International Journal of Social Science and Human Research

**ISSN (print): 2644-0679, ISSN (online): 2644-0695**

Volume 08 Issue 06 June 2025

DOI: 10.47191/ijsshr/v8-i6-15, Impact factor- 8.007

Page No: 4055-4062

# Synergy at Work: How Human-Robot Collaboration Elevates Employee Performance

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**ABSTRACT:** In today's Industry 5.0 workplaces, people and robots are teaming up like never before, blending human ingenuity with robotic precision to boost productivity. This paper dives into what shapes workers' attitudes when collaborating with robots and how these dynamics lift their performance. We propose a conceptual framework that explores trust, adaptability, and clear communication as key ingredients for success. When employees feel comfortable with robotic systems, they tend to tackle tasks with greater confidence and efficiency. The study also looks at how thoughtfully designed collaborative setups foster a sense of teamwork, easing worries about new tech. Things like job satisfaction, opportunities to learn new skills, and a supportive workplace vibe play huge roles in making human-robot partnerships click. Our framework emphasizes that training and open dialogue can spark positive attitudes toward robots, leading to better work outcomes. We also tackle challenges, like gaps in skills or physical strain from working alongside machines and suggest practical ways to smooth out these kinks. By aligning human strengths with robotic capabilities, Industry 5.0 workplaces can unlock lasting productivity gains. This paper adds a fresh perspective to the conversation on human-robot collaboration, offering ideas for companies eager to build thriving, tech-savvy teams.

**KEYWORDS:** Human-robot collaboration, Industry 5.0, employee behavior, performance boost, teamwork framework, tech acceptance.

## 1. INTRODUCTION

Accelerated adoption of Robotic process automation (RPA) has distinctively disrupted organizations in Industry 5.0 (Abdel-Basset et al., 2024; Ghobakhloo et al., 2024; Ren & Clement, 2024). The provenance of Automation and robotics in Industry 4.0 has made it imperative for industries to formulate a collaborative team of humans and robots to achieve higher organizational performance (Gombolay & Shah, n.d.; Leocádio et al., 2024; Rinaldi et al., 2024). Robots have become ubiquitous in manufacturing and industrial settings, compelling managers to strategically govern the HRC teams to avert business losses (Cao et al., 2024; Korivand et al., 2024). "Robots are the autonomous or semiautonomous computer systems that have some ability to move around, and to gather information and to communicate with humans using verbal communication" (Hutler et al., 2024, page 1). Artificial Intelligence (AI) can be defined as non-human intelligence designed to accomplish allocated tasks (Dwivedi et al., 2021; Pillai & Sivathanu, 2020b; Tasioulas, 2018). The application of artificial intelligence has strategic business significance in optimizing logistics, operational efficiencies, consumer preferences, production excellence, etc. (Etinosa Igbinenikaro & Adefolake Olachi Adewusi, 2024). There lies immense potential for the upward progression of collaborative robots in industrial settings supplementing and augmenting human employees for desired business outcomes (Ren & Clement, 2024). For a successful human-robot collaboration, humans need to possess the skillset, competencies, intelligence, decision-making, cognitive abilities, and critical thinking to work as a strong counterpart showcasing optimized performance (Paliga, 2022; Picco et al., 2024; Sarah. L.Muller-Abdelrazeq, Kathrin Schonefeld, 2019). Robots in the workplace cater to numerous advantages such as productivity, competitive advantage, improved organizational performance, and a strong team member to support complex tasks leading to operational efficiencies (Li et al., 2023; Paliga, 2023; Sadangharn, 2022; You et al., 2023).

