MASTER THESIS

Effective Human-Robot Collaboration in the Industry 4.0 Context - Implications for Human Resource Management

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ABSTRACT

This paper investigates effective human-robot collaboration (HRC) and presents implications for human resource management. A review of current literature on human resource management in the industry 4.0 showed that there is limited research on human-robot collaboration in hybrid teams and even less on management of these teams. In order to fill this gap in the literature, this paper investigates factors affecting intention to collaborate with a social robot by conducting a Vignette study. We hypothesised that six technology acceptance factors inspired by the UTAUT (Venkatesh et al., 2013) and the TAM (Davis, 1989); Performance Expectancy, Trust, Effort Expectancy, Social Support, Organisational Support and Computer Anxiety would significantly affect a users' intention to collaborate with a social robot. Furthermore, we hypothesised a moderating effect of a particular HR system, either productivity-based or collaborative. Using data from 109 men and women, this study tested the effect of the aforementioned variables on a users' intention to collaborate with the social robot. Findings were analysed using a Confirmatory Factor Analysis, Hierarchical Multiple Regression and ANOVA. We found that Performance Expectancy, Effort Expectancy and Computer Anxiety significantly affect the intention to collaborate with a social robot. A significant moderating effect of a particular HR system was solely found for Performance Expectancy. Our findings expand the current HRM literature since technology acceptance models are partly applicable in the context of smart technologies in the industry 4.0 and support understanding employees' intention to collaborate with these technologies. Human resource management can support human-robot collaboration by a combination of comprehensive training and education, empowerment and incentives supported by an appropriate HR system.

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1. Introduction

Humans are great at working in teams. However, teams are not only composed of humans anymore but also of artificial intelligence such as robots. In the past years, the phenomenon of human-robot collaboration (HRC) and its' implications for businesses gained popularity and became a frequently discussed topic in different kinds of industries as for example manufacturing as well as the health sector (Charalambous, Fletcher & Webb, 2015). Human-robot collaboration cab be described as "special kind of operation between a person and a social robot sharing a common workspace" (International organisation for standardization, 2011). The term human-robot collaboration appeared after the beginning of the new industrialisation, Industry 4.0, which describes advanced digitalization within companies and the combination of Internet-Future oriented technologies in the field of "smart" objects (Lasi et al., 2014). The concept of industry 4.0 is related to innovative digital technologies like artificial intelligence often as part of social robots (Hecklau, Galeitzke, Flach & Kohl, 2016). Artificial intelligence (AI), referring to technologies allowing machines like computers or social robots to perform tasks which would otherwise require human cognition, plays an increasing role in the concept of this new industrialisation (Cappelli, Tambe & Yakubovich, 2018). A majority of companies already executed several internal changes in order to integrate AI in terms of social robots into their working processes (Lasi et al., 2014). However, integration of AI in companies does not only refer to the most obvious; manufacturing processes, but also increasingly to AI in terms of social robots as teammates. The changes on the work-floor consequently require adaptation by employees. In order to adopt to- and work in this new environment, new workforce competencies and skills and management of these are required (Hecklau et al., 2016). The management of employees and consequently their competencies is part of the HRM function of companies, referring to operations such as recruitment-, selection-, and on- boarding of employees but also training, performance management, advancement of high performers, retention of employees over the long term and the determination of employee benefits (Cappelli et al., 2018).

In contradiction with the need to support employees in managing the consequences which come with human-robot collaboration, it was found that 41% of CEOs do not feel well prepared to manage new analytics themselves (Cappelli & Tambe & Yakubovich, 2018). Furthermore, knowledge on managing the use of artificial intelligence and social robots as part of this new industrialisation is limited (Cappelli et al., 2018). When facing the fact that companies are not ready to manage new analytics, consequently neither to manage the adoption of AI and social robots, questions arise. How will employees interact with AI and social robots as parts of their team and which challenges might arise? What affects collaboration between human employees and social robots? What is the role of HRM in this context?

In order to answer these questions, research on the use of social robots in the team context is needed. Given that the literature of industry 4.0 is in the transition process from early German studies to the development of insight on new global impacts, there are inconsistencies in knowledge on the consequences of HRC and the management of it (Liboni et al., 2019). There have been some studies on the effects of industry 4.0 on HRM; for instance, Hecklau and colleagues (2016) studied organisational challenges related to industry 4.0 and came up with required competencies of the workforce in this new industrialisation. Moreover, Sivathanu & Pillai (2018) report on changes related to HR processes as for example on- boarding and development. Lastly, Liboni et al. (2019) analysed different papers on HRM in the industry 4.0 and concluded that most are related to labour changes, work conditions, the environment and the demand for new skills. When looking for available in-depth literature on collaboration of AI and social robots with humans in teams, one finds that to be an understudied area. There is research on HRC, however knowledge on effective collaboration in hybrid teams (human and social robot) and especially management of this collaboration is rare. Since the new industrialisation will sooner or later affect all industries (Barreto, Amaral & Pereira, 2017), there is a need for an in-depth investigation of the phenomena of human-robot collaboration and how to manage the implications of this collaboration properly (Shamim, 2016).

This study aims to investigate possible factors affecting a users' intention to collaborate with social robots in teams in order to get closer to understanding effective human-robot collaboration. Furthermore, we test for a moderation effect of HR systems that exist inside companies. Finally, we provide implications for Human Resource Management and the HRM literature. The conceptual model of this study is inspired by the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and use of Technology, introduced by Venkatesh, Morris and Davis (2003). We make use of insights from additional theories which provide direction and a grounding for data analysis in this research. In order to investigate a users' intention to collaborate, this study makes use of the Vignette Approach as a combination of experiment and quantitative surveys. Common HR systems and HR tasks are described and conceptualised. Finally, a comparison between Human Resource Management and HR systems, and faced issues in humans' intention to collaborate with social robots is given. This is to generate practical contributions for human resource management and its' management of human-robot collaboration, and recommendations for further research.

The research question this study aims to answer is;

"Which Factors influence Human-robot Collaboration in the Industry 4.0 Context and what are the implications for Human Resource Management?"

This study is a contribution to theory since a study on human-robot collaboration in teams, by examining a users' intention to collaborate while simultaneously testing for a moderating effect of certain HR systems is, to our knowledge, the first of its kind and has not been studied in this composition before. We can expand theories on technology acceptance since our findings show that they are partly true for intention to collaborate, which goes further than acceptance and furthermore we find that these theories are applicable in terms of smart technologies like social robots. We show that different factors are significantly important when it comes to a users' intention to collaborate with a social robot. Therefore, our insights add to the current HR literature, especially human resource management in the industry 4.0. Furthermore, we provide a grounding for future research on actual collaboration between humans and smart technologies. This thesis is a contribution for management, to gain insights on positive and negative issues which affect the collaborative work between humans and social robots in teams. Practical contribution is provided for management by increasing awareness and knowledge on factors which decrease a users' intention to collaborate with smart technologies or on the other hand, factor which might play a crucial role in increasing this intention. With that, businesses and management can gain knowledge on needs of their employees when it comes to collaborative work with smart technologies. We provide insights that, for collaborative work in the industry 4.0, a fitting HR system in combination with an overarching additional HRC system including specific preparation, empowerment and incentives related to the challenges of human-robot collaboration is needed. This enables businesses to enhance management and support of humans working in hybrid teams in order to increase team performance. Lastly, effective management of HRC increases business performance eventually and therefore the market position of the firm.

This paper starts with our theoretical framework and a review of the current literature. After that we examine the method used to gather data followed by the actual findings. Lastly, we will discuss our findings in the light of the aforementioned literature and conclude with implications, limitations and directions for further research.

2. Theoretical Framework

2.1 Industry 4.0 and Human-Robot Collaboration

Collaboration is the process of agents working together in order to achieve a common goal (Terveen, 1995). Later, the term human-robot collaboration derived from the development of the new industrialisation, industry 4.0. Industry 4.0 lead to a technology- push; mechanisation and automation of work processes takes place in order to support the physical work, optimise and analyse the manufacturing process (Lasi et al., 2014). Furthermore, the industry has to deal with an increasing amount of data, which is due to digitalisation and networking. This has the consequence of increased control and more analytical processes inside the organisations (Lasi et al., 2014). The industrial development lead to new smart systems. In industry 4.0, cyber-physical systems combining software, sensors, processor and communication technology increase the value of organisational processes. Nowadays, computers, social robots and algorithms, as forms of automation, are becoming fundamental parts of organisational processes. While humans and social robots tend to have separate working spaces in the past, collaborative social robots allow for direct interaction and collaborative work between humans and artificial intelligence. This execution of operations by a person and a social robot while both share a common workspace, is referred to as human-robot collaboration (International organisation for standardization, 2011). Nowadays, social robots enhance industrial processes like manufacturing, in which they are often working together with human employees at the assembly line. Nevertheless, during the last years humans increasingly search for direct advice by non- human actors (Prahl & Swol, 2017). This is rather by making use of algorithms, or by collaboration with AI in teams. Several authors describe this shift in the use of social robots as "from tools to teammates" (Phillips, Ososky, Grove & Jentsch, 2011). Adoption of social robots as teammates is growing and they increasingly take on complex social-, and collaborative roles (Warta, Kapalo, Best & Fiore, 2016).

We conceptualize human-robot collaboration similar to Hoffman and Breazeal (2004) and thus rather from the standpoint of teamwork in which humans and social robots work together in a partnership instead of acting upon each other. Thus, this form of human-robot collaboration combines competencies of humans and the core competencies of social robots. When we conceptualize HRC in this way, social adeptness and adaptability by the social robot is required. Therefore, the social robot as part of the team must take 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 social robot must be able to perceive the team's intensions, beliefs and goals. Next to this, the social robot must share its own intensions. Interaction among humans and AI, in terms of social robots, requires coordination of activities, communication and joint action (Seeber et al., 2020; Bauer, Wollherr & Buss, 2008). Further, human like execution of tasks by the social robot was found to be important in enhancing interaction among humans and AI (Seeber et al., 2020). In order for successful HRC, commitment by all team members is required.

The social robot which a company decides to work with should fit the type of human-social robot collaboration the company aims to enhance. The form of human-robot collaboration this study examines, requires social adeptness by the social robot as described above and thus a so called "social robot" is used to do so.

2.1.1 Social Robots

Social robots play an important role when it comes to industry 4.0. There are several types of social robots which are applied in different contexts; for example, military-, construction-, agricultural-, or medical social robots, whereas industrial social robots find greatest application in manufacturing processes (Bahrin et al., 2016). Lately, social robots are gaining popularity. This is, since separation of human and social robots' workspace declined over the last years. Humans and social robots are increasingly working together, hand in hand, with increasing variety of functions (Bahrin et al., 2016). While separate human – and social robot working spaces disappear, social robots are becoming part of teams inside firms, as "machines as teammates" (Seeber et al., 2020). Even though there is more to social robots as autonomous teammates compared to today's social robots, social robots are the important first step towards this future scenario.

