Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AF07.20260199
Published: May 13, 2026

Determinants of Trust and Adoption in Human-Robot Collaboration: An Industrial Perspective

Masingita Onica Mohlala and Ngaka Mosia
Industrial Engineering and Engineering Management
School of Engineering and the Built Environment
University of South Africa
Florida, South Africa
mohlamo@unisa.ac.za, mosian@unisa.ac.za

Abstract

Human–robot collaboration (HRC) has become an essential component of modern industrial systems, enabling organizations to combine human expertise with advanced robotic technologies to improve productivity and operational efficiency. Despite these advantages, the adoption of collaborative robots remains inconsistent across industries, largely due to challenges related to trust. This study investigates the determinants of trust and how trust influences the adoption of HRC in industrial environments. A qualitative research approach was adopted, using secondary data from peer-reviewed journal articles, conference publications, and industrial case studies. The data were analysed using thematic analysis to identify patterns related to trust formation, trust dynamics, and adoption behaviour. The findings indicate that trust is shaped by a combination of technical, human, and organizational factors, with reliability and predictability emerging as the most influential determinants. Transparency and communication were also found to be essential in maintaining and restoring trust. The study further shows that trust evolves over time and must be carefully managed to avoid both over-trust and under-trust. An enhanced framework is proposed, integrating dynamic trust monitoring, trust-aware decision making, and human-centred design to support sustainable adoption. The findings provide practical insights for improving the implementation and acceptance of HRC in industrial environments.

Keywords
Human-robot collaboration, Trust, Adoption, Human-centered, Manufacturing.

1. Introduction
Human-robot collaboration (HRC) emerged as a key component of modern industrial systems, enabling the integration of human cognitive capabilities with robotic efficiency. The transition from traditional automation to collaborative systems reflects a broader shift toward flexible and adaptive manufacturing environments. As robots become more common in manufacturing, the focus has shifted from standalone automation to closer collaboration between humans and machines. This shift allows companies to combine human judgment and problem-solving with the speed and precision of robots, leading to higher productivity and more efficient operations. Even so, not all organizations have embraced this change at the same pace.

A major reason for this uneven adoption is trust. Many workers remain uncertain about working alongside robots, often worrying about safety, job security, and whether the systems are truly reliable. These concerns can make people hesitant to engage with collaborative technologies. It highlights that successful human-robot collaboration is not just about having advanced machines, it also depends on addressing human concerns and understanding the broader workplace context. Despite these advancements, the adoption of collaborative robots remains uneven across industries. A major limiting factor is the lack of trust between human operators and robotic systems.

Recent studies show that trust in human-robot systems develops dynamically and can be affected by both technical performance and social interaction cues. Therefore, this study aims to explore the key determinants of trust and their influence on adoption within industrial contexts. The objectives of this study are to identify the key determinants influencing trust in human-robot collaboration, to analyse how trust affects adoption in industrial environments, and to develop a conceptual framework that explains the dynamics of HRC adoption.

2. Literature Review

Human-robot collaboration evolved from isolated automation systems to interactive environments where robots and humans share tasks within a common workplace. This evolution has introduced new challenges related to trust, safety, and system integration.

2.1 Trust Formation in HRC

Trust is recognized as a critical factor influencing the acceptance of robotic systems in collaborative environments. In an industrial human-robot collaboration, trust is shaped by robot reliability, transparency in actions, predictability of performance, and social elements like feedback or promises, which differentially affect trust formation, dissolution, and recovery during tasks such as assembly or manipulation (Chen et al. 2020). In industrial settings where humans and robots work side by side, trust does not happen automatically, it builds over time. People tend to trust robots that are reliable, act in ways they can understand, and behave predictably. These factors influence not just how trust develops, but also how it breaks down and recovers during tasks such as assembly or object handling. Reliability remains the most critical determinant of trust. However, additional factors such as transparency and predictability also play significant role. When robots provide clear indications of their intentions or anticipated actions, users are better able to interpret system behaviour and regain trust following errors. These mechanisms are particularly important in high-risk industrial environments (Charalambous et al. 2016). Trust in HRC is also dynamic, meaning it can increase, decline, and recover depending on system performance and interaction quality. Failures in robotic systems may lead to rapid trust deterioration, particularly when users perceive a lack of control or predictability. However, trust can be restored through appropriate recovery mechanisms such as improved communication, corrective actions, and consistent system performance.

