

HUMAN-ROBOT COLLABORATION IN MANUFACTURING: A SYSTEMATIC REVIEW OF CURRENT STATE, EVOLUTIONARY TRAJECTORY, AND INTEGRATION GAPS

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Driven by the imperative to enhance manufacturing flexibility and resilience, this study undertakes a comprehensive assessment of human-robot collaboration (HRC) technology. Its aims are threefold: to evaluate the current technological landscape, delineate its evolutionary trajectory, and pinpoint critical gaps in existing HRC implementations. The ultimate goal is to synthesize these findings into an integrated technology-effect-application reference map that researchers and practitioners can use to identify priority areas for HRC development, rather than a prescriptive integration framework. Our methodology integrates citation and cluster analysis within a systematic literature review of 121 peer-reviewed articles. Main path analysis was selected over a purely qualitative synthesis because it traces citation-based evolution using a reproducible, quantitative weighting criterion, while K-modes clustering was selected over alternatives such as K-means because it natively handles the categorical (rather than continuous) nature of the technology-effect-application coding. Citation analysis revealed HRC as a multifaceted, multi-field technology still awaiting the formation of an interconnected knowledge system. Subsequently, K-modes-based cluster analysis identified three distinct subgroups across technology, effect, and application dimensions. The analysis yielded a structured taxonomy encompassing 14 unique HRC technologies, 16 associated technological effects, and five industrial applications. Citation network analysis further exposed 11 discrete research clusters, signaling limited cross-disciplinary integration and the nascent state of HRC research interconnectivity. A two-dimensional matrix analysis pinpointed five predominant technologies propelling HRC advancement: data analytics systems, optimization and machine learning algorithms, machine vision systems, sensor networks, and human-machine interfaces. Critically, this analysis simultaneously uncovered significant technological deficiencies, notably in safety protocols and cognitive interaction frameworks, indicating areas ripe for targeted research. This research significantly contributes to the HRC domain by elucidating the contemporary state of HRC technology, charting its developmental path, and comprehensively highlighting persistent research deficiencies.

Keywords: Citation Analysis; Cluster Analysis; Human-Robot Collaboration; Matrix Analysis.

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1. INTRODUCTION

Human-robot collaboration (HRC) has become a central enabler of manufacturing flexibility and resilience, driven by the transition toward Industry 4.0/5.0 and by industry's growing effort to combine collaborative robotics with AI, 5G, and cloud computing (Dobra and Dhir, 2020; Apraiz *et al.*, 2023). As this adoption accelerates, HRC technology is evolving unevenly across application domains, and its developmental trajectory remains poorly mapped (Simões *et al.*, 2020).

Several systematic reviews have already examined HRC from specific angles: Hentout *et al.* (2019) traced a decade of industrial HRC literature, Coronado *et al.* (2022) focused on human-centered performance metrics, Keshvarparast *et al.* (2024) concentrated on collaborative robots in assembly systems, and Liu *et al.* (2024) reviewed cobot applications in manufacturing. While each of these reviews is valuable, they isolate a single facet of HRC — a specific technology, application domain, or evaluation metric — and none jointly characterizes the technologies employed, the effects they produce, and the application fields they serve within one integrated framework. Consequently, the field still lacks a reference model that lets researchers and practitioners see, at a glance, where HRC technology currently stands, how it arrived there, and where unexplored technology-effect-application combinations remain.

This absence of an integrated reference model is the single core gap this study addresses: no existing review jointly documents which HRC technologies are used, what effects they produce, where they are applied, and how this configuration has evolved. Closing this one gap requires three analytically distinct but sequential steps, not three separate motivations. First, because no evidence-based inventory of HRC technologies, effects, and application fields currently exists, this study builds

one directly from the literature. Second, because a static inventory alone cannot show how the field arrived at its current state, this study traces the evolutionary trajectory of HRC research through citation-based main path analysis. Third, because a trajectory alone does not reveal where opportunities remain, this study cross-maps technology, effect, and application through matrix and cluster analysis to expose both current hot spots and unexplored gaps. Together, these three steps allow this study to contribute an integrated technology-effect-application framework for HRC — to our knowledge, the first review to combine citation-based evolutionary analysis with matrix- and cluster-based gap identification — providing researchers and practitioners with a single reference map for prioritizing future HRC research and development.

To this end, this study adopts a systematic, literature-based analysis approach. We inventory the HRC literature to identify the technologies employed, the effects delivered, and the application fields served, and we trace the evolutionary trajectory of this research through citation network analysis. Section 2 reviews related work on HRC and main path analysis; Section 3 describes the retrieval and analytical procedure; Section 4 presents the resulting taxonomy, citation network, matrix, and cluster analyses; and Section 5 discusses their implications together with the study's limitations.

2. LITERATURE REVIEW

2.1. HRC

HRC research has generally been framed around task-sharing between humans and robots in a common manufacturing environment (Liu and Wang, 2018). Early studies emphasized the complementary strengths of the two agents — human sensorimotor flexibility and problem-solving versus robotic precision, speed, and endurance (Green *et al.*, 2008; Zhang *et al.*, 2019) — and this complementarity remains the conceptual foundation of most subsequent work. However, the literature diverges sharply in how it operationalizes “collaboration”: some studies treat HRC primarily as a workspace-sharing and safety problem (Nikolakis *et al.*, 2019; Baratta *et al.*, 2024), others treat it as a communication and information-exchange problem (Kardos *et al.*, 2018; Ansari *et al.*, 2018; Gustavsson *et al.*, 2018), and still others treat it as a human-factors and workload problem (Vasconez *et al.*, 2019). These three streams are rarely reconciled in the same study, which is one reason the field still lacks a single, agreed reference model for what HRC technology should minimally comprise.

The safety-oriented stream is the most mature of the three. Nikolakis *et al.* (2019) and Baratta *et al.* (2024) both argue that safe operation requires a sensor-database-communication framework so robots can perceive and adapt to human behavior in real time; this line of work is strong on hazard mitigation but says comparatively little about how such perception should feed back into task allocation or productivity. The communication-oriented stream (Kardos *et al.*, 2018; Ansaria *et al.*, 2018; Gustavsson *et al.*, 2018) instead prioritizes the channel through which work commands and intentions are exchanged, showing that HRC is only functionally possible once a communication protocol exists between agents — yet these studies tend to treat safety as a downstream consequence of good communication rather than as a first-class design requirement, which is the reverse emphasis of the safety-oriented stream. The human-factors stream (Vasconez *et al.*, 2019) narrows the objective further, defining HRC's purpose as reducing operator workload and fatigue while preserving contact safety; this is a valuable normative goal, but by itself it does not specify which sensing, communication, or control technologies are required to reach it.

Application-domain studies illustrate the same fragmentation from a different angle. Augmented-reality-assisted HRC has been applied to adaptive process improvement (Giorgio *et al.*, 2017), automotive HRC to welding, polishing, and assembly (Cherubini *et al.*, 2016), and oil-and-gas HRC to shared multimodal control. Each domain paper reports technology choices suited to its own context, but none positions its findings against the safety-, communication-, or human-factors-oriented literature reviewed above, so it remains unclear which technologies generalize across domains and which are domain-specific artifacts. This absence of cross-stream and cross-domain comparison is precisely the gap that motivates the technology-effect-application taxonomy developed in Section 4 of this study: rather than adding another single-stream account of HRC, we classify the existing literature along all three dimensions simultaneously so that the relative maturity of each stream, and its coverage across domains, can be assessed systematically instead of anecdotally.

