Factors influencing perceptions of productivity associated with digital manufacturing technology

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ABSTRACT

Industry 4.0, or the fourth industrial revolution, has the potential to transform manufacturing productivity through the integration of digital manufacturing technology. Although digital technologies are considered to have the potential to enhance organisational productivity, the impact of such technologies on humans and the systems they work within is not fully understood. Furthermore, there is also a lack of knowledge related to factors influencing perceived impact of digital manufacturing technology on productivity – improved understanding of public perceptions can provide insight into predicting technology acceptance and developing readiness for the introduction of new workplace technologies. Using a questionnaire approach and factor analysis, this work investigated perceived impact of digital technology on manufacturing productivity. Seven underlying factors associated with productivity were found through principal component analysis and included innovation, adaptability, reliability, performance, quality, time efficiency and risk management. This enabled the questionnaire to be refined, providing a tool that could be used in future research into public perceptions of technology and productivity.

KEYWORDS

Productivity, industry 4.0, digital manufacturing, factor analysis

Introduction

Industry 4.0 refers to the recent wave of technological advancements that are transforming manufacturing processes and industrial workplaces into digital, interconnected environments. The term was first used in Germany in 2011 to describe a new economic policy dedicated to driving development through cyber-physical systems (Mosconi, 2015). Industry 4.0, or the fourth industrial revolution, is viewed as the successor to the three previous industrial revolutions – beginning in the nineteenth century with mechanical manufacturing equipment, followed by electrically powered mass production of the early twentieth century, and finally, automated production and control of manufacturing processes using electronics and information technology, in what is regarded as the digital revolution of the 1970s to the present day (Rüßmann et al., 2015; Kagermann et al., 2013). Industry 4.0 is already somewhat present in the work environment as many of its underlying technologies exist, or are in use, in some rudimentary form (Rüßmann et al., 2015). Technologies considered to be components of Industry 4.0 include autonomous robots, simulation, horizontal and vertical system integration, the Industrial Internet of Things, cybersecurity, the cloud, additive manufacturing, augmented reality, and big data and analytics (Rüßmann et al., 2015). When these technologies are utilised together in a manufacturing context, the outcome is smart manufacturing in a smart factory – where autonomy, sensors and advanced analytics give rise to more flexible, intelligent and dynamic processes (Roblek et al., 2016).

Whilst research provides an indication of the potential benefits that Industry 4.0 technologies could bring to the UK economy, there is little to no indication of how this technology is anticipated to impact workers and their contributions to improved productivity in manufacturing systems. Productivity is a multi-factor, context-dependent concept and is tightly coupled to resource usage and value creation and has frequently been used interchangeably with similar concepts such as performance, efficiency, and profitability (Bernolak, 1997; Tangen, 2005). In its most basic form, productivity can be described as the ratio of units of output to units of input (Chew, 1988). Within manufacturing systems, productivity and performance are sometimes conflated, where performance-based metrics consider factors that reflect the overall productivity of machines or equipment, however, there is limited knowledge related to productivity at different scales and within different contexts, for example, at the whole factory level (Muthiah and Huang, 2006) or for workers engaged in primarily cognitive work (Ramirez and Nembhard, 2004; Gleeson et al., 2017; Sahay, 2005).

As work grows increasingly cognitive in nature, a deeper understanding of the factors that influence knowledge worker productivity may help to inform new methods for measuring individual and organisational productivity. Knowledge workers are defined as workers that work with intangible resources (Drucker, 1959) and as those who apply theoretical and analytical knowledge to develop novel products and services, all within a high-level employment position (Drucker, 1994). Knowledge work, however, is not as easily measurable compared to productivity in more manual production workplaces, where units of output provide a physical quantity upon which productivity measurements can be based. In a review of the literature surrounding the assessment of knowledge worker productivity metrics, Ramirez and Nembhard (2004) found that metrics were based on a combination of one or more dimensions, including quantity of work, costs, time efficiency, worker independence/autonomy, quality of work, task performance efficiency, worker effectiveness, customer satisfaction, worker creativity, project success, worker absenteeism rates, worker perceptions of productivity, and importance of work.

