Gigification, Job Engagement and Satisfaction: the moderating role of AI enabled system automation in operations management

Abstract

Innovative and highly efficient Artificial Intelligence System Automation (AI-SA) is reshaping jobs and the nature of work throughout supply chain and operations management. It can have one of three effects on existing jobs: no effect, eliminate whole jobs, or eliminate those parts of a job that are automated. This paper focuses on the jobs that remain after the effects of AI-SA, albeit with alterations. We use the term Gigification to describe these jobs, as we posit that the jobs that remain share characteristics of gig work. Our study examines the relationship between Gigification, job engagement and job satisfaction. We develop a theoretical framework to examine the impact of system automation on job satisfaction and job engagement, which we test via 232 survey responses. Our findings show that, while Gigification increases job satisfaction and engagement, AI-SA weakens the positive impact of Gigification on these important worker outcomes. We posit that, over time, the effects of AI-SA on workers is that full-time, permanent jobs will give way to gigified jobs. For future research, we suggest further theory development and testing of the Gigification of operations and supply chain work.

1.   Introduction

Artificial Intelligence (AI) is expected to play a critical role in the materialisation of the promises of Industry 4.0 (Wagire et al., 2020). It can assist in new product development (Giannakis, et al., 2020; Lolli et al., 2019), in managing capacity (Roden et al., 2017), in improving firm performance (Dubey, et al., 2020; Wamba-Taguimdje et al., 2020) and in production (Abou-foul et al., 2020), among other tasks. AI should enhance operational excellence of firms and lead to better decision-making (Fatorachian & Kazemi, 2020), while cutting costs and reducing time to market (Abou-foul, Ruiz-Alba & Soares, 2020). However, it will also create challenging work environments, changing the nature of work and employment (Sony & Naik, 2020).

The impact of AI enabled systems automation on jobs has been widely debated in the literature. For instance, Frey and Osborne (2017) modelled the impact of big data and machine learning algorithms on employment and wages in a variety of industries. They predict that jobs in transportation, logistics and office and administrative work are at high risk of AI enabled systems automation, in effect fostering high levels of technology-driven unemployment. This view seems to be supported by a study showing that, within 10 years, 326 million jobs globally will be adversely affected by artificial intelligence (PwC, 2018). Arntz et al. (2016), however, argued that computerisation automates tasks rather than jobs, and their prediction is that most jobs will change rather than disappear as a result of big data and AI systems automation. To understand which jobs will be impacted by AI automation and how, some researchers have looked at the types of work most prone to automation. For instance, Huang and Rust (2018) argued that jobs that are highly mechanical, easy to standardise and are repeatable will most likely be lost to systems automation resulting from widespread adoption of artificial intelligence in businesses, including decision and control processes (Lee and See, 2004). That is, there are different views as to whether AI will mostly destroy jobs in operations management, or, instead, change them.

This study's motivation is to move beyond these debates and, instead, look at the impact of AI automation on workers. It is not yet clear whether artificial intelligence is an opportunity for workers or, instead, a threat (Nam, 2019). On the one hand, artificial intelligence may increase job engagement and satisfaction by assisting with decision-making (PwC, 2018) and augmenting workers' input (PwC, 2018); on the other, it may create displacement and fear of

unemployment (Mokyr et al., 2015; Arntz et al., 2018), and, as a consequence, demotivate workers. As with other technological innovations in operations management, such as mobile technology (see Kim et al., 2015), there is an inherent tension in terms of how technologies may impact on workers' engagement with their work and the satisfaction that they derive from it. The successful deployment of AI in operations and supply chain management requires a holistic approach, which looks beyond the technology and explicitly focuses on the workers affected by its use in production activities (Seyedghorban et al., 2020). Employee knowledge of AI and readiness have been shown to be a critical factor in the success of the deployment of AI (Stentoft et al., 2020). Therefore, in this paper, we examine, at a granular level, the impact of AI systems automation on operations management workers' engagement and their job satisfaction.

The objective of the paper is to build upon research on the changing nature of work itself. This body of research characterises jobs as a series of tasks, which require different types of intelligence to be performed. For instance, Fast-Berglund et al. (2013) refer to humans and technology cooperating in order to simplify jobs and to make the overall system efficient and productive. That automation increases job flexibility is not a new phenomenon (Johnes, 2019; Manyika et al., 2016), yet the introduction of AI is expanding job flexibility into wider areas of the operations and supply chain work, as evidenced by the growth of online systems that coordinate supply chain workers and jobs to be done (Bajwa et al., 2018), creating the phenomenon called the gig economy. Online systems bring together sellers and buyers of labour, physical goods and services, using virtual web- or app-based portals. Such forms of work have given rise to gig workers and is extolled as being a positive employment model in the digital era (PwC, 2018a), with greater numbers employers aiming to gigify their workforce (Storey, Steadman and Davis, 2018). According to Jarrahi et al. (2019), gig work can take many forms including specific time-bound jobs, jobs (gigs) that are done alongside a full or part-time job and multiple gigs being done concurrently. While many people seek full-time work, growing numbers are pursuing portfolio careers (Caza et al., 2018), wanting to work independently (Ashford, Caza and Reid, 2018; Cohen and Mallon, 1999) and flexibly (Manika et al., 2016). For this reason, our study focuses on the respondents' perceptions of their gig work.

Our study is concerned with examining linkages between automation and the flexibilisation of work, on the one hand, and workers' engagement and satisfaction with their job on the other.

The extant literature on the impact of artificial intelligence on the labour market (e.g. Arntz et al., 2016; Frey and Osborne, 2017) tends to focus on full-time work or permanent jobs. Our study considers that the increase in adoption of AI in operations is accompanied by an increase in flexible work, and intends to explore the impact of systems automation on workers' engagement with their job and satisfaction. Specifically, we address the question: '*How does AI Systems Automation impact on workers' job engagement and satisfaction?*' In doing so, we move beyond the important but widely explored question of the likelihood that humans will be replaced by machines in the work environment (e.g. Nica, 2016; Prisecaru, 2016; Peters, 2017; Schwab, 2017; Nam, 2019), and consider the impact on the workers themselves, as urged by Nam (2019) and others.

We find that there is a significant and positive relationship between Gigification and both job engagement and job satisfaction. Our findings also confirm that engagement has a positive effect on job satisfaction. However, we find that workers' engagement and satisfaction decreases when the gigification of work is moderated by digital automation systems.

This paper proceeds as follows. In section 2, we review gig work and develop the notion of Gigification. Then, in section 3, we develop our hypotheses and theoretical model, which set out relationships between Gigification, job engagement and job satisfaction, as well as the mediating effect of systems automation. The methods used, data collection and analysis techniques deployed are explained in section 4. The results of our analysis using structured equation modelling are presented in the subsequent section. Following this, section 6 discusses the results and explicates the theoretical contribution of the paper. Section 7 lays out implications for practice, while the final section outlines the limitations of this work and suggests future research directions.

