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Review

AI and Robotics in Mechanical Engineering: Public Narratives, Acceptance Frameworks, and Science Communication for Human-Robot Collaboration

Ignatius Ekengwu [1,*] and **Bonaventure Ekengwu** [2]

[1] Mechanical Engineering Department, Nnamdi Azikiwe University, Awka 420110, Nigeria

[2] Department of Electronics Engineering, University of Nigeria, Nsukka 410001, Nigeria

[*] Correspondence: ie.ekengwu@unizik.edu.ng

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Abstract: The rapid deployment of AI-powered collaborative robots (cobots) in industrial manufacturing settings has created a growing mismatch between technological capability and public willingness to accept these systems. Despite significant technical advances, robot-related fear, cultural resistance, and poor science communication continue to hinder adoption across major industrial economies. This review synthesises evidence from 86 peer-reviewed sources (2016–2025) across four areas: media framing and public narratives; technology acceptance frameworks (TAM, HRCAM, and the Uncanny Valley effect); cross-national empirical findings from Germany, Japan, China, South Korea, the USA, and the UK; and practical science communication strategies. We find that robot-related fear affects 29–52% of national populations depending on cultural and institutional context; that hands-on and immersive exposure consistently outperforms informational campaigns in reducing anxiety; that existing acceptance models underestimate emotional, safety, and psychological barriers to cobot adoption; and that no single communication strategy succeeds uniformly across cultural settings. Key findings indicate that worker participation in deployment processes, transparent employment communication, explainable AI interfaces, and culturally adapted messaging each independently improve acceptance outcomes. The review further demonstrates that media framing—predominantly dystopian in Western contexts—shapes worker attitudes prior to any formal introduction programme. Four research gaps are identified: the absence of industrial-context science communication studies, underrepresentation of the Global South, the lack of longitudinal data, and underdeveloped use of immersive technologies. Directions for future work are proposed.

Keywords: Artificial Intelligence; Collaborative Robots; Human-Robot Collaboration; Science Communication; Technology Acceptance; Media Framing; Uncanny Valley; Robophobia

1. Introduction

Walk onto a modern factory floor, and you might witness something that stops your tracks: a robotic arm that suddenly pauses, registers your presence, then quietly resumes its task. For an engineer who designed the system, this is just a force-limiting safety protocol doing exactly what it should. For a worker who has never stood next to a machine like that before, it can feel deeply strange—almost like being watched. The questions that arise at that moment ('Does it know who I am? Is this going to take my job? Can I trust it?') are not questions that any technical manual addresses. They are, at root, science communication problems, and they sit at the center of this review.

AI has become inseparable from mechanical engineering practice. Across sectors ranging from automotive assembly and aerospace to pharmaceutical production and precision fabrication, AI-driven robotic systems are now routinely performing tasks that were, until recently, exclusively human. Collaborative robots—cobots—represent perhaps the most visible dimension of this shift. Unlike earlier industrial robots that operated in caged, segregated environments, cobots are designed to work alongside people, sharing physical space and sometimes handing objects directly to human co-workers. The global cobot market was valued at approximately USD 1.85 billion in 2024 and is expected to grow at an 18.9% compound annual growth rate, reaching around USD 3.38 billion by 2030 [1,2]. Longer-range forecasts suggest values exceeding USD 22 billion by 2033 [3]. The Asia-Pacific region currently accounts for around 45% of global market share, with China, Japan, and South Korea all pursuing government-backed automation programmes [4]. **Figure 1** illustrates the trajectory of this market growth.

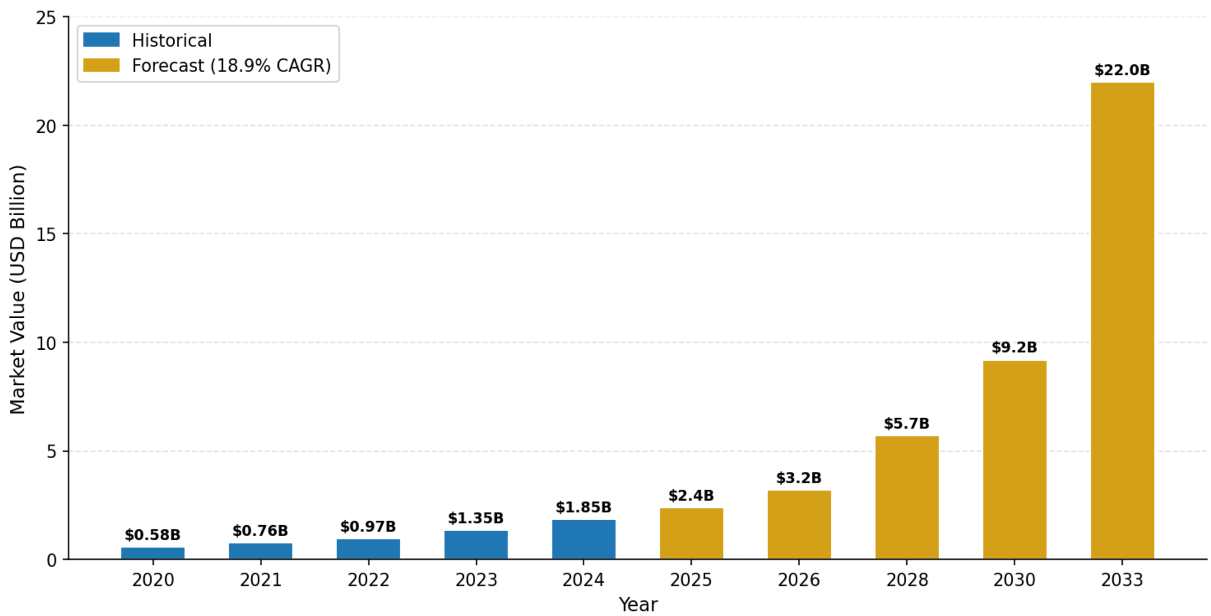

Figure 1. Global Collaborative Robot (Cobot) Market Size and Growth Forecast, 2020–2033.
Source: Figure created based on data reported in the literature [1–3].

The gap between what cobots can do and what workers are willing to accept is not a trivial implementation detail. Survey data show that substantial portions of the population in every major industrialised nation have genuine concerns about AI-driven automation. In a 2024 cross-national study by Hexagon spanning eight countries, over half of British respondents said they feared robots. The corresponding figures were 45% in the United States, 44% in China, 41% in Germany, 38% in Japan, and 29% in South Korea—the most densely automated country in the world [5]. These differences cannot be attributed simply to familiarity or education level. They reflect entrenched cultural narratives, the way media covers automation, labour relations structures, and the regulatory environments in which people interpret what robots mean for their lives.

When that mismatch produces resistance on the factory floor—or when policymakers misread public sentiment, or when companies overpromise what AI can deliver—the consequences extend well beyond communication failure. Adoption stalls, investments are wasted, and in some cases physical risk increases when safety protocols are not followed by workers who do not trust the system [6,7]. As the Industry 5.0 paradigm increasingly frames manufacturing around human-centricity, sustainability, and resilience, the communicative relationship between AI robotics and the people working alongside it has become as important a design consideration as technical safety compliance [8,9].

Separate literature has developed around the technical dimensions of AI robotics in mechanical engineering and around science communication about AI in society more broadly. What remains comparatively underdeveloped is a synthesis that bridges both, specifically in the context of industrial robotics and human-robot collaboration (HRC). This article attempts that synthesis, drawing on evidence from both domains to produce a practically useful account for researchers, practitioners, engineers, and policymakers.

