pace with such technical advancement.

We also recommend that organisations analyse universal rights (e.g., human employees' working hours), quantify the scope and contents of these universal rights, and learn how different employees are influenced by AI. For instance, wealthier employees are more likely to be less influenced by AI compared to lower-skilled workers because well-being of the wealthier is less reliant on ongoing wages (Wright and Schultz, 2018). Future studies need to explore the nature of specific employees when applying AI in the workplace and how to avoid potential employment inequality caused by AI.

6. Conclusion

As technology has been fundamentally altering the nature of the workplace, it is critical for leaders to make decisions on how to best manage their employees. In this article, drawing from the socio-technical system theory, we present a novel theoretical framework to understand how AI impacts employees and organisations in the business and management context. We concluded by providing future research suggestions to researchers and organisations to encourage a successful transition to a more technologically-advanced society. As such, we hope this article can stimulate theoretical and empirical progress in this area to increase the understanding of AI in the workplace.

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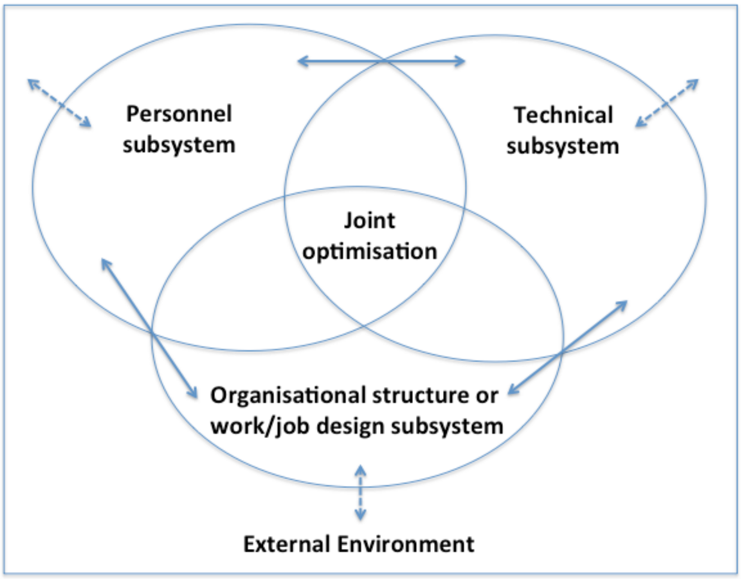

Figure 1. Basic socio-technical work system model (adapted from Bélanger *et al*., 2013; Høyland *et al.*, 2019)

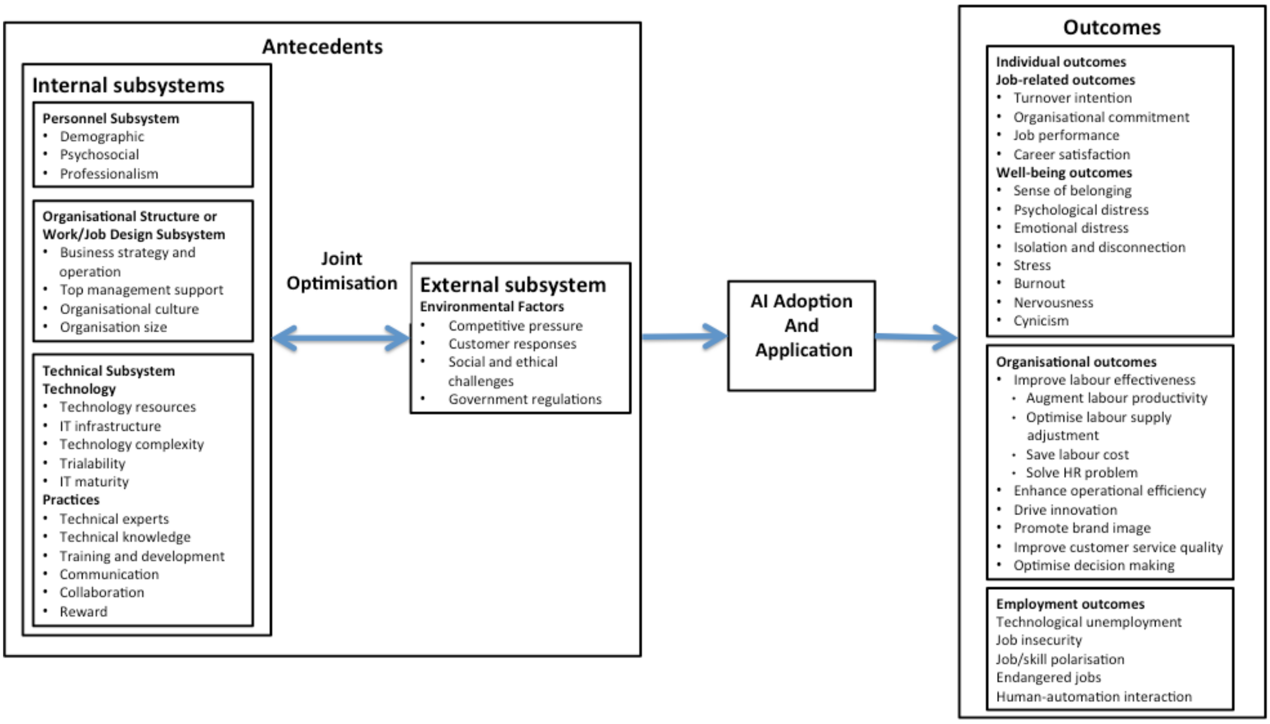

Figure 2. Conceptual Framework of AI adoption and application