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Preparing for Industrial Collaborative Robots:

A Literature Review of Technology Readiness and Acceptance Models

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Abstract

Collaborative robots (cobots) are an emerging technology that are increasingly being introduced into organisations. However, research investigating employee attitudes towards, or assessment of factors predicting acceptance of cobots is limited. A literature review was conducted to identify reliable and parsimonious models of technology acceptance that would hold relevance when applied to cobots. Understanding and facilitating employee acceptance of such technology is important if the improved productivity, job satisfaction and cost savings associated with its implementation are to be achieved. The Technology Readiness Index (Parasuraman, 2000) and Technology Acceptance Model (Davis, 1989) were considered most appropriate as a starting point to empirically explore cobot acceptance.

Keywords: Collaborative robots; cobots; Advanced robotics; Industry 4.0; technological change; technological readiness; technology acceptance.

Preparing for Industrial Collaborative Robots:

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The application of technology in work environments can have profound effects for individual employees and organisations. The rate and variety of technology introduced to workplaces is increasing exponentially and as the Fourth Industrial Revolution expands, Ghislieri, Molino and Cortese (2018) recently called for the need to “deepen the understanding of the interconnection between workers, organizations and technology” (p.4). Several models exist which provide a framework for understanding drivers of, and barriers to, an individuals’ readiness for and acceptance of technology. Awareness of key determinants can assist organisations in how they prepare employees for, and manage the implementation of, new technology. This literature review explores salient models relating to technology readiness and acceptance and evaluates their use in the context of an emerging technology, collaborative robots.

The Changing Face of Work

Technological advancements, like those achieved over the last 200 to 300 years across four industrial revolutions (see Table 1 for a description of each revolution’s contribution), have been a catalyst for economic development, increased productivity and improved working conditions (Healy, Nicholson & Gahan, 2017; Oesterreich & Teuteberg, 2016). Such technological innovations have also fundamentally changed where and how people work.

For many, employment has transformed from working in a single, fixed location, completing manual, repetitive tasks during set, predictable hours to today’s work environment requiring more complex problem-solving and featuring telework (working remotely) and flexible hours. However, the ability to work anywhere, anytime has been associated with significant concerns about declining work-life balance and job satisfaction, in addition to increased burnout (Berg-Beckhoff, Nielsen & Ladekjaer Larsen, 2017; Murray & Rostis, 2007). With particular relevance to working in more automated environments, prolonged or more frequent periods of independent and isolated work with reduced human interaction have also been viewed as a considerable risk to informal learning, organisational commitment and employee motivation, mental health and wellbeing (Ghislieri et al., 2018). Thus, some suggest that the multitude of digital transformations occurring in organisations also require transformation in terms of individual attitudes, ability to cope with technology and rules of engagement (Avci & Gulbahar, 2013).

Table 1

Timeline of Major Revolutions in Manufacturing

Industrial Revolution	Timeframe	Advancements and achievements
First (Industry 1.0)	Circa 1784	Mechanical loom developed in Great Britain, transformed communication, transportation and manufacturing
Second (Industry 2.0)	Circa 1870	United States led developments in electricity and the telephone. Mass production was bourne
Third (Industry 3.0)	Circa 1970	Development of semi-conductors and Computer Numerical Controlled (CNC) automation. Electronics and the Internet enabled a digital communications infrastructure
Fourth (Industry 4.0)	Current	Physical and virtual worlds are merged through cyber-physical systems to produce goods and services (data driven). Machines and products have endless connectivity potential utilising the internet, sensors and micro-computers to communicate remotely and in real-time (i.e. ‘Internet of Things’). Possible to create self-optimising factories (smart factories). Associated technologies include cloud computing, advanced robotics and augmented and virtual reality

Information summarised from: Arnold, Veile and Voigt (2018); Blayone and van Oostveen (2019); Kagermann, Wahlster and Helbig (2013); Vaidya, Ambad and Bhosle (2018); and Winberg and Ahrén (2018).

Furthermore, proficiency in and ability to cope with technology in the workplace is likely to be influenced by competency in both hard skills (IT/technical expertise) and soft skills (e.g. communication, ability to work in multi-functional teams, deal with complex situations, continuous learning; Ghislieri et al., 2018; Healy et al., 2017; Parry & Battista, 2019).

Applications of technology

Context is everything

Blut and Wang (2019) recognise the many and varied contexts in which technology is used. Technology can be used in personal (home) and professional (work) settings. When used in a personal ('consumer') context, technology is used for two main purposes: hedonic (pleasure-oriented; e.g. virtual reality fashion applications) and utilitarian (productivity-oriented; e.g. internet banking). In a work setting, the focus is on productivity gains. In either setting, use of a technology can be either voluntary (objectives can be achieved without using a specific technology) or mandatory (no alternate choice to complete a task or objective). The focus of this review is professional settings where eventual use (application of industrial collaborative robots is emerging) is expected to be mandatory. However, the extent of usage can still vary between individuals in mandatory settings whereby they may decide to "delay, obstruct, underutilize, or sabotage a new technology" (Leonard-Barton, 1988, p.604).

Collaborative robots

Collaborative robots (cobots) are an application of advanced robotics (an emerging technology of Industry 4.0; Autonomous Manufacturing, 2019) and as the names suggests, allow humans and robots to collaborate on tasks where work is performed simultaneously in a co-located area (Kolbeinsson, Lagerstedt & Lindblom, 2018). Both the human and robot are involved in the achievement of a result or project outcome (Müller-Abdelrazeq, Schönefeld, Haberstroh & Hees, 2019) and from this perspective, cobots and humans can be viewed as complementary to each other in the workplace with cobots assisting in complex tasks that cannot be fully automated (Mobile Automation, 2017).

Cobots are a special type of industrial robot and are typically smaller and less powerful than their caged robotic predecessors (traditional industrial robots) and for that reason are perceived to be safer. Their inbuilt ‘smart’/digital technology (i.e. cameras, lasers, sensors) allows them to sense the presence of a human and adjust their movements to avoid collisions (Twentyman, 2017). Cobots are typically used to perform hazardous, sensitive or mundane aspects of tasks (e.g. welding and painting) allowing humans to concentrate on more knowledge-intensive, value-add (revenue generating) activities such as monitoring production efficiencies (TÜV Rheinland, 2017), creating new tasks and responsibilities (Ghazizadeh, Lee & Boyle, 2012). Therefore, the introduction of cobots to a work environment has the potential to reduce injuries (including repetitive strain injuries; Küpper et al., 2019), and increase job satisfaction. However, the impacts of technological change are always multi-faceted and rarely exclusively positive (Brougham & Haar, 2017). For example, fear of job losses is frequently a concern associated with the implementation of technology (Müller-Abdelrazeq et al., 2019; Weiss, Huber, Minichberger & Ikeda, 2016).

Presently, about 3% of all industrial robots sold are cobots with this figure projected to reach 34% by 2025 (Halle, 2018). Manufacturing is currently the principal market for industrial cobots although their uptake is increasing in a number of sectors from construction and agriculture to medical, health care and defence (Maull, Brewer & Maull, 2019). Therefore, working with cobots is an ever-increasing prospect, particularly for younger generations and those currently transitioning to the workforce.

The value of understanding attitudes to and acceptance of technology

For a range of stakeholders (including technology developers and managers in organisations), acceptance and use of a system are important indicators of success when new technology is implemented (Hwang, Al-Arabiat & Shin, 2016). For mandatory settings, in particular, employee satisfaction with the new technology is critical to prevent rejection and minimise absenteeism and turnover (Yousafzai, Foxall & Pallister, 2007a). After all, the anticipated benefits of technology implementation, such as improved efficiency and task performance (Hsiao & Yang, 2011), will not be fully realised if user acceptance is poor and usage is sub-optimal (undermining the cost-benefit proposition of technology investment). Therefore, understanding the factors that influence people's acceptance and usage of technology will aid how it is developed (Taherdoost, 2018; e.g. system requirements), promoted (e.g. communication strategy) and implemented (e.g. tailoring of support and training). The manufacturing industry has long been aware that the characteristics of a specific technology are not solely responsible for why employees accept or reject new technology (Manufacturing Studies Board, 1986; as cited in Slem, Levi & Young, 1995).

Technology acceptance models and frameworks

Terminology

'Technology acceptance' is related to, and sometimes used broadly to encapsulate technology readiness and technology adoption. Parasuraman (2000) defines technology readiness as "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (p.308). It is an individual's predisposition to use new technologies. In general terms, technology acceptance can be defined as a positive decision to use an innovation (Taherdoost, 2018), an observable willingness to use technology (Avci & Gulbahar, 2013). Whereas technology adoption "is not only the choice to accept an innovation but also the extent to which that innovation is integrated into the appropriate context" (Straub, 2009, p.626).

Often, use of these terms seems to be distinguished by the degree of specificity of the technology investigated and the length of exposure to/stage of implementation of the technology. For example, Lin, Shih and Sher (2007) highlight that technological readiness and acceptance are interrelated but the former relates more to an individual's general technology beliefs and the latter to an individual's beliefs of a specific system or technology. Ghazizadeh and colleagues (2012) continue in this vein noting that "…adoption and acceptance have similar meanings but adoption has a slightly broader connotation. Adoption goes beyond acceptance to address patterns of reliance and dependence" (p.40). Given the 'emerging status' of cobots into the workplace, models of adoption are considered to be outside the scope of this review.

Models and Frameworks

The following models have been identified as offering valid and widely utilised frameworks to assess individual technology readiness and acceptance. In order to minimise employee resistance to a new technology, Venkatesh and Bala (2008) encouraged organisations to proactively manage employee perceptions of a new technology and engage in pre-implementation interventions to ensure employee expectations of the technology (and its impact on their work performance) are realistic. Evaluating workforce readiness for and expectations of a new technology prior to any implementation decision is likely to be valuable in shaping the nature and timelines of any subsequent pre-implementation interventions (Renjen, 2019).

Assessing impacts of technological change. Many decades ago, Slem, Levi and Young (1986; as cited in Slem et al., 1995) suggested that the degree of employee cooperation or resistance an organisation faces when technological change is implemented is a result of their beliefs about the impact of the technology and how the technological change is managed. In a study investigating the impact of computer-integrated manufacturing on employees from electronic manufacturing facilities, Levi, Slem and Young (1992; as cited in Slem et al., 1995) proposed a model of factors influencing an individual's attitudes towards the impact of technological change (see Figure 1). Employees can perceive positive impacts from technological change such as personal benefit (e.g. improved skills and career) and job improvement (e.g. more control, more challenging work), and negative impacts, such as personal insecurity (e.g. concern over future work) and job stress (e.g. overload, damaged co-worker relationships). The greater the perceived personal benefit and job improvement, the more likely employees are to cooperate and facilitate the technological change (Slem et al., 1995). How the technological change process is managed was found to be one of the main factors determining perceptions (Levi et al., 1992; as cited by Slem et al., 1995).