2. AI-SA and the changing nature of work

2.1 Gig work

The growing potential of gig work has recently been noted by various scholars (Johnes, 2019; Manyika et al., 2016), and gig work is often promoted as a positive employment method for the AI era (PwC, 2018a).

The phenomenon of gig work has been evident for hundreds of years, if not millennia (Harvey et.al., 2017). However, more recently, this type of job is rapidly developing into a larger part of the world's operations and supply chain labour market. A survey in the UK indicates that the number of people working for online systems at least once a week has doubled from 4.7% in 2016 to 9.6% in 2019 (Anon, 2019a). In 2017, more than 57 million U.S. adults started work outside of their existing workplace in gig work (Hayzlett, 2018). According to Gillespie (2017), the gig economy is expected to form 43% of the U.S. workforce by 2020. In 2018, more than 55% of UK workers in the 18-34-year-old age group were in some form of gig work (PwC, 2018). This growth is enabled by digital systems that bring together sellers and buyers of labour, physical goods and services, using virtual web- or app-based portals. The resulting digitally enabled gig economy creates different relationships between employers, workers and customers through online digital systems (Bajwa et al., 2018).

Gig workers are defined as independent workers with short-term contracts (Jabagi et al., 2019; Kuhn, 2016) or who have zero-hour contracts with organisations or work independently (Petriglieri, Ashford and Wrzesniewski, 2019). Zero-hour contracts are legal contracts of employment that do not commit the organisation or the gig worker to completing a minimum number of paid hours (Koumenta & Williams, 2019). Gig workers are generally younger and have higher educational levels than their counterparts in traditional, full-time employment (Tran and Sokas, 2017). Higher-skilled gig workers tend to be in greater control of their contracts and time schedule, while lower-skilled ones are more likely to be dependent upon employers (Barley and Kunda, 2006).

Gig workers operate through online digital systems typically offering services in warehouses, transportation, operations, production lines and product delivery (Dubal, 2017). With ongoing technological development, the gig economy has been combined with online systems that are driven by mobile applications and digital technology. These online digital systems bring together all parties that provide easy entrance to the job market (de Ruyter, Brown and Burgess, 2018). Technology helps to match employers, employees or customers according to the customers' demand and the workers' skills. Gig workers usually get lower payment or flexible payment based on outcomes of temporary jobs that do not require training (Bajwa et al., 2018). Gig work has been criticised because workers do not have opportunities to get adequate compensation and health insurance when compared with full-time, permanent employees (Bajwa et al., 2018). On the other hand, gig workers' schedules are flexible, with minimal

supervision from the employer, thus workers take their own decision on work methods (Dubal, 2017).

Kässi and Lehdonvirta (2018) developed an online labour index to measure the utilisation of online system labour from English-speaking countries and occupations by analysing the gig works jobs posted on online gig systems such as freelancer.com, guru.com and Mturk.com. Their findings summarise the latest trends in the online gig economy. For example, the gig economy is growing rapidly, and the demand for jobs fluctuates at specific times during the year, such as Christmas. Software development and technology related jobs are in high demand, followed by creative and clerical jobs. The findings showed that the U.S. has the highest number of online jobs, followed by the UK, India and Australia.

2.2   Gigification

Building upon the gig work literature (see Table 1), we introduce the term Gigification as an overarching concept to describe the process of automating full-time, permanent jobs into gig work. Jobs that are highly mechanical and repetitive can be standardised, and are the ones most likely to be automated through AI-SA (Huang and Rust, 2018). Since mechanical processes demand less creativity, they can be accomplished with very little innovative thinking (Sternberg, 1997). Hence, workers in operations and production roles that mostly perform mechanical tasks face a higher risk of AI-SA, according to Frey and Osborne (2015). Analytical intelligence, in turn, is based on the principles of learning and adaptation. Analytical intelligence is concerned with capabilities central to operations management and production control such as mathematical skills, processing information, logic-based reasoning and solving problems while learning from previously solved problems (Stenberg, 2005). Workers in many parts of supply chain and operations management acquire analytical skills and need formal education and expertise to perform specialised, complex tasks. According to Huang and Rust (2018), jobs that contain high levels of analytical intelligence are next most easily automated. They refer to intuitive intelligence as the ability to think creatively and adapt to specific contextual issues. Operations managers use intuitive intelligence when they are required to address problems that they may not have experienced previously (Sternberg, 2005). Finally, empathetic intelligence is recognising and understanding emotions as well as responding in emotionally appropriate ways (Goleman, 1996). It involves nuanced social and interpersonal skills assisting people to understand other people's feelings (Bradford, 2017). Supply chain

professionals, for example, often use higher levels of empathetic intelligence because their tasks involve emotions, relationships, human interactions and interpersonal communications; all of these demand social involvement to a higher degree (Giebelhausen et al., 2014), hence, during customer interaction, employees are expected to exhibit appropriate emotions (Yoo and Arnold, 2016).

Gigification encompasses the continuum of effects AI-SA can have on full-time, permanent jobs. At one end of the continuum, AI-SA may have no effect at all on full-time, permanent jobs, while at the other end, work takes the form of gig jobs only. That is, as organisations move along the Gigification continuum, jobs may become more or less gigified, where the more an organisation implements AI-SA and removes parts of jobs, the greater work that is left over becomes gig-like. In other words, wider use of AI-SA will lead to higher levels of Gigification. In this study, we examine relationships between Gigification and job engagement and job satisfaction. More specifically, this study investigates the moderating effects of AI-SA on these relationships.

In Table 1 below, we set out the dimensions of gig-work and their underpinning attributes. We posit that following AI-SA will share these dimensions and attributes.

Dimension	Attribute	References
Demand	Periods of intense activity alternate with quiet times Could be completed by a zero-hours contractor Has standard working hours Consists of many short-term assignments The volume and type of work fluctuates with time (hourly, daily, weekly, or seasonal or time of year)	Ashford, Caza and Reid, 2018; Dubal, 2017
Ease of Entry	Provides me with a clear sense of identity Requires skills that most people have or could acquire Can be replaced by technology I am able to join a union Requires specific professional qualifications or practical expertise	de Ruyter, Brown and Burgess, 2018

Payment	Can be completed by someone on variable pay rates Payment can be based on completion of pre-agreed deliverables Can be completed by someone paid on time-based rates (hourly, daily, weekly) Can be completed at a lower rate of pay Rewards (e.g. payment, promotion) are influenced by my line manager's feedback	Ashford, Caza and Reid, 2018; Bajwa et al., 2018
Relationship with employer	Can be completed by a freelancer Varies in terms of when and where it's done My job is independent of specified career paths Requires high levels of commitment to the organisation I am working with Involves limited communication to the organisation I am working with	Berkery et al., 2017; Shade, 2018; Biggs and Swailes, 2006; Ashford, Caza and Reid, 2018

Table 1: Attributes of Gigification

3.   Hypotheses development

3.1   Job engagement and satisfaction

Employee engagement is a widely used term (Dubbelt, Demerouit and Rispens, 2019; Robinson et al., 2004) that is generally defined as an indicator of employee outcomes, company success and better financial outcomes (Bates, 2004; Richman, 2006; Saks, 2006). Employee engagement has unique characteristics that consist of cognitive, emotional and behavioural aspects which affect the employees' performance in their job role (Saks, 2006).

