HUMAN-ROBOT COLLABORATION IN A SMART INDUSTRY CONTEXT: DOES HRM MATTER?

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ABSTRACT

This paper investigates effective human-robot collaboration (HRC) and presents implications for Human Resource Management (HRM). A brief review of current literature on HRM in the smart industry context showed that there is limited research on HRC in hybrid teams and even less on effective management of these teams. This book chapter addresses this issue by investigating factors affecting intention to collaborate with a robot by conducting a vignette study. We hypothesized that six technology acceptance factors, performance expectancy, trust, effort expectancy, social support, organizational support and computer anxiety would significantly affect a users' intention to collaborate with a robot. Furthermore, we hypothesized a moderating effect of a particular HR system, either productivity-based or collaborative. Using a sample of 96 participants, this study tested the effect of the aforementioned factors on a users' intention to collaborate with the robot. Findings show that performance expectancy, organizational support and computer anxiety significantly affect the intention to collaborate with a robot. A significant moderating effect of a particular HR system was not found. Our findings expand the current technology acceptance models in the context of HRC. HRM can support effective HRC by a combination of comprehensive training and education, empowerment and incentives supported by an appropriate HR system.

Keywords: Human-robot collaboration; smart industry; human resource management; technology acceptance; vignette study

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INTRODUCTION

Smart and interconnected manufacturing and production technologies are often labelled under the umbrella of smart industry or industry 4.0 (Habraken, 2020), making use of interconnected and digitized systems (Kagermann, Wahlster, & Helbig, 2013). As integral part of this smart industry development, Artificial Intelligence (AI) enables computers and/or robots to perform tasks which would otherwise require human cognition (Tambe, Cappelli, & Yakubovich, 2019). One such smart solution that organizations increasingly use is the collaborative robot or *cobot*, which allows for direct interaction and collaborative work. Whereas in earlier days, technology development was focused on automation, nowadays smart industry technologies enable collaboration between humans and machines (Wilson & Daugherty, 2018). In smart industry, teams will therefore not only be composed of humans but also include these AI-powered robots (e.g. Davenport & Kirby, 2016; Habraken & Bondarouk, 2019).

In the last years, the phenomenon of so-called human-robot collaboration (HRC) has received increasing attention. Collaborative robots enable direct interaction between human operators and robots; thus, instead of robots replacing human workers, HRC allows human workers and robots working together in a shared environment while overcoming the classical division of labour (Liu & Wang, 2018; Villani, Pini, Leali, & Secchi, 2018). HRC is an important part of the new industrial revolution, which is often termed smart industry (the term we adopt in this chapter) or industry 4.0, and describes advanced digitalization and the combination of internet-oriented technologies (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014). Companies adopting smart industry execute several internal changes in order to integrate AI in terms of social robots into their working processes (Lasi et al., 2014). As such, integration of AI does not only refer to changes in manufacturing processes, but is also powering social robots that work as teammates. The corresponding changes on the work-floor consequently require adaptation by employees.

In order to work in this environment, new workforce competencies and management processes are required (Hecklau, Galeitzke, Flachs, & Kohl, 2016). Nevertheless, in the current management literature there are many open questions regarding novel human–AI collaborations (Glikson & Woolley, 2020). Moreover, there has been scant attention for the implications these HRCs have on Human Resource Management (HRM). Knowledge about the use of social robots as driving force behind this new industrialization is limited (Tambe et al., 2019). Since the new industrialization will sooner or later affect all industries (Barreto, Amaral, & Pereira, 2017), there is a need for an in-depth investigation of the phenomena of HRC and how to manage the implications of this collaboration (Shamim, Cang, Yu, & Li, 2016). New questions arise such as: what factors influence employees' willingness to collaborate with social robots? And what is the role of HRM in this relationship? Therefore, this study analyses factors that influence HRC and examines the role of HRM by answering the following research question: 'Which factors influence human-robot collaboration in the smart industry context and what are the implications for human resource management?' This question is answered by employing an online vignette-based experiment containing a short description of situations and a survey. A between-person vignette design is used in which different vignettes are assigned to different groups of respondents. This allows us to draw conclusion on whether HRM serves as support factor on people's intention to collaborate with the robot.

This study contributes to the existing literature on HRC in teams by examining factors that affect users' intention to collaborate with a social robot. In addition, we analyse whether HR systems influence the relationship between technology acceptance and willingness to collaborate. To our knowledge, these relationships have not been studied before and therefore help to further our understanding about HRC and the role of HRM. Our findings show that three technology acceptance factors are important to increase the users' intention to collaborate with a robot. In doing so, we expand the work on technology acceptance and HRC: our findings show that these factors can partly help to explain acceptance of smart technologies. Furthermore, we provide a grounding for future research on actual collaboration between humans and smart technologies. Practical implications are related to the increasing awareness and knowledge on factors which increase or decrease the effectiveness of HRC. We provide insights and argue that, for collaborative work in smart industries, a fitting HR system in combination with specific preparation, empowerment and incentives related to the challenges of HRC is needed. This enables businesses to enhance management and support of humans working in hybrid teams in order to increase team performance.

THEORETICAL BACKGROUND

In this section we shortly introduce the concept of collaborative robots. To understand what determines people's willingness to collaborate with these robots, we discuss technology acceptance theories and show which factors affect this collaboration. Lastly, we discuss the potential role of HRM as support factor.