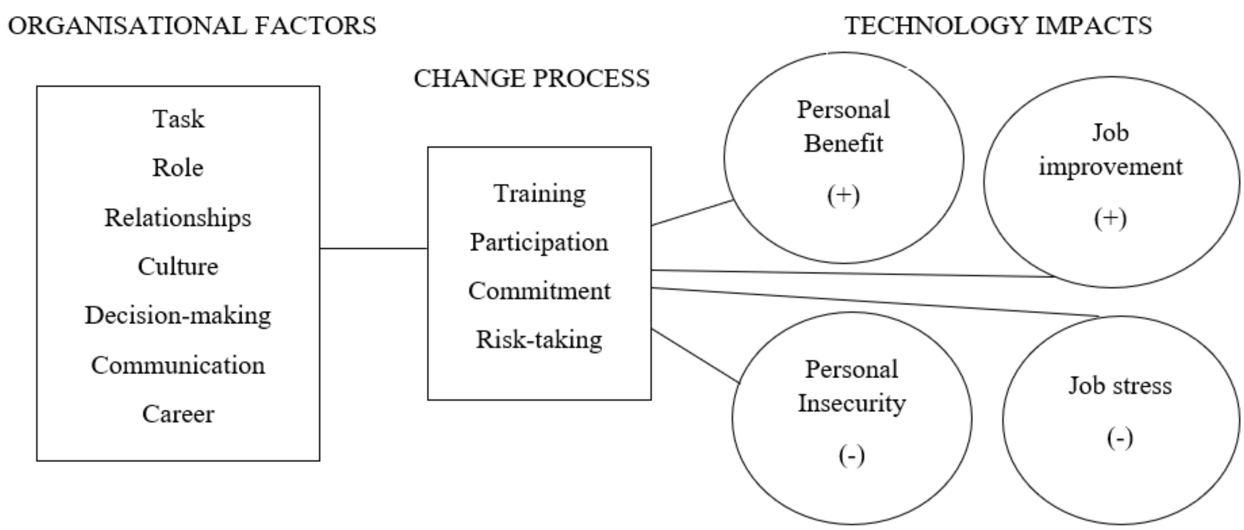

Figure 1. Model of the impacts of technological change (reproduced from Slem et al., (1995)).

Technology Readiness Index. Originally developed to explore customer/consumer reactions to technology implemented by businesses, the Technology Readiness Index (TRI) measures an individual's general beliefs about technology (Parasuraman, 2000; TRI items have also recently been reviewed (reduced) and updated to ensure that the language reflects modern technology experiences, see Parasuraman & Colby, 2015 for a comparison). A person's overall score, considered to be on a continuum from strongly positive to strongly negative, comprises four components: Optimism, Innovativeness, Discomfort and Insecurity (definitions are provided in Table 2). Optimism and Innovativeness are deemed to be motivators of technology use (increasing readiness) whereas Discomfort and Insecurity are likely to inhibit technology use (decrease readiness). Thus, the Index recognises that individuals can have both positive and negative beliefs about technology. In a recent meta-analysis employing structural equation modelling of data from 163 articles, Blut and Wang (2019) recommended that technology readiness is best conceptualised as two-dimensional (motivators and inhibitors) rather than as one (overall score) or four-dimensional, concluding this offers a "parsimonious yet comprehensive" way to measure technology readiness (p.2).

Table 2

Components of the Technology Readiness Index (TRI)

TRI dimension	Definition
Optimism	Tendency to have a positive view of technology and believe that technology offers people increased control, flexibility and efficiency
Innovativeness	Tendency to be a technology pioneer and thought leader
Discomfort	Tendency to perceive a lack of control over technology and feel overwhelmed by it
Insecurity	Tendency to distrust technology, sceptical about its reliability/ability to work properly

Based on Parasuraman (2000).

The TRI has been shown to successfully differentiate between technology usage intentions of consumers (Parasuraman, 2000). Moreover, Blut and Wang (2019) discussed that technological readiness has been positively associated with adoption rates of a range of technology services across both work and home settings (e.g. internet banking, mobile technologies, social robots, self-checkout terminals, remote services, online taxation systems, and cloud computing). However, the author has found limited application of the TRI in mandatory, employee settings. One exception was a study conducted by Chang and Kannan (2006) examining the readiness of 204 US government employees for wireless technology. They found a medium-sized correlation (.47) between overall TRI scores and support for/willingness to use wireless technology in the workplace.

When technology readiness is investigated, it is often done in combination with models of technology acceptance (Erdoĝmuş & Esen, 2011; Lin et al., 2007; Walczuch, Lemmink & Streukens, 2007; Pires, da Costa Filho & da Cunha, 2011). Further to this point, findings from Blut and Wang's meta-analysis (2019) suggest that TRI 'motivators' and 'inhibitors' indirectly predict intentions to use technology and actual technology usage, exerting their influence through perceived ease of use and perceived usefulness – two core constructs of the technology acceptance model. In a consumer setting, technological readiness was shown to primarily influence PEOU (Lin et al., 2007). However, again in a consumer context, Pires et al. (2011) found the TRI constructs to explain only a small amount of additional variation (3%) in intention to use a technology beyond that explained by core TAM constructs.

Technology Acceptance Model. The field of information system research has long pursued the identification of determinants of user acceptance and usage of technology (King & He, 2006) and has proposed several models and frameworks over the last 50 years. Technology acceptance models have largely evolved from social psychology's Theory of Reasoned Action (Fishbein & Ajzen, 1975; as cited in Ma & Liu, 2004), which has been used to explain a range of behaviours (Venkatesh, Morris, Davis & Davis, 2003). The Theory of Reasoned Action suggests that how an individual feels about performing a behaviour (attitude toward behaviour), in combination with perceptions of whether people salient to the person believe s/he should perform that behaviour (subject norm), will determine a person's actual behaviour (Fishbein & Ajzen, 1975; as cited in Ma & Liu, 2004). Essentially, the Theory of Reasoned Action states that beliefs influence attitudes which lead to intentions and therefore generate behaviour (Ma & Liu, 2004).

Drawing on this theory, Davis (1989) empirically tested a model (known as the Technology Acceptance Model; TAM) to predict information technology acceptance and usage in work settings (Hsiao & Yang, 2011; Lin et al., 2007; Venkatesh et al., 2003). TAM proposes that perceived usefulness (PU) of a system/technology and perceived ease of use (PEOU) of a system/technology mediate the relationship between systems characteristics (i.e. external factors) and likelihood of system use (Legris, Ingham & Collerette, 2003). PU an PEOU are antecedents of attitude towards using technology, which in turn predict behavioural intention (BI) to use technology which then predicts actual system use (Davis, Bagozzi & Warshaw, 1989; see Figure 2). 'Attitudes' toward technology refer to a mental state of preparation for action (Müller-Abdelrazeq et al., 2019) and reflect the strength of one's feelings of favourableness or unfavourableness toward the technology (Moon & Kim, 2001).

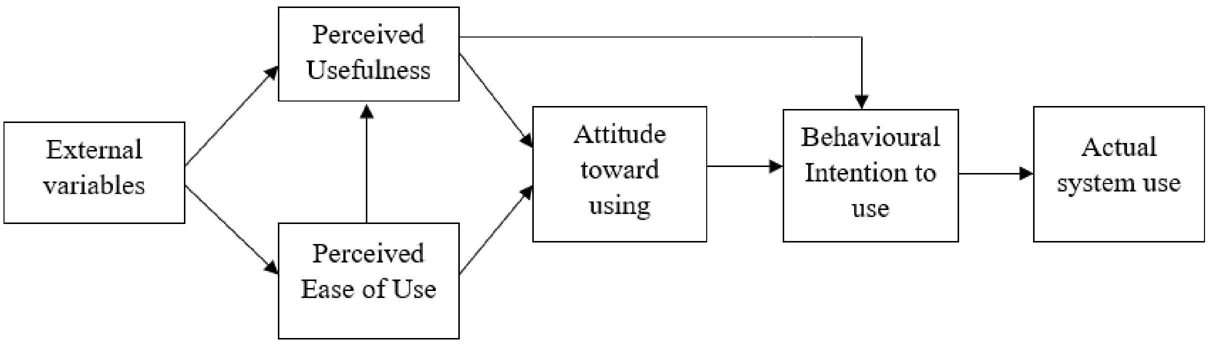

Figure 2. Technology Acceptance Model (TAM; Reproduced from Davis et al., 1989)

Davis (1989) defines PU as “the degree to which a person believes that using a particular system would enhance his/her job performance” (p.320) and PEOU as “the degree to which a person believes that using a particular system would be free of effort” (p.320). The greater the PU of a technology, the more likely the user is to believe a positive use-performance relationship will ensue and the easier a technology or application is to use, the more readily it will be accepted (Davis, 1989).

TAM has been used to assess user acceptance of various technology in a variety of industries including business, education, healthcare and construction (Liu, Lu & Niu, 2018). The model has consistently explained the variability in intentions to use technology and actual use behaviour (Ghazizadeh et al., 2012). As such, it is considered one of the most robust and parsimonious models of technology acceptance (Hsiao & Yang, 2011; Legris et al., 2003; Venkatesh & Davis, 2000).

Meta-analyses by King and He (2006) and Ma and Liu (2004) have shown that the strongest, significant relationship between these constructs is between PU and BI and between PU and PEOU, although there was less overall consistency in the nature of the latter relationship. A weaker, and at times insignificant relationship, was found between PEUO and BI (King & He, 2006; Ma & Liu, 2004). However, some recognise that in mandatory settings, PEOU is a stronger predictor of acceptance compared with PU (Adamson and Shine 2003; Brown et al. 2002). In addition, several researchers argue that when evaluating technology acceptance in mandatory settings, the attitude construct takes on heightened significance (Brown, Massey, Montoya-Weiss & Burkman, 2002; Yousafzai et al., 2007a). However, Horton, Buck, Waterson and Clegg (2001) questioned the validity of how an attitude may be ‘calculated’ and argued for retaining the simplest model possible (i.e. PU, PEOU, BI and actual usage). Furthermore, Turner, Kitchenham, Brereton, Charters and Budgen (2010) established from their systematic literature review of 79 empirical studies of TAM, that researchers do not typically include actual usage measures. However, when they do, the strength and significance of the relationships between PU and PEOU with actual usage is less consistent than the correlation between BI and actual usage. Turner et al. (2010) concluded that PU and PEOU are not necessarily reliable indicators of actual usage and as such, results from studies must be interpreted cautiously and within the context of the specific technology and population sampled.