Various scholars define employee engagement with different concepts from a variety of perspectives, which are summarised in Table 2. Kahn (1990) defines engagement as personal presence that has physical, cognitive and emotional aspects simultaneously. Employees with higher levels of engagement physically present themselves in the job by being there. They are said to be involved cognitively and emotionally, and integrated fully to work, its task and the organisation (Suhartanto et al., 2018; Kahn, 1992). As a counterpoint, Maslach et al. (2001)

define engagement as the opposite to burnout, as engagement requires energy, involvement and enthusiasm for work. That is, employee engagement has a negative relationship with burnout (Bailey et al., 2015; 2017; Schaufeli and Bakker, 2004). In turn, Schaufeli and Salanova (2007) state that highly engaged employees are connected to their work with a higher-level energy and connectivity that enable them to identify themselves with their work.

Concept	Definition	Author
Personal presence	'The harnessing of organisation members' selves to their work roles; in engagement, people employ and express themselves physically, cognitively and emotionally during role performances.'	Kahn, 1990 (p. 694), 1992
Psychological presence	It is a psychological presence with two vital aspects; attention and absorption. Attention: 'cognitive availability and the amount of time one spends thinking about a role' Absorption: 'means being engrossed in a role and refers to the intensity of one's focus on a role.'	Rothbard (2001, p. 656)
In opposition to burnout	Is opposite situation to burnout. It is defined as energy, involvement and efficacy.	Maslach et al., 2001
Positive thoughts	'As a positive, fulfilling, work-related state of mind that is characterised by vigour, dedication and absorption.'	Schaufeli et al. (2002, p. 74)

Table 2: Scholarly definitions of Employee Engagement

Drawing upon Kahn's (1990) research, we suggest that three psychological conditions are antecedents of engagement at work, not only for traditional employees but also gig workers: meaningfulness, safety and availability. According to Saks (2006), meaningfulness conditions can be gleaned from job characteristics and these are one of the antecedents of employee engagement. Similarly, Maslach et al. (2001) found that job characteristics, such as feedback and autonomy, have a positive influence on job engagement. From the literature, we derive

four core job characteristics related to Gigification, namely demand, ease of entry, payment and relation with employer.

Job engagement and job satisfaction refer to positive valence at work (Warr and Inceoglu, 2012). While engagement is related to motivation to act at work (Rich, Lepine and Crawford, 2010), satisfaction is more closely associated with pleasurable emotional states (Locke, 1969). Highly engaged and satisfied employees have a positive impact on company outcomes such as: better performance (Harter, Schmidt and Hayes 2002; Rich, Lepine and Crawford, 2010; Lu and Gursoy, 2013), lower turnover rates (Lu et al., 2016), higher customer satisfaction, and improved profitability (Harter, Schmidt and Hayes, 2002; Richman, 2006). Previous researchers found that job engagement has a positive impact on commitment and job satisfaction (Suhartanto et al., 2018; Soane et al., 2012). Employees who are less engaged with their job tend to leave the organisation (Yalabik et al., 2013). In contrast, a higher level of satisfaction is an important antecedent of job engagement (Macintosh and Krush, 2014; Brunetto et al., 2012; Rayton and Yalabik, 2014). Thus, job satisfaction and job engagement have a two-way interaction. Similarly, Lee, Mazzei and Kim (2018) emphasise that, when the employees trust their organisation and are satisfied with their job, their engagement levels with the organisation are higher.

Therefore, we hypothesise that these characteristics of Gigification are positively associated with gig workers' job engagement (a) and job satisfaction (b).

H1a: Gigification has positive effects on gig workers' job engagement

H1b: Gigification has positive effects on gig workers' job satisfaction

3.2   Automation and job engagement

Employee engagement provides organisations with competitive advantage (Macey et al., 2009). Higher levels of engagement have beneficial effects upon flexibility, innovation and success in the globally changing environment (Eldor and Vigoda-Gadot, 2017). Employees with higher engagement to the organisation provide greater contributions in terms of individual task performance (Rich, Lepine and Crawford, 2010). Various researchers have found employee engagement is a key driver to effect behaviour, individual performance,

organisational performance, productivity and better employee retention (Richman, 2006; Bates, 2004; Baumruk, 2004). Macey et al. (2009) found that employee engagement provides organisations with better financial performance and higher returns on assets, profitability and shareholder value. Higher engagement strengthens relationships between employees and organisations that help employees to have more satisfaction with self-actualisation (Baruch, 2006; Eldor and Vigoda-Gadot, 2017).

The automation propelling the Fourth Industrial Revolution and artificial intelligence brings both opportunities and challenges for employees (Nam, 2019). Technological opportunities, such as online systems, offer employees and businesses the chance to join the growing global marketplace (Ashford, Caza and Reid, 2018). While many people seek full-time jobs, the growing trend of portfolio working, that is being employed in multiple jobs concurrently, means that there are periods where people work independently (Ashford, Caza and Reid, 2018; Cohen and Mallon, 1999). According to Caza et al. (2018), gig workers have more opportunities for a wider portfolio of jobs. Digital systems offer younger people, with limited experience, who face the prospect of long periods of unemployment, opportunities to find multiple jobs with greater flexibility (Manika et al., 2016). Nam (2019) found that technology-mediated work is perceived as a threat and highly associated with job insecurity, which causes negative outcomes for both employees and workers. Therefore, we hypothesise that work automation lowers levels of employee engagement.

H2: System automation weakens the positive relationship between Gigification and employee job engagement

3.3   Automation and job satisfaction

Job satisfaction in the gig economy is related to the measurement of gig workers' assessment of their job (Gleim at al., 2019). It is defined as attitudes and feelings gig workers have to their job and working environment (Churchill, Ford and Walker, 1976). BEIS (2018) produced a report by conducting qualitative research with 150 phone and face-to-face interviews with gig workers in the UK. The research aimed to understand the gig economy, motivations of gig workers and the future of gig work in the UK. The findings of this research suggest that more than half of the participants are highly or fairly satisfied with their gig work. Two important characteristics of gig work have a significant effect upon gig workers' job satisfaction, namely

independence and flexibility. However, as system-mediated work is perceived as a threat, in the sense that human employees will be replaced by machines (Nica, 2016), automation is a negative moderator between the Gigification and job satisfaction. Hence, we hypothesise that:

H3: System automation weakens the positive relationship between Gigification and job satisfaction.