Workers often hesitate to rely on robots due to concerns about safety, unpredictability, and system failures. When these aspects are carefully considered, companies are more likely to see successful adoption of collaborative robots, or cobots. This often leads to better teamwork and greater acceptance from workers. However, making robots too human-like can sometimes have the opposite effect, undermine perceived reliability (Weiss et al. 2021). Most research on HRC in industrial settings is derived from controlled experimental studies designed to simulate real-world manufacturing tasks, such as pick-and-place operations, assembly processes, and maintenance activities. These studies typically involve participants with varying levels of experience in robotics, allowing researchers to examine how trust develops across different user groups (Chen et al. 2020; Kluy and Roesler 2021). Findings from these studies indicate that trust is a dynamic and evolving construct rather than a static attribute.

More often trust is assessed using subjective rating scales in conjunction with behavioural measures of reliance on robotic systems (Charalambous et al. 2016). Optimal collaboration outcomes are achieved when trust is appropriately calibrated, avoiding both over-reliance and under-reliance on the system. These mechanisms are particularly important in high-risk industrial environments. Although long-term empirical evidence remains limited, emerging studies suggest that embedding trust-aware decision-making capabilities into robotic systems can significantly improve human-robot team performance and adoption.

2.2 Determinants of Trust

Trust in HRC is shaped by a range of interconnected factors that influence how users perceive and ultimately adopt robotic systems. Among these, reliability stands out as the most important. When robots perform tasks consistently and with minimal errors, especially in industrial settings like assembly lines, users begin to see them as dependable and capable, which builds confidence and encourages appropriate use (Kluy and Roesler 2021). However, when serious failures occur, trust can quickly decline, particularly if the system does not clearly communicate what went wrong or how it is responding (Felix at al. 2025).

Transparency also plays an important supporting role. When robots make their actions and intentions visible or provide simple explanations, users find it easier to understand what the system is doing (Kluy and Roesler 2021). This understanding becomes especially valuable after an error, as it helps users regain confidence and continue working with the robot. On the other hand, when systems lack transparency, mistakes tend to have a stronger negative impact on trust and can make users more reluctant to engage with the technology (Alhaji et al. 2024).

Another key factor is predictability. When users can anticipate how a robot will behave, it becomes easier to coordinate tasks and work efficiently. Predictable systems support smoother interactions and help users develop a balanced level of trust (Chen et al. 2020). However, if robots behave unpredictably or fail to meet expectations, trust can be undermined, particularly during unexpected errors or breakdowns (Chen et al. 2020; Alhaji et al. 2024).

Beyond technical aspects, social cues such as gestures, feedback or verbal communication also influence trust. These cues can make interactions feel more intuitive and approachable, encouraging users to rely more on the system (Cominelli et al. 2021). However, the impact is not always positive. In some cases, too much emphasis on social interaction can distract users or shift attention away from the task, which may reduce overall effectiveness (Onnasch and Hildebrandt. 2021).

Closely related to social cues is anthropomorphism, where robots are designed with human-like features. While such designs can make robots easier to interact with and increase trust for certain users, they can also create unintended consequences in industrial settings (Cominelli et al. 2021). In particular, overly human-like robots may be seen as less reliable or may divert attention from task execution. This suggests that a careful balance is needed between making robots relatable and ensuring they remain efficient and task-focused (Onnasch and Hildebrandt 2021).

2.3 Trust Dynamics

Trust in HRC develops gradually during the early stages of interaction, often referred to as the formation phase. In these initial encounters, users begin to build trust based largely on how reliably and transparently the robot performs its tasks. For example, in industrial environments such as cobot-assisted assembly, consistent performance with very low error rates quickly leads users to view the robot as capable and dependable (Kluy and Roesler 2021). Systems that behave in predictable ways or that adapt intelligently to human actions, further support this process by making collaboration feel safe and manageable. In some cases, more intuitive interaction methods such as gesture-based controls, allow users to align the actions with the robot more naturally, helping trust to develop more quickly (Campagna et al. 2025). However, not all design elements have positive effects. Features such as human-like appearances or behaviours can sometimes delay trust formation, especially if they distract users from the task itself (Chen et al. 2020).

Once trust has been established, it needs to be maintained through continuous interaction. This maintenance phase depends heavily on how well the system responds to changing conditions and user expectations. In many industrial cases, robots adjust the actions based on user feedback such as prioritising safer tasks first or adapting movement speed and distance, can sustain higher levels of trust over time (Hannum et al. 2020; Campagna et al. 2024). Providing real-time explanations enhances transparency and plays an important role in sustaining trust during routine operations and helps reduce uncertainty by 18% and reinforces user confidence (Kluy and Roesler. 2021; Felix et al. 2025). These ongoing adjustments strengthen adoption by making collaboration smoother and more efficient. However, there is also a risk of over-reliance if the system becomes too predictable or fails to account for human variability, which can negatively affect long-term collaboration outcome (Akkaladevi and Heindl. 2015).