As Huang and Mutlu (2016) describe; collaboration does always require cognitive and communicative mechanisms. This is in order to coordinate the team members actions toward a shared goal. Thus, collaborative social robots must also utilize these mechanisms in order to coordinate their actions with their human partners (Huang et al., 2016). Our conceptualisation of a social robot which allows for human-robot collaboration in teams, is similar to the one of Huang et al. (2016) and Lemaignan et al. (2017); an important characteristic for HRC in general, is that it must be possible for the human to share a common workspace with the robot. Further, the exchange of information might happen through verbal- and non-verbal communication such as gaze by both, the human employee and the social robot. In HRC, the social robot must implicitly and explicitly recognize, understand and participate in communication situation (Lemaignan et al., 2017). Lastly, in order to derive at collaboration and joint actions, the social robot must perceive the intentions and beliefs of the human and the team as a whole.

The social robot which owns these characteristics and already finds successful application in different organisational processes is “Mr. Furhat”, a social robot which is for example used for enhancing unbiased recruitment, supports teachers and medical personnel for example with Alzheimer patients. Mr. Furhat is the “most advanced human- like social robot”. He combines characteristics of for instance usual chatbots and smart speakers in order to build powerful social interactions (Furhat Social robotics, 2019). Mr. Furhat is able to adapt gaze, look, tone of voice and language to particular situations. Social robots are able to react to particular situations and act on their own when needed. The goal of this social robot is to communicate with humans as humans do with one another by “listening, speaking, and expressing some degree of emotion” (Putnam, n.d.). This enables the social robot to directly interact with humans and thus makes it possible to build human-robot teams.

While we conceptualised human-robot collaboration and the type of social robot used in this study, the question on how social robots as teammates, can effectively collaborate with humans and how this is managed, arises.

2.2 Technology Acceptance and Collaboration with Humans

Currently, there is no theory on how human-robot collaboration works effectively, neither on how to manage collaboration. We combine different theories and insights from studies and incorporates them into a conceptual model. The grounding of our conceptual model is built by the TAM (Davis, 1989) and the adjusted unified theory of acceptance and use of technology, UTAUT. These models of technology acceptance deliver important insights on factors influencing human’s adaptation to and acceptance of technologies.

The TAM and UTAUT are limited with regards to the goal of our study since they do not refer to actual usage and collaboration with technologies and further, they do not refer to the technology we aim to investigate (smart technology). Nevertheless, we find that acceptance and intention to use the technology are important steps in order to arrive at intention to collaborate and finally getting closer to understand actual human-robot collaboration. Even though on finds criticism on the TAM and the UTAUT, they provide a frequently used model and systematic grounding to examine factors leading either to IS acceptance or rejection (Lee, Kozar & Larsen, 2003). Furthermore, the UTAUT was found to account for 70% of variance in technology usage intention (Venkatesh et al., 2013). These two models inspire our conceptual model. Since we want to get from acceptance of technology to understanding intention to collaborate and due to the smart technology (social robots) this study aims to investigate, we make use of insights from different scholars, including the TAM and UTAUT, to build our conceptual model. We come up with six variables by combining the scholars and theories on technology acceptance and collaboration. Examining six independent variables as combination of different theories, allows us to increase appropriateness of the research model and derive at users' intention to collaborate instead of solely acceptance. Finally, our conceptual model is made up of six independent variables affecting intention to use the technology;

1. Performance Expectancy
2. Trust
3. Effort Expectancy
4. Social Support
5. Organisational Support
6. Computer Anxiety

We will further refer to these independent variables as *technology acceptance factors*. In order to examine these variables, we take into account the conceptualization and operationalization of the variables as reported in previous scholars, meaning we make use of established scales and measurement items, further described in the Methodology. Even though we assume that there are more factors influencing effective human-robot collaboration (e.g. appropriation of the technology), we focus on the aforementioned variables for two main reasons; First, we focus on variables that were tested in previous studies and showed an effect on users' acceptance and/or intention to collaborate. Second, we focus on the main aspects which we consider as having a high probability to be intertwined with and further affected by human resource management systems in order to draw conclusions on implications for HRM of the future.

2.2.1 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" as described by Venkatesh et al. (2013) in the UTAUT. Venkatesh et al. (2013) used perceived usefulness, as original variables of the TAM as introduced by Davis (1989), and adjusted it as performance expectancy. Perceived usefulness is very similar to performance expectancy and defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Later it was found, that perceived usefulness is significantly correlated with self- reported indicants of using the technology (Davis, 1989). Therefore, the probability of accepting and valuing a particular technology increases in case it enhances daily life. Technology, in our case social robots, need to make tasks easier, enhance convenience and support everyday activities which are executed in teams. In order for the technology to be perceived as useful, it needs to be relevant in the light of the job it is expected to enhance (Ruel, Bondarouk & Van der Velde, 2007) and should bear a relative advantage in contrast to execution of the job without the technology on hand (Venkatesh et al., 2013). 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 social robot affects the users' intention to collaborate.

2.2.2 Trust

Trust is often defined as having confidence in something to do the right action (Gaudiello et al., 2016). Technology needs to be reliable and humans needs to be able to build trust that the system will perform as intended to in order to enhance job performance. Reliability, availability, confidentiality, integrity and maintainability appear to be important when it comes to human-robot trust (Laprie, 1992 as cited in Bischoff & Graefe, 2003). Trust is a major issue when it comes to working with smart technology and has been researched frequently. Different scholars found that trust significantly influences the acceptance of technology, by testing the original TAM (Wu et al., 2011; Faqih, 2011; Pavlou, 2003). Thus, trust can be used to determine overall acceptance of technology (Gaudiello et al., 2016). The development of appropriate levels of trust in social robots is a very critical issue when it comes to human-robot collaboration and regardless of the domain of application (Schaefer, 2013). In order for a functional relationship to be effective, human's trust in the social robot is an essential element (Schaefer, 2013). Unlike humans, who might develop certain kind of trust among each other, social robots might not be subject to this feeling (Freedy et al., 2007). Prahl et al. (2017) describe the importance of the "algorithm aversion" issue in their study. They explain the main problem is the fact that humans expect social robots, or other smart systems, to work perfect by having an error rate of almost zero. However, this is not expected from human colleagues, increasing trust in human- human collaboration. Thus, human often do trust advice by other humans more than advice by technology. The belief in social robot's ability to protect the interests of the team and the organisation is important in order for employees to share and allocate tasks and exchange information with the social robot (Freedy et al., 2007). A social robot should deliver a trustful service and avoidance of failures (De Santis et al., 2008). Fitting to the claim made by Prahl et al. (2017), it was found that reliability is the ultimate factor to determine employees' projections of the social robot's future reliability and perceptions of the social robot. After receiving bad advice by a computer, the technology is often utilized less than advice from human advisors. In turn, unreliable social robots are perceived as less animate, likable, intelligent and safe (Wright et al., 2019). Consequently, very low trust might lead to disuse and ignorance of the social robot. The less trust towards a social robot, the sooner an employee will intervene in its' task completion (Freedy et al., 2007; Hancock et al., 2011) and consequently, human-robot collaboration would be ineffective.

Not only is trust important in performance of the social robot but rather we find trust related to employee's well-being. We borrow the definition of perceived safety from Osswald, Wurhofer, Trösterer, Beck and Tscheligi (2012) and define it as the degree to which an individual believes that using a system will affect his or her well-being. In previous studies, that incorporated the TAM model, it was found that perceived safety is related to the use of a new technologies (Bröhl et al., 2016). In order to guarantee safety, companies need to consider all possibilities in which an employee could be harmed, including physical and also psychological harm (Lasota, Fong & Shah, 2017). Physical safety in human-robot collaboration need to be considered in terms of avoiding unintentional or unwanted contact between human and social robot. Next to that, psychological safety needs to be given, for instance the avoidance of discomfort or stress due to the social robots' characteristics, such as appearance, gaze and speech (Mumm & Mutlu, 2011 as cited in Lasota et al., 2017), in order for the human user to trust the social robot. Stress can have serious effects on employees' health and therefore harm the trust relationship. Even though engineers strive to adjust the social robots' behaviour to human characteristics, violations of social conventions and norms during interactions might occur which eventually negatively affects the trust relationship (Lasota et al., 2017). 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.

2.2.3 Effort Expectancy

Effort expectancy is the degree of ease of use of the system or technology (Venkatesh et al., 2013). The ease of working with a technology finds consideration in several models as for example the original TAM. Also, the technology success model introduced by DeLone and McLean (2003), describe ease-of-use, functionality and more as important facilitators for a high-quality system. 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., 2013). Whether people find a system easy to use includes the ease of learning to operate the system and whether they find it complicated or easy to work with (Venkatesh et al., 2013). Thus, a technology cannot be too complex for humans in order to successfully work with it.

We also propose that clear and understandable interaction with the system need to be ensured in order to keep expected effort related to the use of the system low. This is originally referred to as complexity and derived from the model of PC utilization by Thompson et al. (1991). Clear and understandable interaction includes certain degree of communication between social robots and humans. Communication, in general, describes the interchange of information and interaction of power attitudes and values (Loxley, 1997 as cited in Mickan et al., 2000). In order for organisations to work effectively and in turn for HRC, clear communication processes need to be defined, including continuous collaboration with the goal of knowledge exchange and meeting scheduling (Mickan et al., 2000). The least collaborative effort, therefore the goal of deriving at effective human-robot collaboration, can be accomplished by minimizing individuals' collective effort to gain an understanding of communication (Kiesler, 2005). We expect that the 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.

2.2.4 Social Support

The social environment of employees plays a crucial role in HRC. The culture the organisation stands for, provides employees with norms and values which are ideally transferred into behavioural norms in order to meet organisational expectations (Mickan et al., 2000). Values, norms and goals further strengthen motivation and commitment of employees, while commitment strengthens participation in teamwork (Pearce & Ravlin, 1987 as cited in Mickan et al., 2000). In teamwork, colleagues influence how people behave regarding the use of technology, according to the organisational culture. Venkatesh et al. (2013) refers to this as social influence, meaning whether the individual beliefs that he or she should use the system and whether important individuals expect this, as for instance colleagues or supervisors. Others, for instance the TAM and theory of planned behaviour, refer to the impact of the human's social environment as subjective norms (Davis, 1989; Ajzen, 1991). They explain this impact as whether people, in our case other teammates or colleagues, think it is appropriate to use the system which affects the human who is collaborating with the technology. This is since teamwork is a cooperative effort of team members to achieve a common goal, similar to the

Joint Intentions Theory (Tambe, 1997). The team as a whole affects the team members to work towards the common goal. We find more strengthening arguments for the influence of the social environment on HRC when looking at the psychological attachment theory. This theory states three social influence mechanisms, namely; 1. Compliance, an individual behaves a certain way in order to achieve favourable reactions from others like teammates 2. Identification, in order to maintain the individual's image in the group and 3. Internalisation, when the suggested behaviour is in line with the values of the individual (Kelman, 1958). Individuals accept and adopt a behaviour according to these mechanisms and thus, the theory explains how the use of technology is affected by different social influence processes (Lu, Cui, Tong & Wang, 2020). We argute that acceptance and collaboration with social 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.