3.4   Job engagement and job satisfaction

Schaufeli and Bakker (2004) suggest that highly engaged employees are more likely to be satisfied and less likely to leave their jobs. Kahn (1992) found that engagement provides both individuals and organisations with positive outcomes. Individuals with higher levels of engagement with assigned jobs have favourable effects on outcomes and quality of work. That more-engaged gig workers are more likely be satisfied with their work is confirmed by Maslach et al. (2001), specifically that job engagement increases job satisfaction. Hence, we follow what is widely accepted in the literature: that job engagement has significant positive impact on job satisfaction, and posit that this will hold true in the case of gig workers.

H4: Job engagement has positive impact on job satisfaction

Figure 1 summarises the research hypotheses, developed into a research framework. The framework suggests that Gigification (Demand, Ease of Entry, Payment and Relations with Employers) has positive effects on Job Engagement and Job Satisfaction. We posit that AI Systems Automation (Mechanical, Analytical, Intuitive and Empathetic) had the effect of weakening the relationship between Gigification and both Job Engagement and Job Satisfaction. Lastly, the framework shows that Job Engagement has a positive effect on Job Satisfaction.
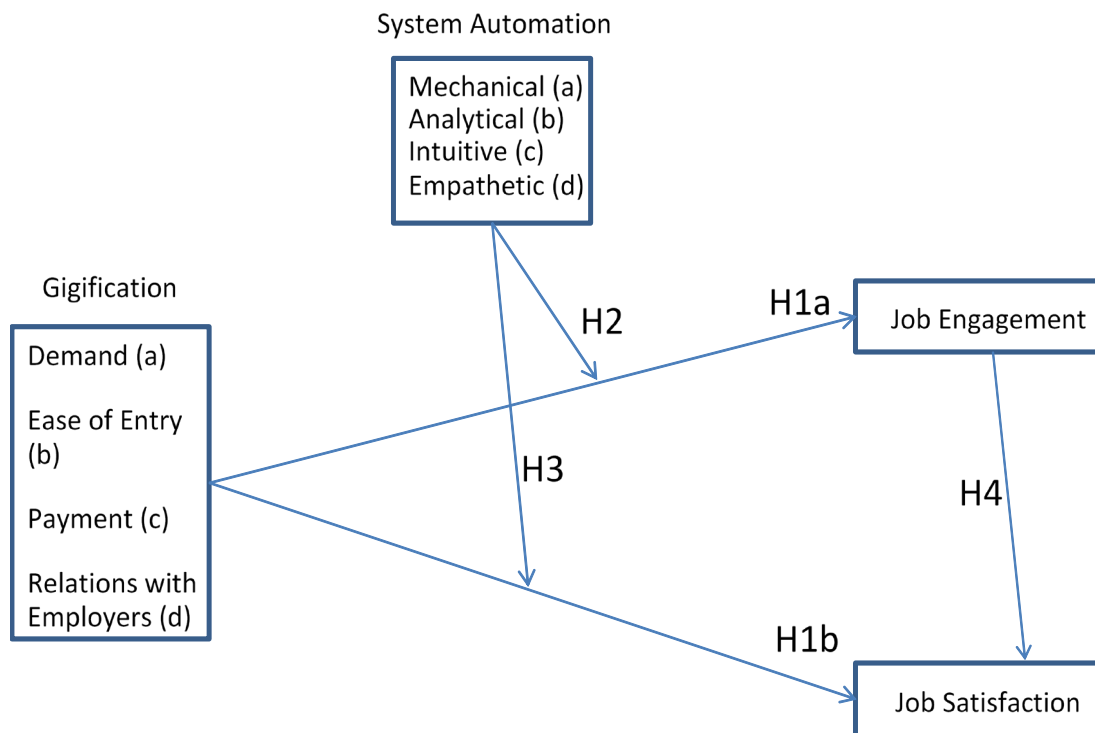
Figure 1: Hypotheses and Research Framework

4. Methods

4.1   Sample Details

We developed an online survey questionnaire to collect data in this study. In this study, we want to capture the perceptions of gig workers, who we define as workers performing income-earning activities outside of traditional, full-time, permanent, longer-term employer-employee relationships. They may treat gig work as their sole source of income or undertake gig work to enhance their income by having multiple, concurrent gigs in addition to their main traditional full-time job. We sent the survey instrument to individuals within the London Borough of Hillingdon, which is the second largest of London's 32 boroughs. Hillingdon has a population of 302,343, according to the 2017 Census. It consists of five districts: Hayes and Harlington, Ruislip-Northwood, Uxbridge, and Yiewsley and West Drayton in the county of Middlesex. The borough has large companies including Heathrow Airport, Apple Inc., Gilead Sciences, Canon Inc., Sharp Corporation, Marks and Spencer and GlaxoSmithKline, as well as numerous small-and-medium-sized employers in the manufacturing sector. Our data were collected by asking participants to scan a QR code on their smartphones that linked to the online survey. Before collecting the main survey data, full ethical approval was granted and a pilot study with

gig workers was conducted to improve the questionnaire design, and to test the robustness of validity and reliability measurement items.

Over 2,000 people in the production and supply chain industry were approached during a three-week period. Table 3 below shows the participants profile in this research. There is a large portion of younger generation in our data, with 70.2% of the sample between 18 to 34 years old, which suggests that the majority of gig workers today tend to be young and familiar with updated information communication technology (e.g. using smartphones regularly). This is consistent with other scholars' findings. For instance, according to Tran and Sokas (2017), when compared with more conventional workers, gig work in production and operations management is preferred by younger people, with higher educational achievements. The participants in this research are mainly from manufacturing, production and supply chain industry, and are highly educated, as 74.5% of them have a university degree or above. Furthermore, 33.9% of the sample have less than two years' work experience, 48.7% have three to 10 years' work experience and 17.2% have more than 10 years' work experience. The participants in this research study are in work, mostly in full-time jobs (42.7%) and with 36.6% working in part-time jobs. Table 3 shows that 43.1% of participants are working in private sector organisations and 44.8% work in the public sector. Just under half of the participants, 47.0%, are working in organisations with more than 250 employees, and 31.9% are in an organization with over 10 and up to 249 employees at the time of data collection. There is potential of common method biases in survey-based research data that cause the indicators to share certain amount of common variation (Guide and Ketokivi, 2015; Dubey et al. 2019; Fosso Wamba et al. 2020; Altay et al. 2018;). There is no common method variance bias detected in our study that our Harman's single-factor test results show only one factor extracted from the test and the variance is 25.3% (below 50%).