However, there are a lot of drivers and barriers that need to be addressed to gain synergy in the HRC team. The drivers such as Perceived usefulness, and perceived compatibility (Ghanem et al., 2017; Parvez et al., 2022; Pillai et al., 2020; Y. S. Wang et al., 2013). Team fluency, trust, safety & security (Aubert et al., 2018; Baraglia et al., 2017; Dagioglou & Karkaletsis, 2021; Groom & Nass, 2007; Hoffman, 2019; Paliga, 2022; Wiese et al., 2021; Zeng et al., 2020), Perceived Anthropomorphism, Emotional engagement (Melián-González et al., 2021; Moussawi & Koufaris, 2019) and various barriers like perceived risk (Hassan et al., 2024; Jayashankar et al., 2018; Mitchell, 1999), automation anxiety (Eißer et al., 2020), negative attitude towards robots (Ajoudani et al., 2018), etc. While progressing in Industry 5.0 the employee needs to reciprocate the role to build good synergy in the collaborative team (Simões et al., 2022; Yamini Ghanghorkar, 2024). Employees' readiness to collaborate with necessary skill sets, competencies, attitudes, and willingness is detrimental to developing synergy in the HRC team (Frijns et al., 2021; Ötting et al., 2022; Seiffer et al., 2021). Some critical incidents of collusion in HRC have led to accidents at the workplace (Li et al., 2023; Liu et al., 2021; Tortorella et al., 2021). Overall, the above-described challenges need to be explored from the employee perspective on their acceptance level, awareness, knowledge, willingness, understanding, and intentions influencing employee adoption of cobots and examination of mediating factors in the process.

Human-robot collaboration is the team where a collaborative partnership is developed to achieve the common aim (Parvez et al., 2022; Terveen, 1995). And, human-robot workspace is a space where robots work concurrently with humans during production operations (ISO/TS 15066:2016(en), 2024, p. 3.3). With team synergy humans and robots working together with a high level of coordination, and collaboration with well-synchronized fluency leads to elevating team performance (Hoffman, 2019; Ramadurai et al., 2024). HRC team synergy prompts results in upgraded overall performance and team fluency (Chacón et al., 2020). Team cognition characterizes the elevation in team performance and interdependencies at inter and intra-level for effective coordination and collaboration (Jiao et al., 2020). Team synergy in HRC leads to competent decision-making, problem-solving, raising the team performance levels (Yamini Ghanghorkar, 2024). An employee needs to be willing and competent to be sufficient to work with robots to create collaborative intelligence (Blaurock et al., 2024). The interdependence work collaboration can significantly impact mental effort and quality of work (Le et al., 2022). Employee perspective on the usefulness of robots plays an important role in seamless collaboration under HRC (Sun et al., 2020). There is a dire need to investigate the employee perspective to integrate humans with robots and achieve team synergy easily (Cao et al., 2024; Seiffer et al., 2021). There needs a thorough investigation of the factors affecting employees in the HRC arrangement, to achieve team synergy (Blaurock et al., 2024; Sadangharn, 2022).

## 2. THEORETICAL FRAMEWORK

The adoption of cobots is ubiquitous in the manufacturing industry (Aquilani et al., 2020; Nourmohammadi et al., 2022). The robot consistently adds to the collaborative intelligence of the revolutionized manufacturing landscapes (Blaurock et al., 2024). Robots are also collaborating with humans in a complex sociotechnical environment of work just not only physically but also at the social front (Weiss et al., 2021). Industry 5.0 is reflective of human-centric industrialization incorporating intelligent robots in manufacturing (Nourmohammadi et al., 2022). The manufacturing industry is maturing with the human-robot collaboration and requires the industry to be ready to tackle possible risks foreseen in it (Ramim-Ul Hasan et al., 2024).Therefore, it requires a careful understanding of the possible factors affecting this collaboration in both positive and negative ways.

### *2.1. Theoretical basis*

#### 2.1.1. **TAM**

The technology adoption model is majorly adopted in papers focusing on the adoption of technology specifically investigating the behavioral intention towards embracing technology. Employee sentiment of perceived usefulness and perceived trust impact the employee's behavioral intentions (Fred D. Davis, 1989). TAM is significantly adopted in the employee studies on their technology-adopting pattern (Parvez et al., 2022). TAM is successfully adopted in studies centering on the analysis of human-centric factors for facilitating human intentions to adopt robots (Molitor, 2020). Since robots are the imminent technology in the manufacturing industry there is scope for learning employees' behavioral intentions towards robots. Therefore, the TAM framework is considered for conducting the research work.