2.2. Main Path Analysis

Main path analysis (MPA) was developed to trace the historical development and evolutionary structure of a citation network by identifying the sequence of most-cited, most-connected papers over time (Yu and Sheng, 2021; Yu and Sheng, 2020; Umair *et al.*, 2022). Its appeal for a technology review such as this one is that it replaces the reviewer's subjective judgment of “which papers mattered” with a traceable, quantitative citation-weight criterion (Lathabai *et al.*, 2018; Yan *et al.*, 2018). However, the algorithms used to compute that weight differ in what they optimize for, and the differences are not merely technical — they affect which papers a review ends up treating as foundational.

The original search-path node pair (SPNP) and node-pair projection count (NPPC) algorithms enumerate all citation paths between two nodes, which is exhaustive but computationally expensive and can overweight papers that sit on many short, low-significance paths. Search path link count (SPLC) instead weights individual links rather than whole paths, which is faster but can undercount papers whose importance lies in connecting otherwise-separate clusters. Search path counting (SPC) was subsequently proposed as a more efficient approximation that most later MPA studies, including this one, adopt as the practical default (Umair *et al.*, 2022). Lu and Liu's (2014) critical-path and multiple-main-path extension further addresses a limitation shared by all four single-path algorithms: a single main path can obscure the fact that a citation network often contains several parallel, equally important developmental trajectories — which is directly relevant to HRC, a field this study shows to be fragmented into multiple, weakly-interconnected sub-literatures rather than a single linear trajectory (Section 4.3).

MPA has been validated across knowledge-diffusion studies (e.g., corporate social responsibility (Lu and Liu, 2014), blockchain (Yu and Sheng, 2020)), extended-trajectory studies (Kim and Shin, 2018; Yu *et al.*, 2022), and patent-citation studies spanning 3D printing, mobile payments, thin-film solar cells (Lai *et al.*, 2021), autonomous driving (Cho *et al.*, 2021), blockchain (Yu and Pan, 2021), and computer graphics (Watanabe and Takagi, 2022). Across these applications, MPA is consistently used to answer one of two questions: what is the dominant technological trajectory (single- or multi-path studies), or where do trajectories diverge into distinct sub-fields (cluster-oriented studies such as Lathabai *et al.*, 2018). Notably, despite HRC's recognized multi-technology, multi-field character, no prior study has applied MPA to HRC citation data. This is a meaningful omission: because MPA both traces a dominant trajectory and can reveal where it fractures into disconnected clusters, it is well suited to answering the two questions this review poses — how did HRC technology evolve, and why has it not yet consolidated into an interconnected knowledge system — in a single analytical step, rather than requiring a separate qualitative literature synthesis for each question.

2.3. Review of Prior Systematic Reviews on HRC

Across the six systematic reviews published on HRC to date (Simões *et al.*, 2022; Semeraro *et al.*, 2023; Hentout *et al.*, 2019; Coronado *et al.*, 2022; Keshvarparast *et al.*, 2024; Liu *et al.*, 2024), several findings recur regardless of scope: the complementarity of human and robot strengths is presented as the foundational rationale for HRC in every review; safety is consistently identified as the most mature and most-published research theme; and each review independently reports a marked increase in publication volume after approximately 2017, mirroring the trend this study also observes (Section 4.1). These convergent findings can reasonably be treated as established baseline knowledge about the field.

The same six reviews diverge, however, on what remains open. Simões *et al.* (2022) call for more workspace-design guidance; Semeraro *et al.* (2023) call for closer integration of machine-learning methods into HRC control; Hentout *et al.* (2019) call for updated coverage beyond their 2008–2017 window; Coronado *et al.* (2022) call for standardized human-centered metrics; Keshvarparast *et al.* (2024) call for more assembly-specific design guidelines; and Liu *et al.* (2024) call for expanded application-domain coverage beyond manufacturing. No review to date, however, has asked the more basic question of which technology-effect-application combinations are already saturated and which remain unexplored across the field as a whole; each instead proposes an extension within its own scope. This meta-level gap, rather than any single scope extension, is what the taxonomy, matrix, and cluster analyses in Section 4 are designed to close.

3. METHOD

This study collects keywords related to HRC from the literature (Simões *et al.*, 2022; Gualtieri *et al.*, 2021). The literature search database, Web of Science, was used in this study. This study adopts the main path analysis to identify the development track of the literature related to HRC. Accordingly, HRC's technologies, effects and applications are summarized, and a technology-effect and a technology-application matrix are further developed. Finally, through the matrix diagram, we conclude the development of HRC technology.

3.1. Keywords and Subject

Keyword selection methods generally fall into four categories: Term Frequency-Inverse Document Frequency (TF-IDF), frequency-based, variance-based, and weight-based methods (Noh *et al.*, 2015). Among these, the frequency method, which identifies keywords by their highest occurrence in the literature, is the most employed and was adopted for this study (Wang *et al.*, 2020).

From an initial pool of 130 articles gathered from the Web of Science, we developed a robust keyword list, which was refined by cross-referencing candidate synonyms against the terminology used in closely related peer-reviewed systematic reviews and standardized bibliometric thesauri (e.g., Web of Science KeyWords Plus), rather than general-purpose or non-scholarly reference sources. Ultimately, four primary keywords were identified to define our search strategy. To filter this initial pool down to the final 121 articles and mitigate confirmation bias, two reviewers independently conducted a manual screening process based on predefined inclusion and exclusion criteria, with any discrepancies resolved through consensus (the details are provided in Appendix A). A total of 9 articles were excluded during this stage because they fell outside the methodological scope of this study or were limited to short conference abstracts, ensuring a reproducible and transparent quality appraisal protocol for the final corpus.

These keywords were structured into a specific literature retrieval string: ((“human-robot collaboration” OR “human-machine collaboration” OR “human-robot interaction”) AND (“human-centered”)). Following a meticulous manual screening process, 121 articles were confirmed as valid and subsequently used for modeling.

3.2. Modeling Procedure

Our research procedure is divided into five stages (Figure 1). The path analysis determines whether the selected literature is cross-referenced or whether subsequent literature converges. Subsequently, the matrix-mapping technique adapted from the patent map analysis method (Yoon *et al.*, 2002) helps visualize research documents, such as pie charts, bar charts, and tables. This matrix-mapping technique effectively conveys information and latent knowledge of documents graphically to further formulate an effective strategy and layout.

This study is conducted through five steps of the retrieval scheme. It produces five types of analysis related to human-robot collaboration technology: fundamental analysis, citation analysis, classification of three features (technology, effect, and application), matrix analysis, and cluster analysis (Figure 2). We use fundamental analysis to understand the development of HRC technology by countries. Citation analysis is used to clarify the citation relationship of HRC literature. By classifying the three features, we will find the technologies used, the effect in play, and the types of application fields from the current HRC literature and carry out an inventory and arrangement. Using matrix analysis, we can clarify the technical layout and technical gap of the current HRC literature to analyze the technical placement, effect and application fields of the HRC literature. Finally, cluster analysis is used to analyze the group of the current HRC literature and to identify the leading technology, effects and applications in the subgroups.