Results from a meta-analysis conducted by Legris and colleagues (2003) reviewing 22 studies revealed that TAM tends to explain approximately 40% of system use. Needless to say, there have been many derivatives and proposed extensions of the original TAM in order to improve its predictability of actual usage as well as provide more concrete mechanisms through which usage can be influenced. The more prominent of these models (approximately eight) have been articulated and reviewed extensively by numerous researchers (Chen, Li & Li, 2011; Lai, 2017; Lee, Kozar & Larsen, 2003; Marangunić & Granić, 2015; Taherdoost, 2018; Venkatesh et al., 2003) and for that reason are not repeated here. However, in short, they add a range of personal and social factors as determinants of PU and/or PEOU.

In their meta-analysis of TAM from 88 studies, King and He (2006) concluded that PU, PEOU and BI can be considered the ‘core’ TAM constructs and that a broader structure has evolved by applying one or more of four types of modifications: inclusion of external factors (e.g. situational involvement, prior usage or experience, personal computer self-efficacy); incorporating factors from other theories (e.g. subjective norm, expectation, task-technology fit, risk and trust); including contextual factors/potential moderators (e.g. gender, culture, technology characteristics); and inclusion of consequence measures (e.g. attitude, actual usage).

Moreover, in a meta-analysis of 145 publications, Yousafzai, Foxall and Pallister (2007b) identified more than 70 external variables that had been included in models of technology acceptance. They categorised these into organisational characteristics (e.g. support and training), system characteristics (e.g. reliability and accuracy, response time), users' personal characteristics (e.g. age, awareness, personality, self-efficacy) and other (e.g. cultural affinity, subjective norms, task characteristics). Four moderating factors were also found across the studies: subject type (student versus professional); method type (experimental versus survey); measurement of usage (subjective/self-report versus objective); and type of technology tested (communication systems (e.g. email), general-purpose systems (e.g. e-commerce), office systems (e.g. word processor), and business systems (e.g. Manufacturing Resources Planning (MRP)). However, Yousafzai et al. (2007b) did not evaluate which measures were most commonly used or effective. In contrast, Lee and colleagues (2003) provided an overview of these relationships from a meta-analysis of more than 100 studies and indicated system quality, training, compatibility, computer anxiety, self-efficacy, enjoyment, computing support, and experience were the most frequently introduced variables. Of these, enjoyment, quality, management support and experience appeared to be among the most consistent in influencing PU, PEOU, or BI.

Venkatesh and colleagues (2003) acknowledged there was significant overlap in constructs between various TAM modifications and extensions and subsequently proposed the Unified Theory of Acceptance and Use of Technology (UTAUT). As shown in Figure 3, this model proposes four independent constructs that directly determine intentions to use technology: performance expectancy (incorporating the PU construct from TAM (Davis, 1989), among other constructs); effort expectancy (incorporating the PEOU construct from TAM (Davis, 1989), among other constructs); social influence; and facilitating conditions (Venkatesh et al., 2003) and four moderators of these relationships (experience, voluntariness, gender and age). Venkatesh and colleagues (2003) found this model to outperform previous TAM iterations, explaining 70% of variance in intentions to use technology. However, in a meta-analysis of 27 studies that utilised the UTAUT model, Dwivedi, Rana, Chen and Williams (2011) found that multiple technology acceptance theories are typically used in conjunction with each other in a single study (TAM being the most frequently used theory alongside UTAUT). Thus, they recommended that future studies employ streamlined models as much as possible in order to avoid repetition and redundancy in constructs.

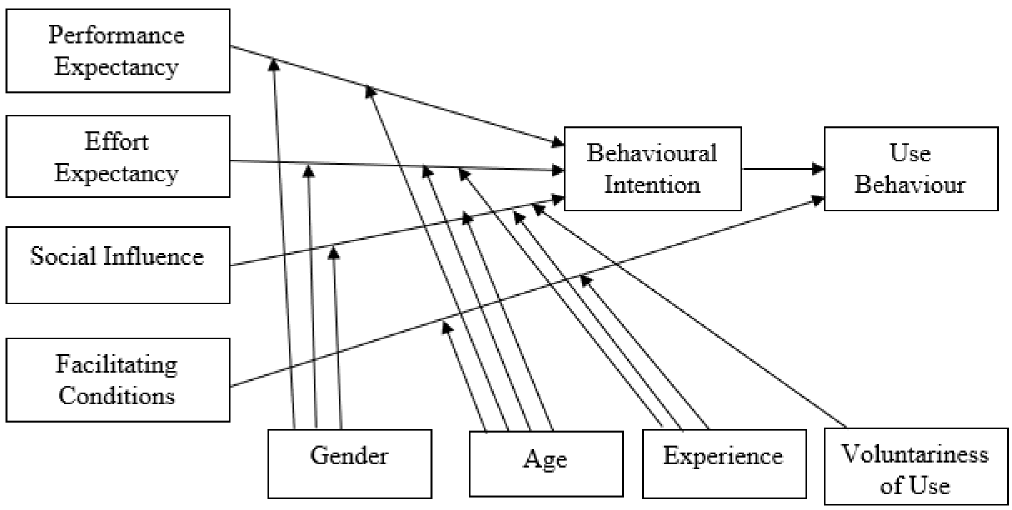

Figure 3. The UTAUT model (Reproduced from Venkatesh et al’s (2003))

Current knowledge about readiness for and acceptance of collaborative robots

Research investigating employee attitudes towards, or assessment of factors predicting acceptance of, industrial collaborative robots (cobots) is limited. A study conducted by Elprama, El Makrini, Vanderborght and Jacobs (2016) with car factory workers is one exception. Their quantitative, repeated measures pilot study used the ‘Almere’ model (a variant of the UTAUT model developed to assess the acceptance of social robots by older adults) as a framework to investigate the impact of cobot social cues (i.e. the degree of anthropometric features such as eyes and arms, like a human) on acceptance. In this study participants completed a task with a specific type of cobot ('Baxter'). Elprama and colleagues (2016) found that the greater the social cues provided by the cobot (e.g. head move toward the object it was manipulating, nodding to understand a gesture), the greater the perceived enjoyment of employees and intention to work with them. Studies evaluating the influence of a specific 'system' or technological feature of cobots on user acceptance appear to be the norm (e.g. Maurtua, Ibarguren, Kidal, Susperregi & Sierra, 2017) and are often qualitative (e.g. Sauppé & Mutlu, 2015).

A more holistic approach has been taken by studies exploring user attitudes towards and acceptance of industrial robots generally. For example, a more recent study by Elprama and colleagues (Elprama, Jewell, Jacobs, El Makrini & Vanderborght, 2017) involved interviews with eight factory workers regarding their perceptions of working with industrial robots. Although not specific to cobots, perceived disadvantages of robot implementation included concerns about job losses and decreased contact with colleagues whilst the main perceived advantage was reduced mental and physical workload. Henderson (2015) conducted a mixed-method study exploring the extent of industrial robot acceptance of 37 employees in an American manufacturing facility. She applied the core constructs of the technology acceptance model (PU, PEOU and BI) as her framework and her findings supported that manufacturing personnel will be accepting of industrial robots if perceived to be useful and easy to use (however analyses were limited due to the small sample size).

Henderson (2015) also examined the influence of workplace culture on receptiveness to technological change and concluded that personnel being given the opportunity to work in teams was positively associated with acceptance of technological change. Further, open communication between management and personnel was shown to be a key factor for personnel to accept technological change, producing increased feelings of organisational support.

Finally, research conducted by Bröhl, Nelles, Brandl, Mertens and Schlick (2016) appears to have provided the largest sample (n=322) and most comprehensive assessment of employee attitudes towards industrial robots currently published, integrating factors of the core TAM (i.e. PU, PEOU and BI) and UTAUT (e.g. subjective norm, job relevance, output quality) frameworks. Moreover, they evaluated attitudes towards two different modes of industrial robots – passive (e.g. robot holds a component so that the human can work on that component) and active (e.g. robot handing over heavy components) and surveyed employees from German production companies who were yet to implement and who had already implemented robots. Their preliminary published results involved correlational analyses only and found medium to high correlations between PU, PEOU, BI and use behaviour suggesting the core constructs of TAM are “transferable to the domain of human-robot interaction” (p.102). No significant difference in attitudes between passive and active robot-mode scenarios was found and no comparison was made between attitudes of employees who currently worked with robots and those who did not (although this was planned for future analyses which do not appear to have been published to date).

Discussion and Conclusion

Numerous models exist to evaluate individuals' acceptance of technology. Davis and colleagues' (1989) core constructs from the Technology Acceptance Model (TAM) (perceived usefulness (PU) and perceived ease of use (PEOU) as antecedents of behavioural intention (BI) to use a technology) have received widespread support as a simple and reliable model to indicate the extent of a technology's acceptance and the likelihood of individuals making optimal use of it. Evidence suggests that PEOU is a stronger determinant of BI to use technology in mandatory, professional settings (Adamson & Shine 2003; Brown et al. 2002). Thus, understanding which external variables are likely to influence PEOU, in particular, will assist organisations in developing interventions to maximise acceptance of new technology. Lee et al.'s (2003) review suggested that prior experience of the new (or similar) technology (i.e. individual characteristics) and managerial support for the new technology (i.e. organisational characteristics) were most consistently associated with greater PEOU. Thus, inclusion of these aspects seems vital when investigating technology acceptance in organisations.

Venkatesh and Bala (2008) called for a greater need to investigate technology acceptance of employees at pre-implementation stages (i.e. stages leading to the actual roll-out of a system). Acquiring an early understanding of employee perceptions and expectations of an impending technology should maximise their acceptance of the technology through the opportunity for the organisation to align expectations with likely realities. Uncovering perceptions and expectations requires assessment of employees' readiness for technology and their perceptions of likely impacts of technological change. Although predominantly used in consumer rather than professional settings, the Technology Readiness Index (TRI; Parasuraman, 2000) is often used in combination with TAM to ascertain the degree to which 'inhibitors' and 'motivators' of technology readiness influence intended use (e.g. Pires et al., 2011; Lin et al., 2007; Walczuch et al., 2007). However, there is a lack of clarity as to what additional explanatory power technological readiness offers above and beyond TAM constructs. This aspect would benefit from further exploration in professional settings.

Industrial collaborative robots (cobots) are an emerging technology of the 21st Century and accordingly, there appears to be a narrow evidence-base relating to employee attitudes towards and acceptance of this technology. The few studies undertaken typically pertain to a specific make of cobot and involve a small participant sample. At the time of this review no (or few) published studies examining acceptance of industrial cobots in the Australian context could be identified. However, the growing value and importance of organisational capability to implement, accept and work with cobots is apparent by the recent release of a ‘Robotics Roadmap for Australia’ (Australian Centre for Robotic Vision, 2018) which includes a case study of cobot implementation at Boeing Australia. A recommendation from the Roadmap was to improve awareness in industry, government and the wider community of the benefits of robotics technologies. Therefore, there is a growing need for research addressing workforce readiness and acceptance of cobots prior to their implementation in a range of industrial settings and workforce types. Quantitative, survey-based research involving elements of TRI and TAM frameworks seems a sensible starting point to build knowledge in this area and develop organisational interventions to better prepare employees for the future of work.