Variables	Sample (n = 232)	Percentage (%)
Gender (subordinate)		
Male	112	48.2
Female	118	50.9
Prefer not to say	2	0.9
Age Group		
18 - 24 years	87	37.5
25 – 34 years	99	42.7
35 – 44 years	32	13.8
45 – 54 years	8	3.4
55 years and above	6	2.6

Highest Qualification		
Secondary / High school	10	4.3
GCSEs / A-Levels	39	16.9
College Apprenticeship	7	3.0
Undergraduate Degree	68	29.4
Postgraduate degree (Masters)	69	29.9
Doctorate	35	15.2
Other	3	1.3
Work Experience		
Less than a year	30	12.9
1 to 2 years	49	21.0
3 to 5 years	70	30.2
6 to 10 years	43	18.5
11 to 15 years	14	6.0
16 to 20 years	12	5.2
Over 20 years	14	6.0
Organisation Type		
Private sector organisation	100	43.1
Public sector organisation	104	44.8
Charity	11	4.7
Social Enterprise	14	14
Other	18	7.8
Organisation Size		
250 + employees	109	47.0
50 - 249 employees	33	14.2
10 – 49 employees	41	17.7
1 – 9 employees	49	21.1

Table 3: Descriptive Statistics

4.2   Measures

Data were collected from the participants using a five-point Likert scale (where 1 = Strongly Disagree and 5 = Strongly Agree) for each item defining Gigification, system automation, job engagement and job satisfaction scales. Questions for Gigification and system automation were derived from the literature. The Gigification construct consists of 19 questions developed under the themes of demand, ease of entry, payment and relation with employer from previous literature (i.e. Ashford, Caza and Reid, 2018; Dubal, 2017; de Ruyter, Brown and Burgess, 2018). Similarly, 23 initial questions were derived for AI system automation based on four themes; mechanical, analytical, intuitive, empathetic (Huang and Rust, 2018). The Job Engagement scale has six items adopted from Saks (2006), wherein a sample item includes 'I am highly engaged in this organization'. In the same vein, this study adopted three items for the job satisfaction scale from literature (Saks, 2006; Netemeyer et al., 2010; Gleim et al., 2019). Exploratory factor analysis (EFA) was conducted in a pilot study to reduce items and define patterns in the data (De Vaus, 2002). Some items were deleted for two reason; items

with factor loading less than .5 and items that were loading more than one factor (Hair et al., 2010). Cronbach alpha was used to control reliability of measures for each construct.

Next, we conducted confirmatory factor analysis to check the significance of items' factor loading and to ensure items were not loading onto another construct. The goodness-of-fit indices for the model ($\chi 2/df = 1.939$; CFI = 0.960; TLI = 0.947; RMR = 0.049; GFI = 0.933; RMSEA = 0.064) are all within a satisfactory range. Tables 4 and 5 set out our results in detail.

	Indicators	Loading	CR	AVE
Automation	Mechanical (AUTO1)	0.501	0.789	0.503
($\alpha = 0.684$)	Analytical (AUTO2)	0.675		
	Intuitive (AUTO3)	0.794		
	Empathetic (AUTO4)	0.592		
Gigification	Demand (GIG1)	0.768	0.906	0.707
($\alpha = 0.822$)	Ease of entry (GIG2)	0.799		
	Payment (GIG3)	0.845		
	Relation with employer (GIG4)	0.835		
Job Engagement	I am able to get involved with activities happening in my organisation (ENG1)	0.881	0.895	0.740
($\alpha = 0.854$)	Being a member of this organisation makes me feel valued (ENG2)	0.894		
	I am highly engaged in this organisation (ENG3)	0.864		
Job Satisfaction	I am happy with the way I work (SAT1)	0.735	0.854	0.663
($\alpha = 0.794$)	I am satisfied with my current role (SAT2)	0.740		
	I am not thinking of quitting my job (SAT3)	0.675		

Table 4 Convergent and Discriminant Validity Test

	CR	AVE	Job Engagement	Gigification	Automation	Job Satisfaction
Job Engagement	0.895	0.740	**0.860**			
Gigification	0.906	0.707	0.684	**0.841**		
Automation	0.789	0.503	0.636	0.599	**0.709**	
Job Satisfaction	0.854	0.663	0.801	0.636	0.655	**0.814**

Table 5: Convergent validity

5. Results

Selecting the best suited and most appropriate statistical analysis tests is a vital decision for researchers (Ramayah et al., 2014). This study used Partial Least Squares (PLS) to test the research hypotheses and goodness-of-fit of the conceptual model. PLS is regarded as the 'most

fully developed and general system' in comparison with other variance-based techniques (McDonald, 1996, p. 240; Hair et al., 2011, Akter et al. 2017). PLS is one of the most salient statistical methods that is conducted in a variety of disciplines including marketing (Rezaei, 2015; Hair et al., 2012), strategic management (Hair et al., 2012a), operations management (Dubey et al. 2019), management information systems (Ringle et al., 2012; Dijkstra and Henseler, 2015) and accounting (Nitzl, 2016; Lee et al., 2011).

PLS is the preferred statistical method to understand relationships between the set of variables (Akter et al. 2017; Peng and Lai, 2012; Hair et al., 2012; Rigdon et al., 2010) when a problematic modelling issue occurs such as non-normal data issues and extremely complex models (Hair et al., 2014). PLS is widely applied in the business management, management information systems and marketing fields with smaller sample sizes and the use of formative indicators (Kock & Hadaya, 2018; Kock, 2019). Unlike the other statistical tools, PLS does not require strong preconditions, such as distribution, research sample size and the measurement scales for constructs (Vinzi et al., 2010). According to Hair et al., (2014), most prominent assumptions to use PLS are: non-normal data, sample size and formative measures. Our research has developed formative measurements and indicators for our research constructs with a relatively small sample size (232). Thus, we posit that PLS is better than other tests as an appropriate method to examine this study's research hypotheses.

The first stage of our analysis was to carry out convergent validity and discriminant validity of the constructs. These results are displayed in Tables 4 and 5. All items have convergent validity higher than the expected threshold of 0.7 and all constructs have average variance extracted (AVE) higher than the threshold 0.5. According to the initial results, the measurement model is accepted as reliable and valid. Thereafter, in the next step, structural model results were tested to see the relationship between the constructs (Hair et al., 2016). Our data analysis results show that the hypotheses we developed are supported, as set out in Table 6.