Building upon Ramirez and Nembhard’s (2004) twelve dimensions, the current work sought to identify factors influencing public perceptions of productivity associated with the introduction of digital technology in manufacturing. Using a questionnaire based on the twelve dimensions and a factor analysis approach, this work developed a greater understanding of expectations involving technology’s impact on human productivity and future manufacturing workplaces. Additionally, the current work aimed to identify factors associated with productivity in digital manufacturing and develop a questionnaire that could be used by industry personnel to understand potential responses to the introduction of new, digital technology in their work environments.

Methodology

Questionnaire design

The twelve dimensions of knowledge worker productivity (Ramirez and Nembhard, 2004) formed the basis of the questionnaire. Multiple statements were created for each productivity dimension, and in total, a bank of 50 statements comparing human capabilities to the capabilities of digital technology was created, where each statement correlated to a particular knowledge worker dimension. For example, one statement read, *“This technology can cope with change to a process better than a human can”*, while another statement asked respondents about their level of agreement to, *“A human can prioritise deadlines better than this technology”*. For each statement, participants were asked to rate their level of agreement on a scale of 1-6 (strongly disagree to strongly agree, respectively). An initial pilot run of the questionnaire was completed to ensure the wording was understandable and non-ambiguous, before being altered to reflect the feedback.

The questionnaire was split into two parts, with the first part being compulsory and the second part being optional. Respondents were asked to watch a short video depicting human workers interacting with digital technologies in a manufacturing work environment. In the first part of the questionnaire, this video showed 'cobots' at work in a factory producing bathroom accessories (Universal Robots, 2017). The second part of the questionnaire contained a video showing technologies such as digital twins, virtual reality and augmented reality being used in various industry settings (Phoenix Contact, 2018).

After viewing each video, participants were presented with the statements and asked to indicate whether they agreed or disagreed with the comparison being made between a human and the digital technology. Six categories of response were provided – strongly agree, agree, slightly agree, slightly disagree, disagree, and strongly disagree. A neutral option for participants to choose was not provided, as it is believed that providing a neutral option allows for hesitance and lack of decisiveness that can be avoided if there is no option (Kalton et al., 1980). There was also a qualitative section at the end of the questionnaire for participants to express any information that could be related to the manner in which they responded to the statements, for example, if they had any previous experience working with digital technology.

Participants

Participants were recruited from the University of Nottingham and surrounding community via email advertisements, flyers, and notices on online noticeboards. 66 participants took part in the study (56.1% male and 43.9% female). Participants ranged in age from eighteen to over 60 years old, (56.1% between 18 and 24 years, 25.8% between 25 and 39 years, 16.7% were 40 years old or more, and one respondent who preferred not to disclose their age (1.51%)). While the majority of participants had some formal educational qualifications, participants represented a diverse set of educational backgrounds, shown in Figure 1. The sample was also split in terms of background and experience with technology. There were 26 respondents from a STEM background (39.4%), while a further 26 respondents were from a non-STEM background (39.4%), and the remaining 14 respondents did not specify their background (21.2%).

Participants did not receive compensation for completing the survey, and the study was approved by the University of Nottingham's Ethics Committee.