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Cobot colleagues: Determinants of apprentice willingness to work with collaborative robots (cobots). An evaluation of a pre-implementation model of technology acceptance

Abstract

Collaborative robots (cobots) are likely to be an increasing feature of workplaces in the future. However, few pre-implementation quantitative studies have been conducted that investigate the antecedents of employee cobot acceptance across different industries. Identifying significant antecedents of cobot acceptance is important if organisations are to achieve the improved productivity and cost savings associated with such technology implementation. The Technology Acceptance Model (Davis, 1989) provides a robust framework to assess determinants of technology acceptance. Using self-report survey data of 92 apprentices, ordinal regression demonstrated perceived ease of cobot use had the strongest influence on cobot acceptance (behavioural intention to work with cobots in the future), fully mediating the effect of perceived usefulness of cobots on acceptance. In addition, affinity for smart technology was a significant predictor of perceived ease of cobot use (and perceived usefulness of cobots). The relevance of these findings for early career employees and organisations is discussed.

Keywords: collaborative robots; technology acceptance; affinity for technology; workplace culture; apprentices

INTRODUCTION

The fourth industrial revolution (Industry 4.0) is upon us, where machines and products have endless connectivity potential utilising the internet, sensors and micro-computers to communicate remotely and in real-time (Arnold, Veile & Voigt, 2018). Associated technologies include cloud computing, advanced robotics and augmented and virtual reality (Autonomous Manufacturing, 2019). Collaborative robots (cobots) are an application of advanced robotics and as the names suggests, allow humans and robots to collaborate on tasks where work is performed simultaneously in a co-located area (Kolbeinsson, Lagerstedt & Lindblom, 2018). Both the human and robot are involved in the achievement of a result or project outcome (Müller-Abdelrazeq, Schönefeld, Haberstroh & Hees, 2019) and from this perspective, cobots and humans can be viewed as complementary to each other in the workplace with cobots assisting in complex tasks that cannot be fully automated (Mobile Automation, 2017). The introduction of cobots in the workplace is likely to change the nature of work by reducing mundane and repetitive work (e.g. welding and painting) and preventing fatigue and injury (e.g. tightening screws on vehicles that are difficult to reach; Küpper et al., 2019) as well as increasing job satisfaction through more knowledge-intensive, value-add (revenue generating) activities such as monitoring production efficiencies and by creating new tasks and responsibilities (Ghazizadeh, Lee & Boyle, 2012; Küpper et al., 2019). However, the introduction of cobots may also decrease contact with colleagues (Elprama, Jewell, Jacobs, Makrini & Vanderborght, 2017), potentially inhibiting informal learning, organisational commitment and employee motivation, mental health and wellbeing (Ghislieri, Molino & Cortese, 2018).

Cobots are a special type of industrial robot and are typically smaller and less powerful than their caged predecessors (traditional industrial robots) and for that reason are perceived to be safer. In addition, they have inbuilt ‘smart’ (digital) technology (i.e. cameras, lasers, sensors) that allow them to sense the presence of a human and adjust their movement to avoid collisions (Twentyman, 2017). Presently, about 3% of all industrial robots sold are cobots with this figure projected to reach 34% by 2025 (Halle, 2018). Today, cobot implementation costs are typically lower than industrial robots due to the reduced infrastructure requirements (Mason, 2019). Manufacturing is currently the principal market for industrial cobots although their uptake is increasing in a number of sectors from construction and agriculture to medical, health care and defence (Maull, Brewer & Maull, 2019). Therefore, working with cobots is an ever-increasing prospect, particularly for younger generations and those currently transitioning to the workforce, such as apprentices.

When technology is implemented in the workplace (professional settings) the purpose is utilitarian where the focus is on productivity gains and use of the technology tends to be mandatory (no alternate choice to complete a task or objective; Blut & Wang, 2019). However, the extent of usage can still vary between individuals in mandatory settings as they may decide to "delay, obstruct, underutilise, or sabotage a new technology" (Leonard-Barton, 1988, p.604). Understanding how to facilitate employee acceptance and use of technology is important for organisations if the anticipated benefits of technology implementation, such as improved efficiency and task performance, are to be realised (Hsiao & Yang, 2011; Turja & Oksanen, 2019). Successful implementation of technology should result in employee job satisfaction with minimal absenteeism and turnover (Yousafzai, Foxall & Pallister, 2007a), as well as significant savings for the organisation (Küpper et al., 2019).

In order to minimise employee resistance to a new technology, Venkatesh and Bala (2008) encouraged organisations to proactively manage employee perceptions of a new technology and engage in pre-implementation interventions (e.g. information sharing, previewing technology/systems, explaining how will assist with job performance) to ensure employee expectations of the technology are realistic. Poor preparation in organisations prior to the introduction of new technology can result in slowed technological implementation and increased costs (Deloitte, 2018). Evaluating the likely acceptance of a workforce to a new technology prior to implementation should provide insight about how best to introduce it, what further preparation is required and may help prioritise technology investments. Research suggests that organisational leaders who obtain such data-driven insights are nearly twice as likely to be "ready to lead their organisations in capitalising on the opportunities associated with Industry 4.0…to be concerned about the ethical use of new technology, and to train their current employees to access the skills required…" (Renjen, 2019, para. 9).

A recent Australian workforce development needs survey identified technicians and trade workers (e.g. electricians, carpenters, mechanics) as occupations in greatest need of training and development (Australian Industry Group, 2016). Construction, manufacturing and automotive are among the principal industries employing technicians and trade workers (Australian Government Department of Employment, Skills, Small and Family Business, n.d.). Employers of these occupations are more likely to develop links with the vocational education and training (VET) sector than with the school or higher education sectors. However, employers have reported higher levels of dissatisfaction with VET graduate problem solving, initiative and enterprise skills and with their knowledge about their chosen career than they do for higher education graduates (Australian Industry Group, 2016). Having a realistic understanding and expectation about a career is an important factor in determining long-term employability and job satisfaction (Čiarnienė, Kumpikaitė & Vienažindienė, 2010). It is important that VET students are cognizant that advances in technology feature as both an opportunity and threat in the job market (Addams & Allred, 2013). Therefore, successful career planning and workplace integration requires regular analysis of personal strengths and weaknesses as well as review of the opportunities and threats existing in the external job market (SWOT analysis; Addams & Allred, 2013).

The purpose of this study is to (1) quantify apprentice willingness to work with cobots in the future; and (2) identify factors that promote apprentice (early career employee) acceptance of cobots. How employee acceptance will be evaluated will now be discussed.

LITERATURE REVIEW

Research investigating cobots typically sits within the field of industrial human-robot collaboration where the focus is largely on improving user safety (Robala-Gómez et al., 2017; Villani, Pini, Leali & Secchi, 2018; Vysocky & Novack, 2016). Research investigating employee attitudes towards, or assessment of factors predicting acceptance of cobots in the workplace is limited, particularly within an Australian context. Published studies examining cobot acceptance tend to evaluate the influence of a specific 'system' or technological feature of cobots on user trust and acceptance (such as comparing interaction mechanisms, for example, pointing gesture and manual guidance; Maurtua, Ibarguren, Kidal, Susperregi & Sierra, 2017) and evaluation is often qualitative (e.g. Charalambous, Fletcher & Webb, 2015; Sauppé & Mutlu, 2015). As a result, to inform selection of an appropriate framework for assessing employee acceptance of cobots, it was necessary to examine studies evaluating acceptance of a range of technologies across different settings, including service industries and learning and consumer (personal use) environments.

The Technology Acceptance Model (TAM; Davis, 1989) has been utilised to assess user acceptance of various technologies in a variety of organisations and industries (e.g. e-shopping; Ha & Stoel, 2009), education (e.g. e-learning management systems; Alharbi & Drew, 2014), healthcare (e.g. bar code medication administration; Song, Park & Oh, 2015) and construction (e.g. wearable technologies such as GPS and physiological sensors; Choi, Hwang & Lee, 2017). The model has consistently explained the variability in intentions to use technology and actual use behaviour (Ghazizadeh et al., 2012). As such, it is considered one of the most robust, flexible and parsimonious models of technology acceptance (Alomary & Woollard, 2015; Hsiao & Yang, 2011; Legris, Ingham & Collerette, 2003; Venkatesh & Davis, 2000).

Like most models of technology acceptance, TAM is grounded in social psychology's Theory of Reasoned Action (Fishbein & Ajzen, 1975; as cited in Ma & Liu, 2004) which in essence, states that beliefs influence attitudes which lead to intentions and therefore generate behaviours (Ma & Liu, 2004). In their meta-analysis of TAM from 88 studies, King and He (2006) concluded that perceived usefulness, perceived ease of use and behavioural intention to use a technology can be considered the 'core' constructs of TAM. Davis (1989) defines perceived usefulness as "the degree to which a person believes that using a particular system would enhance his/her job performance" (p.320) and perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort" (p.320). The greater the perceived usefulness of a technology, the more likely the user is to believe a positive use-performance relationship will ensue and the easier a technology or application is to use, the more readily it will be accepted (Davis, 1989). In a study exploring robot acceptance of 322 production company workers, Bröhl, Nelles, Brandl, Mertens and Schlick (2016) found significant correlations of medium to large effect size between these constructs and concluded this core TAM "is transferrable to the domain of human-robot interaction" (p.102). Thus, based on the evidence reviewed, the core TAM forms the foundation of the preliminary model of cobot acceptance tested in the current study.

Meta-analyses by King and He (2006) and Ma and Liu (2004) have shown that the strongest, significant relationship between these constructs is between perceived usefulness and behavioural intention and between perceived usefulness and perceived ease of use, although there was less overall consistency in the nature of the latter relationship. A weaker, and at times insignificant relationship, was found between perceived ease of technology use and behavioural intention to use it (King & He, 2006; Ma & Liu, 2004). However, some recognise that in mandatory (professional) settings, perceived ease of use is a stronger predictor of acceptance compared with perceived usefulness (Adamson & Shine 2003; Brown, Massey, Montoya-Weiss & Burkman, 2002). In addition, when prior user experience with the technology or system of interest is minimal, perceived ease of use has been shown to have a stronger influence on behavioural intention than does perceived usefulness (Castañeda, Muñoz-Leiva & Luque, 2007; Davis, Bagozzi & Warshaw, 1989; Szajna 1996). Thus, perceived ease of cobot use is anticipated to be a more salient construct in the current study due to cobots being an emerging technology and apprentices having had less opportunity for contact (prior experience) due to working in an industrial environment for a relatively short period.