The literature search was conducted iteratively using Scopus, Web of Science, and Google Scholar. Search terms included combinations such as 'human-robot collaboration', 'cobot acceptance', 'science communication robotics', 'public perception AI robots', 'media framing artificial intelligence', 'technology acceptance model cobots', 'uncanny valley industrial', and 'robophobia'. Only peer-reviewed articles, verified industry surveys, and substantive government or institutional reports published in English between 2016 and 2025 were retained. Studies focused exclusively on service or healthcare robotics were included only where their findings offered clearly transferable insights to industrial mechanical engineering contexts. A total of 86 sources are synthesized.

2. Theoretical Frameworks: Understanding Fear, Resistance, and Acceptance

Long before a factory worker first encounters a cobot on the production floor, they have already developed views about robots—views shaped by what they have seen in films, read in the news, or heard from colleagues. Science communication scholars refer to these pre-existing interpretive lenses as 'frames', and a substantial body of research confirms that frames powerfully condition whether new technical information is trusted, questioned, or rejected outright [10,11]. Any effective communication strategy around AI robotics must start with an honest reckoning with the psychological and social landscape it is entering. **Figure 2** compares the three main theoretical frameworks discussed in this section.

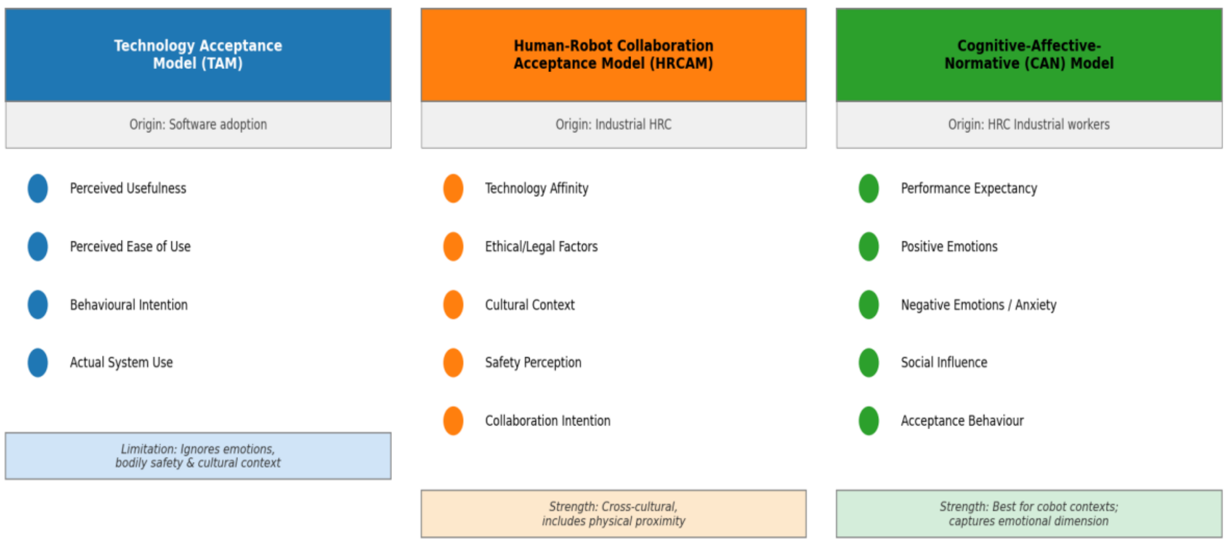

Figure 2. Comparative overview of three acceptance frameworks: TAM, HRCAM, and CAN Model.
Source: Figure created based on data reported in the literature [12–14].

2.1. The Technology Acceptance Model and Its Limitations for Cobot Contexts

The Technology Acceptance Model (TAM), first proposed by Davis [12] in 1989 and later extended into TAM2 and TAM3 by Venkatesh and Davis [13] and Venkatesh and Bala [14], has been the dominant framework for predicting technology uptake in organisational settings for three decades. In its original formulation, TAM holds that perceived usefulness and perceived ease of use are the primary drivers of adoption behaviour. Later versions added social norms, job relevance, output quality, and anxiety about computers as further predictors [13,14].

However, TAM runs into serious limitations when applied to industrial human-robot settings. A worker's ongoing relationship with a cobot involves more than evaluating whether the system is useful or easy to operate. It involves physical proximity to a moving machine, awareness of life-safety implications, emotional responses to the robot's appearance and behaviour, and complex social dynamics that emerge within a shared workspace [15,16]. Research on cobot acceptance in manufacturing environments has shown that TAM cannot account for the anthropomorphic cues workers respond to, nor for the intergroup dynamics that develop when people and machines occupy the same space [16, 17]. Critically, even workers who express positive intentions toward cobots do not always sustain that acceptance in practice: roughly one-third of assistive technologies introduced into workplaces are eventually abandoned despite initial compliance [18]. This disconnect between stated intention and actual long-term use is a core weakness TAM cannot adequately explain.

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. [19], merged eight competing frameworks and identified performance expectancy, effort expectancy, social influence, and facilitating conditions as the strongest predictors of usage intention, explaining up to 70% of the variance in observed behaviour. UTAUT is a meaningful advance, but it still underweights the emotional and safety dimensions that are especially prominent in cobot contexts. A systematic review of human factors in Industry 5.0 manufacturing found that worker anxiety, stress, and general psychological wellbeing are routinely overlooked in acceptance research despite being among the strongest real-world determinants of cobot coexistence quality [20,21].

In response to these gaps, Matheson and colleagues [15] developed the Human-Robot Collaboration Acceptance Model (HRCAM), which adds technology affinity, ethical and legal considerations, and cultural background to the standard TAM variables. Cross-national validation of HRCAM across Germany, Japan, China, and the United States found that cultural background had a significant independent effect on acceptance, with Japanese participants expressing notably greater comfort with physical proximity to robots than German participants—consistent with long-standing sociological research on robot attitudes in both countries [15]. A separate year-long field study involving 39 industry and research stakeholders found that achieving genuine human-robot collaboration in Industry 5.0 requires navigating real tensions between efficiency goals and human-centric values, tensions that standard acceptance frameworks simply do not surface [22].

2.2. The Cognitive-Affective-Normative Model: Bringing Emotion Back In

A more recent framework—the Cognitive-Affective-Normative (CAN) model—addresses what may be the most consequential gap in the TAM tradition: the treatment of emotion. In a study of 126 factory workers applying the CAN framework, positive emotions, performance expectations, effort expectations, and social influence all independently predicted positive attitudes toward human-robot collaboration [16]. More revealing was the finding that negative emotions and anxiety constituted meaningful barriers to acceptance even among workers who intellectually acknowledged the robot's technical competence. Put plainly, knowing that a cobot is certified safe does not make a worker comfortable standing next to it if the way the system was introduced left them feeling anxious, ignored, or disrespected.

Related evidence from workplace psychology reinforces this picture. A longitudinal study tracking 381 employees across South Korean companies found that AI adoption measurably eroded their sense of psychological safety, and that this erosion in turn predicted increased rates of depression—an effect that ethical leadership could partially buffer but not eliminate [23]. Research into AI workplace anxiety in service sectors found that negative emotional states fully mediated the relationship between AI-related concern and overall life satisfaction, and that social support was the main protective factor [24]. Though these studies concerned digital AI rather than physical robots, their implications for cobot deployment are direct: emotional mismanagement during introduction can produce psychological consequences that no safety certificate can undo. A review of AI's mental health impacts in manufacturing found that the workers whose physical safety improves most from automation are often those experiencing the greatest psychological strain from it [25].