Relationships	*B*	Standard error	*t* value	Sig. level	Hypothesis testing
Gigification-> Job Engagement	0.898	0.191	4.701	*p* <0.001	H1a accepted
Automation -> Job Engagement	0.795	0.163	4.881	*p* <0.001	

Gigification -> Job Satisfaction	0.581	0.188	3.077	*p* <0.01	H1b accepted
Gigification*Automation -> Job Engagement	-0.182	0.054	-3.368	*p* <0.001	H2 accepted
Automation -> Job Satisfaction	0.608	0.162	3.760	*p* <0.001	
Gigification*Automation -> Job Satisfaction	-0.134	0.052	-2.570	*p* <0.01	H3 accepted
Job Engagement -> Job Satisfaction	0.685	0.063	10.960	*p* <0.001	H4 accepted

Table 6 Hypotheses tests results

6. Discussion and Contributions

This study contributes to understanding the effects of AI-SA on workers. We studied the effects of technology changes and automation on traditional human jobs and introduced the concept of Gigification – the extent to which automation in the form of AI systems automation will transform jobs being carried out by people. Gigification addresses the bifurcation in the literature regarding whether automation will eliminate jobs either completely or partially. Rather, Gigification provides a continuum, extending from no effects to complete elimination. Gigification is important to theory development, as it creates a space for deeper discussion and analysis of the jobs that remain, rather than the prevailing polarised positions of researchers.

Moreover, we developed and tested a theoretical framework that examines the relationships between Gigification and job engagement and job satisfaction. We theorise that Gigification would have a positive effect on job engagement and job satisfaction. Yet, when moderated by digital systems, we theorise that these would have a negative effect upon the relationship between Gigification and job engagement and job satisfaction.

Our results show that Gigification has a significant positive impact on job engagement, as predicted (H1: β = 0.898; t = 4.701, *p* < 0.001), which suggests that gig workers are more engaged with their job. This finding reinforces knowledge about gig work that has been established in the literature. Gig workers can gain greater levels of flexibility and work more autonomously than conventional full-time employees (Bajwa et. al., 2018).
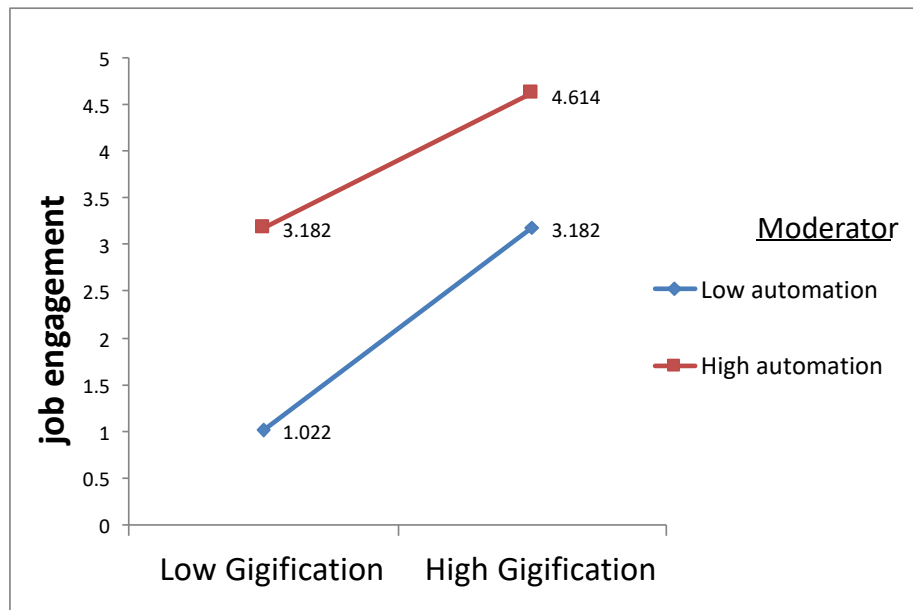
Figure 2 Interaction: **Gigification *Automation -> Job Engagement** AI enabled technology advancement **weakens** the positive relationship between Gigification and job engagement

(Source: The authors)

However, our study reveals that AI systems automation acts as a moderator to reduce the positive relationship between Gigification and job engagement (H2: β = -0.182; t = -3.368, $p <$ 0.001). Instead of increasing workers' engagement with their job, system automation reduces their engagement levels. This is depicted in Figure 2. Some reasons for this reduction in engagement may be the nature of the relationship workers have in their job. Full-time, permanent operations and supply chain workers interact with their line managers, team members and colleagues in other departments, as well as customers, suppliers and other stakeholders. These social relationships and networks provide workers, at all levels, with psychological and emotional fulfilment, which are not available when interacting across AI systems. Digital systems can create higher degrees of isolation, with workers feeling distanced from the others working on the same platform, as communications become electronically mediated. Moreover, gig workers in warehouses and operational jobs know whether they use traditional means or digital systems to find gig work, and that their income will fluctuate from one period to the next. Income volatility is inherent in gig work. The difference between traditional gig work and AI-SA-mediated gig work is the loss of control that gig workers have when operating over digital systems. These systems exert significant amounts of control over workers and issues that affect their livelihood, among other things, the allocation of work, rates of pay, penalties that may be applied for falling short of targets and objectives and the

withdrawal of gig opportunities from a worker. The perceived loss of control may underpin the reason for a reduction in job engagement.