2.2.5 Organisational Support

Often, employees must use and collaborate with technologies. We suggest that the acceptance, and in turn use, of technology is affected by the degree of support the individual receives by the organisation. We find institutional support as an important construct that "reflects assistance or barriers to the behaviour associated with external conditions" (Park, Rhoads, Hou & Lee, 2014). Park et al. (2014) summarized factors that influence technology acceptance and found supporting staff, consultant support, management support and training as relevant. Venkatesh et al. (2013) refers to this kind of support as facilitating conditions. Facilitating conditions can be defines as whether an individual's beliefs that the organisation itself and the infrastructure supports the use of the technology (Venkatesh et al., 2013). Perceived behavioural control, which was already introduced by Ajzen (1991) in the theory of planned behaviour, might be considered as part of organisational support. Perceived behavioural control incorporates knowledge providence by the organisation, a feeling of control and compatibility by the human (Ajzen, 1991). When it comes to knowledge and expertise, the individual who works with the social robot, should have the work related and task specific competency in order to perform (Ley & Albert, 2003). Thus, expertise about social robots and competency of employees to work together is required in human-robot collaboration. Knowledge, skills and attitudes belong to individual's competency or expertise. When it comes to collaboration among humans and social robots, computers or AI, an adequately trained workforce is crucial in order to adopt to change (Sandle, 2019). The model of PC utilization by Thompson (1991), strengthens our argument and describes the importance of guidance, instruction and assistance when individuals are expected to adopt to and work with a new technology. Park et al. (2014) states that a lack of adequate workplace resources in order to use a technology leads to low consideration of the technology as being useful. Nevertheless, there are reports about the absence of expertise, for instance; many companies are failing to prepare their workforce for the future work (Sandle, 2019). A majority of employees did not take part in any training in order to prepare for the future, however most employees expect regular training offerings in relation to digital technology and social robotics (Sandle, 2019). We expect that the users' acceptance and collaboration with technology is influenced by organisational support that enable him or her to do so. We propose the following:

Hypothesis 5: Organisational support affects the users' intention to collaborate.

2.2.6 Computer Anxiety

We define computer anxiety as the extent to which an individual feels unpleasant when using a technology (Park et al., 2014) while we refer to smart technology like social robots. Anxiety reflect the individuals emotional state such as frustration, apprehension and fear, uneasiness or a feeling of arousal (Osswald et al.,2012; Park et al., 2014). Social robots, which are smart technologies, are very complex in contrast to usual technologies like personal computers. These complex technologies require more involvement which might negatively affect the acceptance and adoption by the user. Different scholar provided insights on the significant effect of computer anxiety on attitudes and user behaviour (Venkatesh, 2000; Park et al., 2014; Osswald et al., 2012). Computer anxiety might be viewed from three perspectives as suggested by Torkzadeh and Angulo (1992); 1. The psychological perspective, meaning fear of working with the system and damaging it, 2. The sociological perspective, meaning fear of changes that comes with the technology like social pattern or job demand and 3. The operational perspective, meaning fear of problems related to actual working with the system and performing computer-related tasks. However, many scholars found that anxiety can be seen from the state perspective and thus, is subject to change over time (Chua, Chen & Wong, 1999). Due to arguments from different scholars, we expect that computer anxiety affects acceptance and collaboration with the technology and propose;

Hypothesis 6: Computer anxiety affects the users' intention to collaborate.

2.3 The Role of Human Resource Management

The following section delivers insights into human resource management in the industry 4.0 and examines different HR systems which are considered as moderators during this research. This is, in order to examine the role of- and to find implications for human resource management when it comes to the users' intention to collaborate with the smart technology.

2.3.1 Human Resource Management in the Industry 4.0 Context

HR in the industry 4.0 context is often referred to as smart HR, SHR (Sivathanu & Pillai, 2018) or E-HRM (Bondarouk & Brewster, 2016). On the one hand, it is supposed to bring challenges as for example selection of new technological tools or changes in the organisational culture. While HRM is shifting towards electronic HRM, we also find the risk of distancing, meaning decreasing direct contact between HRM specialists, line managers and workers (Bondarouk & Brewster, 2016). On the other hand, these challenges can bring benefits such as more efficient attraction, retention and development of new talents, often times generation y, and faster and better HR operations (Sivathanu & Pillai, 2018). New emerging technologies, in our case social robots, require changes in different HR disciplines. Sivathanu and Pillai (2018) argue how HR is changing due to the emerging smart industry; emerging technologies, such as AI and big data, and a change in the employee generation, since the trend goes towards generation y and z joining the workforce, bring changes in recruitment, development and off boarding. Recruitment becomes more automated, using AI for resume screening and interviews, development pays greater attention to development apps and virtual training possibilities, and big data help identify low performers in order to support off- boarding (Sivathanu et al., 2018). With that it seems that evolving technologies simplify certain HR processes and increase their efficiency.

We find suggestions for managing employees in the changing industry 4.0; Teamwork is becoming critical in many organisational environments. In highly complex environments such as human-robot collaboration, teamwork is more difficult than simply assigning tasks. Due to the complex environment, unexpected events might arise. Thus, there is an urgent need for HR to support employees when adopting to and collaborating with technologies. This is since implementation and adoption of technologies can be challenging, especially when it comes to involving humans. 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). Therefore, managing the human factor when adopting technologies is crucial (Libert et al., 2020). Scholars suggest that the HR department needs to change further in the future in order to deal with changes in the industry 4.0. Knod et al. (1984) suggests to do so by adopting a proactive stance in helping the infusion of new technologies, like social robots, into the workplace. 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). Change must occur along attraction, retention and development of employees in this new industrialisation. Organisations may need to train their workforce in order to strengthen their awareness and skills. Next to that, they might work on performance assessments, empowering of the workforce also in terms of leadership as well as the creation of incentives. Providing incentives and satisfactory training possibilities has a positive impact on employees' commitment (Jaworski, Ravichandran, Karpinski & Singh, 2018). Knod et al. (1984) argue similar; involving people early, gaining expertise (if necessary, through recruitment) and educate and train the human workforce is necessary for future HRC. From these suggestions one might find that HRM needs a shift in their major processes; planning, recruitment, selection, performance assessment, training and compensation. From these scholars we understand the role that HRM takes in the acceptance, adoption and in the end collaboration with new technologies.

2.3.2 Human Resource Management Systems in the Industry 4.0 Context

We pointed out how human resource management is changing due to changes that come with industry 4.0 and also pointed out suggestions for managing the human factor in the future. Nowadays, most firms work with a certain type of HRM system in order to manage employees. These systems entail characterises of a companies' values and norms and stand for how employees are managed inside the company. We suggest, that certain HR systems rather enable and support human- social robot collaboration while others might have a negative influence or no influence at all. 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. Commitment based HR systems are based on reinforcement of long-term orientation and commitment of employees. This is achieved by long-term compensation and employment security. Companies who apply this system focus on training, development and empowerment and encouragement of employees (Lepak et al., 2002). Companies that work with a compliance- based HR system, focus mainly on economic aspects in the employee-employer relationship and aim to ensure employees' compliance with rules, regulations, and procedures. Employees are subject to follow explicit definitions, a timetable and terms and conditions (Lepak et al., 2002). However, this study focuses on the productivity-based and collaborative HR system since these two are very different and almost contrary and we expect to achieve the most diverse outcome.

In a productivity-based HR system, employees get payed a market-based wage and managers are focused on employees' job performance. Jobs are more often standardized in order to find replacement on 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 et al., 2002). Since our study examines 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 independent variables and the users' intention to collaborate with the social robot is rather neutral or even negative.

Collaborative HR systems are characterised 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 et al., 2002). We expect a positive influence of the collaborative HR system on the relationship between the independent variables and the users' intention to collaborate with the social robot, since this system is rather related to the challenges of human-robot collaboration, especially in the team context, and thus, might positively affect how humans work together with social 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 smart 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 smart technology, such that the relationship becomes stronger when a collaborative HR system is present.

2.4 Conceptual Framework

The conceptual framework of this study is inspired by the initial technology acceptance model (Davis, 1989) and the later adjusted unified theory of acceptance and use of technology by Venkatesh et al. (2013). Next to making use of these theories, we incorporated insights from other theories, scholars and models into our framework. We came up with six independent variables; 1. Performance Expectancy, 2. Trust, 3. Effort Expectancy, 4. Social Support, 5. Organisational Support and 6. Computer Anxiety. These variables are factors related to behavioural intention to accept and use a technology and we expect these to affect the user's intention to collaborate with the social robot. The technology this study is investigating is smart intelligent technology, social robots, which is different from former technologies which were examined using technology acceptance models. The role of Human Resource Management is this model is related to a HR system which we expect to either strengthen or weaken acceptance and collaboration with technology. Therefore, the particular HR System builds the moderator variable of this research, which moderates the relationship between the technology acceptance factors and the users' intention to collaborate with the technology.

This conceptual framework is a visualization of the approach of this study; investigation of factors contributing to users' intention to collaborate with technology and additionally investigation of the moderating role of HRM systems. We believe that intention to collaborate is crucial in order to derive at actual effective human-robot collaboration.

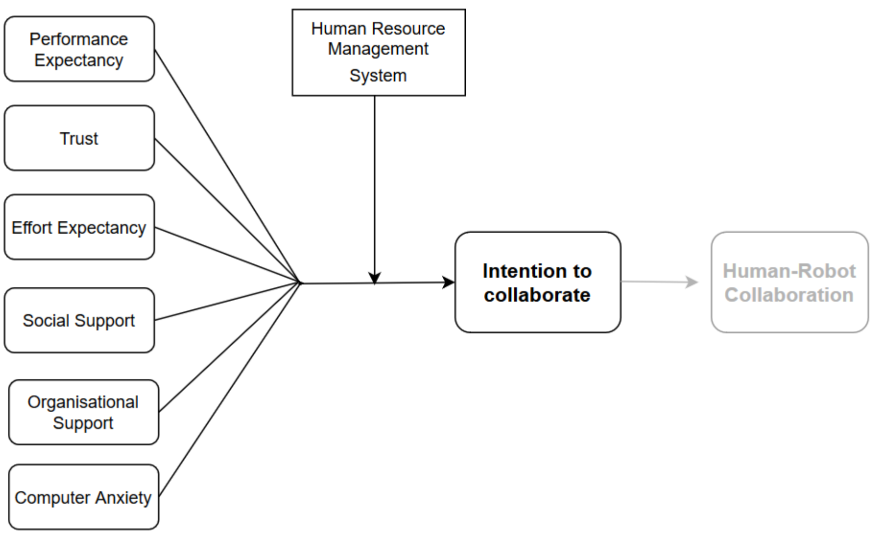

Figure 1: Conceptual Model

3. Methodology

Following we will discuss the methodology used to answer our research question "Which Factors influence Human-robot Collaboration in the Industry 4.0 Context and what are the implications for Human Resource Management". First, we will define the design of this study and the measurement of all variables. After that we will discuss how data was collected and analysed.