Results from a meta-analysis conducted by Legris and colleagues (2003) reviewing 22 studies revealed that TAM tends to explain approximately 40% of system use. There have been many derivatives and proposed extensions of the original/core TAM in order to improve its predictability of actual usage as well as provide more concrete mechanisms through which usage can be influenced. Upwards of 70 different variables external to the core TAM have been empirically studied (Yousafzai, Foxall & Pallister, 2007b). Yousafzai and colleagues (2007b) categorised these into organisational characteristics (e.g. support and training), system characteristics (e.g. reliability and accuracy, response time), user's personal/individual characteristics (e.g. age, awareness, personality, self-efficacy) and other (e.g. cultural affinity, subjective norms, task characteristics). Any additional core variables included in the current model need to hold relevance across the numerous industries in which apprentices work and reflect the context that many organisations are yet to implement cobots (making assessment of task and system characteristics difficult).

Individual characteristics

Technological affinity is among the most frequently assessed user characteristics when investigating human-computer interaction (Haase, Krippl, Ferchow, Otto & Frommer, 2016). Affinity for technology has been described as "a user's propensity to naturally interact with technical systems (i.e. be attracted to technology interaction)" (Franke, Attig & Wessel, 2017, p.1) and can be considered "a key personal resource for successful technology interaction" (Franke et al., 2017, p.1). The term affinity for technology is used by some researchers (Bröhl et al., 2016; Edison & Geissler, 2003; Franke et al., 2017; Lotz, Himmel & Ziefle, 2019) although it is not dissimilar to other concepts such as technology-related self-efficacy (Vestakesh & Bala, 2008) and innovativeness – a personality trait reflecting a tendency to be the first to use a new technology (Walczuch, Lemmink & Streukens, 2007), or be a technology pioneer (Parasuraman, 2000). Technology-related self-efficacy (Brown et al., 2002; Noh, Mustafa & Ahmed, 2014) and personal innovativeness (Walczuch et al., 2007) have been found to predict perceived ease of use of web-based technologies in learning environments and of various software applications in a financial service provider, respectively. Lu, Yao and Yu (2005) demonstrated a significant, positive relationship between personal innovativeness and perceived usefulness as well as with perceived ease of use (although the association was greater for perceived ease of use) in the adoption of wireless internet services in non-work settings. The current study focuses on affinity for smart technologies in view of their use in cobots (e.g. sensors, interoperability with the internet/other systems).

Organisational characteristics

In a meta-analysis of more than 100 studies, Lee, Kozar and Larsen (2003) showed that management support was among the most consistent factors influencing either perceived usefulness, perceived ease of use or behavioural intention to use a system or technology. Key components of management support, as described by Igbaria, Zinatelli, Cragg and Cavaye (1997), include ensuring sufficient allocation of resources and acting as a change agent to create a more conducive environment for information system success. Igbaria and colleagues (1997) stated that lack of management support is a "critical barrier to the effective utilisation of information technology" (p.285). In a review by Lunenburg (2010), common characteristics associated with effective change agents include empathy (leading to improved communication and understanding), linkage (degree of participation in collaborative activities) and proximity (degree of physical and psychological closeness of change agent and organisation members). Considering the pre-implementation context of the current study, a broader concept drawing on aspects of management support was required.

A human relations or people orientation culture (showing care and respect, communicating and fostering collaboration among employees) is one of four different kinds of organisational culture proposed in Quinn and Rohrbaugh's (1981) Competing Values Framework (a widely used model of organisational culture; Boedker et al., 2011). People-oriented cultures have been linked to a range of benefits, including increased workplace safety and reduced injury rates (Amick et al., 2000). In addition, people-oriented leadership behaviours (e.g. showing individualised support) have been found to be positively associated with employee engagement (Podsakoff, MacKenzie & Bommer,1996). When employees are engaged, they are more likely to expend discretionary effort to help their employer succeed (Markos & Sridevi, 2010). Furthermore, Cresswell, Bates and Sheikh (2013) found teamwork and communication to be among key organisational factors associated with effective implementation of large-scale health information technology. Taken together, this study offers people-oriented workplace culture as a relevant organisational characteristic.

Research Hypotheses

The model of cobot acceptance proposed in the current study (see Figure 1) involves two parts and evaluation phases. One, to replicate and confirm the relationship between core TAM constructs in a mandatory, low user experience environment. Three hypotheses are proposed in relation to this:

Hypothesis 1 (HI): Apprentices' perceptions of cobot usefulness will be positively associated with their willingness to work with them in the future (behavioural intention).

Hypothesis 2 (H2): Apprentices' perceptions of ease of cobot use will be positively associated with their willingness to work with them in the future. Moreover, this association will be stronger than that between perceived cobot usefulness and intention to work with them in the future.

Hypothesis 3 (H3): Apprentices' perceptions of ease of cobot use will be positively associated with their perceptions of cobot usefulness.

Two, to determine the ability of individual and organisational characteristics to influence cobot acceptance. Four hypotheses are postulated with respect to this:

Hypothesis 4 (H4): Apprentices' affinity for smart technology will be positively associated with perceptions of cobot usefulness.

Hypothesis 5 (H5): Apprentices' affinity for smart technology will be positively associated with perceived ease of cobot use.

Hypothesis 6 (H6): People-oriented workplace culture will be positively associated with apprentices' perceptions of cobot usefulness.

Hypothesis 7 (H7): People-oriented workplace culture will be positively associated with apprentices' perceptions of ease of cobot use.

METHOD

Research context

Perceptions and acceptance of robotics/cobots by South Australian workers is particularly relevant as the state has been identified as the “most vulnerable” state or territory in Australia to a “robot rollout” (Oxford Economics, 2019, p.33). “The state is Australia’s most manufacturing intensive but has the slowest-growing economy and low levels of manufacturing” (Oxford Economics, 2019, p.33). Identifying mechanisms to improve workforce acceptance and usage of robotic technology is therefore of ongoing importance.

Procedure

The present study analysed data gathered from an online survey exploring apprentice attitudes towards emerging technology (collaborative robots), safety and job satisfaction. The data set was collected for a South Australian State Government-funded (SafeWork SA) project on improving the health and wellbeing of young workers. Apprentices aged 18 years and over and undertaking an apprenticeship/traineeship in building, construction, mining, engineering or automotive through TAFE SA (a vocational education and training (VET) provider) were eligible to participate in the survey. TAFE SA lecturing staff within these courses distributed 1,700 information sheets in classes. Fifteen promotional posters were also displayed in student common areas (e.g. cafeteria) across campuses. A link to the survey was also posted on TAFE SA’s official Facebook page. A financial incentive (a prize draw to win one of six $50 e-gift cards) was offered as a means of increasing response rate. Financial incentives are frequently used in research seeking VET student participation (NCVER, 2018). One hundred and thirty-six students responded to the survey (representing a response rate of approximately 8%).

To minimise survey drop-out rates, the survey was kept as brief as possible and an 'unsure' response option was available for most questions. 'Unsure' response options were subsequently recoded as missing data. The criteria for inclusion in the secondary data set were completion of the core TAM measures: willingness to work with cobots in the future (behavioural intention), perceived ease of cobot use and perceived usefulness of cobots (n=92; see Measures section for more information).

A Mann-Whitney test indicated that age was not significantly different for respondents retained in the data set (Mdn = 22 years) compared to those who were excluded (Mdn = 21 years), U=1729.0, $p>.05$, $r=.12$. Similarly, affinity for smart technology (described in the Measures section below) was not significantly different for respondents retained in the data set (Mdn = 3.56) compared to those excluded (Mdn= 3.67), U=1094.0, $p>.05$, $r=.03$. No significant interaction was found comparing the frequency of men (34%) and women (11%; $p>.05$, Fisher's Exact Test) excluded. In addition, no significant interaction was found in this cohort comparing the frequency of those who had heard of cobots previously (13%) and those who had not (23%; $p>.05$, Fisher's Exact Test).

All questions were asked in the same survey at the same time, creating the potential for common method variance (i.e. where variance in responses is due to the measurement method rather than the constructs assessed; Brougham & Harr, 2018; Podsakoff, MacKenzie, Lee & Podsakoff, 2003; Podsakoff & Organ, 1986). The administration method of the survey mitigated this risk to some extent (i.e. provided anonymity and confidentiality to minimise social desirability bias; Chang, van Witteloostuijn & Eden, 2010) and the results of a statistical procedure often used to evaluate the presence of common method variance (Hartman's One Factor Test; Brougham & Harr, 2018; Podsakoff et al., 2003; Chang et al., 2010) suggested it was not a strong influence on the current data (i.e. unrotated factor analysis resulted in seven factors, with the largest accounting for less than 30% of the overall variance; Brougham & Harr, 2018; Podsakoff & Organ, 1986).

Sample

On average, respondents were 24.0 years old (SD = 6.38 years; median = 21.5 years; age range 18 to 47 years), male (90.2%), born in Australia (94.4%) and spoke English as their first language (96.7%). Respondents were typically undertaking a Certificate III course (93.5%) at a metropolitan TAFE SA campus (87.8%) studying apprenticeships in electrical and renewable energy (41.3%), plumbing and water operations (20.7%) and automotive (14.1%). Respondents were most likely to be completing their apprenticeship with small and medium enterprises (SMEs; 80.0%). SMEs refer to businesses employing less than 200 employees (Australian Bureau of Statistics, 2002) and comprise 99.7% of businesses in Australia and employ 70% of the workforce (SME Connect, 2019). Respondents were at varying stages of completing their apprenticeship with most having commenced their course in 2018 (40.2%), 2017 (28.3%) or 2016 (18.5%).

Awareness of cobots was low, with a minority of respondents (15%) indicating they had heard of cobots prior to the survey. Even fewer respondents were aware of cobots being used in industries relevant to their apprenticeship (6.5%), had seen cobots used in a workplace relevant to their apprenticeship (4.3%) or worked with a cobot in a workplace relevant to their apprenticeship (2.2%).

Measures

All measures were self-report and adapted for use in the original project. Consistent with the scale validation approach recommended by Squires, Estabrooks, Newburn-Cook and Gierl (2011; based on educational and psychological testing in healthcare), original scale development was guided by two key principles: brevity (to enable scales to form part of a broader assessment without burdening the participant) and generality (to apply to a wide range of settings, industries and organisations). Assessment of scale homogeneity was conducted by review of item-total statistics. The removal of scale items was based on any one of the following criteria being met (informed by Nunnally & Berstein, 1994): (1) the item correlated with the total scale score below 0.30; (2) removal of the item would cause a substantial gain (10% or more) in the scale Cronbach's alpha; and, (3) the scale items were highly correlated with each other ($r > .80$). Note, any negative scale items were reversed prior to this assessment such that higher scores reflect a more positive outcome.