#### 2.1.2. **TTF**

TTF is the base for task and technology fitness to align the technology with the tasks in the daily work (Goodhue, 1998). It is imperative to align the technology with the daily work of employees (Alghizzawi, 2021).As TAM only enables us to investigate the behavioral intentions of the employees towards technology adoption, The TTF framework on the contrary helps in determining the association between tasks and technology in AI technology adoption studies (Malik et al., 2020; Pillai & Sivathanu, 2020b; H. Wang et al., 2020). The technology characteristic and task characteristic fitness impact the actual usage of technology at the workplace (Pillai & Sivathanu, 2020b; Zhou et al., 2010).

#### 2.1.3. **Employee performance in Human-Robot collaboration**

Employee well-being and productivity are equally important as robots in human-robot collaboration (Tripathi et al., 2024). Several factors impact the job quality of the employee and need to be addressed to consider the human side of HRC (Baltrusch et al., 2021). Employee intentions and attitudes towards robots impact the quality of work and overall job performance (Sadangharn, 2022). The ergonomics need to be taken into consideration to ensure a safe workstation to enable employees to perform and increase collaborative productivity (Cao et al., 2024). Combining all the required factors necessary to ensure safety, trust, risk, and flexibility enhances employee performance (Ramim-Ul Hasan et al., 2024). The performance-shaping factors significantly impact the employees' behavior and performance, reducing the chances of reducing significant errors (Di Pasquale et al., 2023a).

#### **2.1.4. Behavioural Intention to Adopt Robots**

In Industry 5.0 business concerns are on a human-centric approach to achieve human-robot synergy to gain elevated business output (Parvez et al., 2022). Robots are very much part of every business avenue across industries (Hassan et al., 2024). Humans in HRC collaboration showcase attitude and intention to adopt robots as a work counterpart (Venkatesh, 2012). There are many prevalent factors such as anthropomorphism which significantly affect the intentions of employees to collaborate with robots (Fink, 2012; Obrenovic et al., 2024). The significance of the uncanny valley is prominent and hampers the adoption of robots in the workplace (Betriana et al., 2021). Studying employee behavioral intentions under TAM is useful in measuring intentions' impact on employee performance or actual usage (Pillai & Sivathanu, 2020a).

**2.1.5. Perceived usefulness**

Perceived usefulness can be defined as "the degree to which a person believes that using a particular system would improve his or her job performance." (Davis, 1989, p. 320). The authors mediate a link between perceived usefulness and employee intentions as one impacts the other (Sun et al., 2020). The perceived usefulness makes an individual convinced that the technology will enhance their work performance (Al-Rahmi et al., 2020). It determines how an individual will adapt based on their perception of the usefulness of technology and how it can improve the effectiveness of the work (Sun et al., 2020).

**2.1.6. Perceived trust**

Perceived trust is the most common research variable in the studies of human-robot collaboration (Kopp, 2024; K. M. Lee et al., 2023). In humans trust in working with robots inhibits the behavioral intention of accepting and working with robots to cause collaboration to happen (Kopp, 2024). If the robots are not trusted, this leads to less emotional connection, and they are not accepted to work on the required task (Wiese et al., 2021). To improve the trustworthiness of robots, the employee must have trust that their work performance will enhance in working collaboratively (Zierau et al., 2021).

**2.1.7. Work Engagement**

Work engagement is the cognitive-affective state that impacts the behavior of the person (Paliga, 2022). The nature of work directly impacts the work engagement of the employee with the robots (Carissoli et al., 2023). Employees' workload plays a significant role in mediating the HRC team impacting employee behavior (Jia-Min Li, Ke-Xi Liu, Ji-Fei Xie, 2024). Work engagement in HRC facilitates the behavioral intentions of an employee conclusively impacting the employee performance at large (Sidner et al., 2005).

***2.2. Theoretical framework development***

TAM is extensively used in studies of human-robot collaboration and automation at the workplace (Parvez et al., 2022; Pillai & Sivathanu, 2020a; Rese et al., 2020; Singh et al., 2020). TAM justifies the human decision-making process and behavioral impact while working with robots (Bröhl et al., 2019; ILARIA BARONI et al.,2022).

