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Analysis of Proximity and Risk for Trust Evaluation in Human-Robot Collaboration*

Giulio Campagna[1] and Matthias Rehm[1]

Abstract— **In the emerging phase of industrialization, Industry 5.0, humans will be working alongside advanced technologies such as Artificial Intelligence (AI) and robots to improve the manufacturing process. As a result, it is crucial to evaluate trust in the robot from a human perspective in order to provide a safe environment and balance workloads. Relevant trust indicators in the industrial context include proximity between human and robot, as well as risk associated with robot's performance. In this study, a chemical industry scenario was developed, where a robot assists a human in mixing chemicals. An experiment was conducted for analysing how proximity and risk impact the trust level of the participants. According to the results, there was a higher average trust score in the low proximity (i.e. robot not close to the human) and low risk sections compared to the high proximity and high risk sections of the experiment, respectively. Moreover, statistical analysis indicates that risk had a higher impact on trust than proximity. The findings of this study encourage further research in this area since tools such as AI could be used to control the robot's behavior according to the level of trust between the human and the robot.**

I. INTRODUCTION

With the advent of the Industry 5.0 era, a growing interest has been registered in the development of collaborative robots (cobots) that can work with humans in order to accomplish several tasks. In manufacturing, robots are well integrated because of their qualities such as stamina, speed, precision, repeatability and power, which make them able to do jobs that humans are unable to perform accurately, easily, and in a timely manner. On the other hand, the capacity of decision-making and problem solving-skills as well as the flexibility of the human are essential features that impact the quality of production process. Human-Robot Collaboration (HRC) combines these elements in order to provide benefits [3] in terms of productivity, quality, and safety in manufacturing operations. Thus far, to provide safety in industrial settings, barriers were used to separate the workspace of the robot from the one of the human operator. However, cobots are designed to allow physical interaction with the human workers and thus making it possible to remove the protection barriers [1]. As a result, this enables new forms of physical Human-Robot Interaction (pHRI) as well as reconfiguration of manufacturing process [2]. Based on this perspective, it is essential to provide a safe environment and balance workload.

In HRC, trust plays a key role since the level of trust between human and robot can be a determining factor for the interaction's performance. The appropriate level of trust in human-robot teams is extremely relevant. Under-trust increases the risk of unbalance workload (operator overload) by leading to the robot being disregarded, while over-trust can lead to loss of expensive equipment and collisions with the human due to inefficient monitoring of the robot [4], [5]. In [6], Hancock et al. present a meta-analysis of factors affecting trust in Human-Robot Interaction (HRI). In industrial scenarios, proximity and risk are two relevant trust indicators. Humans' trust levels in robots are influenced by risk, which in turn affects their decisions [7]. The level of risk associated with the interaction depends on the nature of the task involved, perceived capabilities and performance of the robot. People may be less trusting of a robot that handles hazardous materials, for example. Concerning proximity, it could be defined as the physical distance between the human and robot. Close-proximity highly influences trust since the humans tend to feel more stressed and anxious especially if the robot they are collaborating with is large [8] and affected by possible malfunctions and unpredictable movements. As a result, this elicits fear in the operator that considers the robot as a potential danger rather than a trustworthy partner. However, humans tend to trust more robots that have been designed with safety features and systems that are transparent and that communicate feedback so that the operators are aware of the intentions of the robot.

The paper proposes a chemical industry scenario with the robot accomplishing two different tasks: i) handing a beaker to the operator and ii) assisting him with the mixing of chemicals. The decision to focus on a chemical industry scenario was based on its suitability for examining how trust indicators such as performance-based risk and proximity could affect the level of trust of the operators. To this extent, in the experiment, different tasks are developed with different degree of risk and proximity. Post-hoc questionnaires are commonly used to estimate trust (e.g. [9], [10]), therefore, between each section, the Schaefer's 14-item Trust Questionnaire (also know as Human-Robot Trust Questionnaire [11]) is used for the analysis. The long-term goal is to exploit the outcomes of this study for a successive analysis with Artificial Intelligence (AI) with the objective to adapt the robot's behavior to the actual level of trust of the participant in real-time. This approach is aimed to provide a safe and balanced workload in industrial HRC scenarios.