3.1 Research Design

The aim of this study is to provide insights on factors affecting a users' intention to collaborate with smart technologies which is important to derive at actual human-robot collaboration and to provide implications for effective management of HRC by HR departments. In order to answer the research question "Which Factors influence Human-Robot Collaboration in the Industry 4.0 Context and what are the implications for Human Resource Management?", this study conducted a quantitative investigation of HRC using the Vignette approach. Vignette studies combine characteristics of experimental designs and surveys. A Vignette study contains short descriptions of situations or persons, Vignettes, which are shown to respondents. After, respondents usually fill in surveys which are constructed around these scenarios (Atzmüller and Steiner, 2010). This research method was chosen for several reasons. A Vignette study consists of two main elements; a Vignette experiment and a traditional survey. This type of approach usually shows high internal validity, due to the experimental design, and high external validity due to the survey characteristics (Atzmüller and Steiner, 2010). Validity enables us to generalize the outcome of this study and draw conclusions on a broader population. Furthermore, since Vignette studies entail respondent's judgement on specific situations, they allow for detailed investigation on underlying opinions, behaviour and reasons. Since we wanted to gain an in- depth understanding of human acceptance- and collaboration with social robots and the role of HRM, a Vignette approach is appropriate. This Vignette study was designed using a quantitative approach and was conducted online. This enabled us to avoid direct interaction with respondents and thus reduce biases. A mixed design approach was chosen in which different Vignettes were assigned to different groups of respondents. We designed three different Vignettes in order to gain insights on whether the changes in the Vignettes additionally affect respondents and with that HRC.

3.1.1 Unit of Observation

In this study the unit of analysis is human-robot collaboration in teams. The unit of observation were men and women between 18 and 65 years of age in order to secure a balance in age and gender and to provide a generalizable outcome. Attention was also given to differentiation among education levels, in order to provide sufficient control variables and to avoid biased outcomes. We aimed to achieve a balance in age, gender and education. Participants took place in the research on a voluntary basis; thus, they did not get any incentive besides contribution to a meaningful outcome.

Since we also tested for a moderating effect of a given HR system attention was given to an even distribution of the Vignettes across respondents. The online survey software distributed the three different Vignettes randomly and evenly across participants whereas 36 participants received the first Vignette (productivity-based), 35 participants received the second (collaborative) and 38 received the third Vignette (neutral).

In total, 145 people participated in this study however, several cases appeared to invalid due to several missing values and were therefore excluded. Finally, the sample size consisted of 109 cases of which 75 were female and 34 males. Most participants, namely 70, were between 18 and 35 years old. 39 people were between 36 and 65 years old. We found that the level of education among participants was relatively balanced, whereas 46 participants went to a University or equivalent (Bachelor, Master, PhD) and 63 Participants received Highschool degrees, secondary school education or lower

1. Gender

	Frequency	*Percent*	*Mean*	*Std. Error*
Male	34	31.2	3,10	0,14
Female	75	68.8	2,99	0,11
Total	109	100.0		

2. Age

	Frequency	*Percent*	*Mean*	*Std. Error*
18-25	51	46,8	2,98	0,15
26-35	19	17,4	3,15	0,16
36-45	8	7,3	3,18	0,21
46-55	12	11,0	*3,05*	*0,17*
56-65	19	17,4	2,86	0,16
Total	109	100,0		

3. Highest Education

	Frequency	*Percent*	*Mean*	*Std. Error*
Doctoral or equivalent	2	1,8	2,90	0,38
Master or equivalent	16	14,7	3,40	0,15
Bachelor or equivalent	28	25,7	3,53	0,12
Highschool degree	37	33,9	3,23	0,11
Secondary school	16	14,7	*3,00*	*0,15*
Lower Secondary school	9	8,3	3,23	0,20
Other	1	0,9	2,00	0,54
Total	109	100,0		

Table 1: Demographics and Biographical Characteristics

3.2 Measurement

3.2.1 Independent Variables

The independent variables this study examined are; 1. Performance Expectancy, 2. Trust, 3. Effort Expectancy, 4. Social Support, 5. Organisational Support, 6. Computer Anxiety. In order to test which factors influence human-robot collaboration, different statements (survey items) related to the independent variables were given in the survey. We take into account the operationalization, of the variables we chose, as reported in previous scholars. Thus, the survey items were based on insights from different IS models and theories and further extensive literature reviews and can be found below. *Performance expectancy* consisted of three items and was measured according to the existing scale used by Venkatesh et al. (2003) in the UTAUT paper and the scale Davis (1989) in construction of the perceived usefulness variable. *Trust* consisted of four items and was measured by making use of items according to a scale developed by Schaefer (2013), measuring human-robot trust. The third independent variable, *effort expectancy* was again measured using a combination of scale items by Venkatesh et al. (2003) and Davis (1989) who refers to the variable as ease of use and was again measured by three items. *Social support* is sometimes referred to as subjective norms (Ajzen, 1991) or social influence (Venkatesh et al., 2003) and consisted of three items. We made use of the measurement scale used in both scholars and combined them. Our next variable, *organisational support,* was measured by combining items used in the measurement scale by Venkatesh et al. (2003) in measuring facilitating conditions and the scale used by Park et al. (2014) used to measure institutional support. Thus, we used four survey items to measure this variable. Lastly, we measured *computer anxiety*, which consisted of four items, by making use of the measurement scales developed by Venkatesh et al. (2000) and Park et al. (2014) to test computer anxiety in the light of technology acceptance. The measurement items can be found below, in Table 2.

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
Organisational 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

Table 2: Measurement Items per Construct

The grey measurement items were later excluded due to low construct loading and low reliability. The survey items were judged on a five-point Likert scale. Likert scales found successful application in most of the studies we build our measurement scales on. The scale was structured from low to high, thus from strongly disagree to strongly agree, which was later translated into numeric values in order to make use of the SPSS software.

3.2.1.1 Reliability and Validity

In order to ensure reliability of our measures, we conducted a confirmatory factor analysis and checked Cronbach alpha. A factor analysis was executed as special case of structural equation modelling in order to determine which survey items are loading on which variables (factors). CFA allows researchers to identify relationships between variables and factors before conducting the analysis for example when the researcher has a priori idea of underling factors backed up with theory. Furthermore, CFA allows to test hypothesis. CFA belongs to the statistical technique of structural equation modelling, which is known to be robust with different scales (e.g. Likert scales) and furthermore does not require distributional assumptions like normality or skewedness. For our research purpose, CFA appeared to be most appropriate and helps to ensure a reliable and valid outcome. It was found that three items out of the survey provided a very low loading (whether participants believed it was easy to learn how the social robot works, whether they believe guidance is necessary and whether they believe assistance in using the social robot is useful) and decreased construct reliability which is why these items were excluded from the analysis (grey in Table 2).

We found SRMR, as global model assessment and measure of approximate fit which shows whether the correlation matrix implied by the model is sufficiently similar to the empirical correlation matrix, to be .0795 which is below the recommended threshold of .08 and shows that the degree of misfit is not substantial (Henseler, Hubona & Ray, 2016). As measure of internal consistency and reliability, Cronbach alpha was used and calculated for each construct. Usually, Cronbach alpha of 0.7 is referred to as acceptable (Nunnally, 1978). However, several scholars state that this is no universal acceptable reliability value and one finds many scholars that mistakenly reject their whole analysis due to a low Cronbach value. It is rather the case, that an acceptable reliability value depends on the type of research application (Bonett & Wright, 2015). Since three of our six constructs score slightly below 0.7 (still above 0.6) we find these values still acceptable.

Factor loadings and Cronbach Alpha

Construct	*N of Items*	*Cronbach's Alpha*	*Loadings*
Performance	3	0.840	.91, .87, .83
Trust	4	0.755	.73, .69, .75, .85
Effort	2	0.600	.84, .84
Social Support	3	0.655	.68, .81, .78
Organisational Support	2	0.699	.91, .84
Computer Anxiety	4	0.876	.83, .84, .88, .86
Intention to collaborate	3	R^2 = 0.782	.95, .93, .89

Table 3: Factor Loadings and Reliability

In order to further ensure validity and reliability, assumptions need to be considered when making use of statistical methods. Since we use hierarchical regression analysis, we need to consider the sample size. Usually, we speak of a minimum sample size of 50, preferably 100 in multiple regression. With a sample size of 109, we meet this requirement. Other requirements are linearity, constant variance of the error terms, independence of the error terms and normality of the error terms' distribution. In order to ensure linearity and constant variance of the error terms, we looked at the residual plot and found that the relationship looks very linear and error terms seem to be randomly distributed rather than funnelled. The Shapiro-Wilk test confirms normality since we cannot reject the null hypothesis (.236 > .05). Lastly, we can confirm independence of the error terms by using the Durbin-Watsons test which gives a value of 1.4 which is close to 2 and therefore the error terms are independent. Since we meet all assumptions of hierarchical multiple regression analysis and ANOVA we continue with the analysis.

3.2.2 Dependent Variable

The dependent variable of this study is the user's *intention to collaborate* with the social robot. Our aim was to investigate whether the technology acceptance factors affect intention to collaborate and what the role of the HR department is, by integrating HR as moderator variable. We took into account the operationalization of intention to collaborate, as reported in previous scholars. The items of the dependent variable 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. The items per construct can be found above in Table 2 and factor loadings and R-Squared can be found in Table 3.

3.2.3 Moderator Variable

Our aim was to test for a significant effect of the independent variables 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 main Vignette was built on a description of human-robot collaboration in teams. The difference between the Vignettes was related to the type of HR system which is described in the Vignette. Thus, different types of HR systems were described in each Vignette in order to test on whether support of HR has an effect on user's intention to collaborate with the technology. The description of the HR system was based on insights by Lepak and Snell (2002) in which they examined different employment modes and their association with a type of HR system; commitment-based, productivity-based, compliance-based, and collaborative. We built two of our three Vignettes on *the productivity- based and collaborative HR system* model. This is, since these two HR systems are very different and almost contrary. In case the HR system moderates the relationship between the independent and dependent variable, we expected that the difference is examined best by making use of very different HR systems. The third one did not include information about a particular HR system and allowed us to examine whether particular HR systems affect intention to collaborate or not. We conceptualized the first two Vignettes according to Lepak and Snell (2002) as we did in our literature review. Shortly; *collaborative HR systems* are characterised 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 et al., 2002). We operationalized the first two Vignettes, productivity- based and collaborative HR systems, according to Lepak et al. (2002). We included, according to our standpoint, the most relevant and diverse characteristics of the two HR systems which can be found in Table 4. The described HR System can be found as Vignettes in the Appendix.

	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		

Table 4: Operationalisation Vignettes

3.2.4 Control Variables

Control variables used in this study are age, gender and education level. This is in order to ensure a balanced sample, a generalizable outcome and to avoid screwed data. For instance, age might influence users' perception of the technology because certain age groups are not as familiar with technological developments as others. For instance, Venkatesh et al (2003) found that acceptance of technology is higher for younger users. Further, we wanted to ensure that the study outcome is not biased by gender characteristics. This is since different scholars found fundamental differences between men and women as for example Croson and Gneezy (2009) in terms of risk preferences, social preferences, and competitive preference and Venkatesh et al. (2003) who describes that gender roles have an impact on individual attitudes and behaviour.