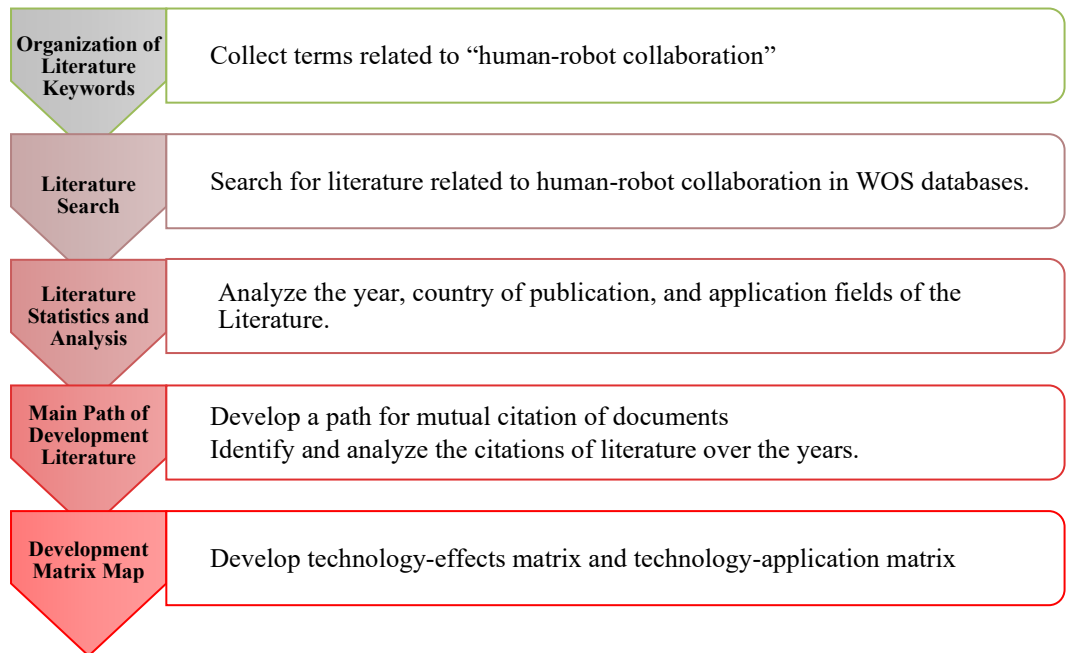


Figure 1. Literature search procedure

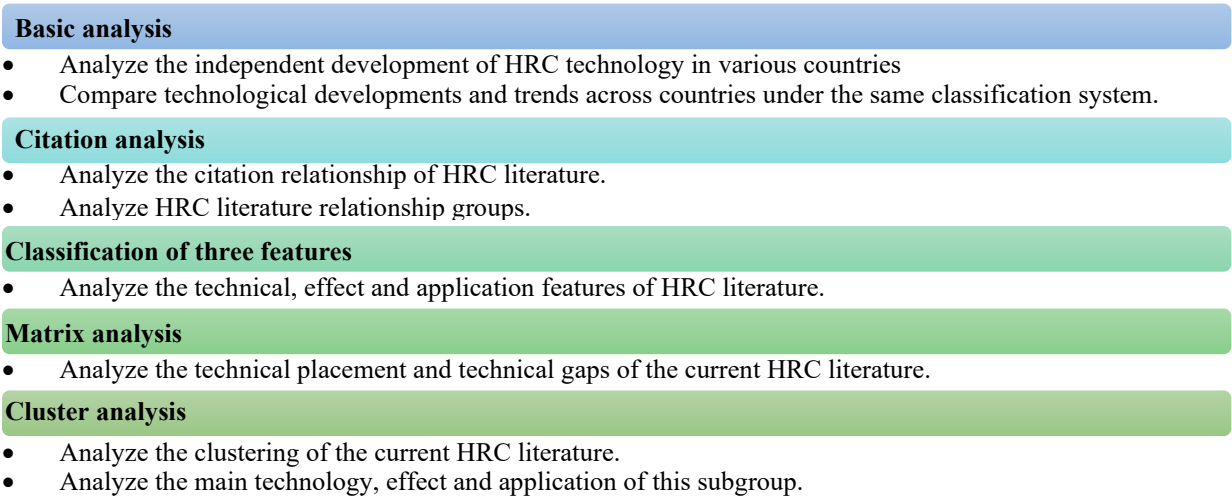
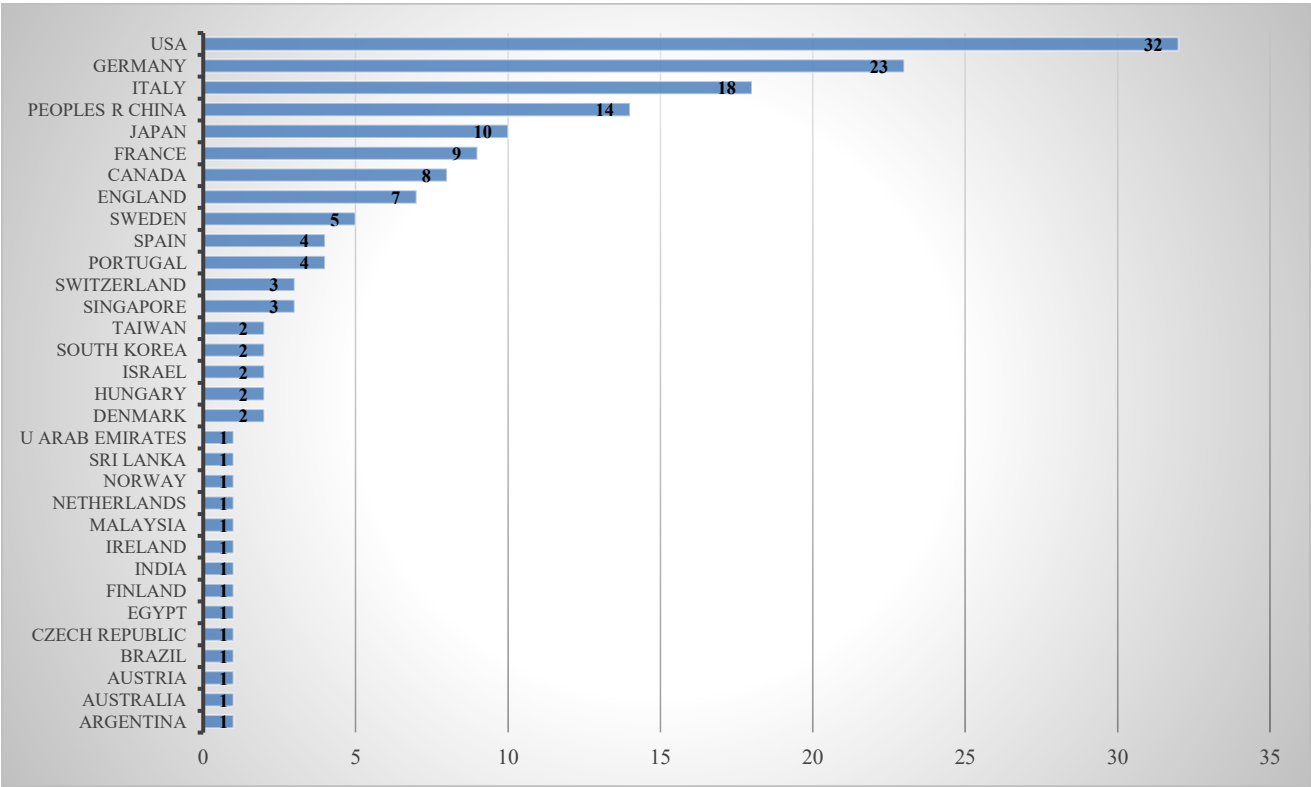