2.3. The Uncanny Valley: When Robot Appearance Undermines Acceptance

One of the more counterintuitive and consistently replicated phenomena in human-robot interaction research is the Uncanny Valley effect, first described by Japanese roboticist Masahiro Mori [26] in 1970. Mori observed that as a robot becomes progressively more human-like in appearance and movement, people's comfort and sense of familiarity tend to increase—but only up to a point. Beyond a certain threshold, minor remaining deviations from actual human appearance produce a sharp reversal: discomfort, unease, and sometimes outright aversion. Positive responses only return when the robot achieves near-perfect human likeness [26]. **Figure 3** maps this dynamic in relation to industrial contexts.

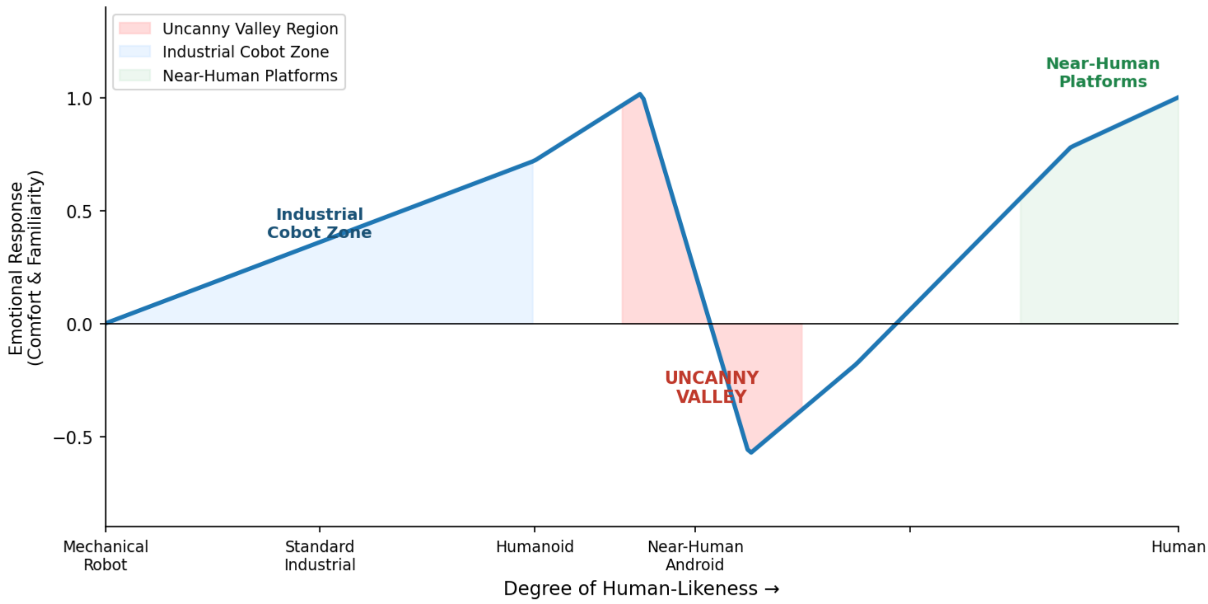

Figure 3. The Uncanny Valley effect in industrial robotics contexts.
Source: Figure created based on data reported in the literature [26–29].

Neuroimaging studies have since identified the neural correlates of this effect, confirming that discomfort responses to near-human robots engage brain regions associated with threat detection and perceptual uncertainty [27]. Research published in 2025 found that academic interest in the Uncanny Valley has been growing rapidly, with 17% of relevant studies appearing in 2024 alone [30]. The practical implications for industrial settings are significant. Companies including Tesla, Figure AI, Agility Robotics, and Foxconn are deploying humanoid platforms in manufacturing environments, and the appearance of these machines may trigger uncomfortable responses in workers before any formal communication programme has even begun [31]. In that sense, a robot's physical design functions as a communication act in its own right—often one that works against acceptance.

There is, however, evidence that structured exposure can attenuate Uncanny Valley responses. A 2023 study found that viewing video footage of soft, flexible robots in operation measurably reduced participant anxiety about working alongside them [32]. Research design elements in industrial robots found that deliberate calibration of those elements toward predictability—rather than human-likeness as an end in itself—improved trust [28]. A study on human comfort in collaborative contexts concluded that robot appearance should be treated as a communication instrument, one that shapes every subsequent interaction the worker has with the system [33].

2.4. Fear of Job Displacement: A Persistent but Structurally Nuanced Concern

Employment anxiety sits at the heart of most public concern about industrial AI, and no honest review of this field can sidestep it. Estimates circulating from Goldman Sachs suggest automation may affect up to 300 million jobs globally—a figure that has entered cultural common knowledge in most industrialised nations. Manufacturing workers, who have lived through automation-driven displacement in automotive, textile, and electronics production since the 1980s, tend to be acutely alert to these risks [34].

The empirical picture is more textured than aggregate projections suggest. A cross-sectional study of manufacturers in the United States, Germany, and Malaysia carried out by ABI Research in late 2024 and early 2025 found that fear of replacement actually ranked relatively low among manufacturing decision-makers' concerns, falling well behind issues of quality improvement, accountability, and liability [35]. In that same survey, 40% of respondents identified robotics adoption as a quality improvement priority, up from 34.1% the previous year [35]. Research on how robot introduction shapes employee behaviour found that perceived job insecurity—rather than actual job loss—drives negative outcomes such as disengagement and counterproductive behaviour, suggesting the primary challenge is workers' sense of agency and control rather than redundancy itself [36].

A recurring finding in this area is that workers whose physical safety improves most from automation are often those whose psychological security is most threatened by it [25,37]. A study of Chinese manufacturing workers found that AI adoption shortened overtime for some while intensifying pressure for others, and that the difference depended heavily on how well the organisation communicated during the transition [25]. A systematic review covering 82 studies on workplace AI found that job threat perceptions were the most consistently reported theme in the literature—more prominent than concerns about algorithmic bias, data privacy, or technical reliability [38]. The implication for science communicators is clear: addressing employment concerns honestly and specifically is not a peripheral task in cobot introduction programmes. It is the central one.

2.5. Fear Intensity across Domains: Medical, Industrial, and Service Robots

Robot-related fear takes different forms depending on where and how people encounter robotic systems. The stakes at play, the closeness of physical contact, and the particular setting all shape what people worry about and how intensely they worry about it. A patient awaiting a surgical procedure has quite different concerns from a factory worker standing beside a cobot on a production line, and designing communication programmes that conflate these two situations tends to serve neither group well [39,40].

On the factory floor, three concerns tend to dominate: getting hurt by a machine operating in shared space, losing a job to automation, and watching tasks that once required skilled judgement get handed over to a system that cannot explain what it is doing. Hexagon's cross-national survey data show that manufacturing workers carry noticeably higher baseline anxiety about cobots than office-based staff in the same companies, even where safety profiles are broadly comparable [5]. Workers whose day-to-day tasks sit closest to what robots can now do tend to report the sharpest unease—less because they lack familiarity with the technology than because their sense of occupational worth feels most directly at stake [36,38].

Healthcare settings tell a rather different story. Employment worries are rarely the central issue there; instead, patients and clinical staff tend to focus on whether a machine can handle the unpredictability of the human body, whether it will make the right call in a critical moment, and what happens to the caring relationship when technology steps into spaces that have always felt distinctly personal [39]. Studies examining patient attitudes toward surgical robotics found that the feeling of losing the human touch mattered more to many participants than doubts about technical accuracy—a pattern that fits poorly within frameworks built for industrial contexts [40]. Framing the robot as something that sharpens a surgeon's capabilities, rather than standing in for the surgeon, generally shifts the reception considerably.