Collaborative Robots in Smart Industry

Human-robot collaboration (HRC) is an important aspect of smart industry, whereby collaboration refers to the process of agents working together in order to achieve a common goal (Terveen, 1995). While humans and robots tend to have separate working spaces in the past, in a smart industry context collaborative robots allow for direct interaction and collaborative work between humans and AI We conceptualize HRC similar to Hoffman and Breazeal (2004) and thus rather from the standpoint of teamwork in which humans and robots work together in a partnership instead of acting upon each other. When conceptualizing HRC in this way, social adeptness and adaptability by the robot is required. Therefore, the robot as part of the team takes on the explicit or implicit intention of the team as its own in order to perform and to achieve a common goal. To do so, the robot should be able to perceive the team's intensions, beliefs and goals, and must share its own intentions (Bauer, Wollherr, & Buss, 2008; Seeber et al., 2020). The type of robot that holds these characteristics is the social collaborative robot (or sometimes called *cobot*). This paper examines people's intention to collaborate and interact with social robots.

Technology Acceptance

We build on and further expand previous work on HRC, by drawing on the technology acceptance literature. The literature on technology acceptance is well established (e.g. Lee, Kozar, & Larsen, 2003), but work on HRC is relatively scant. To advance this field of research, we combine technology acceptance theories. In line with Bröhl, Nelles, Brandl, Mertens, and Schlick (2016, 2019), we argue that acceptance of technology is crucial to predict successful human-robot collaboration or interaction. Inspired by the Unified Theory of Acceptance and Use of Technology (UTAUT) of Venkatesch et al. (2003), we examined factors that can be expected to influence intention to collaborate with a social robot. The technology acceptance literature is limited to the fact that they do not refer to actual usage of and collaboration with technology but rather account for technology usage intention (Venkatesh, Morris, Davis, & Davis, 2003). Therefore, we focus on intention to collaborate in order to get closer to understanding actual HRC. We hypothesized that six factors would affect intention to collaborate, performance expectancy, trust, effort expectancy, social support, organizational support and computer anxiety. We will further refer to these as *technology acceptance factors*. In order to examine these factors, we take into account the conceptualization and operationalization of the variables as reported in previous scholars.

Performance expectancy

Performance expectancy can be defined as 'the degree to which an individual believes that the system or technology will help him or her in performing a job' (Venkatesh et al., 2003). The probability of accepting and valuing a particular technology increases in case it enhances daily life. Technology, in our case, robots need to make tasks easier, enhance convenience and support everyday activities which are executed in teams. We assume that in order for humans to accept and collaborate with technology, it needs to enhance job performance and thus we propose the following hypothesis – *Hypothesis 1: Expected performance of the robot affects the users' intention to collaborate.*

Trust

Trust is often defined as having confidence in something to do the right action (Gaudiello, Zibetti, Sébastien, Chetouani, & Ivaldi, 2016). Tangibility, transparency, reliability and immediacy behaviours are important factors in developing cognitive trust (Glikson & Woolley, 2020). Different scholars found that trust significantly influences the acceptance of technology (Faqih, 2011; Pavlou, 2003; Wu, Zhao, Zhu, Tan, & Zheng, 2011). Thus, trust can be used to determine overall acceptance of technology (Gaudiello et al., 2016). We expect that trust affects how people perceive and, in the end, interact and collaborate with the technology. Thus, we propose – *Hypothesis 2: Trust in the technology affects the users' intention to collaborate.*

Effort Expectancy

Effort expectancy is the degree of ease of use of the system or technology (Venkatesh et al., 2003). Ease of use can be described as whether the technology is easy to facilitate, and therefore free of effort, which enhances the attitudes towards technology (Davis, 1989; Venkatesh et al., 2003). The importance of clear and understandable interaction with the system was already demonstrated by Thompson, Higgins, and Howell (1991), in their model of PC utilization. The least collaborative effort can be accomplished by minimizing individuals' collective effort to gain an understanding of communication (Kiesler, 2005). We expect that the degree of effort related to the use of a technology can either enhance or worsen the acceptance and collaboration with the system. Therefore, we propose – *Hypothesis 3: Effort expectancy related to the technology affects the users' intention to collaborate.*

Social Support

The social environment of employees plays a crucial role in HRC. The culture the organization stands for provides employees with norms and values which are ideally transferred into behavioural norms in order to meet organizational expectations (Mickan & Rodger, 2000). Values, norms and goals further strengthen motivation and commitment of employees, while commitment strengthens participation in teamwork (Pearce & Ravlin, 1987). This is also referred to as social influence, meaning whether the individual beliefs that he or she should use the system and whether important individuals expect this (Venkatesh et al., 2003). The TAM and Theory of Planned Behaviour (TPB) refer to the impact of the human's social environment as subjective norms (Ajzen, 1991; Davis, 1989). We argute that acceptance and collaboration with robots is affected by whether the social environment of an employee enhances and supports this process and propose – *Hypothesis 4: Support by the social environment affects the users' intention to collaborate.*