Trust can also be fragile and often tested during the dissolution and recovery phase, particularly when errors or failures occur. In industrial tasks, significant failures such as incorrect movements or safety risks can cause sharp drops in trust, especially when the robot's actions are unclear or unexpected (Alhaji et al. 2024; Felix et al. 2025). However, trust is not permanently lost. It can be rebuilt through effective recovery strategies, such as clear explanations, corrective actions, and improved system behaviour. For instance, when robots provide feedback about what went wrong or adjust their behaviour based on user input, users are more likely to regain confidence (Felix et al. 2025). In this phase, communication becomes critical, as it helps users understand and re-engage with the system. At the same time, overly human-like features may hinder recovery by increasing perceptions of unreliability after a failure (Onnasch and Hildebrandt 2021). Overall, these phases show that trust in HRC is dynamic, continuously evolving through interaction, performance, and communication (Chen et al. 2020).

2.4 Patterns in Adoption

Adoption in industrial HRC is closely linked to how trust is developed and managed over time. As trust becomes more stable and well-calibrated, collaboration tends to shift from simple, step-by-step cooperation to more seamless and simultaneous interaction. This is particularly evident when robots adapt their behaviour using predictability-based models, allowing them to respond more effectively to human actions (Hannum et al. 2020). In practical manufacturing settings, such as co-carry tasks and assembly lines, studies show that when robots actively consider trust in their decision-making, they can reduce safety risks and improve long-term performance. For instance, robots that deliberately start with low-risk tasks help build user confidence and maintain appropriate reliance over time (Chen et al. 2020; Hannum et al. 2020).

In the broader context of Industry 5.0, the integration of collaborative robots supported by Internet of Thing (IoT) and artificial intelligence (AI) further strengthens adoption by focusing on both efficiency and worker well-being. However, successful implementation also requires careful management of potential challenges, such as over-reliance on automated systems, which can be addressed through dynamic trust monitoring and feedback mechanisms (Adeniyi 2025). Research methods used to evaluate trust in industrial environments also highlight the importance of context-specific factors. For example, trust measurement tools often focus on aspects such as safety, competence, and error recovery, demonstrating that user acceptance is strongly influenced by how systems perform in real operational scenarios (Charalambous et al. 2016).

Furthermore, advancements in interaction design continue to support adoption by making collaboration more intuitive and efficient. In industrial maintenance tasks, the use of gesture-based controls has been shown to significantly reduce task completion time while improving user experience and overall performance (Campagna et al. 2025). These findings suggest that adoption is not driven by a single factor but rather by a combination of trust-aware system design, effective interaction strategies, and continuous adaptation to user needs.

2.5 Research Gap

Although existing studies provide significant insights into the determinants of trust in HRC, several important gaps remain. First, much of the current research is based on controlled experimental settings that simulate industrial tasks, such as assembly operations and pick-and-place activities. While these studies offer valuable understanding of trust formation, maintenance, and recovery, they often lack real-world complexity and long-term validation, particularly within diverse industrial environments. Secondly, prior research tends to examine individual determinants of trust such as reliability, transparency, predictability, and social interaction cues, in isolation. However, in practice, these factors are highly interdependent and dynamically interact over time to influence trust and adoption. There is limited integrated analysis that explains how these determinants collectively shape trust dynamics and impact adoption outcomes in industrial contexts. Thirdly, trust has been identified as a dynamic construct that evolves through phases of formation, maintenance, and recovery, there is insufficient focus on how these trust dynamics directly influence the transition from initial system acceptance to sustained adoption in industrial settings. The relationship between trust calibration and long-term adoption remains underexplored, particularly in complex environments where human variability and system adaptability play a critical role. Lastly, emerging trends such as Industry 5.0 highlight the importance of human-centric design and intelligent systems supported by artificial intelligence and the Internet of Things. However, there is still limited research on how trust-aware decision-making mechanisms can be effectively integrated into these advanced systems to balance performance, safety, and user reliance.

3. Methods

This study adopts a qualitative research approach to investigate the determinants of trust and the influence on the adoption of HRC in industrial environments. A qualitative design is appropriate for this study as it enables an in-depth understanding of human perceptions, behaviours, and interactions with robotic systems, particularly in complex and dynamic industrial contexts.