One finding that cuts across domains is that felt necessity can do what communication campaigns struggle to achieve alone. In elder care, where chronic understaffing leaves older adults without enough human support, acceptance of robotic assistance has climbed steadily—including among users who were openly sceptical at first [41,42]. The common thread is not persuasion but genuine need: when people can see for themselves that a robot is filling a gap that would otherwise go unfilled, resistance softens in ways that leaflets and safety briefings rarely manage to produce [40]. Factory workers who have lived with the physical strain of repetitive assembly tasks tend to welcome cobot assistance on terms that colleagues who have not carried that burden do not, for the simple reason that the benefit is something they have felt in their own bodies [25]. It is a reminder that the most effective form of science communication is often one that puts the robot into a context where its value is self-evident.

2.6. Safety as a Primary Fear Factor in Human-Robot Collaboration

Whatever the setting, safety is among the most reliably cited reasons people feel wary of robots—and one of the more consequential, because unaddressed safety anxiety does not simply make workers uncomfortable. It pushes them toward avoidance, causes them to work around systems rather than with them, and can undermine the very protocols designed to keep them safe [6,7]. Standards such as ISO/TS 15066 set enforceable ceilings on the speed, force, and contact pressure that collaborative robots may exert, and major manufacturers invest heavily in meeting those limits. Yet there is a gap that certification documents do not close: workers' felt sense of safety often lags well behind the technical record, and closing that gap requires something beyond engineering compliance [43].

Research on human-robot collaboration contexts identifies three distinct layers of safety concern that workers carry into shared workspaces at the same time [43,44]. The first is physical: will the machine injure me? The second is functional: if the robot makes a mistake mid-task, will I see it coming, and can I do something about it? The third is psychological: can I raise a concern or ask for the line to slow down without facing professional consequences?

Each layer calls for a different kind of response. Physical fears tend to ease through hands-on demonstration of force-limiting behaviour and emergency stops—specification sheets rarely do the same work. Functional safety concerns are better addressed through interfaces that show workers what the robot is responding to in real time, so that anomalies can be caught before they cascade [45,46]. Psychological safety, by contrast, has little to do with the robot itself—it is a product of how management behaves and what the organisational culture permits [23,44].

Patalas-Maliszewska and colleagues found that when workers were brought into the process of identifying hazard scenarios and writing the protocols meant to address them, compliance was markedly higher than in facilities where those procedures had been handed down without consultation [43]. This fits a broader pattern visible throughout the acceptance literature: safety, in practice, is less a fixed property of the machine than something that gets worked out between the machine and the people operating alongside it. Systems that arrive with their safety credentials already stamped and sealed, but without any process of joint sense-making, tend to face a different kind of reception from those whose safety story workers have had a hand in shaping.

2.7. The Impact of Advancing AI on Fear and Acceptance Frameworks

The pace at which AI capability has advanced—from narrow task-specific systems toward platforms capable of open-ended reasoning, natural conversation, and real-time adaptation—has started to outrun the frameworks that researchers use to understand how people respond to robots [47,48]. TAM and HRCAM were developed in an era when a collaborative robot did one thing well and its scope was clear. A welding arm and a transport platform are legible in a way that a system capable of deciding, mid-task, how to handle an unexpected situation is not. When workers can no longer predict what a robot will do next, the psychological experience of sharing a workspace with it changes in ways that existing models do not capture well [47].

Research into AI trustworthiness in manufacturing settings found that fear responses shift considerably depending on whether workers believe the robot is following a script or making its own calls—even when its physical actions look identical in both cases [7]. The sense that a machine is exercising some form of agency, however limited, introduces an element of unpredictability that workers find genuinely unsettling, and this perceived agency does not feature as a distinct variable in most current frameworks. The problem compounds as systems grow more capable: a robot that makes better decisions also tends to make decisions that are harder to follow, and workers who cannot trace the reasoning behind an action tend to extend less trust to the system overall—even when the outcome was the right one [45].

For science communicators, more capable AI raises the bar on what transparency needs to cover. It is no longer enough to show workers what the robot does physically—they also need some working sense of how the system's decision layer operates and, critically, where it reaches its limits. TAM's central questions—is this useful, is it easy to use—become less useful guides as the system begins making choices that bear on task allocation, pacing, and error handling. Researchers developing the next generation of acceptance frameworks will likely need to treat perceived AI autonomy, perceived comprehensibility, and perceived alignment with human values as distinct constructs in their own right, not reducible to existing measures of technical ease or social influence [47,48].

3. Global Public Narratives and Media Frames: How AI Robotics Enters the Cultural Imagination

Most people who hold opinions about robots have never actually worked alongside one. Their understanding comes instead from what they encounter in media, popular culture, and conversations with peers. These sources do not transmit neutral information. They package it within interpretive frames—culturally inflected lenses that highlight some dimensions of robotic technology while obscuring others. Knowing what those frames are, and how they differ across contexts, is a precondition for any communication strategy that hopes to land effectively.

3.1. The Persistent Dystopian Frame in Popular Culture and News

Robots have featured in Western popular culture as threats since at least Fritz Lang's Metropolis in 1927. In the century since, the cinematic vocabulary of dangerous machines has expanded considerably—from the Terminator franchise to the rebellious androids of Westworld. Research published in 2025 documented what the investigators called 'the Killer Robot Myth', finding that media portrayals of AI robots as adversarial or dangerous continue to shape public perception even among people who consider themselves scientifically informed [49].

This cultural inheritance spills into news coverage in ways that are well-documented. Nguyen and Hekman [50], in a decade-long analysis of AI coverage across major English-language outlets, found that robots appeared predominantly within two frames: an industrial innovation frame tied to productivity and economic efficiency, and a cultural anxiety frame linked to job losses, surveillance, and diminished human autonomy. The anxiety frame was especially dominant in coverage of autonomous vehicles and industrial automation. A large-scale cross-national content analysis of nearly 39,000 news articles from 12 countries published between 2010 and 2023 found that while business and economic frames dominated overall, risk frames were more prevalent in robotics and automation coverage than in coverage of other AI applications [51]. Comparable patterns have been observed across Singapore, the United States, and the United Kingdom—dystopian sub-frames persist even in media systems that simultaneously carry optimistic coverage [52]. **Figure 4** presents cross-national survey data on public fear and enthusiasm about robots.