Organizational Support

Park, Rhoads, Hou, and Lee (2014) examined that support by the institution or organization is an important construct that 'reflects assistance or barriers to the behaviour associated with external conditions'. Further they summarized factors that influence technology acceptance and found supporting staff, consultant support, management support and training as relevant (Park et al., 2014). The concept of organizational support is reflected by the construct of facilitating conditions (Venkatesh et al., 2003). Facilitating conditions can be defined as whether an individual's beliefs that the organization itself and the infrastructure support the use of the technology (Venkatesh et al., 2003). We expect that the users' acceptance and collaboration with technology are influenced by organizational support that enables him or her to do so. We propose the following – *Hypothesis 5: Organisational support affects the users' intention to collaborate.*

Computer Anxiety

We define computer anxiety as the extent to which an individual feels unpleasant when using technology (Park et al., 2014). Computer anxiety is likely to be determined by people's computer skills, which become more important in a smart industry setting. For example, when referring to the increasing global skills gap, Bughin et al. (2018) found that basic cognitive, physical and manual skills will decline during the next years, while demand for technological skills (such as computer skills) will increase. Since robots are very complex in contrast to usual technologies like personal computers, these complex technologies require more involvement and a more diverse skill set which when not present can negatively affect the acceptance and adoption by the user. Different scholars provide insights on the significant effect of computer anxiety on attitudes and user behaviour (Park et al., 2014; Venkatesh, 2000). We expect that computer anxiety affects acceptance and intention to collaborate with the technology and propose – *Hypothesis 6: Computer anxiety affects the users' intention to collaborate.*

The Role of Human Resource Management

In smart industry, teamwork is becoming critical. Especially in highly complex environments, teamwork is more than simply assigning tasks, resulting in an urgent need for HR to support employees when working together with smart technologies (Libert, Cadieux, & Mosconi, 2020). In case employees are not supported properly, adoption to technologies can become stressful, and with that affecting the workers' health and satisfaction, which causes turnover, eventually (Libert et al., 2020). HRM can support organizations and their employees in dealing with changes that come with smart industry. Managers need to design HR practices with the intention to promote innovativeness and learning in the organization (Shamim et al., 2016). In order for employees to adopt to technologies and to effectively work together, a combination of preparation, empowerment and incentives is needed (Libert et al., 2020). Further changes must occur along attraction, retention and development of employees in this new industrialization. Thus, hiring should be on the basis of variety of skills, heterogeneous knowledge and attributes necessary for innovative behaviour (Shamim et al., 2016). Organizations need to design training programmes in a way which enhances the innovative capability and learning (Shamim et al., 2016) in order to strengthen employee's awareness and skills. Stachová, Papula, Stacho, and Kohnová (2019) propose the importance of knowledge sharing, learning and human development in this new industrial revolution. This requires cooperation with external partners like educational institutions in order to arrive at new educational opportunities (Stachová et al., 2019). Next to that, they might work on performance appraisals in order to facilitate learning and innovation, empowerment of the workforce, and the creation of incentives reflecting the contribution of employees to the company. Providing incentives and satisfactory training possibilities has a positive impact on employees' commitment (Jaworski, Ravichandran, Karpinski, & Singh, 2018). Knod, Wall, Daniels, Shane, and Wernimont (1984) argue something similar; involving people early, gaining expertise (if necessary, through recruitment) and educate and train the human workforce is necessary for future HRC. This suggests that HRM needs a shift in its core processes (e.g. hiring, appraisal, training and compensation) to support and facilitate the acceptance, adoption and collaboration with new technologies such as social robots.

Human Resource Management Systems as Moderator

HRM systems entail characteristics of a companies' values and norms and stand for how employees are managed inside the company. We suggest that certain HR systems would enable and support HRC while others have a negative influence or no influence at all. In other words, the effects of the technology acceptance factors are expected to be shaped by the HR system in place, such that a supportive HR system can enhance the positive effects of the acceptance factors while an unsupportive HR system may decrease the effect. For example, high levels of trust and performance expectancy interact with the HR system to increase the willingness to collaborate.

Lepak and Snell (2002) examined different employment modes and their association with a type of HR system: commitment-based, compliance-based, productivity-based, and collaborative. We focus on the collaborative HR system since it can be expected that it can support HRC. We further include the productivity-based HR system due to the fact that it is almost contrary to the collaborative HR system and we expect to achieve the most diverse outcome.

In a productivity-based HR system, employees get paid a market-based wage and managers are focused on employees' job performance. Jobs are more often standardized in order to find replacement in case the employee leaves the firm. Usually, firms which focus on productivity are more likely to establish shorter time horizon in order to ensure productivity and are more result oriented (Lepak & Snell, 2002). Since we examine how humans collaborate with smart technologies in the team context and the productivity-based HR system rather focuses on individual short-term performance, we expect that the effect of this system on the relationship between the technology acceptance factors and the users' intention to collaborate with the robot is rather neutral or even negative. Collaborative HR systems are characterized by sharing of information and development of trust between partners. A joint outcome is crucial and therefore, firms that apply this system invest heavily in relationship building. One finds team building initiatives to be part of this system and evaluations of employees rather emphasize developmental issues such as the extent of learning (Lepak & Snell, 2002). We expect a positive influence of the collaborative HR system on the relationship between the technology acceptance factors and the users' intention to collaborate with the robot, since this system is focused on the challenges of HRC, especially in the team context, and thus, might positively affect how humans work together with robots. Therefore, we expect that – *Hypothesis 7: The presence of a productivity-based HR system negatively moderates the relationship between the technology acceptance factors and employees' intention to collaborate with technology, such that the relationship becomes weaker when a productivity-based HR system is present.*

Hypothesis 8: The presence of a collaborative HR system positively moderates the relationship between the technology acceptance factors and employees' intention to collaborate with technology, such that the relationship becomes stronger when a collaborative HR system is present.