Data for this study were collected using a secondary data approach. Relevant data were obtained from peer-reviewed journal articles, conference publications, and documented industrial case studies on human-robot collaboration. The selected sources included studies focusing on assembly processes, pick-and-place operations, and maintenance tasks, where human-robot interaction is prominent. The use of secondary data allows the study to leverage both theoretical and empirical insights into trust determinants, trust dynamics and adoption patterns. The integration of multiple sources enhances the depth and breadth of the analysis. To ensure robustness and credibility, a multi-source data collection strategy was employed, including:

- Document analysis: Review of academic literature, industry reports, and case studies related to HRC and trust dynamics
- Observational insights: Interpretation of reported industrial scenarios such as assembly operations, maintenance processes, and pick-and-place tasks
- Secondary empirical evidence: Analysis of findings from experimental studies involving human-robot interaction, including trust measurements, system performance, and interaction outcomes

This approach enables the study to capture both conceptual and practical perspectives on trust and adoption in HRC.

The collected data were analyzed using a thematic analysis approach. This method was used to identify recurring patterns and relationships across literature and case insights. The identified themes were then synthesised to develop an integrated understanding of how these factors interact and influence the adoption of human-robot collaboration in industrial environments. To enhance the credibility and reliability of the study, data triangulation was applied by integrating multiple sources of evidence. The use of peer-reviewed literature and documented case studies ensures consistency in findings, while thematic analysis provides a systematic and structured approach to interpretation.

4. Results and Discussion

4.1 Results

The thematic analysis of the reviewed studies resulted in four key themes: trust formation, determinants of trust, trust dynamics, and adoption patterns.

4.1.1 Trust Formation

The analysis of the reviewed studies indicates that trust formation in industrial HRC is highly context-dependent, with early interactions playing a critical role in shaping long-term user perceptions (Charalambous et al. 2016; Alhaji et al. 2024). The findings show that initial experiences with collaborative robots strongly influence the attitude of the workers toward safety, reliability, and usability (Charalambous et al. 2016; Alhaji et al. 2024). Furthermore, the results reveal that trust is multidimensional, consisting of dispositional, situational, and learned components (Loizaga et al. 2024). The willingness of the Workers to accept collaborative robots is influenced not only by system performance but also by initial experience and individual perceptions (Meißner et al. 2020). These findings highlight the importance of designing effective initial interaction experiences to support trust development. This finding provides a foundation for understanding how trust evolves and influences subsequent adoption.

4.1.2 Determinants of Trust

The results identify several key determinants that consistently influence trust across industrial contexts. Among these, robot reliability and predictability emerge as the most significant factors, as consistent system performance strengthens user confidence while failures quickly undermine trust (Kopp et al. 2020; Hopko et al. 2022). The findings further indicate that safety perception and transparency play an essential supporting role (Maurtua et al. 2017). Systems that communicate clearly and provide explanations are more likely to be trusted, particularly during error situations (Ye et al. 2023). In addition, human-related factors, such as attitudes and training, as well as organizational support, significantly influence trust and acceptance levels (Çiğdem et al. 2023; Kopp et al. 2020). These findings demonstrate that trust is shaped by a combination of technical, human, and organizational factors.

4.1.3 Trust Dynamics

The analysis confirms that trust in HRC is dynamic and evolves over time. Trust develops gradually through repeated interactions but can decline rapidly following system failures or negative experiences (Kopp et al. 2020). The results further reveal that different factors influence trust at different stages. Reliability and predictability are more critical during the formation stage, while communication and feedback become more important during trust recovery (Alhaji et al. 2021). Additionally, the study identifies two key risks: Over-trust, which may lead to unsafe reliance on robotic systems and Under-trust, which may result in system rejection or underutilization despite safe design (Legler and Bullinger 2025).

4.1.4 Patterns in Adoption

The findings indicate that the adoption of HRC is influenced by both technical readiness (robot capabilities/configuration) and human-centered factors such as fear of job loss (Kopp et al. 2020). While system performance is important, worker perceptions, including concerns about safety and job security, play a major role in determining acceptance. The analysis also shows that organizational culture acts as a moderator, with companies that actively address worker concerns achieving higher adoption rates. However, adoption does not always result in appropriate system use, as over-trust or lack of training may lead to misuse of collaborative robots (Babamiri et al. 2022). These findings highlight that successful adoption requires both technological capability and effective management of human factors.