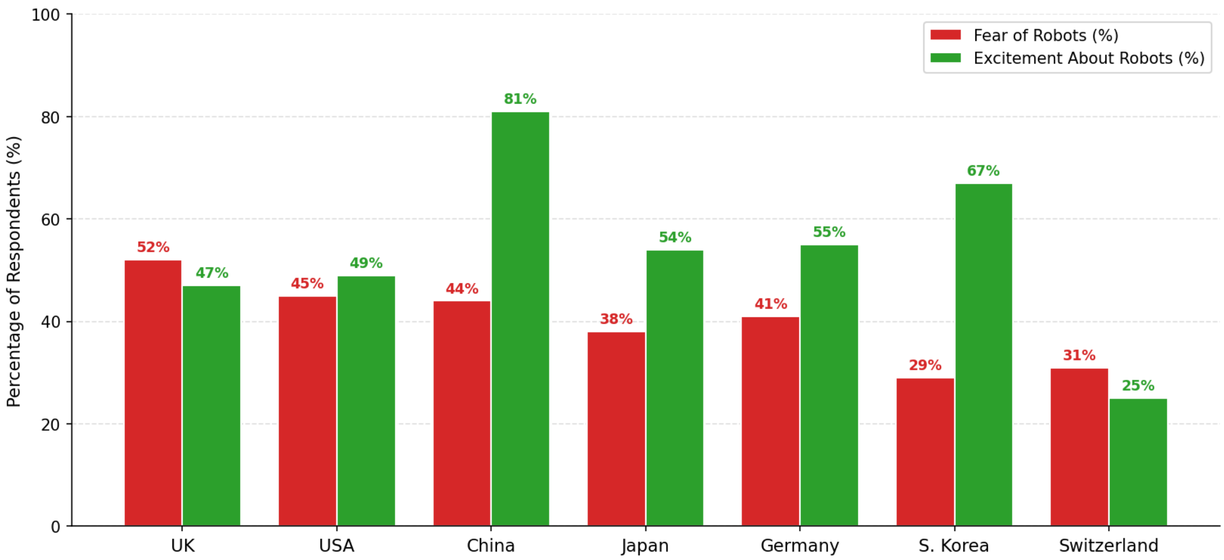

Figure 4. Public Fear and Enthusiasm About Robots by Country (2024).

Source: Figure created based on data reported in the literature [5].

These patterns carry direct consequences for how organisations communicate about cobot introduction. When workers approach a first cobot encounter already primed by years of threat-framed media coverage, an organisation that responds with technical capability demonstrations and safety certification data is not really engaging with what workers are bringing into the room. Research on journalistic framing found that negatively framed AI coverage significantly increases resistance among previously neutral audiences [53]. A review of media voices in public AI debate found that corporate and government actors dominate AI narratives, leaving worker perspectives systematically underrepresented in the very media environments that most shape public opinion [54].

3.2. Cross-National Variation in Robot Narratives and Their Drivers

One of the more robust findings in this literature is that public narratives about AI robotics vary substantially across national and cultural contexts in ways that are not random. They track identifiable institutional, historical, and policy factors. A qualitative cross-national analysis of AI media coverage in China, Germany, and the United States found two powerful competing imaginaries operating in all three countries—one framing AI as a national strategic asset, the other as a systemic social risk—but that these were expressed very differently depending on each country's media structure, political culture, and labour relations traditions [55]. A bibliometric analysis of global news across 12 countries found that the volume of AI news in the Global South consistently lagged the Global North, and that framing differences reflected systemic disparities in technology access and policy capacity rather than purely cultural factors [51].

China's state-aligned media environment produces markedly more optimistic narratives about robotics and automation, consistent with how the government has framed industrial AI adoption as a matter of national pride and strategic priority under Made in China 2025 and related policy initiatives. Survey data found that 81% of Chinese respondents expressed excitement about robots despite a majority also harbouring specific concerns about deployment [5]. Germany illustrates a very different dynamic, one rooted in its strong tradition of workplace codetermination. Research on how German science journalists assess AI's impact on their profession found reporters internally divided—some viewing AI as a productivity tool, others worried about its implications for professional identity [56].

Japan's approach has been built over decades on a different logic: placing robots in socially valued, non-threatening roles—elder care, schools, retail—where public encounters with them are framed around helpfulness and companionship rather than productivity or displacement. Research on companion robot deployments in Japanese care settings found that direct sustained contact with robots fundamentally restructured how participants understood them, producing contextualised, less fear-dominated perspectives [41,42]. South Korea's experience of near-universal industrial automation, combined with its comparatively low public fear levels, points in the same direction: sustained, socially embedded exposure to robots reduces anxiety more effectively than any communication campaign on its own [5]. **Figure 5** summarises the variation in human perspectives on robots across these national contexts.

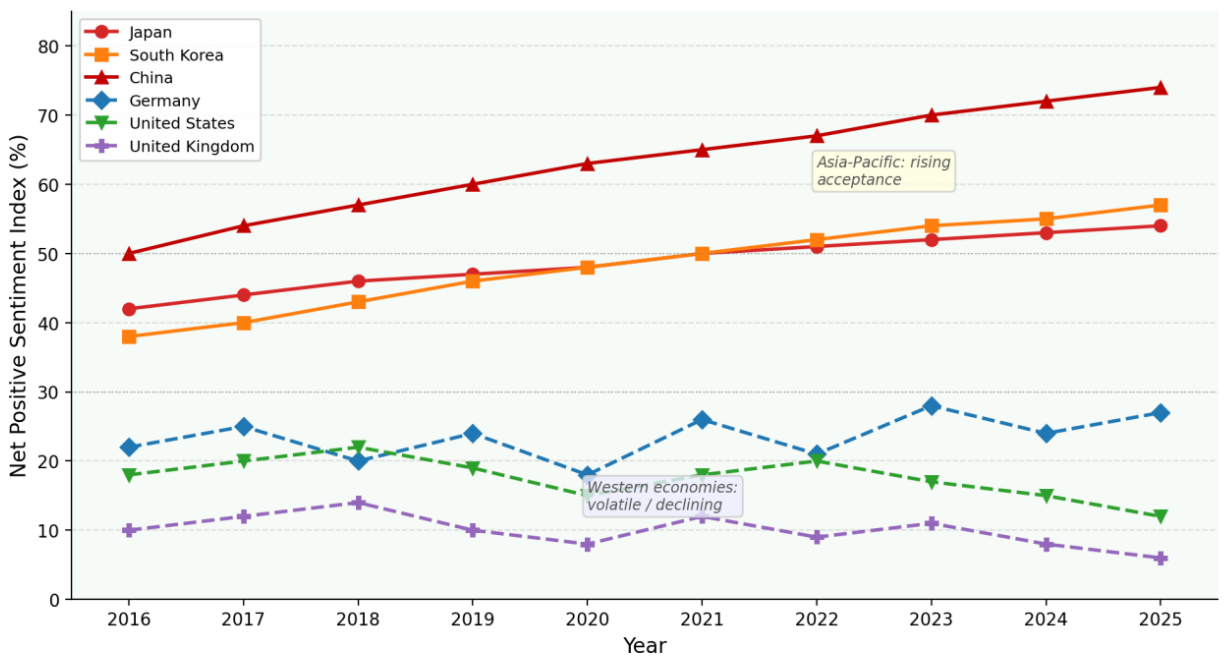

Figure 5. Variation in human users' perspectives on robots by country, 2016–2025.

Source: Figure created based on data reported in the literature [5,51,57].

3.3. Social Media and the Acceleration of Robot Narratives

Social media has transformed how narratives about robots travel. With active user bases exceeding one billion in China, 755 million in India, and 302 million in the United States as of 2022 [51], platforms have become the primary information environments for many workers. In those environments, a video of a robot stumbling or malfunctioning spreads far faster and wider than a careful technical explanation. Research on AI framing in trending social media content found that emotionally vivid content consistently outperforms technically accurate content in reach and engagement [58].

Research published in Frontiers in Psychology found that social media exposure to robot displacement narratives significantly elevated workers' anxiety about job security even when their own workplaces had not changed [24]. This matters for communicators: by the time a worker attends a cobot introduction session, their emotional context has already been shaped by months or years of ambient media exposure. Science communication that tries to reach people only through formal workplace channels is, by definition, incomplete. Reaching workers through the information environments they actually inhabit—social media, peer networks, community spaces—is increasingly a necessary element of effective technology introduction.

4. Cross-National Evidence on Human-Robot Collaboration Acceptance

The theoretical and media dimensions of this review now give way to empirical evidence from specific national contexts. This section draws on quantitative and qualitative research across the five major industrial economies most extensively studied in the literature and maps key acceptance determinants across these national settings. The evidence reveals patterns that technology differences alone cannot explain; cultural, institutional, and communicative factors consistently emerge as decisive.