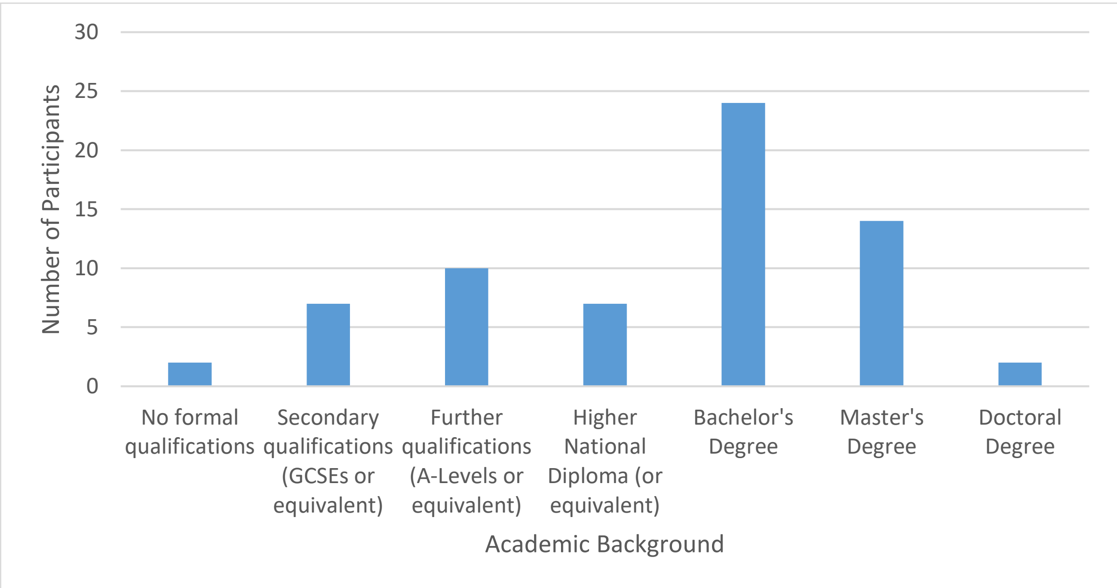

Figure 1: Distribution of participant educational qualifications

Analysis procedure

Factor analysis can be used to identify underlying factors from within a set of variables in a data set. A Principal Component Analysis (PCA) was conducted whereby maximum variance was extracted before being placed into the first factor. All variances explained by the first factor were then removed before calculating maximum variance for the second factor and so forth. This enabled groups of highly intercorrelated variables to be identified and matched to an underlying factor. In this study, exploratory factor analysis was used, as the number of underlying factors represented by the data was not initially known. Through conducting an exploratory PCA with Varimax rotation and excluding results with a loading of less than 0.4, the number of underlying factors was identified.

Statements were phrased with either a positive or a negative view towards the technology's capabilities. In order for the factor analysis to be completed, all responses were converted to a positive scale in the technology's favour (in other words, a response that agreed with a statement that favoured human capabilities was changed into a response that disagreed with a statement favouring the technology's capabilities).

Results

Factor identification

Due to the much lower response rate to questions related to the second video, findings here are based entirely on responses to the first video's questions (n = 66). Responses to each question were given a rating on a 1 to 6 scale, with scores being reversed for negatively worded statements so that higher numbers on the scale represented a favourable attitude towards the technology. The average response for each dimension was then calculated in order to understand current perceptions about the digital technology's capabilities. The scree plot (Figure 2) that was produced from the factor analysis of responses to the first video of the questionnaire indicated that there were seven underlying factors to the questionnaire statements. Following this, the rotated component matrix revealed the specific variables/statements that form each underlying factor.