Conceptual Framework

We build on previous work on HRC. Primarily inspired by the UTAUT model, we hypothesized that six factors would positively affect the intention to collaborate: performance expectancy, trust, effort expectancy, social support, organizational support and computer anxiety. In addition, to study the role of HRM, we included different HRM systems as moderators. We hypothesized a moderating effect of the HR system on the relationship between the technology acceptance factors and the intention to collaborate, such that this relationship would be strengthened or weakened when the HR system was in place. Based on the work by Lepak and Snell (2002), we hypothesized that a *collaborative HR system* reinforces the relationship between the technology acceptance factors and HRC, whereas a *productivity-based HR system* would be detrimental in this relationship (Fig. 1).

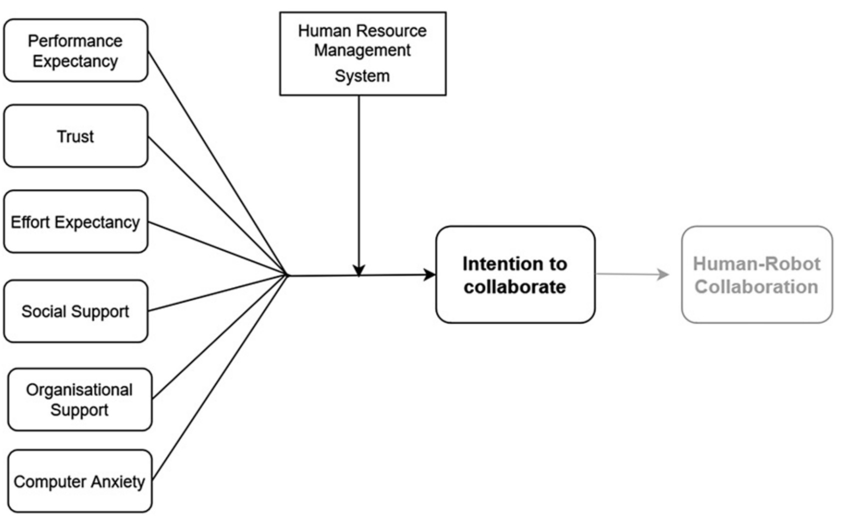

Fig. 1. Conceptual Model.

METHOD

Research Design and Data Collection

We adopted a quantitative experimental approach by investigating HRC using a vignette study, which combines characteristics of experimental designs and surveys. A vignette study contains short descriptions of situations or persons and a survey which respondents usually fill in afterwards (Atzmüller & Steiner, 2010). This type of approach usually shows high internal validity due to the experimental design, and high external validity due to the survey characteristics (Atzmüller & Steiner, 2010). We chose a between-person vignette design, meaning that each participant only reads one vignette which allows for comparisons across participants (Atzmüller & Steiner, 2010). This enables us to see whether the vignettes yield different effects on respondents and the relationship between the technology acceptance factors and intention to collaborate.

Participants of this study were men (31%) and women (69%) between 18 and 65 years of age. Attention was also given to differentiation among education levels, in order to provide sufficient control variables and to avoid biased outcomes. The online survey software distributed the three different vignettes randomly and evenly across participants. In total, 145 people participated in this study, with a valid sample size of 96 cases. Data were collected by making use of the web-based software Qualtrics XM. Participants were recruited through LinkedIn, PoolPool and personal networks. Participation in this study took seven minutes on average.

Measures

The survey consisted of 24 statements, where 21 items measured the independent variables and three items measured the dependent variable. Participants had to judge these statements on a five-point Likert scale (see Appendix 1).

Technology Acceptance Factors

We take into account the operationalization of the variables, as reported in previous scholars, thus items are based on insights from different technology acceptance models and theories. *Performance expectancy* consists of three items, measured according to the existing scale used by Venkatesh et al. (2003) in the UTAUT paper and the scale by Davis (1989) in construction of the perceived usefulness variable. *Trust* consists of four items and is measured by making use of items according to a scale developed by Schaefer (2013), measuring human–robot trust. Effort *expectancy* consists of three items and is measured using a combination of scale items by Venkatesh et al. (2003) and Davis (1989), who refer to the variable as ease of use. *Social support* is a combined scale, made up of the measure used by Ajzen (1991) to examine the subjective norm variable and the scale used by Venkatesh et al. (2003) to measure social influence, consisting of three items. Next, *organizational support* is measured by four items, combining items used by Venkatesh et al. (2003) in measuring facilitating conditions and the scale used by Park et al. (2014) to measure institutional support. Lastly, we measure *computer anxiety*, consisting of four items, by using the measurement scales developed by Venkatesh (2000) and Park et al. (2014) to test computer anxiety in the light of technology acceptance.