Core TAM variables

Prior to the items asking about cobots, the following definition (developed from Nichols, 2017) was provided, "cobots are a new generation of robots, not enclosed by any type of fencing or cage that are designed to work alongside humans and to interact and collaborate with their users, responding quickly to what's going on around them".

Behavioural intention to work with cobots (the primary outcome/dependent variable of the model) was measured with a single item ("I would be willing to work with cobots in the future") coded 1 = 'strongly disagree' to 5 = 'strongly agree'. Perceived ease of cobot use was also measured by a single item ("I think cobots will be easy to work with") coded 1 = 'strongly disagree' to 5 = 'strongly agree'. No internal consistency assessments of reliability are possible for these single-item scales. These measures have been operationalised by a single item previously (Bröhl et al., 2016; Turja & Oksanen, 2019; Turner, Kitchenham, Brereton, Charters & Budgen, 2010).

Perceived usefulness of cobots was operationalised by 16 items (coded 1 = 'strongly disagree' to 5 = 'strongly agree') which were adapted from Slem, Levi and Young's (1995) 36-item Technological Change Survey. The perceived usefulness of cobots scale was designed to assess beliefs about the influence of cobots on five dimensions: job improvement (four items), job stress (two items), personal benefit (two items), personal insecurity (two items) and safety and wellbeing (six items). Slem et al.'s (1995) survey did not include any safety and wellbeing items. These items were added due to the safety benefits associated with cobots (Twentyman, 2017) and growing concern over how technology may shape workplace interactions (Ghislieri et al., 2018).

Examination of the internal consistency of the perceived usefulness of cobots scale indicated there was no redundancy in items (i.e. no inter-item correlations exceeded .80) although six items were removed because of low item-total correlations (i.e. <.30) or their removal resulted in a substantial gain in the alpha reliability coefficient. Therefore, 10 items were retained and entered into principal components analysis. The factorability of the 10 perceived usefulness items was examined using several well-recognised criteria (Pedhazur & Pedhazur-Schmelkin, 1991). Firstly, it was observed that all items correlated at least .3 with at least one other item, suggesting factorability. Secondly, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .85, above the recommended minimum value of .60 (Tabachnick & Fidell, 1996) and Bartlett's test of sphericity was significant (χ^2 (45) = 477.6, $p<.001$). The communalities were all above .3, further confirming that each item shared some common variance with other items. Given these overall indicators, the data were deemed to be suitable for principal components analysis.

From the principal components analysis, two factors were extracted from the scale items, the first accounting for 53.0% of variance and covariance in the items (eigenvalue = 5.30), the second accounting for 10.8% of variance (eigenvalue = 1.08). However, visual inspection of the scree plot and parallel analysis (Patil, Singh, Mishra & Donavan, 2017) supported the extraction of one factor. Thus, it was concluded that the perceived usefulness of cobots scale in this context has good reliability and is best considered as unidimensional (see

Table 1). The mean of the 10 items was therefore computed and for interpretability and consistency with the other core TAM variables, rounded and categorised into ‘strongly disagree’ (included value range: 1.00 to 1.49), ‘disagree’ (included value range:1.50 to 2.49), ‘neither agree nor disagree’ (included value range: 2.50 to 3.49), ‘agree’ (included value range: 3.50 to 4.49) and ‘strongly agree’ (included value range: 4.50 to 5.00).

Additional TAM variables

Affinity for smart technology was included as an individual characteristic. Smart technology was described in the survey as “electronic devices which are connected through the internet (often wireless) to other devices or networks and can operate interactively, e.g. computers, ipads, mobile phones, apps, software, robots” (developed from IGI Global, n.d).

Affinity for smart technology was operationalised by 10 items adapted from Bröhl et al.’s (2016) survey and Parasuraman’s Technology Readiness Index (Parasuraman, 2000; Parasuraman & Colby, 2015). The included items were most aligned with Parasuraman’s ‘Innovativeness’ factor, a demonstrated motivator of technology use (Parasuraman, 2000) and predictor of perceived ease of technology use (Walczuch et al., 2007). Examination of the internal consistency of the affinity for smart technology scale indicated there was no redundancy in items although one item was removed because of low item-total correlations. Therefore, nine items were retained and entered into principal components analysis. Suitability for principal component analysis was indicated by: all items correlated at least .3 with at least one other item; the KMO measure of sampling adequacy was .87; Bartlett’s test of sphericity was significant (χ^2 (36) = 358.0, $p<.001$); and all communalities were above .3.

From the principal components analysis, one factor was extracted from the scale items accounting for 52.3% of variance and covariance in the items (eigenvalue = 4.71). This is consistent with the theoretical basis of the scale development. The affinity for smart technology scale is unidimensional and has good reliability (see Table 2). Moreover, the nine-item reliability coefficient is comparable to the reliability reported for the Innovativeness dimension of the Technology Readiness Index (Parasuraman & Colby, 2015). The mean of the nine items was computed for use as a continuous predictor variable.

People-oriented workplace culture (operationalised by nine items coded 1= ‘strongly disagree’ to 5 = ‘strongly agree’) was included as an organisational characteristic. The items were designed to reflect themes such as effective communication, trust and teamwork. Examination of the internal consistency of the people-oriented workplace culture scale indicated there was no redundancy in items and nor were there low item-total correlations. Deletion of any item would not make a substantial change to the alpha reliability coefficient. Therefore, all nine items were retained and entered into principal components analysis. Suitability for principal components analysis was indicated by: all items correlated at least .3 with at least one other item; the KMO measure of sampling adequacy was .89; Bartlett’s test of sphericity was significant (χ^2 (36) = 475.4, $p<.001$); and the communalities were all above .3.

From the principal components analysis, two factors were extracted from the scale items, the first accounting for 57.5% of variance and covariance in the items (eigenvalue = 5.17), the second accounting for 12.6% of variance (eigenvalue = 1.13). However, visual inspection of the scree plot and parallel analysis supported the extraction of one factor. Thus, it was concluded that people-oriented workplace culture is best represented as a single measure and has good reliability (see Table 3). The mean of the nine items was therefore computed for use as a continuous predictor variable.

Analysis

Structural equation modelling is a preferred analytical technique in non-experimental research designs to evaluate the fit of data to a proposed theoretical model (Mancha & Leung, 2010). Structural equation modelling is valued because it provides a comprehensive approach, allowing for the examination of multiple relationships across multiple variables without compromising statistical power and while accounting for measurement errors (de Boer & Ȧström, 2017; Mancha & Leung, 2010). Recommendations about adequate sample sizes for structural equation modelling vary considerably (Wolf, Harrington, Clark & Miller, 2013), including a widely accepted rule of thumb of 10 observations per indicator variable (Nunnally, 1967) to a general minimum estimate of 200 (Mancha & Leung, 2010). Overall, the literature suggests the sample size of the current dataset is insufficient for structural equation modelling. Instead, ordinal regression (using an ordered logit model) was conducted in SPSS (Version 25.0) to determine the predictive value of variables within each part of the proposed model of cobot acceptance. None of the regression models conducted violated the assumption of proportional odds (test of parallel lines, $p>.05$).

Due to the categorical nature of most variables and non-normal distributions, non-parametric descriptive statistics were conducted. Response options in ordinal variables were collapsed as much as possible whilst retaining meaningfulness (i.e. combining ‘disagree’ and ‘strongly disagree’) to minimise the proportion of cells with expected cell counts less than 5.

RESULTS

Core TAM Variables

Descriptive Statistics

On average, apprentices were ambivalent about the usefulness ($M=3.20$, $SD=0.59$), ease of use ($M=3.10$, $SD=0.91$) and acceptance of (future willingness to work with) cobots

(M=3.40, SD=0.94), evidenced by means around the scales' midpoint where 3.00 represents 'neither agree nor disagree'. More specifically, 63.0% of apprentices neither agreed nor disagreed that cobots would be useful/improve job performance (compared to 28.3% who agreed or strongly agreed cobots would be useful and 8.7% who disagreed or strongly disagreed) and 45.7% of apprentices neither agreed nor disagreed that cobots would be easy or effortless to use (compared to 33.7% who agreed or strongly agreed cobots would be easy to use and 20.7% who disagreed or strongly disagreed). However, apprentices were in fact most likely to be accepting of/willing to work with cobots in the future (53.3% agreed or strongly agreed, compared to 34.8% who neither agreed nor disagreed and 11.9% who disagreed or strongly disagreed).

Figure 2 shows apprentices' perceptions of cobot usefulness had a positive relationship of medium effect size (r_s = .30 to .49; Cohen, 1988) with their intention to work with cobots, supporting hypothesis 1. This relationship was confirmed (Fisher's Exact Test, $p<.05$) and is illustrated in Table 4; 69.2% of apprentices who considered cobots to be useful indicated they would be willing to work with them in the future, compared to 50.0% of apprentices who were ambivalent about their usefulness and 25.0% of apprentices who indicated cobots were not useful.

Apprentices' perceptions of ease of cobot use also had a positive relationship with their intention to work with cobots (see Figure 2) and this was of greater magnitude (although still of medium effect size) than the relationship between perceived usefulness and intention to work with cobots, supporting hypothesis 2. This relationship was confirmed (Fisher's Exact Test, $p<.01$) and also shown in Table 4; 77.4% of apprentices who rated cobots as easy to use were willing to work with them in the future compared to 47.6% of apprentices who were ambivalent about the effort required to use them and 26.3% of apprentices who rated cobots as difficult to use.

There was a strong, positive relationship between apprentices' perceptions of ease of cobot use and cobot usefulness, supporting Hypothesis 3. This relationship was confirmed (Fisher's Exact Test, $p<.001$) and is shown in Table 5; 61.3% of apprentices who believed cobots are easy to use rated them as useful compared to 14.3% of those who were ambivalent about their ease of use and 5% of those who reported cobots to be difficult to use.

The positive associations demonstrated between the core TAM constructs support the utility of the TAM in an early (pre-implementation) cobot acceptance context. The relative contributions of perceived usefulness and perceived ease of use at predicting cobot acceptance was determined through ordinal regression.

Ordinal regression

As shown in Table 6, there was a statistically significant association between perceived cobot usefulness and intention to work with cobots ($p<.05$), between perceived ease of cobot use and perceived cobot usefulness ($p<.01$), and between perceived ease of cobot use and intention to work with cobots ($p<.01$). This confirmed zero-order relationships among the variables and that mediation was likely; Baron & Kenny, 1986). As reflected in Step 4 of Table 6, perceived ease of cobot use remained a significant predictor of willingness to work with cobots after controlling for perceived cobot usefulness. Perceived cobot usefulness was no longer a significant predictor of cobot acceptance when adjusting for perceived ease of cobot use. These findings support a full mediation model (Baron & Kenny, 1986) where perceived ease of cobot use is a fundamental driver of early cobot acceptance in a mandatory, low prior experience environment. Moreover, the odds of being willing to work with cobots in the future (agree and strongly agree) for those who viewed working with cobots to be easy (agree and strongly agree) was 6.6 times greater than for those who viewed working with cobots to be difficult (disagree and strongly disagree; Odds Ratio (OR) = 6.62, 95% confidence interval (CI): 1.25, 35.97).