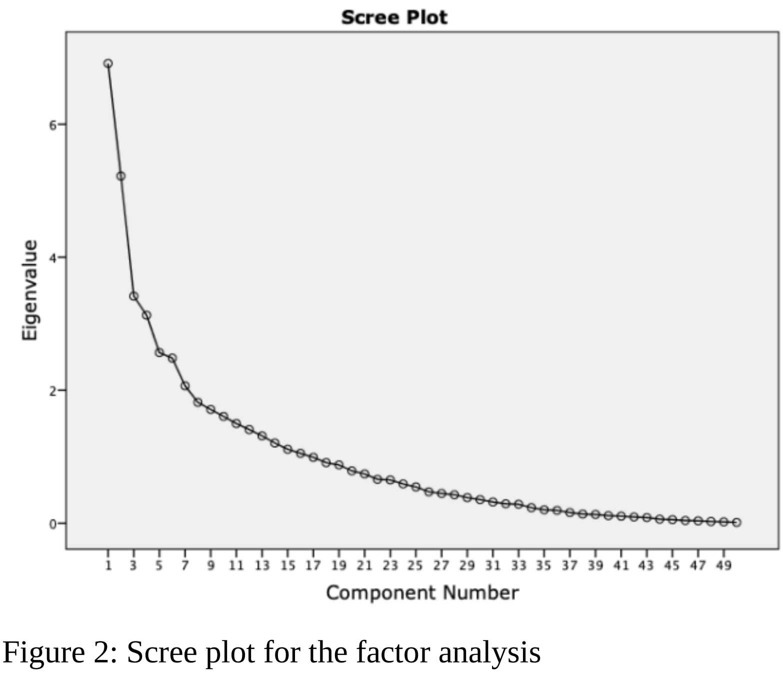

Figure 2: Scree plot for the factor analysis

The rotated component matrix indicated three instances of cross loading, however, since these had absolute values just slightly above 0.4 (which was chosen as the cut-off for significant values) they were deemed to be insubstantial. Based on these findings, seven factors were identified as being related to: innovation (factor 1), adaptability (factor 2), reliability (factor 3), performance (factor 4), quality (factor 5), time efficiency (factor 6) and risk management (factor 7). This was based upon the variables that formed each component and was discussed and agreed by three independent observers as being suitable.

Further analysis examined the questionnaire responses based on differences in age, gender and educational background. Results are shown in Table 1, Table 2 and Table 3, where mean ratings are given (standard deviations in parentheses) and significant effects ($p<0.05$) are indicated with an asterisk. Using a one-way ANOVA approach, there were no significant differences between age group and attained level of education in any of the productivity-related factors, however, a t-test identified a significant difference was observed in perceptions surrounding quality outputs of the cobot system versus human work between male ($\mu = 3.79$, $\sigma = 1.03$) and female participants ($\mu = 4.31$, $\sigma = 0.84$), with female participants rating the potential quality of cobot work higher than male participants did, $t(65) = -2.31$, $p = 0.024$.

Table 1: Mean rating and standard deviations by factor and gender

Factor	**Male (n = 37)**	**Female (n = 29)**
Adaptability	3.97 (1.04)	3.88 (0.97)
Innovation Capability	2.33 (0.84)	2.49 (0.86)
Performance	5.09 (0.99)	5.26 (0.96)
Quality *	3.79 (1.03)	4.31 (0.84)
Reliability	4.39 (0.56)	4.20 (0.76)
Risk Management	3.60 (0.88)	3.36 (0.88)
Time Efficiency	4.02 (1.01)	4.24 (0.85)

Table 2: Mean rating and standard deviations by factor and age group

Factor	**18-24 (n = 37)**	**25-39 (n = 17)**	**>40 years (n = 13)**
Adaptability	4.02 (0.90)	3.49 (1.12)	4.32 (0.98)
Innovation Capability	2.24 (0.65)	2.60 (0.99)	2.54 (0.85)
Performance	5.29 (0.66)	5.08 (1.15)	4.85 (1.44)
Quality	3.89 (1.02)	3.90 (0.95)	4.46 (0.89)
Reliability	4.41 (0.58)	4.00 (0.71)	4.39 (0.72)
Risk Management	3.51 (0.76)	3.47 (1.15)	3.56 (0.88)
Time Efficiency	3.91 (0.95)	4.15 (0.96)	4.62 (0.78)

Table 3: Mean rating and standard deviations by factor and level of education

Factor	< Undergrad degree (n = 20)	Bachelors (n = 31)	Postgraduate degree (n = 17)
Adaptability	3.99 (1.09)	3.85 (0.96)	4.01 (1.02)
Innovation Capability	2.32 (0.82)	2.48 (0.97)	2.35 (0.63)
Performance	5.37 (0.91)	5.05 (0.92)	5.12 (1.17)
Quality	4.00 (1.17)	4.09 (0.89)	3.88 (0.95)
Reliability	4.43 (0.61)	4.32 (0.63)	4.14 (0.74)
Risk Management	3.49 (0.99)	3.58 (0.88)	3.37 (0.79)
Time Efficiency	4.31 (0.90)	4.05 (0.95)	4.00 (1.02)