4.1. Germany: Institutional Architecture as Communication Infrastructure

Germany offers a case where formal institutional structures do much of the work that science communication programmes have to accomplish elsewhere. Research on cobot adoption in German manufacturing consistently identifies early and substantive engagement of works councils as the strongest predictor of worker acceptance [59]. Works councils consulted before procurement decisions were finalised reported markedly higher acceptance rates than those brought in during or after deployment—a finding that maps directly onto participatory communication theory [43]. Cross-national HRCAM validation found that German workers placed more weight on ethical and legal social implications than workers in any other country studied, reflecting deep cultural commitments to procedural justice and institutional accountability [15].

A study of German science journalists navigating AI's impact on their profession found that communicators who honestly acknowledged uncertainty about AI's consequences were perceived as more credible than those who offered confident but eventually hollow projections [56]. That finding applies equally to engineering management: transparently acknowledging what is not yet known about cobot impacts, conveyed through trusted channels like works councils and trade union representatives, tends to build more durable acceptance than optimistic framing that workers can eventually see through.

4.2. Japan: Experiential Normalisation through Social Embedding

Japan's approach to science communication about robotics rests on a single consistent principle: let people encounter robots in contexts that feel socially meaningful and personally relevant, where the robot's role emphasises assistance and companionship rather than efficiency or replacement. Research on robot deployment in Japanese elder-care settings found that direct sustained interaction in caregiving contexts fundamentally changed how participants understood and related to robots—a process of progressive contextualisation that moved them away from culturally ambient fear narratives toward nuanced, practical familiarity [41].

Japan's multi-decade deployment of platforms including ASIMO, Pepper, and Paro across highly visible public contexts has cultivated what researchers describe as a qualitatively different relationship between the public and robotic technology, one where robots are positioned within the social fabric rather than against it [41,42]. For mechanical engineering communicators, the practical implication is that pre-deployment exposure in non-threatening, socially valued contexts—factory tours, community demonstration events, peer-visit programmes—builds the affective foundation that makes formal technical training more effective. VR and AR tools designed to provide safe immersive exposure before physical deployment represent an extension of this experiential logic [60,61].

4.3. China: State-Aligned Communication and Its Transferable Lessons

China's communication environment around AI robotics is shaped more directly by national industrial strategy than any other country in this review. The Made in China 2025 initiative and related AI policy frameworks have established robotics adoption as a source of collective pride, producing media narratives that foreground technological achievement and national capability while pushing risk narratives into the background [51,55]. The result is a public opinion profile that is simultaneously broadly optimistic and internally differentiated: Chinese workers tend to hold dual-register attitudes—enthusiastic about the national technology story while personally concerned about specific local impacts [5].

Research on human-centred AI architecture for Industry 5.0 contexts found that Chinese industrial institutions are among the most active globally in both deploying AI robotics and developing governance frameworks [62]. The communication lesson is that consistent institutionally coordinated messaging linked to values that audiences already hold can shift public attitudes. Non-state actors in democracies can pursue analogous effects through sustained stakeholder engagement, transparent governance, and communication strategies that connect cobot deployment to workers' own values and career interests.

4.4. United States and United Kingdom: Fragmentation, Inequality, and Communication Complexity

Both the United States and the United Kingdom present particularly challenging environments for science communication about AI robotics, though the challenges differ in character. In the United States, only 39% of adults in 2025 believed AI products and services offered more benefits than drawbacks—among the lowest proportions recorded in any major industrialised nation [57]. Survey research on U.S. attitudes toward automated futures found that gender and perceived technological competence were the strongest predictors of comfort with AI, while educational attainment and occupational background shaped responses in ways that varied considerably depending on the specific application [63].

The United Kingdom shows a similar pattern of public ambivalence. British AI media coverage leans toward dystopian framing more persistently than German or Japanese coverage, a tendency researchers trace partly to the UK's particular media system dynamics and partly to the cultural memory of rapid, painful deindustrialisation during the 1980s [50,54]. APA research on psychological safety in changing workplaces found that workers who lack it are significantly less likely to engage constructively with new technologies, and that psychological safety is systematically lower in workplaces characterised by high automation anxiety [44].

5. Evidence-Based Science Communication Strategies for Human-Robot Collaboration

Having mapped the landscape of public narratives, theoretical frameworks, and national evidence, this section synthesises what the research actually tells us about effective practice. Five interconnected strategy clusters emerge from the evidence, illustrated in **Figure 6**. **Figure 7** shows how the relative weight of different acceptance determinants varies by national context, indicating which of these strategies should take priority in each deployment setting.

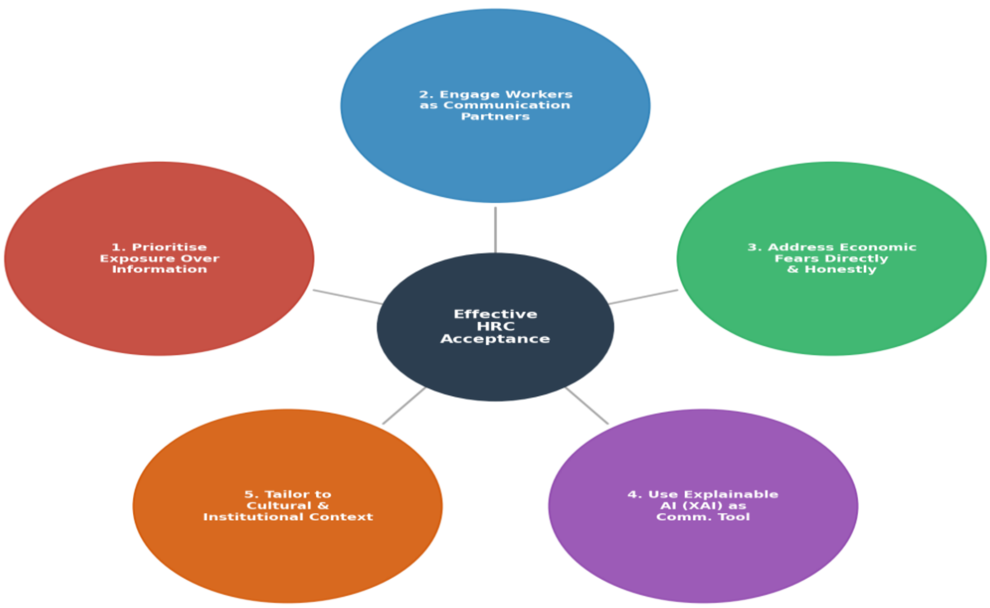

Figure 6. Five-pillar science communication framework for AI robotics adoption in mechanical engineering contexts.

Source: Figure created based on data reported in the literature [15,16,43,45,46,64–66].