Figure 2. Proposed five stages for literature analysis

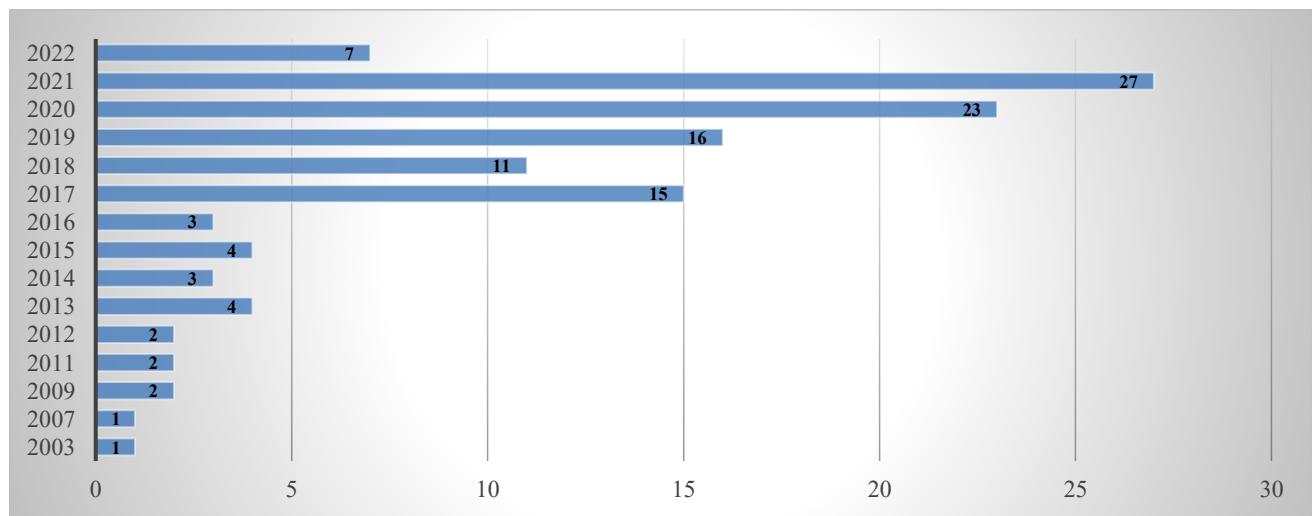
4. RESULTS AND DISCUSSION

4.1. Descriptive Data Analysis

The development of HRC technology by countries is carried out. A quantitative analysis of articles by country allows a comparison of technological developments and trends. The results show that the United States produces the most significant HRC articles, followed by Germany and Italy (Figure 3a). The statistics (Figure 3b) show that HRC articles increased significantly after 2017.



(a) By country



(b) By year

Figure 3. HRC-related research article distribution

4.2. Proposed HRC Categorization System

This study conducted a content analysis based on the 39 research articles obtained by the main path analysis and classified them according to three features: technology, effect, and application (Table 1).

Table 1. Technology, effect, and application categorization

NO.	Technology	Total Article Count	Effect	Total Article Count	Application	Total Article Count
#1	Human Factors Engineering	5	Physical Perception	32	General Industry	20
#2	Sensor	24	Task Perception	3	Manufacturing	4
#3	Human-Machine Interface	21	Production Scheduling	2	Service	9
#4	Machine Vision	25	Production Forecast	1	Medical	4
#5	Machine Hearing	1	Behavior Prediction	10	Gaming	1
#6	Cloud	0	Learning Ability and Self-Organization	25	-	-
#7	Data Analysis	30	Data Organization and Integration	33	-	-
#8	Cognition Computing	4	Decision-Making and Support	7	-	-
#9	Optimization and Machine Learning	28	Disruption, Diagnostic, and Prevention	14	-	-
#10	Prevention and Safety	13	Route Plan	8	-	-
#11	Internet Security	1	Robot Accurate Motion Control	1	-	-
#12	Wireless Communication	1	Robot Safety Trajectory	2	-	-
#13	Wearable Device	1	Intention Aware and Predict	2	-	-

NO.	Technology	Total Article Count	Effect	Total Article Count	Application	Total Article Count
#14	Persuasive Robotics	2	Joint Torque	5	-	-
#15	-	-	Influence User Behavior	2	-	-
#16	-	-	User Experience	1	-	-

Each feature is categorized based on a systematic investigation procedure by grounded theory and through constant keyword searches and filtering of the research article's content. 'Technology' refers to the technical content. Fourteen technology categories are identified: human factors engineering; sensor; human-machine interface; machine vision; machine hearing; cloud; data analysis; cognition computing; optimization and machine learning; prevention and safety; internet security; wireless communication; wearable device; persuasive robotics. 'Effect' refers to the functions achieved by using technology. Sixteen effect categories are identified, namely, physical perception; task perception; production scheduling; production forecast; behavior prediction; learning ability and self-organization; data organization and integration; decision-making and support; disruption, diagnostic, and prevention; route plan; robot accurate motion control; robot safety trajectory; intention aware and predict; joint torque; influence user behavior; user experience. 'Application' refers to the application domains of technology. Five applications are identified: general industry; manufacturing; service; medical; and gaming.

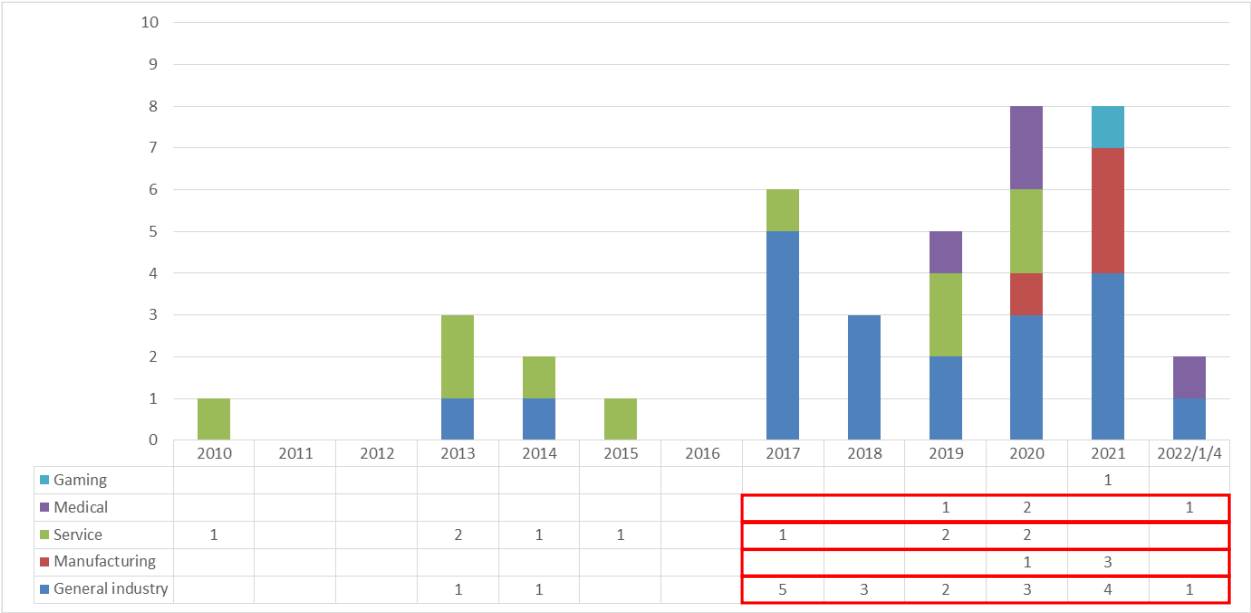
The statistics from the proposed category system show that most techniques are related to data analysis, followed by optimization, machine learning, and machine vision (Figure 4a). The effect is mainly reflected in data organization and integration, followed by physical perception, learning ability and self-organization (Figure 4b). Moreover, most of the technologies are adopted by general industry, followed by service, manufacturing, and medical (Figure 4c).