Lastly, we wanted to avoid screwed data or outliers due to the education respondents received and thus we control for education level. We conclude, that age, gender and education level have proven to be important control variables in previous studies (Venkatesh et al., 2003; Park et al., 2014; Schaefer, 2013) and are thus relevant in the context of this study.

3.3 Data Collection

Data was collected using a Vignette study and mixed design approach instead of a within-subject design. In mixed designs, different groups of respondents are confronted with different Vignettes, however within each group the respondents receive the same Vignettes to judge using a survey (Atzmüller et al., 2010). In this study, three types of Vignettes were randomly assigned to respondents, one Vignette per person. The Vignettes were built on a description of human-robot collaboration in teams. The difference between the Vignettes was in the introduction of a particular HR system.

Data was collected by making use of the web-based software Qualtrics XM. This software allowed for evenly and randomly distributed Vignettes across respondents. The Link to the survey was mainly distributed online over Facebook, Instagram, LinkedIn and a survey distribution platform called PoolPool where students take part in the research of other students. Furthermore, the survey was distributed across friends, colleagues and family and forwarded to third parties. In the end, 145 individuals participated. The survey included an introduction about the study and the researcher for information purposes. After this, questions about demographics (age, gender and education) and the description of the Vignette followed. In order to avoid missing data, the question that followed needed to be completed before the participant was able to complete the next part of the survey. The survey consisted of 24 statements, whereas 21 items measured the independent variables and three items measured to dependent variable. Participants had to judge these statements on a five-point Likert scale. Participation in this study took about 10 minutes.

3.4 Data Analysis

In order to measure whether Performance Expectancy, Trust, Effort Expectancy, Social Support, Organisational Support and Computer Anxiety have an effect on users' intention to collaborate with the technology (social robots), this study made use of statistical tests using the SPSS software and additionally the ADANCO software. Using the ADANCO software, we conducted a confirmatory factor analysis. Since we pre-determined the factor structure and furthermore wanted to test hypothesis, CFA appeared to be most appropriate. CFA, as special case of structural equation modelling, shows which items, included in the survey, were loading on which constructs of the conceptual model. In case statements were not loading on the particular variable (construct) or in case of very low loading, the item was removed from the construct. This was in order to increase construct validity since low factor loadings indicate that these items reflect the construct to a limited extent. After that, sum scores for each factor were calculated. Sum scores were calculated by computing a new variable in SPSS, while summing up all items that were loading on a particular construct. In order to test for reliability of the construct, Cronbach Alpha was used. After determining the different constructs, we conducted a hierarchical regression analysis. This was in order to test our hypothesis and thus determine whether the technology acceptance factors indeed have an effect on the dependent variable. 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. Afterwards, we conducted a post-hoc test by creating three separate regression models for each vignette group. Finally, ANOVA was used in order to test whether the difference in mean of the dependent variable, between the groups who received different Vignettes, is significant. This study makes use of regression analysis and ANOVA despite arguments that we cannot use a parametric test with an ordinal scale (Likert scale). We argue differently; it is indeed true that parametric methods should not be used on ordinal data since one cannot assume normality thus, the question arises how robust ones' Likert scale is. While Likert items may truly be ordinal, Likert scales which consist of sums across many different items measuring one construct, will be interval (Norman, 2010), which is true for our analysis. Another argument is, that even though conceptually a Likert scale is ordinal, it was found that this is indeed irrelevant to the analysis because the computer can only draw conclusions about the numbers themselves (Gaito, 1980). In our case, we distribute the numbers per scale item reasonably and make the assumption that the distance between categories is equal (1= strongly disagree, 2= disagree, 3= neutral, 4= agree, 5= strongly agree), which enables us to make inferences about means and differences. Different scholars suggest that one can treat ordinal Likert scales as continuous; either when the variables have 5 or more categories because in this case they can be treated as continuous without any harm to the analysis (Johnson & Creech, 1983; Norman, 2010; Sullivan & Artino, 2013; Zumbo & Zimmerman, 1993) or in case sum scores were created by summing up at least two survey items, which results in a higher number of categories than we usually see for ordinal Likert scales, resulting in continuous variables (StatisticsSolutions, n.d.). Thus, we used hierarchical multiple regression analysis to examine the relationship between the independent, the dependent and the moderator variables.

4. Findings and Results

This chapter presents the findings of this study, regarding effective human- social robot collaboration and implications for HRM. Descriptive results of the study are given, followed by a detailed hierarchical multiple regression analysis of the technology acceptance factors and their effect on the users' intention to collaborate. The regression analysis contains three models whereas the third model presents the interaction terms in order to examine whether the type of HR system has an effect on the relationship between the technology acceptance factors and the users' intention to collaborate with the social robot. Additionally, we conducted three separate regression analyses (per vignette group) as post-hoc test. Furthermore, analysis of variance is conducted in order to see whether the mean value of intention to collaborate differs between the vignette groups.

4.1 Descriptives

We present the means, standard deviations and correlations for the variables of this study below in Table 5. We do not find evidence to suggest multicollinearity since the Variance Inflation Factors are between 1.2 and 3.8 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 .658, are under the recommended threshold of .75 (Ashford & Tsui, 1991).

Correlations

	Mean	*SD.*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. Performance	3.24	0.93							
2. Trust	3.37	0.81	0.483**						
3. Effort	3.34	0.83	0.455**	0.658**					
4. Social Support	3.54	0.72	0.290**	0.299**	.313**				
5. Organisational Support	3.38	0.94	0.288**	0.463**	.454**	0.14			
6. Computer Anxiety	2.97	0.98	0.553**	0.645**	.572**	.246**	.578**		
7. Intention to collaborate	3.22	1.02	0.634**	0.626**	.618**	.269**	.438**	.836**	

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

Table 5: Means, Standard Deviations and Correlations

We found significant positive correlations between performance expectancy, trust, effort expectancy, social support, organisational support, computer anxiety and the users' intention to collaborate with the social robot. These significant positive correlations suggest that a higher expected performance by the social robot, higher levels of trust, a higher amount of social an organisational support as well as low expected effort when working with the social robot and low levels of anxiety by the user (both recoded) are associated with higher user intention to collaborate with the social robot. The mean values for the technology acceptance factors are balanced around a value of 3. The mean value for participants final judgement on their intention to collaborate is slightly above 3. This means that the number of people who would like to collaborate and the number of people who would not like to is almost even, but slightly more positive than negative.

Since we are not solely interested in the relationship between the technology acceptance factors and the users' intention to collaborate with the social robot but further on whether this relationship might be moderated by the type of HR system which is present in a company, we created interaction terms in order to analyse this phenomenon. In order to create these interaction effect, we created three dummy variables out of the different vignettes and standardized the variables. The mean and standard deviation can be found in Table 6.

Descriptive Statistics

	Mean	*Std. Deviation*
Performance x Productivity HR System	0.03	0.51
Performance x Collaborative HR System	0.14	1.07
Performance x Neutral HR System	-0.30	1.98
Trust x Productivity HR System	0.01	0.52
Trust x Collaborative HR System	0.12	1.24
Trust x Neutral HR System	-0.20	1.75
Effort x Productivity HR System	0.00	0.57
Effort x Collaborative HR System	0.02	1.11
Effort x Neutral HR System	-0.03	1.82
Social Support x Productivity HR System	-0.01	0.64
Social Support x Collaborative HR System	0.03	1.17
Social Support x Neutral HR System	-0.03	1.49
Organisational Support x Productivity HR System	-0.05	0.62
Organisational Support x Collaborative HR System	0.01	1.10
Organisational Support x Neutral HR System	0.15	1.66
Computer Anxiety x Productivity HR System	-0.05	0.59
Computer Anxiety x Collaborative HR System	0.08	1.19
Computer Anxiety x Neutral HR System	0.02	1.64

Table 6: Standardized Mean and Standard Deviation of Interaction Terms

We find that the mean values for participants who received the first Vignette (productivity-based HR system) are continuously lower than these for participants who received the second Vignette (collaborative HR system). Therefore, a collaborative HR system has the effect, that the scores related to the technology acceptance factors increase.

In general, we found slightly differences across gender-, age-, and education groups when it comes to their score in the survey. It was found that women scored slightly lower on intention to collaborate than men. Furthermore, the lower age groups, between 18 and 45, scored slightly higher on intention to collaborate. However, across the age groups, a significant amount of participant was rather neutral. When controlling for education level, we saw a similar picture as for the other control variables, meaning a slightly difference. Participants who received higher education (University degrees) scored higher on intention to collaborate with the social robot than participants with (high-) school degrees. In general, we find that males, people from the younger generation and people who received high education are more likely to collaborate with the social robot than women, older people or people who received general education.

*Gender / * Intention to collaborate*

		Strongly Disagree 1	1,33	1,67	2	2,33	2,67	3	3,33	3,67	4	4,33	4,67	*Strongly Agree* 5
Male	Count	1	0	1	4	3	1	1	0	7	7	0	7	2
	% within Gender	2,9%	0,0%	2,9%	11,8%	8,8%	2,9%	2,9%	0,0%	20,6%	20,6%	0,0%	20,6%	5,9%
Female	Count	1	4	4	8	4	5	11	12	7	12	1	5	1
	% within Gender	1,3%	5,3%	5,3%	10,7%	5,3%	6,7%	14,7%	16,0%	9,3%	16,0%	1,3%	6,7%	1,3%

*Age / * Intention to collaborate*

		Strongly Disagree 1	1,33	1,67	2	2,33	2,67	3	3,33	3,67	4	4,33	4,67	*Strongly Agree* 5
18-25	Count	2	2	1	6	4	4	5	7	7	6	0	6	1
	% within Age	3,9%	3,9%	2,0%	11,8%	7,8%	7,8%	9,8%	13,7%	13,7%	11,8%	0,0%	11,8%	2,0%
26-35	Count	0	2	0	4	0	1	2	1	4	2	0	3	0
	% within Age	0,0%	10,5%	0,0%	21,1%	0,0%	5,3%	10,5%	5,3%	21,1%	10,5%	0,0%	15,8%	0,0%
36-45	Count	0	0	0	0	1	0	1	0	2	2	1	1	0
	% within Age	0,0%	0,0%	0,0%	0,0%	12,5%	0,0%	12,5%	0,0%	25,0%	25,0%	12,5%	12,5%	0,0%
46-55	Count	0	0	0	1	1	1	2	2	0	4	0	1	0
	% within Age	0,0%	0,0%	0,0%	8,3%	8,3%	8,3%	16,7%	16,7%	0,0%	33,3%	0,0%	8,3%	0,0%
56-65	Count	0	0	4	1	1	0	2	2	1	5	0	1	2
	% within Age	0,0%	0,0%	21,1%	5,3%	5,3%	0,0%	10,5%	10,5%	5,3%	26,3%	0,0%	5,3%	10,5%