The results of our study show that Gigification has a positive relationship with job satisfaction. Yet, the relationship between Gigification and job satisfaction, when moderated by digital systems, weakens the positive relationship (H3: $\beta = -0.134$; $t = -2.570$, $p < 0.01$). These findings are depicted in Figure 3. According to Harvey et al. (2017), one of the consequences of gig work is to reduce the levels of commitment employers have towards their workers. Organisations focus upon their shorter-term needs and put in place arrangements, such as zero-hours contracts and on-call arrangements, and implement policies that allow them to change their staffing levels with greater flexibility. Workers become marginalised, with little or no certainty of income, and they are expected to undertake work without financial rewards. Consequently, workers remain in a less powerful position relative to employers (Harvey et al., 2017). Matching our data analysis results, automation is more likely to replace jobs that have Mechanical and Analytical features, while jobs with Intuitive and Empathetic features are affected to a lesser extent by AI systems automation. As jobs become more gigified, workers take up piecemeal, temporary work, leading not only to jobs becoming precarious but also workers' identity as experts or professionals becoming precarious (Braganza et al., 2020; Petriglieri, Ashford and Wrzesniewski, 2019). As workers feel less in control of their shorter- and longer-term welfare, their levels of anxiety increase, making gig working less attractive. The extant research shows that gig workers usually have lower job loyalty, engagement and trust in their employer (Huang and Lin, 2016; McDonald and Makin, 2000; Ang and Slaughter, 2001). In line with the literature (e.g. Schaufeli and Bakker, 2004), we found that job engagement significantly mediates the effect of gigification and job satisfaction. That is, for gig workers, too, job engagement plays a significant role in job satisfaction.
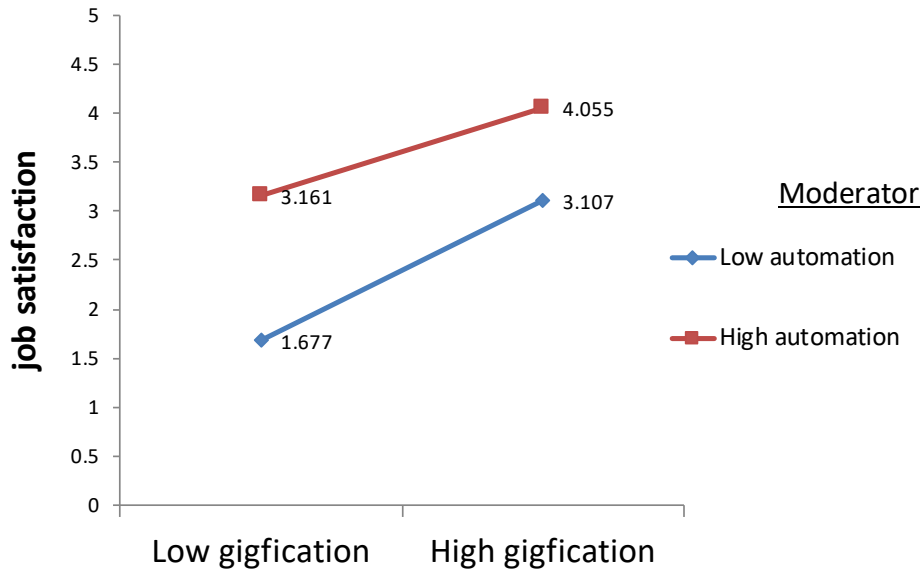
Figure 3 Interaction: Gigification *Automation -> Job Satisfaction AI enabled technology advancement weakens the positive relationship between Gigification and job satisfaction.

7. Implications for Practice

Organisations need to be clear about entire jobs that are disappearing (Frey and Osborne, 2017) due to AI systems automation in their operations and supply chain activities. Where entire jobs are disappearing, employers and policymakers need to put in place support mechanisms that enable operations workers to cope with the changes in employment. According to recent research, one action that employers may take is to provide training programmes that enable workers to move to newer roles and jobs that are expected to be emerge (Sony & Naik, 2020). This requires operations directors, policymakers, and educational institutions to work together to create and implement curricula that supports the needs of businesses in the AI-SA era.

Automation of significant tasks, by which we mean full-time, permanent jobs, will lead to higher levels of gig work. The gig economy has, over many centuries, taken on various guises and forms. The novel element of the 21st century gig economy is that gig work is mediated through AI system automation (Kenney and Zysman, 2016). These digital systems, often at the heart of the sharing economy, are changing the ways in which work is organised and jobs performed (Sutherland and Jarrahi, 2018). The sharing economy enables consumers and suppliers to obtain and distribute products or services between the two sides for free or for price on digital platforms (Davlembayeva, Papagiannidis and Alamanos, 2019). Digital platforms

are having significant effects on the relationship between workers and their employers. We propose two distinct categories for digital platforms: Macro and Micro. Macro platforms are created, from inception, as online digital business models that support a wide variety of human activities and interaction and consist of powerful algorithms that are driven by big data and utilise global cloud computing network. Macro platforms have disrupted industries, often globally, and created what is referred to as the sharing economy, gig economy and the on-demand economy. These platforms can be two-sided or multisided, as they bring together a variety of stakeholders, consumers, suppliers, distributors, and manufacturers in an ecosystem. Macro platforms become the central hub around which the ecosystem revolves. Some well-known examples of macro digital platform include Facebook, Uber, Google, Amazon, Slack and Airbnb. Digital platforms, driven by big data and AI, are expected to expand in all sectors. New macro digital platforms businesses are being launched almost daily, with new services and products being offered. These platforms have gigification built into their design; in other words, many of the jobs created by these platforms are based on the principles of gig working.

Micro digital platforms are created and implemented within incumbent, traditional organisations. These digital platforms evolve from the organisation's context, culture and activities. Micro platforms can support quite narrow activities, such as employees filling in their timesheets or can support entire processes, such as a production line. Like macro platforms, micro platforms run on algorithms, data, and network computing. The stakeholders of micro platforms are primarily internal to the organisation. Micro platforms can be independent of each other or can be integrated to cover greater areas of organisational activity. Within organisations, micro platforms have the effect of changing the locus of work, control, and responsibility. Micro platforms can have the effect of centralisation, replacing tasks people did with automation. As work is automated, specific tasks can be completed and moved around from one function or individual to another. Responsibilities can be shifted remotely as intelligent workflows and algorithms calibrate where jobs are best completed. The ability to work with and process information becomes a greater part of the job. Moreover, access to one or more digital platforms enables employees to work remotely rather than in a predetermined workplace. The extent to which people interact on a face-to-face basis is limited and may take the form of periodic team meetings, off-site conferences, or training events.

The effects of these digital platforms are illustrated graphically in Figure 4, which shows along the left-hand axis varying types of skills from highly mechanical / analytical skills, through to