(a) By technology



(b) By effect



(c) By application

Figure 4. Development trend of HRC by category

4.3. Citation Analysis

To extract the structural core of the literature, a main path analysis was performed using the SPC algorithm variant to calculate edge traversal frequencies across the global directed acyclic citation graph. The 39-article citation (the details refer to Appendix A) backbone was subsequently isolated by applying a structural weight threshold that filtered out minor peripheral paths, preserving only edges with a top 15% value. This specific threshold ensures that only the primary, highly traversed evolutionary trajectories of the domain are captured for main path analysis, providing a reproducible and objective basis for tracking the field's historical development.

In this study, 121 articles were used for main path analysis, which shows a total of 39 article citation relationships, and this situation presents multiple independent article citation relationship groups (Figure 5), which are divided into 11 groups. This situation indicates that HRC has a multi-faceted development and application of multi-field technology. In addition, the existing HRC articles have not yet been closely interconnected, and the technologies used by each application would still be independent, which is a typical pattern of technology in its developing stage (Wang *et al.*, 2016).

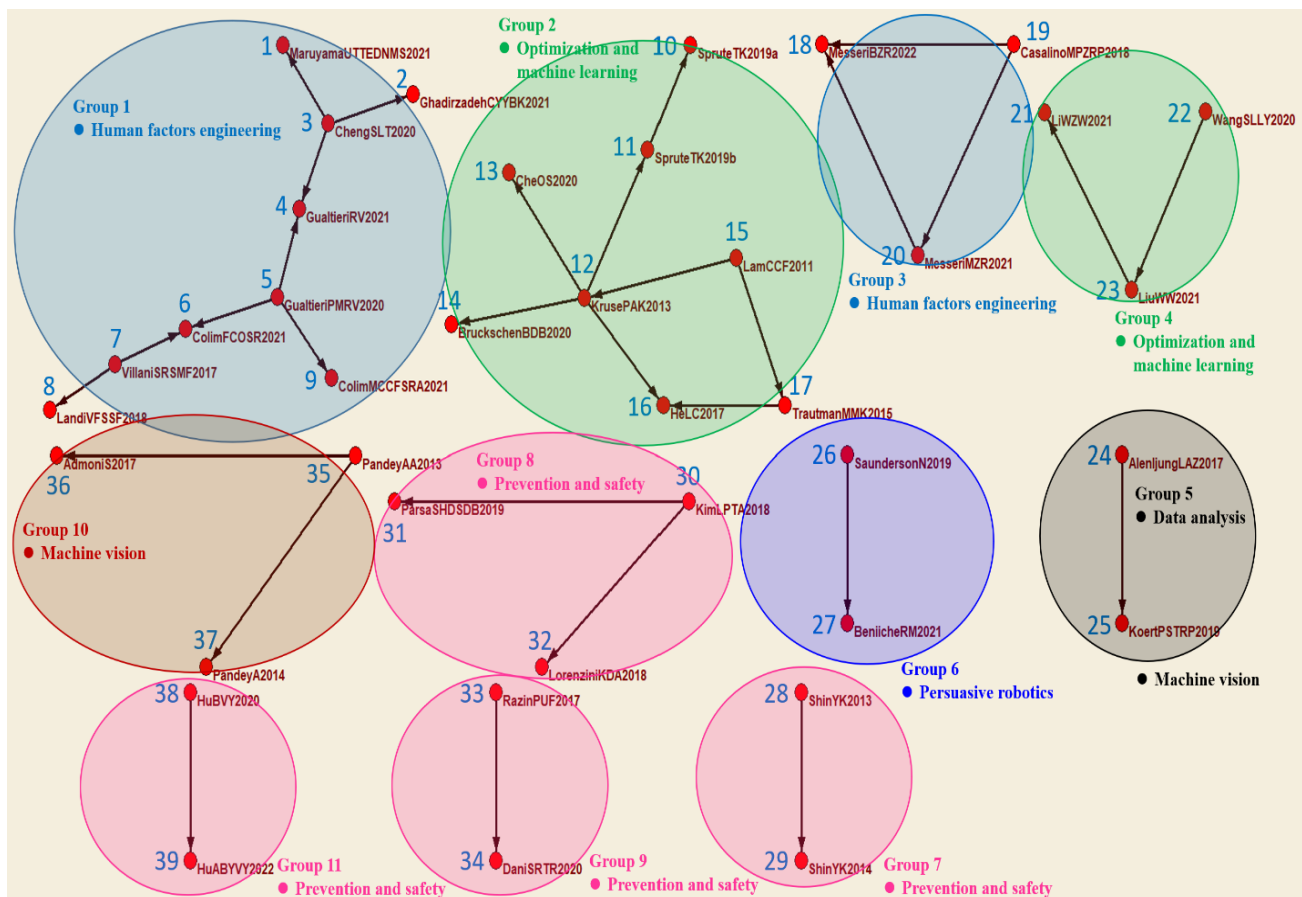


Figure 5. Main path analysis

This fragmentation admits more than one explanation, and the citation data alone cannot distinguish between them. It may reflect HRC's genuine multi-disciplinarity, in which sub-communities legitimately pursue different technical problems in parallel. It may instead reflect disciplinary isolation — for example between engineering-oriented and cognitive-science-oriented HRC research — which would be a less benign explanation, since it implies missed opportunities for cross-fertilization. It may also be, at least in part, an artifact of this study's restrictive search strategy (a single database and a keyword string requiring “human-centered” as a co-occurring term; see Section 3.1), which could exclude papers that would otherwise bridge two or more of the 11 groups. The developing-stage interpretation offered above is therefore one plausible reading among several; distinguishing between them would require either a broader citation corpus or a qualitative content analysis of why the 11 groups fail to cite one another, both of which we identify as directions for future research (Section 5).

Each independent group has its representative technology. The technology used in groups 1 and 3 is human factors engineering, whereas the technology used by groups 2 and 4 is optimization and machine learning. The technology used by group 6 is persuasive robotics. Groups 7, 8, 9, and 11 all use prevention and safety. The technology used by Group 10 is machine vision. Finally, Group 5 adopts two technologies: data analysis and machine vision.

Notably, although the techniques used in groups 1 and 3 are the same, the direction of effect by the two groups is different. The same is true for other independent relationship groups. Groups 2 and 4 solve the effect of robot route plan, gait analysis and multimodal control, respectively. Group 6 solves the effect of robot influence. Group 5 solves the effect of social robots and intention awareness and prediction. Group 10 solves the effect of task perception and active socialization.

Groups 7, 8, 9, and 11 solve the effect of pulley optimization, avoiding potential personal injury, human intent and safety trajectory and active physical human–robot interaction. Groups 7, 8, 9, and 11 are identified as separate communities because the main path analysis groups publications according to their citation relationships rather than their research topics. Papers within each group cite one another more frequently than papers in other groups, resulting in four distinct citation clusters. The limited citation links among these groups indicate that they have evolved as relatively independent research streams. Despite being structurally separated, the four groups share a common research focus on occupational prevention and safety. Since the studies in these groups all address issues such as hazard identification, accident prevention, risk assessment, workplace safety, and safety management, they were collectively categorized under the broader theme of “Prevention and Safety.” The separation of these groups therefore reflects differences in their knowledge development rather than differences in their overall research objectives. Each group may represent a distinct subfield or methodological approach within prevention and safety, such as safety management frameworks, risk assessment models, behavioral safety interventions, or computer vision-based safety monitoring. Although these streams have different citation histories, they contribute to the same overarching research area.