The remainder of this paper is organized as follows. In Section II, elated work is presented. The methodology is treated in Section III while Section IV describes the results. A discussion of the principal findings is reported in Section

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V. The conclusion and future works are presented in Section VI.

II. RELATED WORK

The Industry 5.0 paradigm combines the advantages of Industry 4.0 (digitalization and automation) with a renewed emphasis on human-centric manufacturing [14]. Several points are highlighted, including the usage of renewable biological resources as well as the importance to support industry with research and innovation while ensuring the human as centre pillar in the production process [12]. The most relevant key element is HRC which allows the operators to focus on jobs that require creativity, problem-solving, and decision-making, while machines can handle repetitive or dangerous tasks with high accuracy and thus reducing waste and costs [13]. For example, cobots can support humans in a shared workspace by performing tasks independently, simultaneously, sequentially, or in a supportive manner [15]. According to [16], there is safety, physical, cognitive and psychological health at the base of the Industrial Human Needs Pyramid. As consequence, a trustworthy relationship between humans and machines is needed to guarantee the aforementioned safety and health and enabling self-actualisation and potential fulfillment as well.

In the context of industrial and collaborative robotics, trust is regarded as one of the most important human-centered quality factors [17]. Lee and See [18] defined trust in automation as the belief that an agent would help achieve an individual's goals in situations characterized by uncertainty and vulnerability. Nevertheless, this definition needs further elaboration considering the concept of trust appropriateness, i.e. the relationship between the capabilities of the machine and the trust level of the operator. In [19], Muir and Moray showed that the trust levels of the human were heavily correlated with the machine's performance. Task performance could be impaired if the operator does not trust the robot's capabilities. Therefore, trust is considered an important factor in influencing performance in certain situations. Performance-based trust is centered on the robot being trusted to be reliable, capable and competent in the accomplishment of the task [20].

Hancock et al. [6] classified the elements that affect human's trust towards the robot in three main categories that are human-related (e.g. propensity to trust, demographics, expertise, personality), robot-related (e.g. reliability, level of automation, proximity, anthropomorphism) and environmental (e.g. task type, physical environment). As a result of the study, the robot's characteristics, particularly performance-based factors, have the greatest influence on perceived trust in HRI. Risk is a relevant component that is heavily associated with the performance of the robot to accomplish a task. High-risk scenarios are required to properly observe trust level differences in HRI [22]. Robinette et al. [25] studied how a guiding robot's performance could influence the level of trust of the people. In low-risk scenario, after a robot's mistake, the persons reported a lack of trust but they continued to follow its instructions. On the other hand, people stopped using the robot during high-risk emergency situations. According to [21], military applications can also be used as an example where a high-risk level affects trust significantly. Humans can be replaced by robots in many high-risk occupations as a result of their superior performance in dangerous environments [28]. Despite the fact that industrial robots designed for HRI should not harm people, the perception of the risk can still negatively impact the performance. In an industrial framework, also proximity covers an important role in building trust between humans and robots. Human-robot close-proximity interaction is a relatively new paradigm for interaction [23]. According to Shiomi et al. [24], a robot must first be perceived as safe by the human partner in order to successfully integrate within the human environment. During a HRC task, both mental (e.g. the impact of the robot's size) and physical safety are important [8]. An attempt to study how proximity influences trust in HRC is provided by the analysis of Story et al. [27]. A collaborative cell with a human and robot team was used to replicate an assembly task. In this case there was no significant change in trust in correlation to proximity level due to the small size of the robot and high success rate. However, the authors state that a larger industrial robot may have a different influence. In the study [26], MacArthur et al. investigated how robot's proximity can affect trust of humans in a maintenance hallway. Results reported that people had a lower trust level in cases of close proximity to the robot. In conclusion, both risk and proximity are key factors to consider when analyzing the dynamics of trust in industrial HRC.

The primary objective of this study is to examine how proximity and risk affect the trust of operators in a HRC cell that simulates a chemical industry scenario where a robot assists a human.