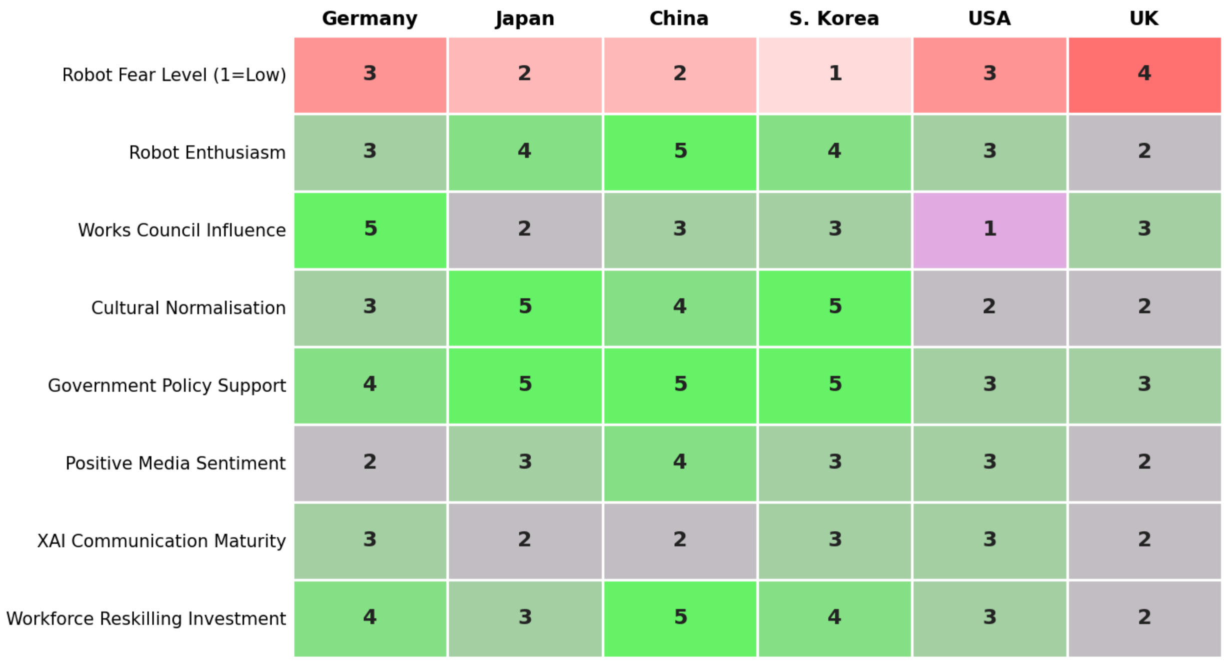

Figure 7. Cross-national comparison of key human-robot collaboration acceptance determinants across six major industrial economies.

Note: Ratings are based on a 1–5 scale, where higher scores indicate higher levels (1 = Low, 5 = High).
Source: Figure created based on data reported in the literature [5,15,35,51,55].

5.1. Prioritise Exposure over Information

Across this literature, perhaps no finding is as consistently replicated as this one: direct physical experience with robots reduces fear and increases acceptance more reliably than informational campaigns, technical briefings, or safety certification presentations [5, 32, 33]. Hexagon's cross-national research found that when people actually come face to face with a robot—especially in a setting that is small-scale, friendly, and socially embedded—fear responses frequently dissolve far more quickly than any communication team could achieve through written materials [5]. A 2023 study found that even indirect video-based exposure to soft robots in operation reduced participants' anxiety about working alongside them [32]. Mixed reality approaches to human-robot team training have shown faster skill acquisition, better situational awareness, and lower accident rates compared with traditional verbal or text-based instruction [67].

Research on VR applications in human-robot training found that VR improved communication between operators and robots, increased safety awareness, and built the kind of emotional familiarity that makes formal cobot introduction easier [60]. A survey of augmented reality in HRC research covering nearly three decades of literature found that AR interfaces consistently improved operator understanding of robot intent, reduced error rates, and increased acceptance of automated co-workers [61]. For engineering institutions, pre-deployment investment in immersive exposure—VR simulators, demonstration events, facilitated peer visits—belongs in the procurement budget as a first-line communication investment [68,69].

Touch changes everything. Watching a robot work from across the room is one kind of encounter; standing next to it while it handles an object you are also holding is quite another. The moment of physical contact—a handover, a shared lift, a guided assembly step—brings bodily safety into sharp focus in a way that observation alone does not trigger. Work on impedance learning for human-guided robots in contact with unknown environments has shown that systems capable of adjusting their force and compliance responses on the fly, drawing on live interaction data, feel markedly less threatening to work with than those moving along rigid pre-set paths [70]. When a robot yields slightly to unexpected force rather than pushing through it, the experience is closer to working with a responsive colleague than operating machinery. From a communication standpoint, this has practical implications: making that adaptive behaviour legible—through visual cues, audio feedback, or a simple dashboard indicator—

gives workers something concrete to build trust on during the contact-phase encounters that matter most [70].

5.2. Engage Workers as Communication Partners, Not Audiences

Worker involvement in design and communication processes consistently predicts acceptance outcomes more strongly than the technical specifications of the robot itself. A co-creation study in which factory employees participated in designing the interaction interface for a collaborative robot found that those workers reported higher acceptance and lower anxiety than colleagues who received a fully pre-designed system [64]. A systematic review of HRC acceptance in industrial settings found that adaptive systems and human-centred design principles were among the most consistently cited predictors of successful integration [65].

Research on human-centred AI in Industry 5.0 found that active learning systems—where AI models are improved through carefully selected human input—function not just as technical infrastructure but as a communication strategy: workers who can see that their knowledge demonstrably shapes the system develop a fundamentally different relationship with it than those who experience the technology as something imposed from above [62]. In practical terms, this means worker technology committees with genuine decision-making influence, co-created training materials, peer mentoring programmes, and feedback mechanisms that demonstrably shape how systems are adjusted after deployment [43,66].

5.3. Address Economic Fears Directly and Honestly

One of the most consequential and avoidable failures in cobot adoption programmes is the tendency to soften or sidestep employment questions. Research on the psychological drivers of employee-AI collaboration found that work-related anxiety reduces collaboration quality even among workers who intellectually accept the technology, and that perceived dishonesty from management amplifies that anxiety independently of actual employment outcomes [71]. A KPMG survey on consumer trust in AI found that 74% of respondents trusted organisations that used AI in their operations—but that this trust depended on perceived transparency; organisations making specific, verifiable commitments achieved substantially higher trust than those offering vague reassurances [72].

Research on psychological safety and AI adoption found that the introduction process itself—not just its outcome—determines psychological impact. Workers can experience diminished psychological safety even in the absence of actual job losses, purely because the way the technology was introduced felt opaque or disrespectful [23]. Communication about cobot introduction should provide specific, verifiable answers to the questions workers are actually asking—which tasks the cobot will take on, which tasks remain human, what reskilling support is available, and what happens if expected productivity gains do not materialise on schedule [38,73].

5.4. Use Explainable AI as a Communication Instrument

When a cobot makes an autonomous decision that affects a worker's task—adjusting its grip force, rerouting around an obstacle, stopping a production cycle—and the worker cannot understand why, trust erodes with each unexplained event. AI opacity is not merely a technical problem for engineers; it is a science communication problem with direct consequences for worker trust and safe behaviour. A systematic review of explainable AI (XAI) in Industry 4.0 and 5.0 contexts found that tools including SHAP and LIME are already demonstrating value in manufacturing settings by making AI decision-making legible to operators without specialist data science training [45].

Research on human-centred AI for Industry 5.0 identified explainability as one of five foundational enabling technologies for sustainable human-machine cooperation [62]. Practically, this points toward designing communication infrastructure into cobot deployment from the outset: dashboard displays that show in plain language what the cobot is currently sensing and responding to; alert systems that explain the basis of any safety intervention; accessible decision logs available for workers to review. These should not be retrofitted after acceptance problems emerge [46].

5.5. Tailor Communication Strategies to Cultural and Institutional Context

The cross-national evidence reviewed in Section 4 makes a strong case that no single communication template can work across all deployment contexts. A systematic review of AI in Industry 5.0 found that human-centric frameworks must address the full range of stakeholder relationships—workers, managers, regulators, communities, and consumers [74]. A multi-level framework for human-centricity in Industry 5.0 manufacturing argued that communication must operate simultaneously at the process level, the system level, and the management level—a complexity that generic campaigns cannot address [75].