4.4. HRC Matrix Development

4.4.1. Matrix Analysis

The two-dimensional matrix analysis of the techniques and effects of HRC articles shows that several research techniques have created a variety of effects, which are currently hot topics (refer to Figure 6a with solid line). Figure 6a indicates that the techniques discussed in most HRC articles include data analysis (Technology #7) for data organization and integration (Effect #7), optimization and machine learning (Technology #9) for learning ability and self-organization (Effect #6), machine vision (Technology #4) for physical perception (Effect #1), sensor (Technology #2) for physical perception (Effect #1), and human-machine interface (Technology #3) for data organization and integration (Effect #7).

In Figure 6a, bubble area (and the number printed inside each bubble) represents the number of articles reporting that specific technology-effect combination, taken directly from the underlying technology-by-effect frequency matrix; for example, the bubble at the intersection of “Data analysis” and “Data organization and integration” is sized according to a value of 26, indicating 26 articles report this pairing.

On the contrary, several technical gaps were also found (refer to Figure 6a with a black dashed line). The details of HRC-related technology and effect gaps are shown in Table 2.

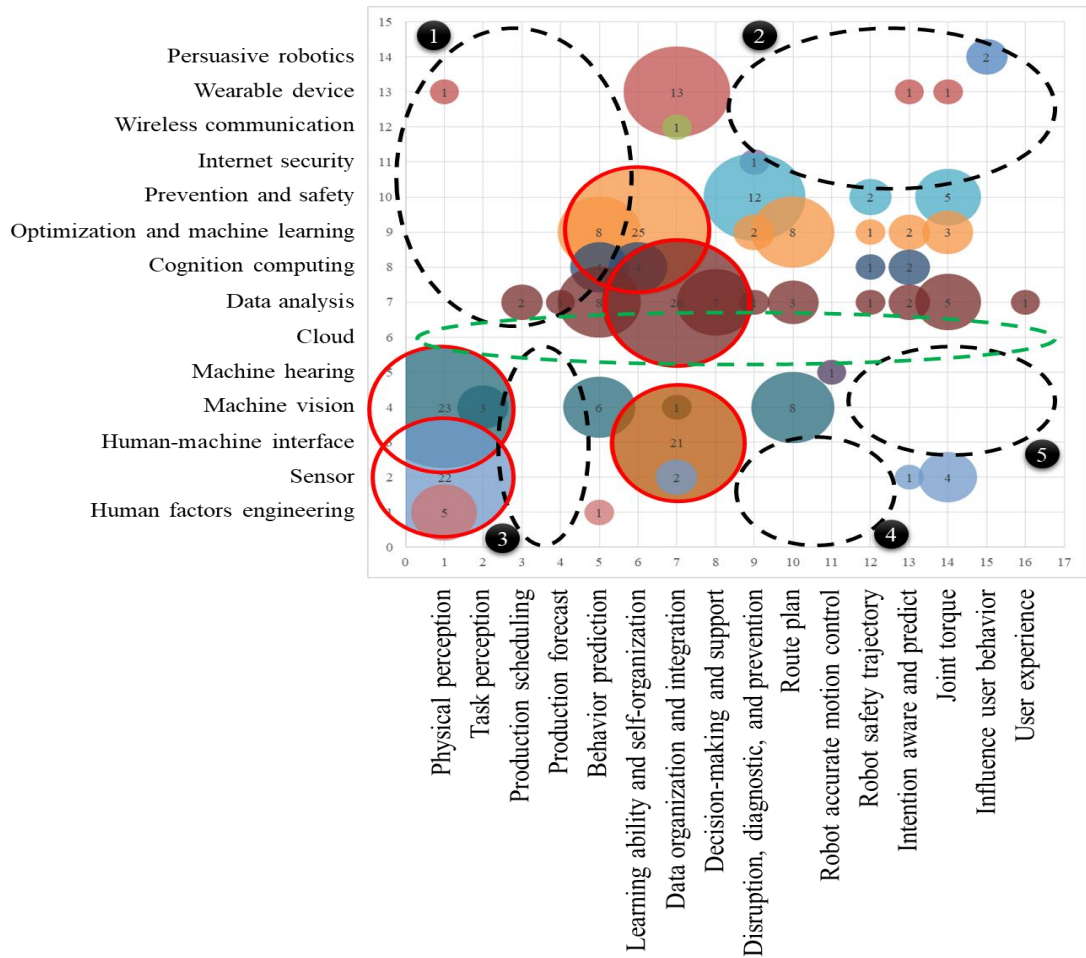
Table 2. HRC-related technology and effect gaps comparison

Black Dashed Line	Technology	Effect
1	Data Analysis, Cognition Computing, Optimization and Machine Learning, Prevention and Safety, Internet Security, Wireless Communication, Wearable Devices, Persuasive Robotics	Physical Perception, Task Perception, Production Scheduling, Production Forecast, Behavior Prediction, Learning Ability and Self-Organization
2	Internet Security, Wireless Communication, Wearable Devices, Persuasive Robotics	Disruption, Diagnostic, and Prevention, Route Plan, Robot Accurate Motion Control, Robot Safety Trajectory, Intention Aware and Prediction, Joint Torque, Influence User Behavior, User Experience
3	Human Factors Engineering, Sensor, Human-Machine Interface, Machine Vision, Machine Hearing	Production Scheduling, Production Forecast

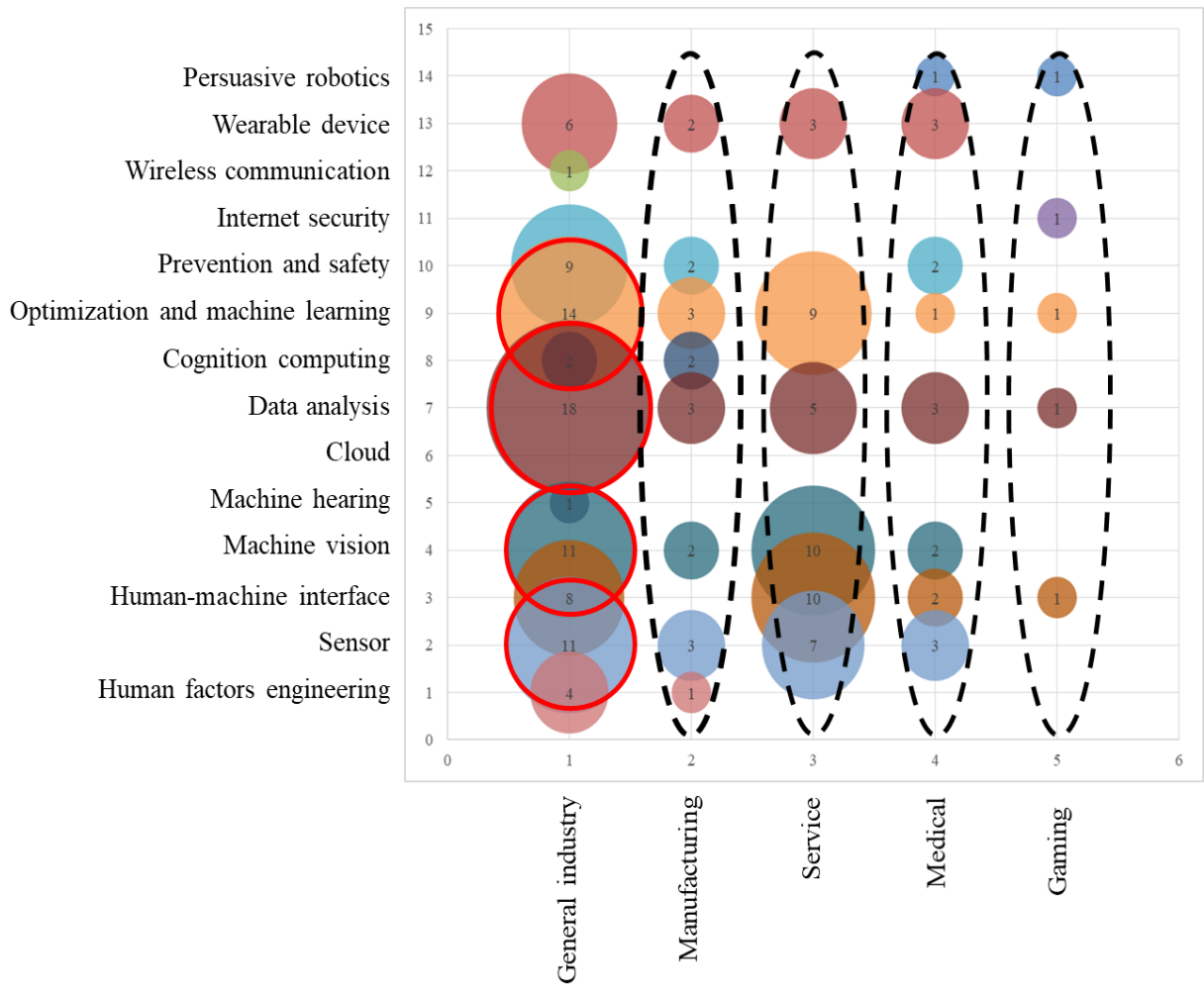
Black Dashed Line	Technology	Effect
4	Human Factors Engineering, Sensor, Human-Machine Interface	Disruption, Diagnostic, and Prevention, Route Plan, Robot Accurate Motion Control, Robot Safety Trajectory
5	Human-machine interface, Machine Vision, Machine Hearing	Robot Safety Trajectory, Intention Aware and Predict, Joint Torque, Influence User Behavior, User Experience