Various context-specific variables are required to get a clearer understanding of the antecedents leading to the actual usage of the robots eventually impact employee performance (Al-Yacoub et al., 2021; Di Pasquale et al., 2023b; S. Hopko et al., 2022; Nourmohammadi et al., 2022). For a similar application, the considered variables for the study can be listed as perceived usefulness (Al-Rahmi et al., 2020; Pillai & Sivathanu, 2020a), perceived trust (Hancock et al., 2009), perceived trust (S. K. Hopko et al., 2024; Kopp, 2024; Rahman & Wang, 2018), work engagement (Blaurock et al., 2024; Paliga, 2022; Ren & Clement, 2024; Zel et al., 2020; Zel & Kongar, 2020), behavioral intentions (C. Lee et al., 2018; Norton et al., 2022; Parvez et al., 2022), Actual usage (Kopp, 2024; Lu et al., 2020; Pillai & Sivathanu, 2020b), task characteristic (Alghizzawi, 2021; H. Wang et al., 2020), technology characteristic (Malik et al., 2020; Pillai & Sivathanu, 2020b)Task technology fit (Alghizzawi, 2021; DL Goodhue, 1995; Goodhue, 1998).

## 3. PROPOSED CONCEPTUAL FRAMEWORK

Multiple factors elevate employee performance while working with robots. The extensive literature lists various factors in the literature which are comprehensively presented in the conceptual framework. These factors affect the behavioral intentions of the employee, which eventually impact the employee's acceptance, perception, and attitude towards the robot (Gupta et al., 2019) leading to employee performance enhancement.

As depicted in Figure 1, the perceived usefulness and perceived trust impact the employee behavioural intentions, which eventually lead to employee performance enhancement.

## 4. CONCLUSION

Perceived usefulness, perceived trust, and work engagement are important factors largely influencing the employee behavioural intentions, which closely impact the employee performance enhancement. However, there can be more such factors that affect human employee perception, attitude, and psychology, leading to employee behaviour of actual usage of robots at the workplace. In the future, more such factors related to employee behaviour under HRC.

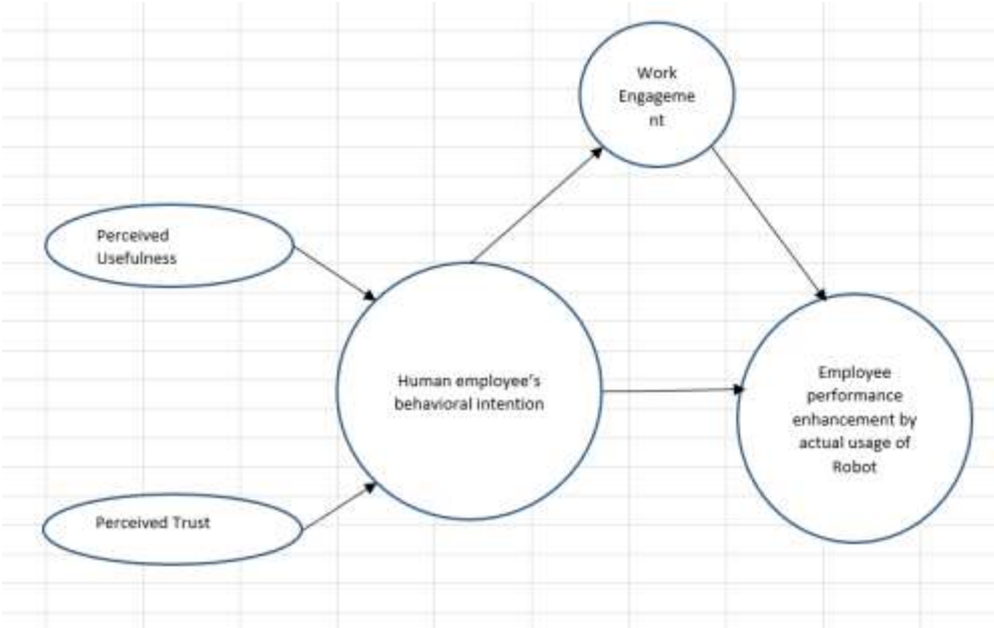


**Figure 1: Conceptual Framework**

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