Intention to Collaborate

The dependent variable of this study is the user's *intention to collaborate* with the robot. We take into account the operationalization of intention to collaborate, as reported in previous scholars. The items used were whether participants believed working with the robot is a good idea, whether they think they would collaborate with the robot eventually and whether they believe they would like working together with the robot. These were based on two scales used by Venkatesh et al. (2003) to measure attitude towards using a technology and further to measure users' intention to use a technology.

HRM System

Our aim was to test for a significant effect of the technology acceptance factors on intention to collaborate. We expected that this relationship is moderated and thus, subject to change when a specific HR system is in place. In order to test for a moderating relationship, three different scenarios (vignettes) were used. The difference between the vignettes was related to the different types of HR systems, which were described. We conceptualized two vignettes according to Lepak and Snell (2002) as we did in our literature review. Shortly, *collaborative HR systems* are characterized by trust between partners and team building while in a *productivity-based HR system*, managers are focused on employees' job performance which are more often standardized (Lepak & Snell, 2002). The third vignette did not include information about a particular HR system and serves as reference category (Table 1).

Table 1. Operationalization HRM Systems.

	Productivity	Collaborative	No HR System
Standardized jobs	X		
Functional teams and networks		X	
Emphasize job performance	X		
Seek to increase short-term productivity	X		
Focus on interpersonal relations		X	
Result based	X		
Assessment of quality and quantity of output			
Focus on team performance		X	
Group-based incentives		X	
Straight salary	X		

Control Variables

Control variables used in this study are age, gender and education level which have proven to be important control variables in previous studies (Croson & Gneezy, 2009; Park et al., 2014; Schaefer, 2013; Venkatesh et al., 2003) and are thus relevant in the context of this study.

Data Analysis

Data were processed with SPSS version 26 and AMOS version 26. *First*, descriptive statistics (means, standard deviations), multi-collinearity statistics and correlation coefficients were computed to determine distribution of data and the relationships between the variables. Further, based on Gao, Mokhtarian, and Johnston (2008), Mardia's coefficient of multivariate kurtosis and its critical ratio was used as an indicator of multivariate normality (>-1.96, <1.96). In order to test for reliability of the construct, we estimated

Cronbach Alpha (>0.6) based on Churchill's (1979) and van Griethuijsen's et al. (2015) suggestion for a critical value. The level of statistical significance for the relationships was set at 95% ($p < 0.05$).

Second, ANOVA was estimated in order to show whether there is a significant difference in mean between the groups who received different vignettes.

Third, we conducted confirmatory factor analysis (CFA). CFA is known to be robust with different scales (e.g. Likert scales), but does require distributional assumptions. We checked for multivariate normality, sufficient sample size, priori model specification and random sample distribution. Based on CFA, outliers and three measurement items were excluded, due to low loading on the particular construct. In order to determine the best fitting measurement model, a competing measurement modelling strategy was used (Table 2).

Table 2. Model Fit Statistics.

Fit Indices	Cut-Off Criterion
Absolute fit indices	
Chi-square ($\chi 2$)	Lowest comparative value between measurement models
$\chi 2$/df	<5
Approximate fit indices	
Root means square error of approximation (RMSEA)	<0.08 but >0.01
Root mean square residual (RMR)	<0.08
Incremental fit indices	
Comparative fit index (CFI)	>0.90
Tucker-Lewis index (TLI)	>0.90

Source: Adapted from Hu and Bentler (1999).

In order to determine data-model fit, we employed a sequential evaluation process. We refer to Hu and Bentler (1999), who examined various fit indices used to evaluate model fit, to discriminate between models and to determine data-model fit. The model with the highest model fit was retained for further analyses.

Finally, we conducted multiple hierarchical regression analysis, considering the recommended minimum sample size of 50 and normal distribution of error terms. The hierarchical multiple regression analysis consisted of three models: the first model included solely the control variables, the second model included also the technology acceptance factors (independent variables) and the third model included the interaction terms in order to test for a moderating effect of a particular HR system.

RESULTS

Descriptive Statistics, Consistencies and Correlations

We present the means, standard deviations and correlations for the variables of this study below in Table 3. We do not find evidence to suggest multicollinearity since the variance inflation factors are between 1.4 and 1.6 and thus far below the recommended threshold of 10 (Belsley, Kuh, & Welsch, 2005; O'brien, 2007). Furthermore, the correlations between the independent variables, with a maximum of 0.688, are under the recommended threshold of 0.75 (Ashford & Tsui, 1991).

Table 3. Means, Standard Deviations and Correlations.

	Mean	SD	1	2	3	4	5	6
1. Performance	3.28	0.87						
2. Trust	3.38	0.80	0.466**					
3. Effort	2.67	0.78	−0.435**	−0.628**				
4. Social support	3.67	0.63	0.363**	0.416**	−0.460**			
5. Organizational support	2.64	0.91	−0.361**	−0.532**	0.436**	−0.254**		
6. Computer anxiety	3.04	0.96	−0.567**	−0.688**	0.580**	−0.391**	0.596**	
7. Intention to collaborate	3.21	0.97	0.628**	0.651**	−0.590**	0.431**	−0.445**	−0.845**

Note: **Correlation is significant at the 0.01 level (2-tailed).

Measurement Models

To determine the best measurement model, four competing theoretically informed CFA models were estimated.