III. METHODOLOGY

A. The Human Subject Study

To investigate how proximity and risk influence the trust level of the operator, a chemical industry scenario was developed. To evaluate each of the two trust indicators, a related task was formulated.

Referring to the analysis of proximity, the task concerned the robot placing a beaker on a box in front of the human. Two different situations were designed where the level of proximity was different. In the low-proximity situation (Fig. 1a), the robot performed as it was instructed, i.e. it grasped the beaker and placed it appropriately in the target position. In contrast, in the high-proximity case (Fig. 1b), the robot grasped the beaker but, before placing it on the box, it approached the operator really close.

Concerning the risk study, a scenario involving mixing chemicals was developed. There were two beakers each one containing a different chemical. After grasping a beaker, the robot had to reach the other beaker held by the human, and then pour the chemical into it. Similar to the proximity test, two conditions were designed present. In the low-risk case (Fig. 1c), the robot completed the pouring task accurately

(a) Low-proximity condition.

(b) High-proximity condition.

(c) Low-risk condition.

(d) High-risk condition.

Fig. 1: The chemical industry scenario.

without malfunctioning. For the high-risk situation (Fig. 1d), it was decided to implement a risky behavior: the robot appeared to pour onto the human hand before effectively pouring into the beaker.

The analysis consisted of testing the following hypotheses:

- **H1**: Participants report lower trust when the robot is close (high proximity case).
- **H2**: Participants report lower trust when the robot appear to pour on the human hand (high-risk case).
- **H3**: As a trust indicator, performance-based risk adversely impacts trust more than proximity.

B. Experimental Setup

To assist the human in the aforementioned HRC scenario, the Universal Robots UR10-CB3-Series Robot[1] was used. This industrial robotic arm is designed to conquer difficult tasks with high precision and reliability. Packaging, palletizing, assembly, and pick-and-place are among the most appropriate applications. The UR10 cobot, featured with 6 rotational joints, is a versatile collaborative industrial robot delivering high payload (10 kg) lift, wide working range (1300 mm from the base joint) and 125 Hz as frequency communication. The UR10 robot was equipped with RG6 (OnRobot), a 2-fingered flexible gripper that provides up to 150 mm stroke. In this experiment, the grasping phase and the path planning of the robot were pre-programmed using Python. As a safety precaution, a protective zone was established and an assistant kept an emergency button on hand to stop the robot in case the participants displayed unexpected behavior.

With the purpose to simulate a realistic scenario, the participants and the assistant were equipped with personal protective equipment: a laboratory coat, gloves and eye protection glasses. Concerning the chemicals, the beaker held by the human contained baking powder while the beaker grasped by the robot had water inside. As a result, the reaction phase produced only carbon dioxide, thus ensuring operator safety. Nevertheless, this was only revealed after the experiment was completed. In fact, the chemicals were declared dangerous and harmful at the beginning of the test. To further intensify the high risk condition of the experiment, a bottle of gasoline was placed next to the robot during the risk task where the robot had to assist the human in mixing the chemicals. This approach ensured all safety measures

[1]https://www.universal-robots.com/cb3/

were met and provided a realistic scenario to conduct the analysis.

C. Procedure

The experiment involved forty subjects. In order to avoid influencing the evaluation of trust of the participants, twenty subjects were randomly assigned to the proximity study and twenty to the risk analysis. To provide an accurate investigation, the participants were recruited with differences in age, gender and familiarity with robots.

With reference to the proximity test, 12 males and 8 females with different age (*M*=27.3, *SD*=6.34) were selected. Concerning familiarity with robots, only 5 participants had practical experiences while other subjects had seen them either in reality (3 participants) or in the media (1 participant). The remaining 11 subjects did not have familiarity with robots.

Regarding the risk analysis, 11 males and 8 females with diverse age (*M*=25.55, *SD*=3.2) participated. Familiarity with robots was limited as in the previous case. Only 5 participants had experience working with them while others had seen them in exhibitions (1 participant) or social media (2 participants). In this case, 12 subjects were not familiar with robots.