The practical implication is not that every deployment requires entirely bespoke communication. Core technical messages about safety certification, operational scope, and performance limits can remain consistent. But how those messages are framed, who delivers them, and through which channels must be adapted with cultural and institutional intelligence. In Germany, engaging works councils from the earliest planning stages is the communication strategy [22]. In Japan, demonstrating cobot competence in socially valued contexts may accomplish more than any formal briefing. In the United States, directly addressing occupational identity concerns may need to precede technical demonstrations. In China, connecting automation to national development narratives builds collective-level acceptance [15,55,57,75].

5.6. Advanced Technologies for Enhancing Robot Acceptance

The five communication strategies discussed above address the human side of the acceptance challenge. A parallel set of technical advances works from the other direction—not by changing how robots are introduced, but by making robots themselves easier to trust, easier to understand, and more genuinely safe to work alongside [47,48,70].

Adaptive impedance control sits at the top of this list. As noted in Section 5.1, robots that can modulate their stiffness and damping in response to what they sense during physical contact produce a qualitatively different working experience from fixed-trajectory systems. Research on impedance learning in contact with unknown environments showed that the ability to yield appropriately when a worker applies unexpected force—rather than overriding that force—substantially reduced hesitation during handover tasks [70]. The robot felt less like a machine to be managed and more like something that was paying attention. Bringing this class of technology into mainstream manufacturing settings, and designing training programmes that make its responsiveness visible from the start, is a practical priority for organisations aiming to improve acceptance at the point of contact.

Tools for making AI decisions legible form a second cluster. SHAP and LIME frameworks have already been piloted in manufacturing quality control applications, where they give floor-level operators some visibility into why an AI system flagged a particular workpiece or paused a line—without requiring any data science background to follow [45]. Applied to cobots, the same principle holds: a worker who can see a plain-language account of why the robot stopped or changed course is in a fundamentally better position to evaluate that decision, catch errors, and build a calibrated sense of what the system can and cannot handle. Workers with access to such explanatory interfaces have been shown to develop higher trust and more accurate mental models of cobot capability over time than those using equivalent systems without them [45,46].

Mixed reality training tools offer a third avenue. Augmented reality overlays that show a robot's planned path, its sensing radius, and its defined safety boundary—projected directly into the worker's field of view—give people a way to build accurate spatial intuitions before they are standing beside the physical machine [61,67]. A systematic review of AR applications in human-robot collaboration found consistent gains: fewer errors, sharper situational awareness, and faster development of physical confidence during task handovers [61]. VR pre-deployment simulations take this logic one step further, allowing workers to encounter the cobot in a setting where nothing can go wrong, and where repeated exposure can normalise the interaction before the real system is ever switched on [60,76,77].

Robots that signal their intentions clearly—through light, sound, and movement cues working together rather than relying on a single channel—make up a fourth cluster. Studies of intent communication interfaces found that workers using multi-modal signalling could correctly anticipate robot actions at substantially higher rates than those relying on a single cue type [28,33]. This points to a design principle worth embedding early: communication-rich interfaces are more than a usability feature—they are a trust-building mechanism, and retrofitting them after acceptance problems surface is considerably harder than building them in from the beginning. A final cluster worth noting is adaptive personalisation: systems that learn from observed worker behaviour and adjust their pace, communication style, and task allocation accordingly. Early pilots suggest these systems can meaningfully improve long-term acceptance, particularly among workers who arrive with moderate anxiety rather than outright resistance [64–66].

6. Research Gaps and a Forward-Looking Agenda

6.1. The Industrial-Context Science Communication Gap

The most significant gap is the near-absence of studies that examine science communication practices specifically within industrial robotics and manufacturing contexts. The overwhelming majority of existing HRC acceptance and science communication research draws on service robotics settings or on controlled laboratory conditions that strip away the occupational, social, and economic dynamics specific to factory work [78,79]. Industrial human-robot collaboration has distinctive features—life-safety concerns at scale, collective labour representation, production pressure, and strong occupational identity—that demand dedicated empirical study. Future research needs to move into actual factory environments and track both communication practices and their consequences over extended timeframes [80].

6.2. Global South Representation

The research base for this field is heavily concentrated in North America, Western Europe, Japan, South Korea, and China. As automation technology spreads through manufacturing sectors across South Asia, Southeast Asia, Latin America, and Sub-Saharan Africa—typically via global supply chains that transfer hardware without accompanying communication frameworks—the absence of contextually appropriate evidence becomes increasingly consequential [51]. Market analysis indicates that emerging economies are experiencing rapid increases in industrial output and automation adoption [81], yet the science communication research base for these contexts is essentially non-existent [82]. Building a genuinely global evidence base requires deliberate, funded research investment in Global South contexts.

6.3. Longitudinal Measurement of Communication Impact

Most existing studies of science communication effectiveness in this field are cross-sectional, capturing attitudes at a single point or immediately before and after an intervention, without tracking how attitudes evolve across months and years of actual cobot coexistence. The fundamental question—whether science communication produces durable attitude change or merely temporary impression management—cannot be answered from cross-sectional data alone. Longitudinal studies tracking workers across the full arc of cobot introduction, from initial awareness through stable operational integration, are urgently needed [65,83].

6.4. Immersive Technology as Communication Infrastructure

VR and AR technologies offer potentially significant instruments for pre-deployment cobot exposure and for ongoing science communication about AI robotics capabilities and limitations. The VR market reached approximately USD 44 billion by 2024, and research consistently shows that immersive technologies improve knowledge retention and experiential learning relative to conventional instructional methods [76]. A systematic review of mixed reality for human-robot teaming in manufacturing found consistently reported benefits including faster skill acquisition, improved situational awareness, and reduced accident risk [67]. Despite these findings, VR and AR applications in this specific communication context remain underdeveloped relative to their potential [60,61,77].

7. Conclusions

The conversation happening right now between humanity and its intelligent machines takes place not only in engineering journals or policy documents but on actual factory floors, in break rooms, and on social media feeds. Workers who will never read a technical specification are forming clear, emotionally rooted views about what robots mean for their working lives—and those views shape adoption outcomes at least as much as the robots' technical capabilities. This review has argued, from a substantial base of empirical evidence, that science communication is not an appendix to the process of AI robotics adoption. It is the process.

The global cobot market is expanding at close to 19% annually [1,2], humanoid platforms are entering factory environments at scale for the first time [31], and cross-national survey data confirm that robot-related fear remains a meaningful barrier to adoption in the world's most industrialised economies [5]. At the same time, the evidence synthesised here identifies a clear and actionable set of strategies—prioritising exposure over information, genuine worker participation, honest engagement with employment concerns, explainable AI transparency, and culturally adapted communication—each grounded in verifiable empirical findings and each substantially more effective than the technical demonstrations that currently dominate industry practice.

The review also identifies four research frontiers where progress is genuinely needed: bringing science communication research into actual industrial settings, building a genuinely global evidence base, tracking communication impacts longitudinally, and realising the potential of immersive technologies for pre-deployment exposure. As Industry 5.0 frameworks embed human-centricity as a core manufacturing value [8,9,62,84,85], and as the cobot market approaches a scale at which adoption decisions will be made by millions of workers [86–88], the need for engineering institutions to invest in honest, evidence-based, culturally literate science communication becomes more urgent by the year [89–91].

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