4.1.5 Key Claims and Evidence

The analysis of the reviewed studies reveals several key insights regarding the role of trust in HRC. One of the strongest findings is that robot reliability and predictability consistently emerge as the most influential determinants of trust. Across multiple qualitative and quantitative studies, systems that demonstrate consistent and error-free performance are more likely to be perceived as competent and dependable, thereby strengthening user confidence and supporting collaboration outcomes (Kopp et al. 2020; Hopko et al. 2022).

Another significant finding is that early interactions between workers and collaborative robots play a critical role in shaping long-term trust. Evidence from case studies and qualitative research indicates that users' first experiences often create lasting impressions, influencing how they perceive safety, usability, and system reliability. Positive early encounters tend to foster openness and acceptance, while negative experiences may lead to persistent resistance, even when system performance improves (Alhaji et al. 2024; Charalambous et al. 2015; Meißner et al. 2020).

The findings also highlight the importance of organizational communication and training in enhancing both trust and adoption. Studies consistently show that when organizations provide clear information about system capabilities, safety protocols, and intended benefits, workers are more likely to accept and effectively engage with collaborative robots. Training programs further improve confidence by reducing uncertainty and improving user competence (Kopp et al. 2020; Çiğdem et al. 2023).

In addition, the analysis identifies trust calibration as a critical challenge in HRC environments. Both over-trust and under-trust were found to negatively affect system performance and safety. Over-trust may lead users to rely excessively on robotic systems without proper oversight, increasing the risk of errors or accidents. Conversely, under-trust may result in resistance to system use, limiting the potential benefits of collaboration. These findings suggest the need for mechanisms that support balanced trust levels (Alhaji et al. 2021; Legler and Bullinger 2025).

Finally, the results indicate that contextual and experiential factors are more influential than demographic characteristics in shaping trust. Worker perceptions are largely influenced by task conditions, prior experience, and workplace environment rather than factors such as age or gender. Similarly, negative attitudes toward automation were found to hinder adoption, even in cases where the technology is reliable and safe (Nguyen et al. 2025; Çiğdem et al. 2023).

4.2 Discussion

The findings confirm that trust is a central determinant of both adoption and sustained use of HRC systems. The analysis shows that early user experiences play a critical role in shaping long-term trust, emphasizing the importance of positive initial interactions during implementation. A key insight from the study is that trust is dynamic and requires continuous calibration. The presence of both over-trust and under-trust highlights the need for adaptive systems that support appropriate reliance. Feedback mechanisms, particularly those that provide explanations during system errors, are essential for maintaining trust over time. In addition, the study demonstrates that while technical factors such as reliability remain critical, organizational interventions such as training and communication significantly enhance trust and adoption outcomes. Finally, the findings suggest that contextual factors, such as workplace environment and user experience, have a greater influence on trust than demographic characteristics. This reinforces the importance of adopting a human-centred approach in the design and implementation of HRC systems.

These findings extend existing literature by demonstrating that trust is not only a determinant of adoption but also a continuous process that must be actively managed throughout the collaboration lifecycle. The study further highlights the importance of integrating technical performance with human-centred design to achieve sustainable adoption.

4.2.1 Enhanced Framework for Trust-Driven Adoption in HRC

The findings of this study highlight the importance of integrating adaptive mechanisms that actively manage the dynamic nature of trust in human-robot collaboration. In particular, three key elements: dynamic trust monitoring, trust-aware decision making, and human-centred design emerge as critical components for enabling sustainable adoption (Figure 1).