At the beginning of the experiment, a printed consent form and a description of the task (either proximity or risk test) were provided to the participant. Afterwards, the subject was asked to answer the 6-item Propensity to Trust Questionnaire [29] in order to determine a baseline level of trust towards machines. After reverse coding the second question, the answers (based on a 5-point Likert scale) were used to calculate the trust score by performing an average. Upon completion of this preliminary questionnaire, the assistant helped the participant to wear the protective equipment before starting the experiment. The participant had to repeat the assigned task for each section ("high" and "low" conditions) as aforementioned in the Section III.A. Between each section, the Schaefer's 14-item Trust Questionnaire [11] was provided to the subject. The 14-item human-robot trust scale provided an overall percentage score across all the elements. Trust score was calculated by first reverse coding the "Have Errors", "Unresponsive" and "Malfunction" items, and then performing an average of all the responses. To ensure a solid statistical analysis, the order in which the participants performed the two sections was balanced: ten participants did the task first in the "low" condition and then in the "high" condition, and ten subjects did the opposite. Each participant required 15 minutes to complete the experiment.

IV. RESULTS

In this section, the principal findings are reported concerning how proximity and risk affected the operator's trust.

Propensity to trust was calculated for participants in both the proximity (*M*=3.85, *SD*=0.64) and risk analysis (*M*=3.61, *SD*=0.63). A Shapiro-Wilk test indicated that the sample of propensity to trust scores for the participants of the risk scenario followed a normal distribution (p=0.94) while it did not follow a normal distribution in the case of the subjects for the proximity scenario (p=0.01). Considering these results, a non-parametric test was needed to assess if there was statistically significant difference between the two groups. According to Mann-Withney test, there was no statistically significant difference between the two samples of trust scores (U=146, p=0.149). Therefore, the successive analyses of trust with Schaefer's 14-item Trust Questionnaire were not influenced by propensity to trust.

Two-way mixed ANOVA was performed to examine trust level (dependent variable) towards the robot, with trust indicators (i.e. proximity and risk) as between-subject variable, and condition (i.e. low and high) as within-subject variable. Prior to the computation of two-way mixed ANOVA, the necessary assumptions were checked. A Shapiro-Wilk test reported that each sample of trust scores follows a normal distribution ($p>0.05$) for all the combination of the two factors (within-subjects factor and between-subjects factor): low-proximity, high-proximity, low-risk, high-risk. There was homogeneity of variances, as assessed by the Levene's test for equality of variances ($p>0.05$). The Box's M test showed that there was homogeneity of covariance matrices (*Box's M*=0.607, p=0.903). Having only two levels of repeated measures, the Mauchly's sphericity test was not needed. Since all the assumptions were satisfied, the two-way mixed ANOVA could be performed. There was a significant main effect of the "low" and "high" conditions on the trust scores, $F(1,38)=64.32$, $p<0.05$, $\eta^2=0.629$. Average trust scores were significantly higher on "low" condition (*M*=74.66, *SD*=7.16) than "high" condition (*M*=55.41, *SD*=16.03). There was a significant main effect of trust indicators on trust scores $F(1,38)=8.17$, $p=0.007$, $\eta^2=0.177$. Trust scores in proximity case (*M*=69.02, *SD*=12.88) were higher than risk case (*M*=60.60, *SD*=17.31), thus confirming the third hypothesis. There was also a significant interaction effect between the conditions and the trust indicators $F(1,38)=4.096$, $p=0.05$, $\eta^2=0.097$. Considering this last result, a series of additional post-hoc tests were required.