Finally, we also found in various HRC technologies that cloud technology (Technology #6) has not been mentioned in these articles from the past to the present. Therefore, the current cloud technology has gaps in its effect (refer to Figure 6a with a green dashed line).

The technology-application matrix (Figure 6b) shows that HRC-related articles are unevenly distributed in the matrix. Most articles exist in the general industry (Application #1). For instance, data analysis (Technology #7) is used in general industry (Application #1); optimization and machine learning (Technology #9) are used in general industry (Application #1); machine vision (Technology #4) is used in general industry (Application #1); sensors (Technology #2) are used in general industry (Application #1) (refer to Figure 6b with solid line). However, there are still gaps in the technology-application matrix. For instance, manufacturing (Application #2), service (Application #3), medical (Application #4), and gaming (Application #5) (refer to Figure 6b with a black dashed line).



(a) Technology vs. Effect



(b) Technology vs. Application

Figure 6. Two-dimensional matrix analysis on HRC. Bubble area and the number printed inside each bubble indicate the number of articles reporting the corresponding technology-effect combination (e.g., the bubble at the intersection of “Data analysis” and “Data organization and integration” denotes 26 articles).

4.4.2. Cluster Analysis

In this study, the K-modes cluster analysis is used to construct the cluster distribution of HRC articles in the three features: technology, effect, and application. The K-modes algorithm adopts the measurement of heterogeneity, can deal with classification attribute data (Nguyen, 2018), and its complexity converges in linear time (Khan and Ahmad, 2013). In the K-modes algorithm, the smaller the degree of heterogeneity, the smaller the distance (Sajidha *et al.*, 2021).

The K-modes clustering analysis was executed utilizing Huang *et al.*'s (2005) initialization strategy to establish stable initial cluster modes based on categorical attribute frequencies. The mathematical convergence criterion for the algorithm was defined as the absolute stability of partition assignments, where iterations terminated when the total within-cluster cost function was minimized, and zero data points shifted cluster membership between successive loops (capped at a maximum of 100 iterations). By explicitly defining these initialization parameters and convergence boundaries, the resulting three-group clustering partition remains robust, stable, and completely independent of arbitrary assignment bias.

To determine the optimal number of clusters for the K-modes analysis and ensure the partition reflects the true structure of the data rather than an arbitrary choice, a comprehensive grid search was executed across a range of K values (from K = 1 to 10). Because the K-modes algorithm utilizes a simple matching dissimilarity measure for categorical attributes rather than Euclidean distance, standard continuous metrics like the traditional Silhouette coefficient are not directly applicable. Instead,

the optimal cluster size and partition quality were mathematically evaluated using the K-modes cost function — which measures total within-cluster heterogeneity — alongside cluster purity metrics. When applying the elbow method to the cost function curve (Buchana, 2025), a distinct inflection point was observed at $K = 3$, representing a significant drop in cost from $K = 2$, after which the reduction in heterogeneity plateaued. This optimized 3-cluster solution achieves a minimal total within-cluster cost that demonstrates high internal cohesion, balancing model compactness with descriptive power. Furthermore, to verify cluster separation and meaningful partitioning, we calculated the category utility score, which confirmed that the groups are distinct and structurally meaningful. Consequently, $K = 3$ was selected as the optimized solution, through which the HRC articles are categorized into three distinct subgroups (Figure 7).

Group A indicates that optimization and machine learning (Technology #9) are heavily used to resolve learning ability and self-organization (Effect #6) and are applied in the service (Application #3). Group B shows that data analysis (Technology #7) is used to resolve data organization and integration (Effect #7) and is applied in the general industry (Application #1). Group C indicates that machine vision (Technology #4) is used to resolve physical perception (Effect #1) and is applied in manufacturing (Application #2).

4.5. Discussion

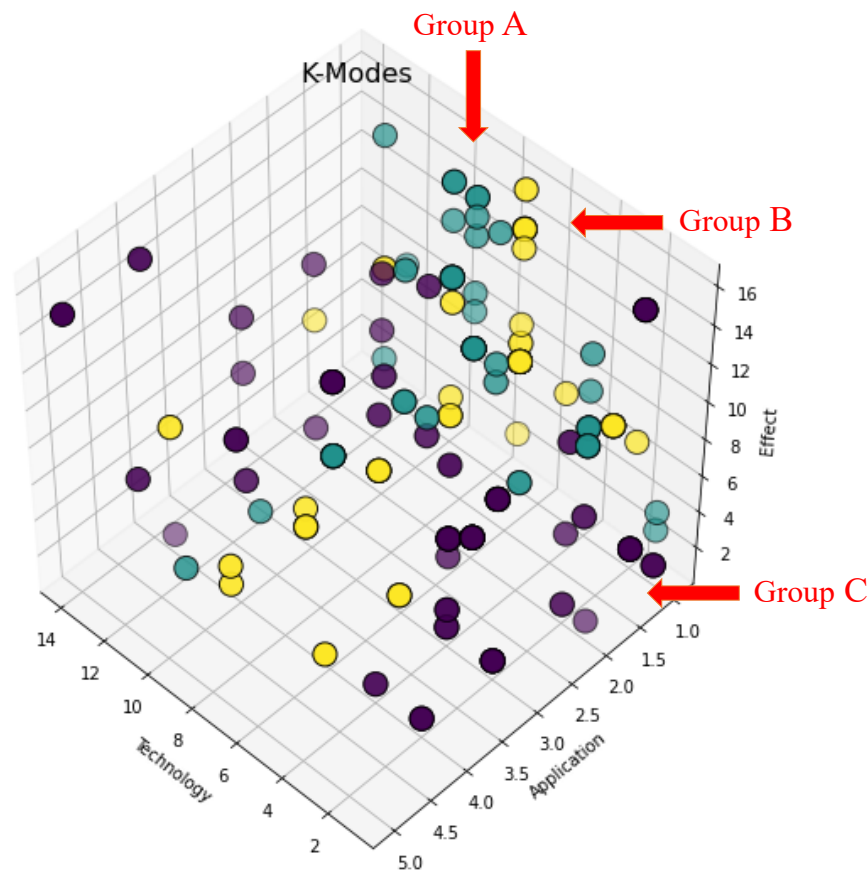
HRC technology is an essential topic for industry and academia (Liu and Wang, 2017). It is found that after 2017, the literature has increased dramatically, which shows that the issues regarding HRC technology have been paid close attention to. The main path of HRC technology identifies several important technologies, such as human factors engineering, optimization and machine learning, persuasive robotics, prevention and safety, machine vision, and data analysis. Those studies mainly focus on gesture recognition of personnel, prediction of personnel behavior, perception of sweeping robots, task perception and active socialization, avoiding potential personal injury, robot influence, etc., and may also be a trend of development in the future.