Additional TAM variables

On average, respondents were not lacking affinity for smart technology (M=3.50, SD=0.64) and tended to report experiencing a people-oriented workplace culture (M=3.70, SD=0.74), evidenced by means approaching 4.00 which represents ‘agree’ on the constructs’ scales. Affinity for smart technology correlated significantly with perceived cobot usefulness; they had a moderately-sized, positive association such that greater affinity for smart technology was related to greater perceived cobot usefulness (see Figure 2), supporting hypothesis 4. A Kruskal-Wallis H test confirmed this relationship by showing a statistically significant difference in affinity for smart technology between the different cobot usefulness groups, H(2) = 8.79, p <.05, with a mean rank affinity score of 26.94 for “not useful” (disagree and strongly disagree), 44.44 for “ambivalent” (neither agree nor disagree) and 57.12 for “useful” (agree and strongly agree). Post hoc tests of pairwise comparisons indicated the only significant difference in affinity for smart technology scores was between the “not useful” and “useful” groups (p<.05; also see Table 7 for descriptive statistics).

Perceived ease of cobot use also had a significant positive relationship of medium effect size with affinity for smart technology (see Figure 2) where greater affinity was associated with greater perceived ease of cobots, supporting hypothesis 5. A Kruskal-Wallis H test showed a statistically significant difference in affinity for smart technology scores between the different ease of use groups, H(2) = 9.18, p <.05, with a mean rank affinity score of 31.87 for “difficult” to use (disagree and strongly disagree), 46.56 for “ambivalent” (neither agree nor disagree) and 55.39 for “easy” to use (agree and strongly agree). Post hoc tests of pairwise comparisons showed the only significant difference in affinity scores was between the “difficult” and “easy” groups (p<.01; also see Table 8 for descriptive statistics).

Together, these findings suggest that affinity for smart technology is an important individual characteristic facilitating cobot acceptance in apprentices.

A people-oriented workplace culture was not significantly associated with apprentices' perceptions of cobot usefulness (see Figure 2) and therefore hypothesis 6 was not supported. In contrast, a small but significant positive correlation existed between people-oriented workplace culture and perceived ease of cobot use (see Figure 2). This supports hypothesis 7. However, a Kruskal-Wallis H test did not show a statistically significant difference in people-oriented workplace culture scores between ease of use groups ($H(2) = 3.32$, $p > .05$; also see Table 8) suggesting this result may be spurious. Overall, these findings suggest that this organisational characteristic may be less relevant to facilitating cobot acceptance in apprentices. Logistic regression was conducted to further clarity the relationship of additional TAM variables to those of the core TAM.

Ordinal regression

There was a statistically significant association between perceived cobot usefulness and affinity for smart technology ($p<.01$; see Table 9). For every one unit increase in affinity for smart technology, the odds of perceiving cobots as useful (agree and strongly agree) tripled (OR=2.98, 95% CI: 1.35, 6.54). Table 9 shows there was a statistically significant association between perceived ease of cobot use and affinity for smart technology, adjusting for people-oriented workplace culture ($p<.05$) whereas there was no statistically significant association between perceived ease of cobot use and people-oriented workplace culture, adjusting for affinity for smart technology ($p>.05$). For every one unit increase in affinity for smart technology, the odds of perceiving cobots to be easy to use (agree and strongly agree) increased by 2.5 times (OR=2.50, 95% CI: 1.17, 5.34). This result indicates that people-oriented workplace culture is not a salient factor influencing cobot acceptance in apprentices.

Affinity for smart technology and people-oriented workplace culture did not have significant direct effects on behavioural intention to work with cobots, controlling for each other (see Table 9). This result reinforces the value of incorporating the core TAM constructs rather than solely assessing affinity for smart technology and willingness to work with cobots.

DISCUSSION

The present study sought to establish the likelihood of collaborative robot (cobot) acceptance in early career workers (apprentices) in South Australia and identify the factors that may influence their intentions to work with cobots in the future. The results indicated low awareness of and exposure to cobots which is not unexpected given advanced robotics is an emerging technology. Despite limited awareness of cobots, the results also showed that more than half of apprentices who responded were willing to work with them in the future. This is a positive outcome that may encourage manufacturing, construction, automotive and agricultural organisations, for example, to consider cobot implementation. At the time of the study, rates of cobot awareness and/or acceptance in other employee groups (in Australia or internationally), had not been examined. The nearest comparator available related to European Union citizens' attitudes toward robots in which a public survey reported 6% of citizens had experience using robots at work and that 48% were "relatively comfortable about the idea of a robot assisting them at work" (Special Eurobarometer 382, p.5). Overall the findings of the current study align with those of European Union citizens.

This study utilised core constructs from Davis's (1989) Technology Acceptance Model (TAM) which offer a parsimonious framework for this study's pre-implementation, low cobot awareness context. The significant, moderate to large correlations found between perceived ease of cobot use, perceived usefulness of cobots and willingness to work with cobots in the future (behavioural intention) are consistent with Bröhl et al.'s (2016) findings and support their conclusion that the original TAM model is appropriate for studies of human-robot interactions. In addition, the results of this study demonstrated that perceived ease of cobot use had a direct effect on behavioural intention, fully mediating the effects of perceived usefulness of cobots on intention to work with them. This finding suggests that in a professional setting, it doesn't matter how useful an organisation or stakeholder claims a new technology to be, if employees find it difficult to use, acceptance is likely to be limited. This outcome is consistent with previous studies of technology acceptance in mandatory (Adamson & Shine 2003; Brown et al. 2002) and low prior experience environments (Castaneda et al., 2007; Davis et al. 1989; Szajna 1996). All hypotheses associated with the core TAM constructs were supported and corroborate the flexibility and robustness of TAM across a variety of technology and user settings.

Regarding the additional TAM variables explored in this study, affinity for smart technology was found to positively influence both perceived ease of cobot use and perceived cobot usefulness. This finding is (in part) in contrast to the results of Bröhl and colleagues (2016) who examined the relationship between technological affinity and perceived ease of robot use in production workers and found a negative association (although they did not distinguish between workers with/without prior experience with robots). They reasoned their finding may be a result of those with greater affinity being more informed about technology and subsequently having more prejudices about it. However, they did not evaluate the relationship between technological affinity and perceived usefulness which may have offset a more critical evaluation of ease of technology use. Regardless, it is possible that there is a threshold at which affinity for technology may increase perceptions of the effort required to use a technology (and reduce perceptions of its usefulness) and negate intentions to use it. Further exploration is warranted to identify the parameters of a possible threshold, requiring a more diverse sample, both in terms of prior experience with cobots, age and field of apprenticeship.

In the current study, a people-oriented workplace culture was postulated to have a positive relationship with apprentice perceptions of cobot usefulness and ease of use via increased communication, teamwork and employee engagement. However, these relationships were not supported. The absence of a significant relationship between these measures is likely to be multifactorial and include a lack of insight from apprentices (early career workers) as to what a people-oriented workplace culture looks like (i.e. not have alternate points of reference leading to inflated ratings) and the use of a composite, non-validated scale (i.e. items are not sufficiently specific about organisational practices or comprehensive in topic to identify relevant differences). Broader examination of Quinn and Rohrbaugh's (1981) competing values framework may provide a more sound basis for exploring the role of workplace culture in cobot acceptance. For example, using this framework, Ruppel and Harrington (2001) found both "an atmosphere of trust and concern for other people (ethical culture) and flexibility and innovation (developmental culture)" facilitated intranet implementation (p.37).

None of the additional TAM variables assessed had direct effects on behavioural intention to work with cobots, supporting Legris et al.'s (2003) findings that additional variables are fully mediated by perceived ease of use (and perceived usefulness in their case). These findings highlight that perceived ease of use, and subsequently behavioural intention to work with cobots, can be influenced by non-technical/system factors, augmenting the opportunities available to promote and grow cobot acceptance in employees prior to cobot implementation.

Implications

The present study has several implications for early career employees and SMEs, in particular. Individuals with greater affinity for technology are well-placed to accept the introduction of new technologies in the workplace, typically finding them easier to use than those less inclined to gravitate to technology. Thus, assessment of affinity for smart technology (or similar constructs) should be a key element of the employee selection and professional development processes. When employees understand their natural preferences and interests they can engage in informed career planning and develop more realistic expectations of their career (leading to greater job satisfaction; Čiarnienė et al., 2010). When organisations understand their workforce's propensity to engage with technology, they can more accurately determine implementation timelines (e.g. more gradual and with reduced functionality for teams with lower affinity for technology) and target training and support. In addition, such knowledge can assist with optimising the allocation of individuals to teams to ensure an appropriate 'affinity' mix. Forms of training and support could extend to the pairing of employees (e.g. mentoring, buddying) with diverging degrees of affinity for smart technology. When technology implementation does occur, employees with greater affinity for technology are likely to form crucial 'process champions' (a knowledgeable person who understands the technology and its benefits; Charalambous et al., 2015) who can increase the likelihood of successful implementation through knowledge exchange, support and encouragement (Charalambous et al., 2015; Scannell, Calantone & Melnyk, 2012).

Limitations

This study has four principal limitations which need to be considered when interpreting the findings. Firstly, given the low response rate, the sample may not be representative of apprentices. Survey respondents are often known to have different characteristics from non-respondents (Lee & Polidano, 2010). In this instance, respondents to the survey are likely to be more interested in cobots and thus have greater affinity for technology than non-respondents. Consequently, the degree of willingness to work with cobots may be overestimated. The strength of the relationships between study measures may change in a more representative sample.

Secondly, both independent and dependent measures were self-report which can increase the risk of common method variance such that “self-report data can create false correlations if the respondents have a propensity to provide consistent answers to survey questions that are otherwise not related” (Chang, van Witteloostuijn & Eden, 2010. p.178). To avoid this type of measurement error, future research on technology acceptance should aim to: collect data from different sources, including more objective data (e.g. from co-workers, independent observations) or collect data from different points in time; measure the dependent variable in more than one way; use different response anchors for different constructs; and randomise the order of questions (Chang et al., 2010). Common method variance is one reason attributed to why behavioural intention to use technology has a weaker association with objective measures (e.g. data from computer/device) of actual use compared to self-reported usage (Straub, Limayem & Karahanna-Evaristo, 1995; Szajna, 1996).