Multiple t-tests (paired and independent t-tests) were conducted using Bonferroni adjusted alpha level of 0.0083 per test (0.05/6). Two paired-sample t-tests were performed to test if there was a difference in trust under "high" and "low" conditions, separately for each trust indicator (low proximity-high proximity, low risk-high risk). Afterwards, two between-subjects unpaired t-tests were computed: low proximity-low risk, high proximity-high risk. The other two pairwise comparisons, i.e. low proximity-high risk and high proximity-low risk are not reported because they are not relevant for the study, but they were considered for the Bonferroni correction of the alpha level. The normality assumption, needed for both paired and unpaired t-tests, was checked with the Shapiro-Wilk test. For the paired-sample t-tests, the Shapiro-Wilk test showed that the distribution of the difference in trust scores concerning the pairwise comparisons low proximity-high proximity and low risk-high risk followed a normal distribution ($p>0.05$). Shapiro-

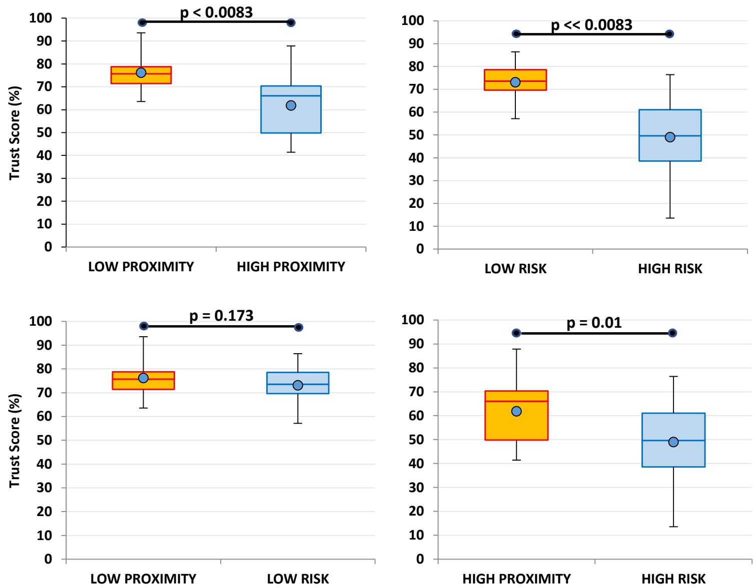

Fig. 2: Results of the post-hoc tests with Bonferroni correction (alpha level: 0.0083).

Wilk test confirmed the normal distribution of the data for each group present in the unpaired t-tests. With reference to the independent t-tests, homogeneity of variances was analyzed. According to the F-Test Two-Sample for Variances, homogeneity of variances was satisfied for the pairwise comparisons low proximity-low risk and high proximity-high risk (p>0.05). Therefore, two independent t-test assuming equal variances were performed. The results indicated that the average trust scores were significantly higher in low-proximity case (M=76.21, SD=6.75) than high-proximity situation (M=61.82, SD=13.64), ($t(19)$=4.545, p<0.0083) and thus confirming the first hypothesis. Considering risk as trust indicator, average trust scores were significantly higher in low-risk case (M=73.11, SD=7.38) than high-risk situation (M=49, SD=15.97), ($t(19)$=6.682, $p \ll 0.0083$) and, therefore, corroborating the second hypothesis. The pairwise comparisons high proximity-high risk and low proximity-low risk were non-significant. The outcomes are summarized in Fig. 2.

V. DISCUSSION

The purpose of this study was to examine how proximity between human and robot as well as performance-based risk affected human trust in HRC industrial settings. Statistical tests supported the hypotheses and thus confirmed that the aforementioned trust indicators had a relevant impact on the trust of the operator. The participants reported lower trust level when the robot was close. There could be several factors contributing to this outcome, including the operator's stress over the large size of the robot or the possibility to be hit. A significant difference in trust level was also seen in the risk analysis where the participants showed lower trust when the risk was high, i.e. when the robot appeared to pour on the human hand. As confirmed by these results, performance-based risk is a critical factor that influences trust. As illustrated in Fig. 2, there was no significant difference in terms of trust scores between low-proximity case (robot not close to the human) and low-risk situation (no danger of chemicals harming the participants). However, according to the statistical tests, even in the high-proximity and high-risk cases there was no significant difference in trust levels, but it can be observed a larger spread of higher trust scores in high-proximity situation. In addition, as reported in Section IV, two-way mixed ANOVA showed that, in general, risk adversely impacted trust levels more than proximity. At the end of the experiments, participants had the possibility to provide additional feedback in order to consider further improvements of the experimental scenario and the analysis of other relevant trust indicators. A number of people reported that their level of trust in the robot could have been affected by greater speed, since they would have been concerned about the velocity of a robot of a large size approaching them. Therefore, the analysis of speed as trust indicator would add further knowledge in the investigation of the elements that affect trust in industrial HRC. Additionally, it would be interesting to examine how different propensities to trust machines affects the effective evaluation of trust in robots. Limitation of the study was the pre-programmed control of the robot, even if the participants were not aware. A dynamic system will be developed, including several unexpected behaviors to overcome the robot's predictability. Additionally, this will allow the operator to move around the workspace without being constrained to assume a fixed position.