Building on the main-path trajectory identified above, the present study reveals the ongoing technologies and gaps that HRC possesses. In terms of technology, we found that data analysis, optimization, machine learning, and machine vision technology have become hot technical topics in HRC technology in recent years. Through the development of these technologies, robots can be endowed with learning, data processing and vision capabilities so that robots can use their eyes to judge autonomously like humans, such as product type, product assembly process, operator behavior status and other information. In addition to autonomous judgment, the robot can learn the operator's assembly process and apply it to education and training. For example, the robot learns the workflow of an experienced operator. One can operate the process when a junior operator wants to operate under the robot's guidance. Robots already have the visual sense of “eyes” like humans. In the future, robots may be endowed with other senses, such as ears (auditory perception), mouth (speaking), nose (olfactory perception), and hands (tactile perception). Most of the research is still at the level of vision, and there is no research on other perception capabilities of robots, which is also an important direction for future technological development.

Turning from technologies to the effects they produce, most of the articles revolve around the three popular effect issues of HRC: data organization and integration, physical perception, and learning ability and self-organization. The effects of the popular technologies we discussed before are produced for some purposes, such as personnel gesture recognition, personnel behavior prediction, sweeping robot perception, etc. Data organization and integration are achieved by collecting large amounts of data. Physical perception enables robots to perceive a series of human behaviors. Learning ability and self-organization enable robots to have the ability to learn by themselves. Currently, most of the research is based on humans, aiming at the perception and monitoring of human behavior, and mainly focuses on behavior and action. Through the perception and monitoring of robots, the safety of personnel in the workplace is greatly improved. However, few studies have explored the human state. For example, in the workplace, changes in the physical state (heart rate, fatigue, pressure) of personnel will affect the safety of personnel during HRC. These effects have not been found in our current investigation results and may be an essential part of HRC in the future.

This absence is directly visible in the taxonomy itself: none of the sixteen effect categories in Table 1 corresponds to real-time physiological-state monitoring (e.g., heart rate, fatigue, or stress signals) explicitly. This observation highlights a clear conceptual boundary in the current literature: existing safety frameworks predominantly respond to external spatial and kinematic variables, leaving internal human physiological factors as a largely unexplored frontier for future adaptive safety systems.

Finally, a few articles on HRC technology discuss cloud technology — a smaller but distinct pattern relative to the technology and effect trends discussed above — which is also a significant finding. Cloud technology is inseparable from new technologies such as the Internet of Things and cloud computing. 5G has brought the benefits of high speed and low latency, which can lead to a large number of applications, such as integrating AR/VR and DT technology by combining 5G and VR glasses, providing visual information for junior personnel education and training in the future, and this may be the next key development technology.



Note: The number of HRC technology article groups and the number of articles in each group

Group	Color Notation	Article Count	Main features of the Group
A	Green	28	'Optimization and machine learning' technology is used to resolve 'learning ability and self-organization' effect, and was applied in the 'service' application.
B	Yellow	29	'Data analysis' technology is used to resolve 'data organization and integration' effect, and was applied in the 'general industry' application.
C	Purple	25	'Machine vision' technology is used to resolve 'physical perception' effect, and was applied in the 'Manufacturing' application.

Figure 7. Three-dimensional analysis of HRC articles

5. CONCLUSION

This study set out to close a single gap: the absence of an integrated, evidence-based reference model documenting which HRC technologies are used, what effects they produce, where they are applied, and how this configuration has evolved. Analyzing 121 articles, we produced a taxonomy of 14 technologies, 16 effects, and five applications; traced the field's evolution through main path analysis, which surfaced 11 weakly-interconnected citation subgroups; and cross-mapped technology, effect, and application through matrix and cluster analysis, which identified five currently dominant technologies (data analysis, optimization and machine learning, machine vision, sensor, and human-machine interface) alongside a three-cluster structure linking specific technology-effect-application combinations.

Taken together, these results suggest that HRC is not a single maturing technology but a set of partially overlapping sub-fields that have each made local progress — in safety, in perception, in learning-based control — without yet converging on shared methods or a shared evaluation vocabulary. The five hot technologies identified in Section 4.4.1 represent the field's current center of gravity; the technology-effect and technology-application gaps in Table 2 represent the combinations that remain untested despite being technically plausible; and the physiological-state gap noted in Section 4.5 represents a specific, actionable direction rather than a generic call for “more research.” For research planning, this implies that near-term contributions are more likely to come from filling identified gaps within established technology streams (e.g., extending sensor and machine-vision methods to physiological-state monitoring) than from introducing entirely new technology categories. For practitioners selecting HRC solutions, the matrix results in Section 4.4.1 offer a way to check whether a candidate technology-effect pairing already has a body of precedent to draw on or falls into a comparatively untested gap. Concretely, of the five hot technologies identified, data analysis and optimization/machine learning show the broadest effect coverage and are therefore the lowest-risk starting point for organizations with limited HRC experience, whereas prevention-and-safety and cognition-computing technologies remain comparatively under-connected to effects and applications (Table 2) and represent higher-risk, higher-payoff investments better suited to organizations that can absorb longer development cycles. Leaving a gap unaddressed is not neutral: the safety-related gaps in particular (Table 2, rows 2 and 4) coincide with effects — route planning, robot safety trajectory, intention awareness — whose absence has direct implications for operator safety in deployed HRC systems, making them a priority for near-term applied research rather than a purely academic concern.

This study's claims hold under specific boundary conditions that should guide how they are used. Because the corpus was retrieved from a single database (Web of Science) using a keyword string requiring “human-centered” as a co-occurring term, the taxonomy and gap analysis describe the human-centered, English-language, peer-reviewed segment of HRC research rather than the field as a whole; practitioner reports, patents, and non-English literature are not represented, and papers using different terminology for human-centered HRC may have been missed. Because the K-modes cluster solution and the citation-subgroup count are specific to this corpus and retrieval window, both should be re-evaluated as the literature grows rather than treated as fixed properties of the field. Future work should therefore extend retrieval to Scopus and IEEE Xplore to test whether the taxonomy and gap structure reported here are retrieval-artifact-free, formally justify cluster count using quantitative criteria such as silhouette or gap-statistic analysis, and apply the same technology-effect-application framework to practitioner and patent sources so that the academic picture developed here can be compared against industrial practice. Furthermore, future work is encouraged to expand upon the current review methodology by implementing a fully specified, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-compliant screening protocol. This will include a formal documentation of rigid inclusion and exclusion criteria, an explicit quality-appraisal framework, and a multi-reviewer cross-verification process to further enhance reproducibility and minimize selection bias.

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APPENDIX A – SUPPLEMENTARY DATA

The screening records and the 39-article main path citation data are accessible online from <https://drive.google.com/drive/folders/1LVkLy9LVCAB30agTQb6-MwKXQYIWgJL?usp=sharing>