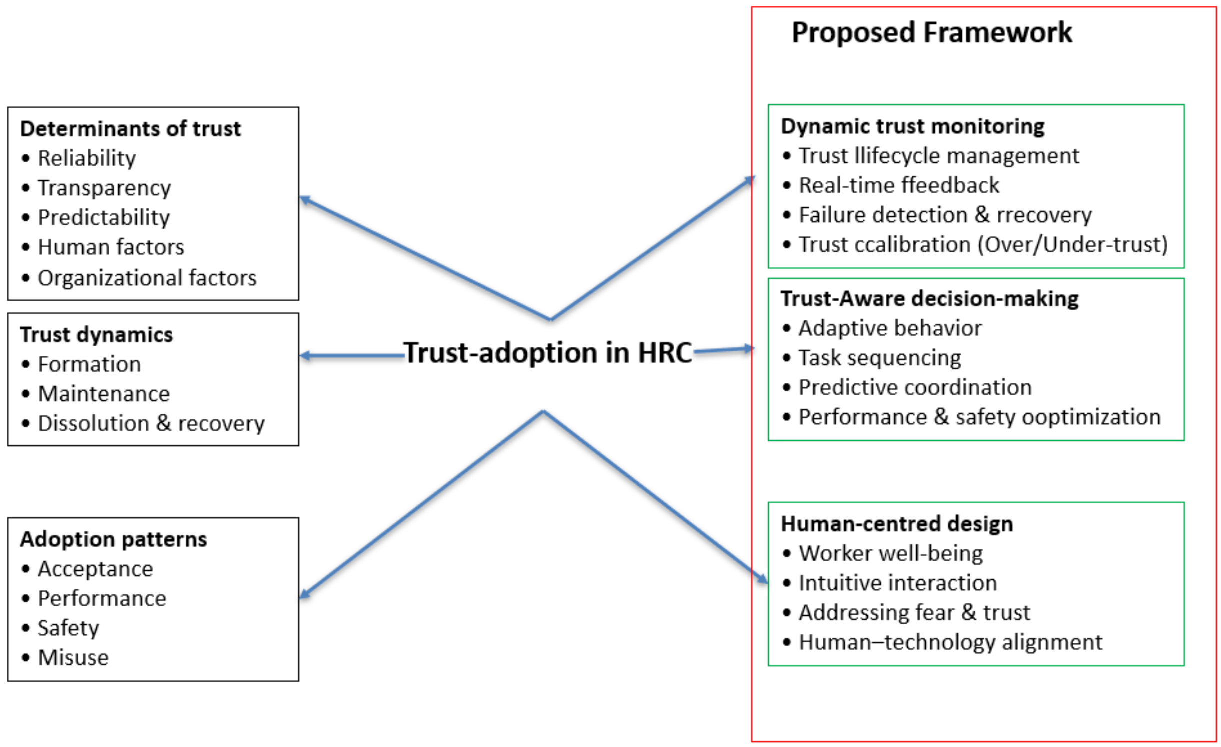

Figure 1. Proposed additional elements of Trust adoption in HRC

4.2.1.1 Dynamic Trust Monitoring

Dynamic trust monitoring operates as a continuous mechanism for managing trust throughout the collaboration lifecycle. It plays a crucial role in supporting all phases of trust dynamics, including formation, maintenance, and recovery. During the maintenance phase, monitoring enables robotic systems to adjust behaviour based on user feedback, such as adapting task sequencing or movement parameters, thereby sustaining user confidence over time. In the dissolution and recovery phase, monitoring allows systems to detect declines in trust and trigger appropriate feedback mechanisms, such as explanations or corrective actions, to restore user confidence. Furthermore, dynamic monitoring contributes to effective trust calibration by preventing both over-trust and under-trust. By providing continuous feedback and transparency, it helps users maintain an appropriate level of reliance on robotic systems, reducing risks associated with misuse or rejection. In this context, dynamic trust monitoring serves as a bridge between trust dynamics and adoption outcomes, enabling smoother and more reliable collaboration.

4.2.1.2 Trust-Aware Decision Making

Trust-aware decision making represents an active layer within the framework, where robotic systems incorporate human trust levels into their behaviour and task planning. This capability enables systems to dynamically adjust actions based on user confidence, ensuring that collaboration remains safe and effective. For example, during early interactions, robots may prioritize low-risk tasks to build initial trust, gradually increasing task complexity as confidence grows. This strategic sequencing supports trust formation and reduces uncertainty. Additionally, trust-aware systems enhance team performance by predicting human actions and adapting accordingly, which improves coordination and reduces safety risks in shared workspaces. Within the broader context of Industry 5.0, this capability is supported by advanced technologies such as artificial intelligence and the Internet of Things, enabling systems to become more responsive and human centric. Despite its importance, the integration of trust-aware decision-making mechanisms remains an emerging area, highlighting a need for further research.

4.2.1.3 Human-Centred Design

Human-centred design (HCD) serves as a foundational principle that underpins the entire framework. It shifts the focus from purely technical performance to a balanced approach that prioritizes both efficiency and worker well-being. Within the framework, HCD plays a critical role in addressing human-related determinants of trust, such as safety concerns, fear of job loss, and usability challenges. By designing intuitive interaction methods such as gesture-based controls and clear communication interfaces, HCD reduces user uncertainty and enhances system acceptance. In addition, HCD supports the development of adaptive, trust-aware systems by ensuring that technological solutions are aligned with human needs and expectations. This approach is central to Industry 5.0, where collaborative systems are designed to enhance both productivity and human experience. Overall, the integration of human-centred design reinforces the role of trust as a mediating factor, ensuring that system design directly supports effective and sustainable human-robot collaboration.