VI. CONCLUSION

Trust has been shown to be a crucial factor governing human robot collaboration. Trust measurement is mainly based on questionnaires and thus does not allow to adapt robot behavior during the interaction. To develop data-driven trust assessments, it is essential to know more about the influence of different categories of trust indicators. In this study, it was analysed the impact of robot and context related factors, i.e. proximity and task-risk. A chemical industry scenario was developed in which a robot assisted the operator in handing over the beaker to him and mixing chemicals. Handing over a beaker was designed to analyse proximity's effects, while mixing chemicals examined risk's effects. The results highlighted how different level of proximity and risk affected trust. Lower trust scores were registered when the robot was close to the human (high proximity case) or when there was the risk that the robot could pour the chemicals on the human hand (high risk case). By comparing the aforementioned trust indicators (i.e. proximity and performance-based risk), the statistical tests reported that risk adversely impacted trust more than proximity. As future works, the analysis of speed and propensity to trust will be investigated to add further knowledge on which are the factors that affect trust in industrial HRC. The results of this investigation contribute to understanding the dynamics of trust in industrial HRC environment and the integration of robots into operator's workspace. This analysis was the pillar and the initial phase to provide a framework that guarantees a safe interaction between the human and the robot. Sensor fusion and AI will be used to categorize trust levels of the operators and, therefore, being able to control the robot appropriately to provide safety and balance workload.

REFERENCES

[1] Vicentini, F. (2021). Collaborative robotics: a survey. Journal of Mechanical Design, 143(4).

[2] Mishra, R. (2021). Confirmation of a measurement model for manufacturing flexibility development practices. International Journal of Quality & Reliability Management, 38(1), 317-338.

[3] Gervasi, R., Mastrogiacomo, L., & Franceschini, F. (2023). An experimental focus on learning effect and interaction quality in human–robot collaboration. Production Engineering, 1-26.

[4] Hald, K., Rehm, M., & Moeslund, T. B. (2021, August). Human-Robot Trust Assessment Using Top-Down Visual Tracking After Robot Task Execution Mistakes. In 2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN) (pp. 892-898). IEEE.

[5] De Visser, E. J., Peeters, M. M., Jung, M. F., Kohn, S., Shaw, T. H., Pak, R., & Neerincx, M. A. (2020). Towards a theory of longitudinal trust calibration in human–robot teams. International journal of social robotics, 12(2), 459-478.

[6] Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y., De Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. Human factors, 53(5), 517-527.

[7] Park, E., Jenkins, Q., & Jiang, X. (2008). Measuring trust of human operators in new generation rescue robots. In Proceedings of the JFPS International Symposium on Fluid power (Vol. 2008, No. 7-2, pp. 489-492). The Japan Fluid Power System Society.

[8] Charalambous, G., Fletcher, S., & Webb, P. (2016). The development of a scale to evaluate trust in industrial human-robot collaboration. International Journal of Social Robotics, 8, 193-209.

[9] Yagoda, R. E., & Gillan, D. J. (2012). You want me to trust a ROBOT? The development of a human–robot interaction trust scale. International Journal of Social Robotics, 4, 235-248.

[10] Schaefer, K. E., Chen, J. Y., Szalma, J. L., & Hancock, P. A. (2016). A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. Human factors, 58(3), 377-400.

[11] Schaefer, K. E. (2016). Measuring trust in human robot interactions: Development of the "trust perception scale-HRI". In Robust intelligence and trust in autonomous systems (pp. 191-218). Boston, MA: Springer US.