- *Model 1* tested our hypothesized measurement model. The model consists of six factors matching our six variables. Performance expectancy included three items, trust four items, two items were loading on effort expectancy, social support included three items, organizational support two items and four items were loading on computer anxiety.
- *Model 2* tested a five-factor model that was fitted to the dataset in which items that loaded on organizational support were fitted to load directly on effort expectancy. Other factors were modelled the same as in Model 1.
- *Model 3* tested another five-factor model, fitted to the dataset in which items that loaded on computer anxiety, were fitted to load directly on effort expectancy. Other factors were modelled the same as in Model 1.
- *Model 4* tested another five-factor model that was fitted to the dataset in which items that loaded on trust were fitted to load directly on computer anxiety. Other factors were modelled the same as in Model 1.

The model fit statistics can be found in Table 4 and indicate that our hypothesized measurement model, Model 1, fitted the data better ($\chi^2_{(120)} = 187.852$; $\chi^2/df = 1.57$; CFI = 0.91; TLI = 0.89; RMSEA = 0.07 [CI: 0.055–0.098]; RMR = 0.065) than any of the other competing measurement models. As such, Model 1 was retained for further analyses.

Table 4. Model Fit Comparison.

Model	χ2	df	χ2/df	CFI	TLI	RMSEA		RMR	Meets Criteria
						Value	CI [90%]		
Model 1	187.852	120	1.57	0.91	0.89	0.07	0.055–0.098	0.065	Yes
Model 2	210.854	125	1.69	0.89	0.87	0.09	0.65–0.105	0.068	No
Model 3	200.568	125	2.01	0.9	0.88	0.08	0.059–0.100	0.069	No
Model 4	200.242	125	1.6	0.9	0.83	0.08	0.58–0.100	0.07	No

ANOVA

We conducted ANOVA, which examined the difference in mean between the three different vignette groups. Table 5 shows the mean scores for Vignette 1 (M = 0.243), Vignette 2 (M = −0.078) and the neutral Vignette (M = −0.164). Table 6 shows that the scores for intention to collaborate are not significantly different for the three groups (p = 0.228).

Table 5. Mean Scores on Intention to Collaborate of the Different Groups.

Descriptives	N	Mean	Std. Deviation
Productivity HR system	32	3.44	0.9142
Collaborative HR system	32	3.14	0.8834
Neutral	32	3.05	1.081
Total	96	3.21	0.9687

Note: Dependent Variable: Intention to collaborate. Vignette 1: Productivity HR System; Vignette 2: Collaborative HR System.

Table 6. ANOVA.

Intention to Collaborate	Sum of Squares	Df	Mean Square	F	Sig.
Between groups	3	2	1.485	1.501	0.228
Within groups	92	93	0.990		
Total	95	95			

Multiple Hierarchical Regression Analysis

In Table 7 the results of the multiple hierarchical regression analysis are presented. Model 1 includes the control variables. Model 2 additionally includes the technology acceptance factors to test the first six hypotheses. Model 3 further includes the moderators (vignettes) and Model 4 additionally includes the interaction effects in order to determine whether there is a moderating effect of the type of HR system on the relationship between the independent and dependent variables.

Model 1 shows that gender has a significant negative effect on intention to collaborate (ß = −0.50, p = 0.030), although this significance disappears in models 2, 3 and 4. Model 2 presents that three out of the six technology acceptance factors have significant effects on intention to collaborate, which are performance expectancy (ß = 0.18, p = 0.008), organizational support (ß = 0.15, p = 0.027) and computer anxiety (ß = −0.68, $p < 0.001$). Trust (ß = 0.06, p = 0.395), effort expectancy (ß = −0.10, p = 0.161) and social support (ß = 0.06, p = 0.314) do not have significant effects on intention to collaborate. Therefore, we accept hypothesis 1, 5 and 6, performance expectancy, organizational support and computer anxiety significantly affect the users' intention to collaborate with the robot. Moreover, we reject hypothesis 2,3 and 4, the effect of trust, effort expectancy and social support on intention to collaborate is not significant. Model 3 further includes the vignettes as predictors and shows that there is no significant effect of vignette 1 (ß = 0.2, p = 0.131) and vignette 2 (ß = 0.09, p = 0.196) on intention to collaborate. Model 4 tested the

Table 7. Results of the Multiple Hierarchical Regression Analysis.

Intention to Collaborate Predictor variables	Model 1	Model 2	Model 3	Model 4
Gender	−0.50*	−0.15	−0.12	−0.13
Age	−0.06	−0.03	−0.03	−0.05
Highest education	0.12	0.01	0.01	−0.02
Performance expectancy		0.18**	0.18	0.4**
Trust		0.06	0.07	−0.03
Effort expectancy		−0.10	−0.10	−0.29*
Social support		0.06	0.06	−0.1
Organizational support		0.14*	0.15*	0.33*
Computer anxiety		−0.68**	−0.68**	−0.73**
Productivity HR system			0.2	0.17
Collaborative HR system			0.09	0.09
Performance × productivity HR system				−0.25
Performance × collaborative HR system				−0.15
Trust × productivity HR system				0.11
Trust × collaborative HR system				0.15
Effort × productivity HR system				0.26
Effort × collaborative HR system				0.16
Social support × productivity HR system				0.11
Social support × collaborative HR system				0.12
Organizational support × productivity HR system				−0.23
Organizational support × collaborative HR system				−0.13
Computer anxiety × productivity HR system				−0.01
Computer anxiety × collaborative HR system				0.07
R^2	0.1	0.78	0.78	0.81
R^2 Change	0.1	0.67	0.01	0.03