Education / Intention to collaborate*

		Strongly Disagree 1	1,33	1,67	2	2,33	2,67	3	3,33	3,67	4	4,33	4,67	*Strongly Agree* 5
Doctoral or equivalent	Count	0	0	0	1	0	0	1	0	0	0	0	0	0
	% within Highest Education	0,0%	0,0%	0,0%	50,0%	0,0%	0,0%	50,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Master or equivalent	Count	0	0	0	4	1	1	1	1	4	2	0	2	0
	% within Highest Education	0,0%	0,0%	0,0%	25,0%	6,3%	6,3%	6,3%	6,3%	25,0%	12,5%	0,0%	12,5%	0,0%
Bachelor or equivalent	Count	0	1	0	1	1	3	1	4	5	6	0	6	0
	% within Highest Education	0,0%	3,6%	0,0%	3,6%	3,6%	10,7%	3,6%	14,3%	17,9%	21,4%	0,0%	21,4%	0,0%
Highschool degree	Count	2	3	1	4	4	1	5	4	5	3	0	3	2
	% within Highest Education	5,4%	8,1%	2,7%	10,8%	10,8%	2,7%	13,5%	10,8%	13,5%	8,1%	0,0%	8,1%	5,4%
Secondary school	Count	0	0	2	0	1	1	4	3	0	4	1	0	0
	% within Highest Education	0,0%	0,0%	12,5%	0,0%	6,3%	6,3%	25,0%	18,8%	0,0%	25,0%	6,3%	0,0%	0,0%
Lower Secondary school	Count	0	0	2	1	0	0	0	0	0	4	0	1	1
	% within Highest Education	0,0%	0,0%	22,2%	11,1%	0,0%	0,0%	0,0%	0,0%	0,0%	44,4%	0,0%	11,1%	11,1%
Other / Andere	Count	0	0	0	1	0	0	0	0	0	0	0	0	0
	% within Highest Education	0,0%	0,0%	0,0%	100,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%

Table 7: Intention to collaborate per control variable

4.2 Hypotheses

In Table 8 the result of the hierarchical regression analysis is presented. In Model 1 we find the control variables, Model 2 additionally includes the independent variables and each vignette (HR System). Model 3 further includes 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. Further, we present the R Squared values.

Intention to collaborate			
Predictor Variables	*Regression Model 1*	*Regression Model 2*	*Regression Model 3*
Gender	0.42*	-0.01	-0.01
Age	-0.09	-0.06	-0.07
Highest Education	0.07	0.07	0.08
Performance		0.21**	0.09
Trust		0.04	0.01
Effort		0.17*	0.28*
Social Support		-0.01	0.04
Organisational Support		-0.08	-0.08
Computer Anxiety		0.64***	0.67***
Productivity HR System		-0.02	0.01
Collaborative HR System		0.00	-0.01
Performance x Productivity HR System			0.29
Performance x Collaborative HR System			0.16*
Trust x Productivity HR System			-0.14
Trust x Collaborative HR System			0.09
Effort x Productivity HR System			-0.15
Effort x Collaborative HR System			-0.08
Social Support x Productivity HR System			-0.08
Social Support x Collaborative HR System			-0.04
Organisational Support x Productivity HR System			0.05
Organisational Support x Collaborative HR System			-0.10
Computer Anxiety x Productivity HR System			-0.04
Computer Anxiety x Collaborative HR System			-0.05
R^2	0.24	0.88	0.90
R^2 *Change*	0.06	0.72	0.03

a Dependent Variable: Intention_to_collaborate

b Vignette1: Productivity HR System ; Vignette2: Collaborative HR System

Table 8: Results of the Regression Analysis

While Model 1 shows that gender has a significant positive effect on intention to collaborate (ß = 0.42, p = .047), this changes over Model 2 and 3 were we found a non-significant effect. Model 2 further presents that three out of the six independent variables have significant effects on the dependent variables, which are Performance expectancy (ß = .208, p = .002), Effort expectancy (ß = .172, p = .014) and Computer anxiety (ß = .639, p < .001). Therefore, we accept hypothesis 1, 3 and 6 which tell that performance expectancy, effort expectancy and computer anxiety significantly affect the users' intention to collaborate with the social robot. Due to the beta score, we can say that computer anxiety has the largest impact on a users' intention to collaborate. Further, we reject hypothesis 2,4 and 5 namely that trust, social support and organisational support would have a significant effect on the user's intention to collaborate with the social robot. In terms of organisational- and social support, we did not only find no significant effect on intention to collaborate but even a slightly negative one. Therefore, a one-unit increase in social- and organisational support has a slightly negative effect on the users' intention to collaborate. While the correlation between all variables is positive, the sign for organisation- and social support is changing in our regression model. The sign for social support changes after effort expectancy is added to the regression mode while the sign for organisational support changes after computer anxiety is introduced.

Model 3 of the regression analysis tested the moderation hypotheses, namely that the presence of a productivity-based HR system negatively moderates the relationship- and that the presence of a collaborative HR system positively moderates the relationship between the technology acceptance factors and employees' intention to collaborate with technology (Hypothesis 7 and 8). In order to examine the possible moderation effect, we created interaction terms between the technology acceptance factors and two vignettes, thus two types of HR systems, the productivity-based system and the collaborative system. The third vignette was the neutral HR system which serves as reference category in this regression model and is therefore not included. Model 3 includes these interaction effects. The analysis shows that the interaction effect between performance expectancy and the present collaborative HR system is significantly positive at the .05 level (ß = .165, p = .04). Therefore, Hypothesis 8 is supported in that the HR system moderates the relationship between performance expectancy and employees' intention to collaborate. More specifically, a collaborative HR system positively moderates the relationship between performance expectancy (technology acceptance factor) and employees' intention to collaborate with technology.

Nevertheless, we have to reject Hypothesis 7 since the effect of the productivity-based HR system on the relationship between performance expectancy (technology acceptance factor) is neither significant nor negative as we suggested. For the other technology acceptance factors; trust, effort, social support, organisational support and computer anxiety, we can only partly support Hypothesis 7 and 8 in terms of the sign of the relationship. We did not find a significant positive or negative effect of certain HR system on the relationship between the technology acceptance factors and the users' intention to collaborate. Even though the effect of these factors is not significant we might state the direction of the relationship. The interaction effect between the productivity-based HR system and trust is negative as expected while the interaction effect between the collaborative HR system and trust is positive, also as expected (Hypothesis 7 and 8). In terms of effort expectancy, the interaction effect between the productivity-based HR system as well as between the collaborative HR system and intention to collaborate is negative, while the latter was not expected. This is also the case for social support. In terms of organisational support, we get a switched outcome while the interaction effect between the productivity-based HR system and intention to collaborate is positive- the interaction effect between the collaborative HR system and intention to collaborate is negative, reverse to what was expected. Lastly, computer anxiety shows a negative interaction effect between the productivity-based HR system as well as between the collaborative HR system and intention to collaborate. Even though Table 6 indicates certain difference between mean value for the technology acceptance factors related to the different Vignettes introduced, the effect of the interaction terms on the dependent variable are very diverse and therefore only partly support Hypothesis 7 and 8, since only the performance interaction terms was indeed significant. Worth mentioning is the change in the R-Squared from Model 1 to Model 3 while we achieve an R-Squared value of .9. This value indicates that 90% of the variance in the dependent variable is predictable from our technology acceptance factors.

In order to strengthen our findings, we decided to include an ANOVA Table which looks at the different scores on intention to collaborate for the three different Vignette groups. Table 9 shows that the scores for dependent variable are not significantly different for the three groups ($p = 0.56 > \alpha = 0.05$).

Intention to collaborate

	Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
Between Groups	1	2	0.60	0.59	0.56
Within Groups	107	106	1.01		
Total	108	108			

Table 9: ANOVA - Dependent Variable

Even though the ANOVA shows no significant difference in means between the vignette groups on intention to collaborate, we were interested to look at the difference between the Vignette groups in a more detailed way, meaning separately and on a factor level. Therefore, we conducted three separate multiple hierarchical regression analyses, meaning a separate analysis per Vignette group (productivity-based, collaborative, neutral). The separate analyses serve as post-hoc test. The group who received the Productivity-based Vignette can be found in Table 10, the Collaborative Vignette group can be found in Table 11 and the Neutral Vignette group can be found in Table 12.

Intention to collaborate			
Predictor Variables	*Regression Model 1*	*Regression Model 2*	*Regression Model 3*
Gender	0.42*	0.01	0.01
Age	-0.09	-0.07	-0.07
Highest Education	0.07	0.08	0.08
Performance		0.21***	0.17**
Trust		0.04	0.12
Effort		0.17**	0.23**
Social Support		-0.01	-0.05
Organisational Support		-0.08	-0.18
Computer Anxiety		0.64***	0.64***
Productivity HR System		-0.02	-0.04
Performance x Productivity HR System			0.22
Trust x Productivity HR System			-0.25
Effort x Productivity HR System			-0.11
Social Support x Productivity HR System			0.01
Organisational Support x Productivity HR System			0.15
Computer Anxiety x Productivity HR System			-0.02
R^2	0.24	0.88	0.89
R^2 Change	0.06	0.72	0.01

a Dependent Variable: Intention_to_collaborate

Table 10: Results of the Regression Analysis – Interaction terms productivity-based HR System

We see that the results of the group who received the productivity-based vignette, are very similar to the results in table 8. Solely the sign for the interaction between social support and the productivity-based HR system changed and became positive.

Intention to collaborate			
Predictor Variables	*Regression Model 1*	*Regression Model 2*	*Regression Model 3*
Gender	0.45*	-0.01	-0.04
Age	-0.09	-0.06	-0.07
Highest Education	0.07	0.07	0.07
Performance		0.21**	0.17*
Trust		0.04	-0.03
Effort		0.17*	0.22**
Social Support		-0.01	-0.01
Organisational Support		-0.08	-0.03
Computer Anxiety		0.64***	0.65***
Collaborative HR System		0.01	-0.02
Performance x Collaborative HR System			0.13
Trust x Collaborative HR System			0.10
Effort x Collaborative HR System			-0.05
Social Support x Collaborative HR System			-0.02
Organisational Support x Collaborative HR System			-0.13
Computer Anxiety x Collaborative HR System			-0.04
R^2	0.24	0.88	0.89
R^2 Change	0.06	0.72	0.02

a Dependent Variable: Intention_to_collaborate

Table 11: Results of the Regression Analysis – Interaction terms collaborative HR System

Also, table 11, which includes the results of the group who received the second vignette which was based on a collaborative HR system, is very similar to our hierarchical regression analysis in Table 8 and we cannot find a significant difference to these results.