5. Conclusion

This study examined the determinants of trust and their influence on the adoption of human–robot collaboration (HRC) in industrial environments. The findings confirm that trust is not only a critical factor in the initial acceptance of collaborative robots but also a key driver of their sustained and effective use. Through a qualitative and thematic analysis, the study identified that trust is shaped by a combination of technical, human, and organizational factors.

Among the identified determinants, reliability and predictability emerged as the most significant in establishing trust, while transparency and communication play an essential role in maintaining and restoring trust during interaction. The results further demonstrate that trust is a dynamic construct that evolves through phases of formation, maintenance, and recovery, and must be continuously calibrated to avoid both over-trust and under-trust. These dynamics directly influence how users interact with robotic systems and ultimately determine adoption outcomes.

The study also highlights that adoption is not solely dependent on technological capability but is strongly influenced by human perceptions, organizational support, and workplace context. Early user experiences, training, and communication strategies are particularly important in shaping long-term trust and acceptance. Additionally, the findings show that trust acts as a mediating factor between system design and adoption, reinforcing the need for trust-aware approaches in the development and implementation of HRC systems.

A significant contribution of this research is the development of a framework that integrates trust determinants, trust dynamics, and adoption patterns. This framework provides a comprehensive understanding of how trust evolves and influences collaboration in industrial environments, offering valuable insights for both researchers and practitioners.
From a practical perspective, organizations should prioritize reliable system performance, enhance transparency through clear communication, and invest in training programs to support user confidence. Furthermore, adopting human-centred design approaches and incorporating adaptive, trust-aware systems can significantly improve collaboration outcomes.

Future research should focus on validating the proposed framework using empirical data, exploring long-term trust dynamics across different industries, and developing adaptive systems capable of real-time trust calibration. Such advancements will be essential for ensuring safe, efficient, and sustainable human–robot collaboration in increasingly complex industrial settings.

References

Chen M, Nikolaidis S, Soh H, Hsu D, Srinivasa S. Trust-aware decision making for human-robot collaboration: Model learning and planning. ACM Transactions on Human-Robot Interaction (THRI). 9(2):1-23. 2020.

Weiss A, Wortmeier AK, Kubicek B. Cobots in industry 4.0: A roadmap for future practice studies on human–robot collaboration. IEEE Transactions on Human-Machine Systems. 51(4):335-45. 2021

Kluy, Lina, and Eileen Roesler. Working with industrial cobots: The influence of reliability and transparency on perception and trust. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. Vol. 65. No. 1. Sage CA: Los Angeles, CA: SAGE Publications. 2021.

Charalambous, George, Sarah Fletcher, and Philip Webb. The development of a scale to evaluate trust in industrial human-robot collaboration. International Journal of Social Robotics 8.2 .193-209. 2016.

Glawe F, Kremer L, Vervier L, Brauner P, Ziefle M. Trust and Human Autonomy after Cobot Failures: Communication is Key for Industry 5.0. arXiv preprint arXiv:2509.22298. 2025.

Alhaji B, Büttner S, Sanjay Kumar S, Prilla M. Trust dynamics in human interaction with an industrial robot. Behaviour & Information Technology. 44(2):266-88. 2025

Cominelli L, Feri F, Garofalo R, Giannetti C, Meléndez-Jiménez MA, Greco A, Nardelli M, Scilingo EP, Kirchkamp O. Promises and trust in human–robot interaction. Scientific reports.11(1):9687. 2021

Onnasch L, Hildebrandt CL. Impact of anthropomorphic robot design on trust and attention in industrial human-robot interaction. ACM Transactions on Human-Robot Interaction (THRI).11(1):1-24. 2021

Campagna G, Frommel C, Haase T, Gottardi A, Villagrossi E, Chrysostomou D, Rehm M. Fostering trust through gesture and voice-controlled robot trajectories in industrial human-robot collaboration. In2025 IEEE International Conference on Robotics and Automation (ICRA). 11853-11859. IEEE. 2025

Hannum C, Li R, Wang W. Trust or not?: A computational robot-trusting-human model for human-robot collaborative tasks. In 2020 IEEE International Conference on Big Data (Big Data). 5689-5691. IEEE. 2020.

Akkaladevi SC, Heindl C. Action recognition for human robot interaction in industrial applications. In 2015 IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS). pp. 94-99). IEEE. 2015.