Thirdly, despite demonstrating good internal consistency, the scales used have not been validated with other measures. Tao (2009) proposes conducting qualitative interviews to test the face and content validity of adapted questionnaires. This process has been conducted by Bröhl et al. (2016) in their investigation of human-robot cooperation in production systems and by Henderson (2015) in her examination of workplace culture on the acceptance of industrial robots in the manufacturing industry. Thus, focus groups with apprentices and SMEs may help inform future scale development of the constructs included here.

Lastly, involvement of a larger sample would be beneficial so that structural equation modelling could be utilised to simultaneously evaluate the relationships between all cobot acceptance model constructs as a whole, rather than in two parts, further clarifying and accounting for any interaction effects.

Conclusion

Employee acceptance of technology implementation is important in terms of organisational productivity and profitability as well as individual job satisfaction and wellbeing. As applications of Industry 4.0 technologies, such as collaborative robots, continue to grow so too does the need for organisations to be prepared for how their workforce may respond. The findings from the current study suggest that understanding and fostering employee technical attributes such as affinity for technology can facilitate early acceptance of cobots. More research is required to develop specific interventions that can best utilise and build this personal characteristic and support employees to thrive in an increasingly technological work environment.

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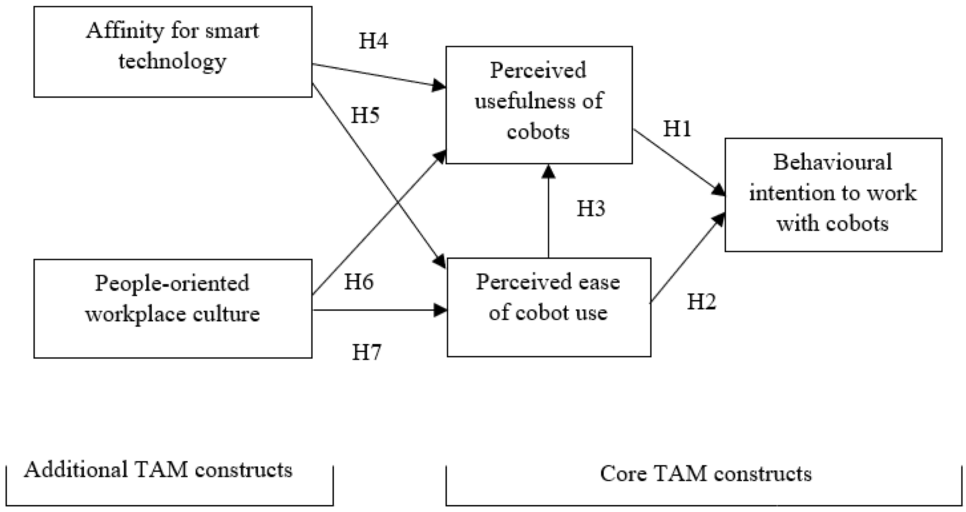

Figure 1: Proposed study model of cobot technology acceptance (willingness to work with cobots)

Table 1: Perceived usefulness of cobots item characteristics (n=88[1])

Scale item: I think cobots will…	Corrected Item-total Correlation	Factor loading
Give me more control about how I do my work	.68	.75
Increase my skills	.64	.71
Improve my career progression	.73	.80
Improve workplace safety	.60	.69
Improve the quality of my work	.75	.82
Prevent injuries	.67	.75
Make my work more interesting	.54	.61
Reduce my fatigue on the job	.51	.59
Prolong my career in this industry	.75	.81
Decrease workplace conflict	.63	.71
Eigenvalue	5.30	
Percentage variance	53.0	
Cronbach's α	0.90	

[1]Listwise deletion resulted in the removal of four cases.

Table 2: Affinity for smart technology item characteristics (n=90[1])

Scale item: In general…	Corrected Item-total Correlation	Factor loading
I enjoy using smart technologies	.76	.83
I trust smart technologies	.71	.80
I am confident using smart technologies	.64	.71
When needing information, I turn to smart technologies before other sources (e.g. talking to someone)	.52	.60
Other people come to you for advice on new technologies	.65	.74
It is important to me to have the most current technologies available	.65	.73
Smart technologies improve the quality of my life	.66	.75
I know how to troubleshoot problems when smart technologies fail	.47	.57
I believe smart technologies are reliable	.66	.74
Eigenvalue	4.71	
Percentage variance	52.3	
Cronbach's α (9-item)	.88	

[1]Listwise deletion resulted in the removal of two cases.

Table 3: People-oriented workplace culture item characteristics (n=90[1])

Scale item: In general…	Corrected Item-total Correlation	Factor loading
Communication between managers and staff usually works well	.80	.85
Communication within our work team usually works well	.69	.77
There is a good level of trust between managers and staff	.80	.86
There is a good level of trust within our work team	.68	.76
Employees can raise work-related concerns with their manager	.82	.87
It is unusual to experience bullying or harassment	.75	.81
There is a lot of conflict in my workplace	.36	.44
Management emphasise the importance of teamwork	.70	.78
I have received training to be able to work in a team	.44	.56
Eigenvalue	5.17	
Percentage variance	57.5	
Cronbach's α	.90	

[1]Listwise deletion resulted in the removal of two cases.

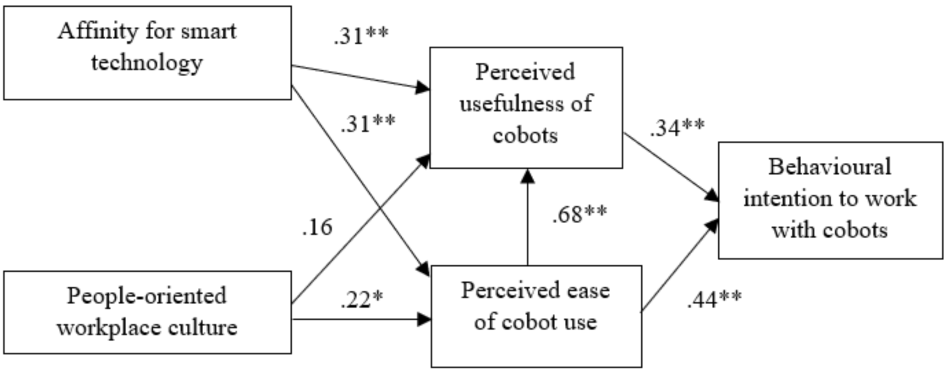

Figure 2: Cobot acceptance model with correlation coefficients (Spearman's Rho) as strength of associations, *p<.05, **p<.01.

Table 4: Relationship between ordinal independent (predictor) and ordinal dependent (outcome) measures of the core TAM.

	Willing to work with cobots in the future (behavioural intention)		
	"Unwilling" (Strongly Disagree/ Disagree; n=11)	"Ambivalent" (Neither agree nor disagree; n=32)	"Willing" (Strongly agree/ Agree; n=49)
Perceived usefulness of cobots	N (%)	N (%)	N (%)
"Not useful" (Strongly disagree/Disagree)	4 (50.0)	2 (25.0)	2 (25.0)
"Ambivalent" (Neither agree nor disagree)	6 (10.3)	23 (39.7)	29 (50.0)
"Useful" (Strongly agree/Agree)	1 (3.8)	7 (26.9)	18 (69.2)
Perceived ease of cobot use	N (%)	N (%)	N (%)
"Difficult (Strongly disagree/Disagree)	7 (36.8)	7(36.8)	5 (26.3)
"Ambivalent" (Neither agree nor disagree)	4 (9.5)	18 (42.9)	20 (47.6)
"Easy" (Strongly agree/Agree)	0 (0.0)	7 (22.6)	24 (77.4)

Table 5: Relationship between perceived cobot usefulness and ease of use in apprentices

	Perceived usefulness of cobots		
	"Not useful" (Strongly disagree/ Disagree; n=8)	"Ambivalent" (Neither agree nor disagree; n=58)	"Useful" (Strongly agree/ Agree; n=26)
Perceived ease of cobot use	N (%)	N (%)	N (%)
"Difficult (Strongly disagree/Disagree)	7 (36.8)	11 (57.9)	1 (5.3)
"Ambivalent" (Neither agree nor disagree)	1 (2.4)	35 (83.3)	6 (14.3)
"Easy" (Strongly agree/Agree)	0 (0.0)	12 (38.7)	19 (61.3%)

Table 6: Test of model effects summary for core TAM ordinal regressions

Sequence order	Dependent variable	Independent variable	Chi-square (df)	p value
1	BI_C	PU_C	9.31 (2)	.010
2	$PEOU_C$	PU_C	28.89 (2)	.000
3	BI_C	$PEOU_C$	16.76 (2)	.000
4	BI_C	PU_C	.79 (2)	.673
		$PEOU_C$	8.66 (2)	.013
		PU_C*$PEOU_C$	1.92 (3)	.589

BI_C = Behavioural intention (willingness to work with cobots in the future); PU_C = Perceived usefulness of cobots; $PEOU_C$ = Perceived ease of cobot use.

Table 7: Relationship between perceived usefulness of cobots and proposed antecedents

	Perceived usefulness of cobots		
	"Not useful" (Strongly disagree/ Disagree; n=8)	"Ambivalent" (Neither agree nor disagree; n=58)	"Useful" (Strongly agree/ Agree; n=26)
Affinity for smart technology (Median)*	2.89	3.50	3.89
People-oriented workplace culture (Median)*	3.67	3.67	4.00

*Note: 1 = Strongly disagree, 2 = Disagree, 3= Neither agree nor disagree, 4 = Agree, 5 = Strongly agree

Table 8: Relationship between perceived ease of cobot use and proposed antecedents

	Perceived ease of cobot use		
	"Difficult" (Strongly disagree/ Disagree; n=19)	"Ambivalent" (Neither agree nor disagree; n=42)	"Easy" (Strongly agree/ Agree; n=31)
Affinity for smart technology (Median)*	3.22	3.56	3.78
People-oriented workplace culture (Median)*	3.50	3.78	4.00

*Note: 1 = Strongly disagree, 2 = Disagree, 3= Neither agree nor disagree, 4 = Agree, 5 = Strongly agree

Table 9: Test of model effects summary for additional TAM ordinal regressions

Dependent variable	Independent variable	Chi-square (df)	p value
PU_C	AFT_S	7.37 (1)	.007
$PEOU_C$	AFT_S	6.98 (1)	.008
	WC	2.91 (1)	.088
BI_C	AFT_S	3.26 (1)	.071
	WC	.24 (1)	.623

PU_C = Perceived usefulness of cobots; AFT_S = Affinity for smart technology; $PEOU_C$ = Perceived ease of cobot use; WC = People-oriented workplace culture; BI_C = Behavioural intention (willingness to work with cobots in the future).