Intention to collaborate

Predictor Variables	*Regression Model 1*	*Regression Model 2*	*Regression Model 3*
Gender	0.42*	-0.01	0.00
Age	-0.09	-0.06	-0.07
Highest Education	0.07	0.07	0.08
Performance		0.21***	0.39***
Trust		0.04	0.05
Effort		0.17*	0.06
Social Support		-0.01	0.00
Organisational Support		-0.08	-0.11
Computer Anxiety		0.64***	0.59***
Neutral HR System		0.00	0.00
Performance x Neutral HR System			´-0.10*
Trust x Neutral HR System			-0.01
Effort x Neutral HR System			0.07
Social Support x Neutral HR System			0.02
Organisational Support x Neutral HR System			0.01
Computer Anxiety x Neutral HR System			0.03
R^2	0.24	0.88	0.89
R^2 *Change*	0.06	0.72	0.02

a Dependent Variable: Intention_to_collaborate

Table 12: Results of the Regression Analysis – Interaction terms neutral HR System

Worth mentioning is Table 12. Here we find that the signs of the interaction terms are mostly positive while only the interactions between trust- and performance and the neutral HR system are negative. Furthermore, we find that there is a significant interaction effect of the neutral HR system on the relationship between performance expectancy and intention to collaborate. This significant interaction effect can be found in the simple slope model in Figure 2.

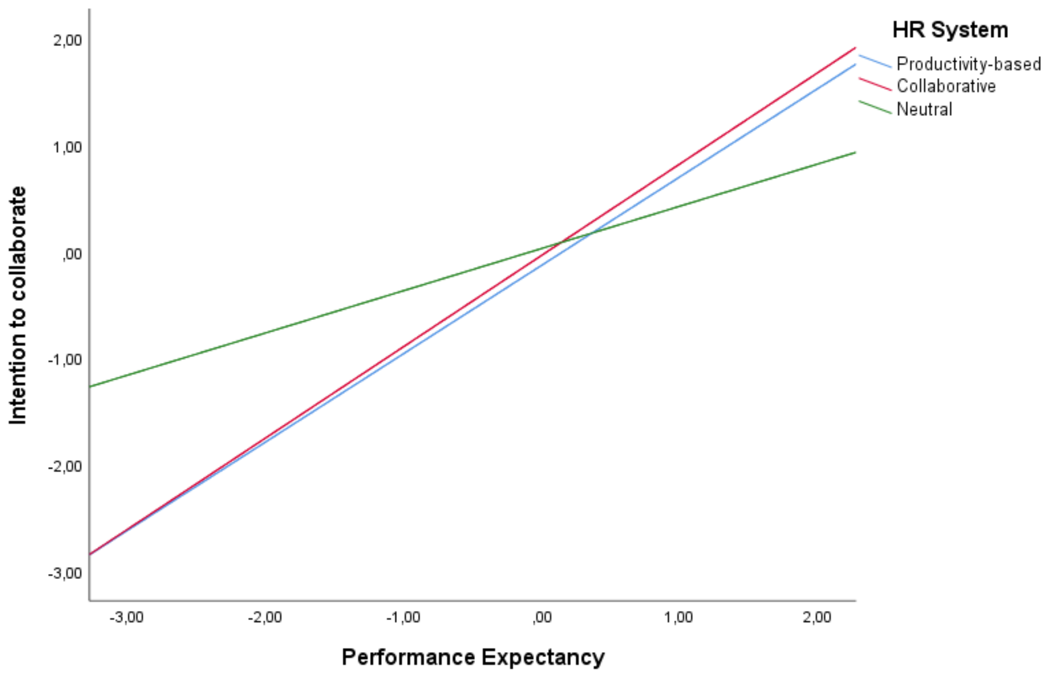

Figure 2: Interaction plot

The simple slope model shows that the relationship between performance expectancy and the users' intention to collaborate is different according to the vignette (HR system) they were introduced to. While we expected the relationship to be negative for the productivity-based system, rather neutral for the neutral HR system and positive for the collaborative system, the plot shows that this is not the case. While the productivity-based system shows a slightly less positive effect than the collaborative system on the relationship between performance expectancy and the users' intention to collaborate, the neutral vignette stands out since it has, to a certain extent, a less positive effect than the productivity-based or collaborative HR system.

5. Discussion

The aim of this thesis was to investigate factors that affect a users' intention to collaborate with smart technologies (social robots) in teams in order to derive at a conclusion for effective human-robot collaboration in the industry 4.0 context and specially to draw implications for Human Resource Management. We will now discuss the main results and the theoretical and practical implications. After, limitations of this research are presented and direction for future research is given.

5.1 Main Results

We found that all technology acceptance factors of this study; Performance Expectancy, Trust, Effort Expectancy, Social Support and Computer Anxiety, are significantly correlated with a users' intention to collaborate with a social robot. However, when testing our conceptual model with hierarchical regression analysis and additionally conducted a post-hoc test, we found that only performance expectancy, effort expectancy and computer anxiety have a significant effect on the users' intention to collaborate with the social robot. Not only that social-, organisational support and trust do not have a significant effect anymore, but also the sign for social- and organisational support changes so that they appear to have a negative effect. They key idea behind this phenomenon is confounding and suppression. Falk and Miller (1992) refer to this as suppressor effect, meaning when the path coefficient in regression and the correlation do not have the same sign, the original relationship has been suppressed by other variables. We believe that we are dealing with real suppression whereas an important predictor variable (for us necessary in order to understand the true relationship between the independent and dependent variables) suppresses the effect of another predictor variable. In our case, social- and organisational support change their sign when computer anxiety and effort expectancy are introduced to the regression model. Further, the significance of these variables and the trust variable disappears when the other technology acceptance factors are introduced. When a real suppressor effect occurs, Falk and Miller (1992) advise that the correct sign for interpretation is that presented by the path coefficient.

Thus, performance expectancy significantly affects the users' intention to collaborate with the social robot and we can argue with Davis (1989) in that perceived usefulness is significantly correlated with self- reported indicants of using the technology. We found that most participants believed the social robot would be relatively useful in their job and that it would make tasks easier. We can agree with Davis (1989) who stated that acceptance and valuation of a technology increases in case it enhances daily life. Furthermore, our results let us agree with Venkatesh et al. (2013) who argued that in case a technology allows for a relative advantage in comparison to executing a task without it, it will be perceived as useful. Also, effort expectancy significantly affects the users' intention to collaborate with the social robot and we support Davis (1989) and Venkatesh et al. (2013) in that technology which is easy to facilitate and therefore free of effort will enhance the attitudes towards it. The fact that participants were positive regarding working with the system, shows that the technology appears to be easy to use and to work with. This gives us reason to agree with Davis (1989) and Venkatesh et al. (2013); lower effort enhances the users' attitudes towards technology and a feeling of control and compatibility by the human is crucial in order to accept and work with technologies (Ajzen, 1991). The third significant effect on users' intention to collaborate is given by computer anxiety while the scores of participants on that variable were very mixed, from total rejection to full collaboration. The individual emotional state of a user significantly affects him or her. We can agree with different scholars who provided insights on the significant effect of computer anxiety on attitudes and user behaviour (Venkatesh, 2000; Park et al., 2014; Osswald et al., 2012). The users' intention to collaborate with the social robot is the dependent variable while half of the participants would collaborate with the social robot eventually. This shows that the participants in our study do not fully support the use of smart technologies in team settings.

We would also like to briefly mention that we found a significant difference among age groups, meaning that the older generation was less likely to collaborate with the social robot. Therefore, we can support Venkatesh et al (2003) who found that acceptance of technology is higher for younger users.

We were also interested if the presence of certain HR system in the company the user works with has a moderating effect on the relationship between the technology acceptance factors and users' intention to collaborate. We found that the introduction of a specific HR system, either productivity-based, collaborative or neutral, does only have a significant effect on the relationship between performance expectancy and the users' intention to collaborate with the social robot. The effect on the other technology acceptance factors is not significant. The significant difference lies in the introduction of the neutral vignette, whereas this group scores significant lower on intention to collaborate than the collaborative and productivity-based group, who score almost similar. We suggest that the effect was only significant on performance expectancy due to a methodological issue since the Vignettes explicitly stated how each HR system is related to increasing performance and productivity. Therefore, we suggest that participants transferred this information on the items which measured performance expectancy. In general, we found that a productivity-based HR system does not negatively moderate the relationship between the technology acceptance factors and dependent variable. This study deals with collaboration in teams between humans and smart technologies while the HR system we introduced is rather focused on individual short-term performance. Thus, we expected a negative effect however, participants were not influenced by this. Similar, a collaborative HR system does not significantly positively moderate the relationship between the technology acceptance factors and employees' intention to collaborate with technology. Since we introduced this HR system as related to the challenges of human-robot collaboration, especially in the team context, we expected that it would positively affect the user. This gives us reason to argue that the HR system of a company, whether it is focused on productivity, a joint outcome or whether no specific system is mentioned, is not enough when it comes to working with a completely new, smart system, meaning special support (next to the HR system) is needed in all kind of organisational cultures and human resource management departments.

5.2 Theoretical Implications for Human Resource Management

This study has some theoretical implications for human resource management in the industry 4.0. Our results show that several factors are significantly important in order to strengthen the users' intention to collaborate with the social robot; performance expectancy, effort expectancy and computer anxiety. These have significant effects on the users' intention to collaborate with a social robot, while the effect of social- and organisational support as well as trust were not significant. Earlier studies and theories on technology acceptance suggested the effect of performance and effort on a users' behavioural intention (Davis,1989) and the significant effect of whether individuals show computer anxiety related to a technology (Venkatesh et al., 2013). We can confirm these findings and even expand these theories on technology acceptance since they appear to be partly applicable when it comes to working with smart technologies like social robots. These theories were not tested before in the context of smart technologies. The TAM (Davis,1989) is therefore also applicable in this context. Nevertheless, we cannot fully support the complete UTAUT to be true in the light of our study (Venkatesh et al., 2013) since we did not find a significant effect for social- and organisational support which are similar to Venkatesh's social influence and facilitating conditions. The TAM and the UTAUT do not explain collaboration but rather a behavioural intention to accept and use technology thus, we cannot particularly conclude on actual collaboration. Rather we might state that the TAM and UTAUT are partly applicable to understand intention to use and collaborate with smart technologies like social robots but we cannot confirm if they explain actual collaboration.

When it comes to a users' intention to collaborate in order for effective human-robot collaboration to happen, preparation is a very important factor. We argue like Knod et al (1984), that it is important for HRM to adopt a proactive stance by including the user, who has to work together with the social robot eventually, as early as possible, meaning when the social robot is first introduced in the company. There is a need for preparation (Libert et al., 2020) in terms of educating users at an early stage. Education must not only include actual (on-the-job) training but also educating on general facts and features regarding the smart technology. The user must perceive the technology as useful from the beginning in order for adoption and acceptance, which is important in order to derive at collaboration. Furthermore, the user needs to perceive some kind of control over the technology to strengthen empowerment (Libert et al., 2020) and to receive a feeling of safety. This is also important in order to avoid the development of some kind of anxiety regarding the technology or even an aversion. After preparing and empowering the users, actual training should follow. This is in order to strengthen the users' awareness and skills (Libert et al., 2020; Knod et al., 1984). Education, training and on-the-job-training appear to be useful alternatives in order to respond to the wishes of participants and furthermore, to avoid stress which affects the workers' health and satisfaction and eventually turnover (Libert et al., 2020). Also, we would like to state the importance of the time after the aforementioned introduction phase. In order to ensure continuous human-robot collaboration, support by the HR Management cannot stop after training and education. Incentives and other methods like performance assessment prove to be useful methods in empowering the user on a long-term basis and to gain commitment (Jaworski et al., 2018). Thus, in order for user 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).