Note: Dependent Variable: Intention to collaborate. Vignette 1: Productivity HR System; Vignette2: Collaborative HR System. Confidence level: *≤ 0.05, **≤ 0.01.

moderation hypotheses for which we additionally included interaction terms between the technology acceptance factors and the productivity-based – and collaborative HR system. The neutral vignette serves as reference category in this regression model and is therefore not included. The analysis shows no significant interaction effects. Therefore, we have to reject hypothesis 7 and 8 since the effect of the productivity-based HR system as well as the effect of the collaborative HR system on the relationship between the technology acceptance factors and employees' intention to collaborate is neither significant nor negative/positive as we suggested. Worth mentioning is the significant change in the *R*-Squared from Model 1 to Model 2 ($R^2 = 0.78$, $p < 0.001$). From Model 2 to Model 3, we do not find a significant change in *R*-Squared ($R^2 = 0.78$, $p = 0.265$); this is also the case from Model 3 to Model 4 ($R^2 = 0.81$, $p = 0.516$). Our final Model achieves an *R*-Squared value of 0.8., thus 80% of the variance in the dependent variable is predictable from our technology acceptance factors. Due to the significant *R*-Squared change value in Model 2, we will use Model 2 as our results and as input for the discussion.

DISCUSSION

We found that performance expectancy, organizational support and computer anxiety have a significant effect on the people's intention to collaborate with a social robot. Performance expectancy has a significant positive effect on the users' intention to collaborate with the robot; supporting Davis (1989) in that perceived usefulness is significantly correlated with self-reported indicants of using the technology. Most participants expect the robot to be relatively useful in their job and that it would make tasks easier. We underline the claim by Davis (1989), who stated that acceptance and valuation of a technology increases in case it enhances daily life. Second, organizational support significantly affects the users' intention to collaborate with the robot, meaning that in case individuals believe that the organization itself and the infrastructure support the use of the technology, the intention to collaborate with a robot increases (Venkatesh et al., 2003). Support by the institution or organization is therefore a significant important construct. Next, computer anxiety shows a significant negative effect on users' intention to collaborate. Computer anxiety is also referred to as the individual emotional state of a user and we found that this state affects whether individuals intend to collaborate with a robot. We would like to point out that computer anxiety is very much determined by computer skills, while referring to the global skills gap showing the ever-increasing demand for such technology-focused skills (Bughin et al., 2018). Our results correspond with earlier findings that showed significant negative effects of computer anxiety on attitudes and user behaviour (Park et al., 2014; Venkatesh, 2000). Finally, half of the participants agreed that they would collaborate with the robot eventually showing that the participants in our study do not fully support the use of smart technologies in team settings.

In our analysis, we also tested whether the presence of a particular HR system would moderate the relationship between the technology acceptance factors and users' intention to collaborate. We found that the presence of a particular HR system does not have a significant effect on the relationship between the technology acceptance factors and intention to collaborate.

Theoretical Implications for Human Resource Management

This study has theoretical implications for HRM in the smart industry context. Our results show that three technology acceptance factors are significantly important in order to increase the users' intention to collaborate with the robot; performance expectancy, organizational support and computer anxiety. With this, we can reinforce earlier findings (Davis, 1989; Venkatesh et al., 2003) and partly expand the theories on technology acceptance since individual factors show relevance in the context of collaboration between smart technologies and the human workforce.

In the transformation process towards human resource management in smart industry, companies need to take on a strategic approach. Intellectual capital and intellectual capital management are key in order to ensure competitive advantage (Stachová et al., 2019). Thus, HRM needs to focus on human capital, thus their employees, relationship capital with regards to external partner and structural capital in terms of organizational processes (Stachová et al., 2019).

In order to sustain human capital on a long-term basis, organizations must educate and engage their human capital early. We like to reiterate Knod et al. (1984) in it is important for HRM to adopt a proactive stance by including the user, who has to work together with the robot eventually, as early as possible. Education must not only include actual (on-the-job) training but also educating on general facts and features regarding the smart technology. Usefulness and performance of the smart technology must be perceived from the beginning in order for adoption and acceptance. Education and early involvement also serve in terms of a feeling of control and safety, which strengthens empowerment (Libert et al., 2020). Education in terms of technological skill development can further mitigate computer anxiety. In order to strengthen the users' awareness and broaden and deepen their skill set, training possibilities represent an important feature in HRC (Knod et al., 1984; Libert et al., 2020). Training can mitigate stress which affects the workers' health and satisfaction and eventually turnover (Libert et al., 2020).

In order to ensure successful long-term HRC, support by the HRM cannot stop after training and education but must consider relational capital. This includes sustainable learning and sustainable employee development. The involvement of partnerships with external parties, like educational institutions, is important in order to bring new knowledge to the internal environment. These intentional inflows and outflows of knowledge help to accelerate internal innovations (Stachová et al., 2019). Moreover, in order to strengthen the relationship to employees, incentives and other methods like performance assessment prove to be useful methods in empowerment and commitment (Jaworski et al., 2018).