Finally, in order to determine the relative importance of each factor towards perceptions of productivity, a one-way ANOVA was performed to assess the influence of each productivity factor on participant ratings. A significant difference between the seven productivity factors was identified, $F(6, 475) = 58.48$, $p < 0.001$. A post hoc Tukey Pairwise Comparisons test revealed that the mean rating given related to the technology's performance ($\mu = 5.16$, $\sigma = 0.98$) was significantly different from all other factors. Ratings given to the factors for reliability ($\mu = 4.31$, $\sigma = 0.65$), efficiency ($\mu = 4.11$, $\sigma = 0.95$), quality ($\mu = 4.01$, $\sigma = 0.98$), and adaptability ($\mu = 3.93$, $\sigma = 1.00$) were significantly different from risk management ($\mu = 3.50$, $\sigma = 0.88$) and innovation ($\mu = 2.40$, $\sigma = 0.84$), while ratings for risk management was also significantly different from ratings given to innovation.

Discussion

Through the factor analysis, seven factors associated with individuals' perceptions of how a digital technology would impact productivity were identified. Perceptions of productivity were associated with the degree to which the technology could come up with innovative or creative solutions (factor 1), was adaptable (factor 2), and performed reliably (factor 3). The ANOVA highlighted that, independent of gender, age, or educational background, perceptions surrounding digital technology performance versus human performance were strongest. Given that ratings were designed so that a higher rating indicates stronger positive perceptions towards the technology than versus a human worker, this indicated that participants watching the cobot video perceived the level of performance more positively towards cobots than to human workers. Similarly, factors involving perceptions of system reliability, efficiency, and quality were all rated more positively in favour of the cobots than human workers. However, humans were perceived to be able to demonstrate a greater degree of adaptability, be able to respond to and manage risk more effectively, and develop innovative or creative solutions to problems than the cobots in the video.

Although we originally anticipated that there may have been differences in perspectives based on demographic factors, exploratory analysis of this data did not detect any significant differences. The one exception to this regarded perceived quality of work, where ratings from female participants were more favourable towards the cobots than ratings from male participants. Otherwise, it did not appear that age or educational background significantly affected perceptions, although it must be noted that, particularly with regard to age, the sample had fewer participants in the older age group. Further investigation specifically targeting individuals in different age groups would be needed to explore this question in greater depth.

At the end of the questionnaire, participants were also provided with a qualitative section to express any further thoughts on digital manufacturing or the questionnaire itself. Multiple participants responded that the impact that digital technology would have on jobs and labour costs should be considered in addition to the new skills required for operating, programming or managing the technology that may be needed to exploit the benefits of the technology fully. A number of participants also indicated that they believed technology to be superior to humans and that investing in technology was an effective way to improve productivity. Moreover, comments from those participants who completed both sections of the questionnaire (for both the cobot video as well as the AR/VR video) included one participant indicating they felt the questionnaire was more suited to the cobot video rather than the AR/VR video, indicating that future studies on perceived impact of technology may be influenced by different factors depending upon the technology in question.

In terms of study limitations, it is important to note that the questionnaire findings were based on a relatively small sample that was moderately skewed towards people under the age of 40 years old and who had either completed a graduate or postgraduate degree or were in the process of completing one. Furthermore, most people lacked familiarity with cobots and AR/VR, at least in work-related contexts, and so few participants' perceptions were influenced by direct workplace experience with such technology. In order to provide greater insight into factors influencing perceived impact of technology, future research ought to expand the sample size and seek out a sample more representative of the broader population.

Conclusion

Using a questionnaire approach, the current work explored attitudes towards digital manufacturing technology, specifically cobots, and their perceived impact on productivity. The initial twelve knowledge worker dimensions that formed the basis of the questionnaire were reduced to seven factors associated with perceptions of digital manufacturing productivity. These factors were innovation capability, adaptability, reliability, performance, quality, time efficiency, and risk management. From these factors, the questionnaire was refined into a set of 31 statements from the original 50. In future research, this questionnaire can be used to assess employee/customer/stakeholder opinions towards digital technology being considered for investment in industry.

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