Second, our findings suggest that age plays an important role in willingness to collaborating with technologies, thereby contributing to the literature about the acceptance of technologies. Also, other scholars show that differences in adopting to certain technologies exists between age, gender and education (Venkatesh et al., 2003; Park et al., 2014; Schaefer, 2013). While we strongly advice to not disadvantage anyone because of their age, gender or education, we rather want to demonstrate that there are differences between certain individual characteristics which are either associated with a higher intention- or a lower intention to collaborate with the social robot.

Lastly, we contribute to the literature on HRM systems, by integrating different HRM systems as moderator variables in our study and examined their influence. Today most firms work with certain HR systems (we examined the collaborative and productivity-based) which entail characterises of the companies' values and norms. While the productivity- based HR system is focused on individual performance, the collaborate system is focusing on joint team outcomes. Usually, one would expect a difference in users' intention to collaborate with a social robot regarding the HR system which is in place in a firm. Also, Lepak and Snell (2002) examined different HR systems and the effect on human capital and found significant effect, while we did not find a significant effect. This might indicate that literature on HR systems from industry 3.0 is not perfectly applicable in industry 4.0 anymore. Thus, we further add to the HR literature since HR systems in the context of smart technologies in the industry 4.0

might yield a different effect than they used to. We argue that when it comes to adoption to and collaboration with new, smart technologies - preparation, empowerment and incentives are needed no matter what kind of HR system is in place. We do not want to challenge Lepak and Snell (2002) by denying the importance of an HR system which fits the norms and values of a company, quite the reverse. However, we want to clarify that, when it comes to collaboration with smart technologies in the industry 4.0, a fitting HR system alone might not provide enough support but rather the combination with an overarching additional system including specific preparation, empowerment and incentives related to the challenges of human-robot collaboration is needed.

5.3 Practical Implications for Human Resource Management

We found that the TAM is applicable to smart technologies which are often found in the industry 4.0. Human-robot collaboration can be created more effectively when keeping the Technology acceptance model (Davis,1989) in mind. For managers, the TAM can provide direction for effectively managing the human factor in human-robot collaboration. The expected performance of the social robot is important to perceive by the employees in order to strengthen their intention to collaborate in hybrid teams. Providing employees with detailed information opportunities and drawbacks that the technology brings, can thus strengthen their intention to collaborate. Further, HR managers can support this intention by keeping the effort related to the new technology (social robot) as small as possible. Low effort related to learning to operate the system and working together with it supports employee's positive intention to collaborate. 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 and efficient selection of fitting employees for hybrid teams can strengthen effective human-robot collaboration. Our findings cannot fully support Lepak and Snell (2002) in their argument that strategic value and uniqueness of human capital differs across the type of HR systems, however we still consider a fitting HR system as important for effective human resource management. We suggest that for effective human-robot collaboration, intention to collaborate is decisive and intention can be strengthened by high expected performance, low effort and low anxiety. These factors in combination with a fitting HR system significantly contribute to effective human-robot collaboration.

5.4 Limitations and Suggestions for Further Research

As with every study, we want to draw attention to the limitations that come with our research. One limitation is the method we used, a Vignette study. One might argue that self-reported data might be biased since our study deals with human behaviour. Further research could address this issue by adopting a qualitative research method like interviews or observations in order to avoid self- reporting 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. Therefore, respondents were fantasising about actual human-robot collaboration. We believe that the introduction of the HR system as a text was not strong enough for participants to put themselves into the situation we aimed for. Also, since we did not use a manipulation check in order to see whether participants actually experienced the manipulation, we cannot be sure that they were actually fully aware of the introduced HR system. Furthermore, we believe that when it comes to smart technologies, special support of a firm is always required since people are not very aware of smart technologies yet. Therefore, due to the method and the novel technology, most participants might have overread the content of the Vignette or at least it moved to the background after they read about human-robot teams. The fact that a social robot is introduced as a teammate gained all the attention while the present HR system lost its' worth for that moment. We again suggest that this might be addressed in future research for instance by a case study in an organisation that implemented certain HR system in order to observe the effect of this HR system directly.

In studying effective human-robot collaboration, we also find a limitation regarding our sample. While we aimed for a balance in gender, it turned out that 69% of respondents were female while 31% were male. Next to that, we experienced that most participants are either of German or Dutch nationality. Further research could address this by distributing the survey randomly and evenly. Furthermore, data collection could take place in different countries while our data might be limited to the Dutch and German population.

While we examined which factors affect human-robot collaboration, the role of the HR system and the implications for human resource management, further research could investigate explicit methods and procedures for managing human-robot collaboration in the industry 4.0.

6. Conclusion

Managing the human factor in the industry 4.0 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; Sivathanu & Pillai, 2018; Liboni et al., 2019) rather than effective human-robot collaboration in hybrid teams. Seeking to fill this gap in the human resource literature, this study aimed to answer the research question; "Which Factors influence Human-Robot Collaboration in the Industry 4.0 Context and what are the implications for Human Resource Management?" Our findings show that performance expectancy, effort expectancy and computer anxiety significantly affect the users' intention to collaborate with the social robot. Since we studied intention to collaborate with social robots, rather than actual human-robot collaboration, we can only suggest that performance expectancy, effort expectancy and computer anxiety in turn actually affect human-robot collaboration and conclude that our findings are more meaningful for behavioural intention to collaborate than actual collaboration.

In general, we found that employees need to experience the usefulness of the social robot for instance by simplification of tasks or performance increase. Furthermore, collaboration should be free of effort by reliability and clear interactions, and availability of the necessary skills and knowledge. Lastly, perceived control and a feeling of pleasure and relaxation when working with the social robot is crucial. The support for the proposed moderating effect of certain HR system was weak, as we only found a significant interaction effect for performance expectancy. We demonstrate the importance of the technology acceptance factors and a fitting HR system in firms. We recommend human resource management departments to provide comprehensive preparation, including training and education, empowerment and incentives to support the employees' intention to collaborate with the technology, and finally actual human-robot collaboration in hybrid teams.

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8. Appendices

Appendix 1: Vignettes

Page 1: Introduction

As part of my Master Thesis, I am conducting a study on human-robot collaboration and I am happy that you are willing to participate! This study contains a scenario that you should read beforehand. After that you are invited to rate the statements below, in relation to the scenario given to you before. Please imagine that the scenario is about you, thus you are the employee described in the scenario. Your answers are treated anonymously and results are solely used as part of my Master Thesis.

Part 2: Vignette

1: Pictures (same for each group)

(Retrieved from Furhatsocial robotics.com)

Vignette 1 (Productivity- based HR System):

You are a team member of the project management team at a big Automotive company. Your job is highly standardized and this is why you are getting a straight salary without any incentives or bonuses. Your company emphasizes job performance and productivity. You are employed with the goal to deliver results and keep the company's performance high.

During the last years, the firm you are working for became highly digitalised and automated, just like many others in the branch. In their industrial processes, your firm is already working with many social robots for example in the manufacturing process. Your firm is always up to date on the newest trends and developments in the industry and became aware of the newest social robot; "Mr. Furhat". Mr. Furhat" is a social robot, "the most advanced human- like social robot". Mr. Furhat is for example used for enhancing unbiased recruitment in firms, to support teachers and also medical personnel for example with Alzheimer patients. He is able to adapt gaze, look, tone of voice and language. He can react to particular situations and act on his own when needed. This enables the social robot to directly interact with humans and thus makes it possible to build human-robot collaboration for instance in teams.

It was decided, that Mr. Furhat is going to be the new member of your project team.

Vignette 2 (Collaborative HR System):

You are a team member of the project management team at a big Automotive company. The company you are working for finds a functional team and network building very important. Your managers are rather focused on increasing interpersonal relations among employees than individual productivity. You are working in teams on a daily basis and therefore, you are also judged on team- performance and receive incentives when you accomplish a goal together with your team.

During the last years, the firm you are working for became highly digitalised and automated, just like many others in the branch. In their industrial processes, your firm is already working with many social robots for example in the manufacturing process. Your firm is always up to date on the newest trends and developments in the industry and became aware of the newest social robot; “Mr. Furhat”. Mr. Furhat” is a social robot, “the most advanced human- like social robot”. Mr. Furhat is for example used for enhancing unbiased recruitment in firms, to support teachers and also medical personnel for example with Alzheimer patients. He is able to adapt gaze, look, tone of voice and language. He can react to particular situations and act on his own when needed. This enables the social robot to directly interact with humans and thus makes it possible to build human-robot collaboration for instance in teams.

It was decided, that Mr. Furhat is going to be the new member of your project team.

Vignette 3 (No input about HR System):

You are a team member of the project management team at a big Automotive company. During the last years, the firm you are working for became highly digitalised and automated, just like many others in the branch. In their industrial processes, your firm is already working with many social robots for example in the manufacturing process. Your firm is always up to date on the newest trends and developments in the industry and became aware of the newest social robot;

“Mr. Furhat”. Mr. Furhat” is a social robot, “the most advanced human- like social robot”. Mr. Furhat is for example used for enhancing unbiased recruitment in firms, to support teachers and also medical personnel for example with Alzheimer patients. He is able to adapt gaze, look, tone of voice and language. He can react to particular situations and act on his own when needed. This enables the social robot to directly interact with humans and thus makes it possible to build human-robot collaboration for instance in teams.

It was decided, that Mr. Furhat is going to be the new member of your project team.

Appendix 2: Survey

Control Variables

1. **Gender**
   Male
   Female
   Other/ Prefer not so say

2. **Age**
   18-25
   26-35
   36-45
   46-55
   56-65

3. **Highest education**
   Doctoral or equivalent
   Master or equivalent
   Bachelor or equivalent
   Highschool degree
   Secondary school
   Lower Secondary school
   Other

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
Organisational 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

Appendix 3: Descriptives

Frequency per Survey Item

Frequency Statistics

		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	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	I believe it is easy to work together with the robot	I believe interaction with the robot is clear and understandable	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
N	Valid	109	109	109	109	109	109	109	109	109	109	109	109
	Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean		3,35	3,49	2,91	3,39	3,64	3,39	3,12	3,31	3,35	3,60	3,44	3,63
Std. Deviation		1,13	1,00	1,08	0,98	1,06	1,11	1,12	1,01	0,96	0,89	0,91	1,03

Frequency Statistics

		I believe support of the management in working with the robot would be important to me	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	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	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
N	Valid	109	109	109	109	109	109	109	109	109	109	109	109
	Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean		3,63	4,44	4,08	3,42	3,37	2,82	2,94	3,00	3,13	3,35	3,41	2,94
Std. Deviation		1,03	0,73	0,83	1,11	1,05	1,15	1,17	1,09	1,22	1,15	1,08	1,07

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