creative / experience-based skills to social / emotional skills. The categories of jobs along the top of Figure 4 show the effects of partial gigification and significant gigification. The axis at the bottom of Figure 4 provides a temporal dimension. We argue that operations and supply chain jobs will be affected in three board ways as a consequence of AI-SA: some permanent jobs will continue to exist, some will be eliminated, and others will be gigified. Jobs that are highly mechanical, and analytical will be the most affected in terms of jobs disappearing. With Partial AI-SA, full-time jobs will remain and there will be a significant growth in these jobs being gigified. The significant implementation of AI-SA will lead to greater numbers of jobs being eliminated altogether, leaving room for fewer full-time jobs and most new jobs being created will be fully gigified. Whereas much of the current thinking suggests that work with higher levels of creativity, social and emotional skills will be less affected by AI-SA, we posit that these jobs will be pared down by automation. Partial AI-SA of jobs that require creative thinking and experience-based skills leads to some of these jobs being eliminated, but not as many as mechanical / analytical skills jobs. We suggest that the rate of full-time, permanent job elimination will be felt to lesser extent for work requiring creative skills. Nonetheless, over time, with Significant AI-SA, jobs that require creativity, cumulative knowledge and experience will disappear, leading to fewer full-time jobs, and those jobs that remain will involve higher levels of gigification. We posit that there will be more creative / experience gigified jobs than mechanical / analytical gigified jobs. Jobs that are based on people exhibiting social and emotional skills will not be protected from increases in AI-SA. The pace at which full-time, permanent jobs requiring these skills disappear will be slower than jobs requiring the other two types of skills. Nonetheless, Partial AI-SA will mean some jobs disappearing and the gigification of this type of work. A Significant implementation of AI-SA will mean many more gigified jobs and fewer full-time, permanent jobs. Our findings suggest that work that remains after the introduction of AI-SA will have the attributes of gig work – in other words, work that is time-bound, carried out alongside other gigs or jobs and income earned is from activities outside long-term employer / employee relationships. The spread of Gigification across all aspects of operations and supply chain management is enabled by increasing levels of AI-SA. There will be new jobs created by AI-SA, as new opportunities as operations and supply chain are transformed. These jobs are likely to be gigified from inception to optimise flexibility at every level of the organisation.
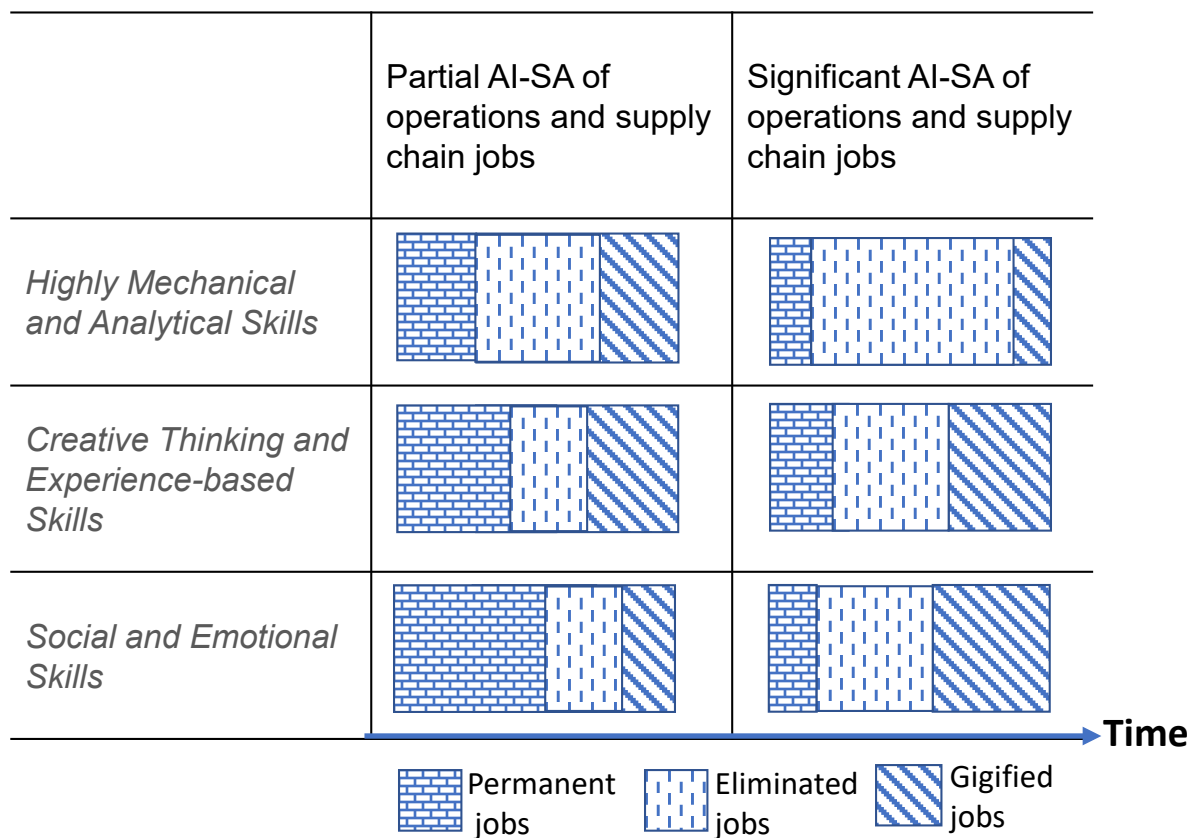
	Partial AI-SA of operations and supply chain jobs	Significant AI-SA of operations and supply chain jobs
Highly Mechanical and Analytical Skills		
Creative Thinking and Experience-based Skills		
Social and Emotional Skills		

Permanent jobs   Eliminated jobs   Gigified jobs   **Time**

Figure 4: Gigification and AI Automation Jobs changes (Source: The authors)

8. Limitations and future directions

The limitations of our study are embedded in the methods we used and point the way for further research. This study has used the single informant questionnaire design and cross-sectional data which is based on the linear assumption which might be limited to offer depth insights (Wamba et al. 2020; Ketokivi and Schroeder, 2004). Most notably, we have identified that job engagement and job satisfaction decrease when work is mediated using digital systems. Our quantitative analysis does not enable us to specify precise reasons for the negative relationship. Moreover, our sample is drawn from a single borough in London. A study covering wider geographic areas can be conducted, including but not limited to London, the whole of the UK, multiple cities and multiple countries with longitudinal data or multi-informants from a sampling unit may help for our future research..

Our study examines the effects of AI-SA on the relationship between Gigification, job engagement and satisfaction. We suggest that full-time, permanent jobs will increasingly become more gig-like. The Gigification of work at each level of operations and supply change

management needs to be understood in greater detail. The longer-term consequences of operations and supply chain management jobs being gigified will lead to the erosion of the profession and expertise gained over many decades. There is a need for not only further quantitative studies but also in-depth case studies to examine the deeper effects of Gigification. We feel this seam of research is rich for further theory building and testing.

Our study introduces Macro and Micro digital platforms to provide greater clarity for further research. The longer-term effects, benefits and risks of macro and micro platforms have yet to be explored fully. They give workers a greater degree of choice by letting them select the amount of time spent working, the actual hours of work and by allowing employees to determine where they work. However, both types of platforms can make work more precarious. Gig workers face income insecurity (Ashford et al., 2018), may be uncertain as to their status, may not have a voice in decisions taken, which erodes their ability to influence strategic and operational decisions made by digital platform managers. Macro and micro digital platforms can have the effect of disempowering workers.

Our research reveals that organisations need to identify the jobs that are going to be gigified and understand the extent of Gigification at the level of jobs and tasks in operations and supply chain management. The notion of under-employment is not new to economists and management scholars; see, for example, Feldman (1996), who conceptualises underemployment in terms of several factors such as education, work duties, field of employment, wages and permanence of the job. Our research suggests that people prefer to have some level of control over their future, so they may continue to be engaged and satisfied with gig working. Digital systems that remove workers' ability to balance the competing demands will leave operations and supply chain workers disengaged and dissatisfied.

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