Adeniyi, A.O. The Role of Trust in Human-Robot Interaction: A Perspective on Factors Influencing Trust Development. International Research Journal of Innovations in Engineering and Technology - IRJIET, 9(6), 112-118. Article DOI https://doi.org/10.47001/IRJIET/2025.906013.2025

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

Loizaga, E., Leire Bastida, S. Sillaurren, Ana Moya, and N. Toledo. "Modelling and Measuring Trust in Human–Robot Collaboration." Applied Sciences. https://doi.org/10.3390/app14051919. 2024.

Meißner, Antonia, Angelika Trübswetter, Antonia S. Conti-Kufner, and Jonas Schmidtler. Friend or Foe? Understanding Assembly Workers' Acceptance of Human-robot Collaboration. ACM Transactions on Human-Robot Interaction (THRI) 10 : 1 - 30. https://doi.org/10.1145/3399433. 2020.

Kopp, Tobias, M. Baumgartner, and Steffen Kinkel. Success factors for introducing industrial human-robot interaction in practice: an empirically driven framework. The International Journal of Advanced Manufacturing Technology 112 : 685 - 704. https://doi.org/10.1007/s00170-020-06398-0. 2020.

Hopko, Sarah K., Ranjana K. Mehta, and P. Pagilla. Physiological and perceptual consequences of trust in collaborative robots: An empirical investigation of human and robot factors.. Applied ergonomics 106 : 103863 . https://doi.org/10.1016/j.apergo.2022.103863. 2022.

Maurtua, I., A. Ibarguren, Johan Kildal, L. Susperregi, and B. Sierra. Human–robot collaboration in industrial applications." International Journal of Advanced Robotic Systems 14. https://doi.org/10.1177/1729881417716010. 2017.

Ye, Yang, Hengxu You, and Jing Du. Improved Trust in Human-Robot Collaboration With ChatGPT. IEEE Access 11: 55748-55754. https://doi.org/10.1109/access.2023.3282111. 2023.

Çiğdem, Şemsettin, I. Meidutė-Kavaliauskienė, and B. Yıldız. Industry 4.0 and Industrial Robots: A Study from the Perspective of Manufacturing Company Employees." Logistics. https://doi.org/10.3390/logistics7010017. 2023.

Legler, F., & Bullinger, A. How to achieve human-centered automation: the importance of trust for safety-critical behavior and intention to use in human-robot collaboration. Frontiers in Organizational Psychology. https://doi.org/10.3389/forgp.2025.1669782. 2025

Babamiri, M., et al. "Insights into the relationship between usability and willingness to use a robot in the future workplaces: Studying the mediating role of trust and the moderating roles of age and STARA." PLoS ONE, vol. 17. https://doi.org/10.1371/journal.pone.0268942. 2022.

Nguyen, Cam Tu, Thu Nguyen, Lanhui Cai, Kum Fai Yuen, and Xueqin Wang. A perception-based investigation on logistics robot adoption: from an integrated perspective of trust formation and technology acceptance. The International Journal of Logistics Management (2025). https://doi.org/10.1108/ijlm-03-2023-0088. 2025.

Biographies

Masingita Onica Mohlala is a Lecturer in the department of Industrial Engineering and Engineering Management in the college of Science, Engineering and Technology at the University of South Africa (UNISA), Florida, South Africa. She holds a Master of Engineering in Management and Information Systems Engineering from Nagaoka University of Technology, Japan, a Master of Business Administration (MBA) from the University of Witwatersrand, South Africa and a Postgraduate Certificate in Education in Senior phase and Further Education and Training Teaching from University of South Africa (UNISA). Her research interests include optimization, sustainability, supply chain and quality management systems. She is a member of SAIIE.

Ngaka Mosia is a Lecturer in the department of Mechanical and Industrial Engineering, in the school of Engineering and a College of Science, Engineering, and Technology at the University of South Africa (Unisa), in Gauteng, South Africa. He holds a BSc (Hons) in Applied Science from the University of Pretoria (UP), a BTech in Industrial Engineering from the University of Johannesburg (UJ), a MPhil in Engineering Management from the University of Johannesburg (UJ), and a post-graduate certificate in Distance Education from the University of Maryland University College (UMUC). He has journals, conference papers, and posters. His research interests include technology-mediated teaching and learning and Productivity improvement through mechanization, and healthcare optimization. He is a member of SAIIE & IEOM and Nadeosa & DEASA.