Support from HRM can be directly linked to increased employee performance (Lee & Bruvold, 2003). Structural capital includes organizational processes, policies and culture. HRM contributes to enhancement of structural capital by providing space, support and security when it comes to novel HRC. A culture that values self-efficacy further enhances perceived support and work engagement as well as satisfaction and commitment (Caesens & Stinglhamber, 2014). Thus, in order for users to adopt to technologies and to effectively work together on a long-term basis, a combination of preparation (including training and education), empowerment and incentives is needed (Libert et al., 2020).

We contribute to the literature on HRM systems, by integrating different HRM systems as moderator variables in our study. In contradiction to Lepak and Snell (2002), we did not empirically find that these HRM systems are positively related to HRC. We argue that besides a fitting HR system, HRM must go through an overarching additional change process in order to successfully manage humans in HRC. Furthermore, we argue that the relation between particular HRM systems and their practices should be studied further.

Practical Implications for Human Resource Management

We found that technology acceptance models are applicable to study HRC. We believe that intention to collaborate, and in turn HRC, can be enhanced when keeping the significant technology acceptance factors in mind. For managers, these models can provide direction for effectively managing the human factor in HRC. The expected performance of the robot is important to perceive by the employees in order to strengthen their intention to collaborate in hybrid teams. Providing employees with detailed information on opportunities and drawbacks the technology brings can thus strengthen their intention to collaborate. Further, not just internal education but also collaboration with external educational institutions in order to bring new knowledge inside the company enhances HRC. HR managers can support intention to collaborate by providing the necessary environment, including infrastructure but also support and a fitting company mission. Lastly, HR managers can enhance collaboration in hybrid teams by being aware of employees' anxiety related to new technologies. Anxiety affects the intention to collaborate, thus support in skills development and efficient selection of fitting employees for hybrid teams can strengthen effective HRC. Although in our study, the interaction between acceptance factors and HR systems is limited, we consider a fitting HR system as important for effective HRM. We suggest that for effective HRC, intention to collaborate is decisive and intention can be strengthened by high expected performance, high organizational support and low anxiety. These factors in combination with a fitting HR system contribute to effective HRC.

Limitations and Suggestions for Research

An important limitation is the use of self-reported data in this vignette study, which bears the risk of self-reporting biases. Further research could address this issue by adopting a qualitative research method like interviews or observations in order to avoid these biases. Furthermore, the vignette was built by written descriptions of different HR systems. Respondents had to use their imagination in order to put themselves into the described scenario. We did not use a manipulation check in order to see whether participants actually experienced the manipulation; therefore, we cannot be completely sure that they were actually fully aware of the introduced HR system. In studying effective HRC, we also find a limitation regarding our sample. We aimed for a balance in gender, but it turned out that 69% of respondents were female while 31% were male. Next to that, we experienced that most participants were either of German or Dutch nationality. Further research could address this by distributing the survey randomly and evenly. While we examined which factors affect HRC, the role of the HR system and the implications for HRM, further research could investigate explicit methods and procedures for managing HRC in the smart industry.

CONCLUSION

Managing employees in the smart industry is a topic of interest for researchers as well as managers. Previous research generally focused on changes related to HRM processes (Hecklau et al., 2016; Liboni, Cezarino, Jabbour, Oliveira, & Stefanelli, 2019; Sivathanu & Pillai, 2018) rather than management of effective HRC in hybrid teams. Seeking to fill this gap in the human resource literature, this study aimed to examine factors affecting HRC when certain HR system is in place. Our findings show that performance expectancy, organizational support and computer anxiety significantly affect people's intention to collaborate with a social robot. We demonstrate the importance of the technology acceptance factors and a fitting HR system in firms. Based on our findings and support by Hecklau et al. (2016), who argue that in smart industry there are three main areas of HRM development: personal development, team development (collaboration) and organizational development, we emphasize that HRM matters in effective HRC in smart industry settings. We provided recommendations to HRM in terms of provision of comprehensive preparation, including training and education, empowerment and incentives in order to support HRC in hybrid teams.

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APPENDIX 1

Measurement Items per Construct[a]

Construct	Items
Independent variables	
Performance expectancy	I believe that I would find the robot useful in my job
	I believe that using the robot would make it easier to do my job
	I believe that using the robot would improve my job performance
Trust	I believe the robot is reliable
	I believe the robot would perform as instructed
	I believe working with the robot is not dangerous
	I believe I would be relaxed and calm when working with the robot
Effort expectancy	I believe it is easy to learn how the robot works
	I believe it is easy to work together with the robot
	I believe interaction with the robot is clear and understandable
Social support	I believe my team would expect me to work with the robot
	I believe my teammates would be happy if I work with the robot
	I believe support of the management in working with the robot would be important to me
Organizational support	I believe guidance and instruction is necessary to work with the robot
	I believe assistance in using the robot would be useful
	I believe I have the skills and knowledge necessary to work with the robot
	I believe I would be able to control the robot
Computer anxiety	I believe I would not have concerns about using the robot
	I believe a robot would not scare me at all
	I believe I would feel comfortable when working with the robot
	I believe I would not hesitate to use the robot
Dependent variable	
Intention to collaborate	I believe working with the robot is a good idea
	I believe I would collaborate with the robot
	I believe I would like working with the robot

[a]The grey measurement items were later excluded due to low construct loading and low reliability. All survey items were judged on a five-point Likert scale.