[12] Rožanec, J. M., Novalija, I., Zajec, P., Kenda, K., Tavakoli Ghinani, H., Suh, S., ... & Soldatos, J. (2022). Human-centric artificial intelligence architecture for industry 5.0 applications. International Journal of Production Research, 1-26.

[13] Nahavandi, S. (2019). Industry 5.0—A human-centric solution. Sustainability, 11(16), 4371.

[14] Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. Journal of Manufacturing Systems, 61, 530-535.

[15] El Zaatari, S., Marei, M., Li, W., & Usman, Z. (2019). Cobot programming for collaborative industrial tasks: An overview. Robotics and Autonomous Systems, 116, 162-180.

[16] Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., ... & Bao, J. (2022). Outlook on human-centric manufacturing towards Industry 5.0. Journal of Manufacturing Systems, 62, 612-627.

[17] Coronado, E., Kiyokawa, T., Ricardez, G. A. G., Ramirez-Alpizar, I. G., Venture, G., & Yamanobe, N. (2022). Evaluating quality in human-robot interaction: A systematic search and classification of performance and human-centered factors, measures and metrics towards an industry 5.0. Journal of Manufacturing Systems, 63, 392-410.

[18] Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. Human factors, 46(1), 50-80.

[19] Muir, B. M., & Moray, N. (1996). Trust in automation. Part II. Experimental studies of trust and human intervention in a process control simulation. Ergonomics, 39(3), 429-460.

[20] Law, T., & Scheutz, M. (2021). Trust: Recent concepts and evaluations in human-robot interaction. Trust in human-robot interaction, 27-57.

[21] Maurtua, I., Ibarguren, A., Kildal, J., Susperregi, L., & Sierra, B. (2017). Human–robot collaboration in industrial applications: Safety, interaction and trust. International Journal of Advanced Robotic Systems, 14(4), 1729881417716010.

[22] Hannibal, G., Weiss, A., & Charisi, V. (2021, August). " The robot may not notice my discomfort"–Examining the Experience of Vulnerability for Trust in Human-Robot Interaction. In 2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN) (pp. 704-711). IEEE.

[23] Lasota, P. A., Rossano, G. F., & Shah, J. A. (2014, August). Toward safe close-proximity human-robot interaction with standard industrial robots. In 2014 IEEE International Conference on Automation Science and Engineering (CASE) (pp. 339-344). IEEE.

[24] Shiomi, M., Zanlungo, F., Hayashi, K., & Kanda, T. (2014). Towards a socially acceptable collision avoidance for a mobile robot navigating among pedestrians using a pedestrian model. International Journal of Social Robotics, 6(3), 443-455.

[25] Robinette, P., Howard, A. M., & Wagner, A. R. (2017). Effect of robot performance on human–robot trust in time-critical situations. IEEE Transactions on Human-Machine Systems, 47(4), 425-436.

[26] MacArthur, K. R., Stowers, K., & Hancock, P. A. (2017). Human-robot interaction: proximity and speed—slowly back away from the robot!. In Advances in Human Factors in Robots and Unmanned Systems: Proceedings of the AHFE 2016 International Conference on Human Factors in Robots and Unmanned Systems, July 27-31, 2016, Walt Disney World®, Florida, USA (pp. 365-374). Springer International Publishing.

[27] Story, M., Webb, P., Fletcher, S. R., Tang, G., Jaksic, C., & Carberry, J. (2022). Do speed and proximity affect human-robot collaboration with an industrial robot arm?. International Journal of Social Robotics, 14(4), 1087-1102.

[28] Çiğdem, Ş., Meidute-Kavaliauskiene, I., & Yıldız, B. (2023). Industry 4.0 and Industrial Robots: A Study from the Perspective of Manufacturing Company Employees. Logistics, 7(1), 17.

[29] Merritt, S. M., Heimbaugh, H., LaChapell, J., & Lee, D. (2013). I trust it, but I don't know why: Effects of implicit attitudes toward automation on trust in an automated system. Human factors, 55(3), 520-534.