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Systematic Review

Assessing Safety in Physical Human–Robot Interaction in Industrial Settings: A Systematic Review of Contact Modelling and Impact Measuring Methods

S. M. B. P. B. Samarathunga [1,2], Marcello Valori [1,*], Giovanni Legnani [2] and Irene Fassi [1]

1 Institute of Intelligent Industrial Technologies and Systems for Advanced Manufacturing, National Research Council of Italy, Via Alfonso Corti, 12, 20133 Milan, Italy; buddhika.samarathunga@stiima.cnr.it (B.P.B.S.S.M.); irene.fassi@stiima.cnr.it (I.F.)

2 Department of Mechanical and Industrial Engineering, University of Brescia, Via Branze, 38, 25123 Brescia, Italy; giovanni.legnani@unibs.it

* Correspondence: marcello.valori@stiima.cnr.it

Abstract: As collaborative robots (cobots) increasingly share workspaces with humans, ensuring safe physical human–robot interaction (pHRI) has become paramount. This systematic review addresses safety assessment in pHRI, focussing on the industrial field, with the objective of collecting approaches and practices developed so far for modelling, simulating, and verifying possible collisions in human–robot collaboration (HRC). To this aim, advances in human–robot collision modelling and test-based safety evaluation over the last fifteen years were examined, identifying six main categories: human body modelling, robot modelling, collision modelling, determining safe limits, approaches for evaluating human–robot contact, and biofidelic sensor development. Despite the reported advancements, several persistent challenges were identified, including the over-reliance on simplified quasi-static models, insufficient exploration of transient contact dynamics, and a lack of inclusivity in demographic data for establishing safety thresholds. This analysis also underscores the limitations of the biofidelic sensors currently used and the need for standardised validation protocols for the impact scenarios identified through risk assessment. By providing a comprehensive overview of the topic, this review aims to inspire researchers to address underexplored areas and foster innovation in developing advanced, but suitable, models to simulate human–robot contact and technologies and methodologies for reliable and user-friendly safety validation approaches. Further deepening those topics, even combined with each other, will bring about the twofold effect of easing the implementation while increasing the safety of robotic applications characterised by pHRI.

Keywords: human–robot collaboration (HRC); power and force limiting; physical human–robot interaction (pHRI); collaborative robots; cobots; robot safety; collision modelling; biomechanical models; impact measuring technologies; biofidelic sensor

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1. Introduction

Human–robot collaboration (HRC) has become a well-established trend of robotic implementation in many robot applications, particularly within the frameworks of Industry 4.0 and 5.0. Modern industrial paradigms leverage advanced technologies to transform traditional industrial, manufacturing, healthcare, and domestic processes [1]. The primary goal of HRC is to facilitate robots working alongside humans in a safe and efficient manner, thereby enhancing productivity and reducing the physical demands placed on human workers [2].

Collaborative robots, also known as cobots, are engineered to coexist with humans directly within shared workspaces. Outfitted with sophisticated sensors and safety mechanisms, cobots can detect and react to human presence, fostering a safer and more cooperative work environment. Their user-friendly programming and adaptability make them suitable for tasks requiring close human–robot interaction [3,4]. Cobots' adaptability and safety features make them suitable for dynamic environments, boosting productivity and enhancing workplace ergonomics by taking on physically strenuous or repetitive tasks [5,6]. On the other hand, inadequate safety measures could lead to a significant risk of injuries to workers, given that most industrial robots lack awareness of their environment [7]. While there is a demand for more intuitive and efficient human–robot interaction (HRI) methods to enhance the usability and performance of HRC, these methods must be developed in line with safety standards [8,9].

It is worth observing that, as robots increasingly operate in close proximity to humans, without the physical separation provided by traditional barriers and fences, the potential for accidents rises due to unpredictable human behaviour and the complex dynamics of robot movements. To address these challenges, implementing effective safety measures is crucial. International safety standards provide comprehensive guidelines for hazard analysis and risk assessment, which are the main references for mitigating risks related to HRI in industrial settings and laying the foundation for designing robust safety systems [10,11]. Moreover, the implementation of robust safety systems not only provides physical protection, but also fosters trust and comfort among human workers. This psychological aspect is indeed essential for achieving efficient and productive collaboration, as ensuring safety in HRI is not merely about preventing physical harm but also involves creating a secure environment that promotes psychological well-being [12]. A systematic approach to safety enables the full potential of collaborative robots to be realised while safeguarding human operators. By addressing both physical and psychological safety concerns, HRC can significantly enhance productivity and minimise potential hazards [13,14]. Safety assurance in collaborative workspaces involves two primary layers: algorithms for safe space-sharing between humans and robots and enabling technologies for data acquisition and environmental analysis [15]. Various methodologies have been proposed to address these safety concerns, including collision avoidance strategies [16], impact detection systems [17], and mechanical and software devices designed to minimise the consequences of human–robot impacts [18].

Focusing on the European context, a review of international safety standards and certification procedures highlights the importance of compliance with safety regulations to facilitate the integration of collaborative robots into industrial settings [8]. In the worldwide community, the evolution of safety standards envisaging HRC has been driven by the need to address the unique hazards posed by these collaborative environments, as traditional safety measures, such as physical barriers and sensor-based systems, are often inadequate for ensuring the safety of workers in close proximity to robots [19]. As a result, in the last decade, new standardisation deliverables have been developed to provide guidelines for the safe design, implementation, and operation of collaborative robot systems. As a well-established reference document, the Technical Specification ISO/TS 15066 [20] provides guidelines for the safe design, implementation, and operation of collaborative robot systems, emphasising the importance of hazard analysis and risk assessment in designing and implementing safety measures. It provides guidelines for embedding passive and active safeguards in robot systems and designing collaborative workspaces to minimise the risk of hazardous interactions. However, challenges remain in verifying the sufficiency of safety measures and ensuring their effective implementation in real-world scenarios. The latest editions of the two reference Type-C standards for industrial robotics, ISO 10218-1 [21] and 10218-2 [22], recently published after the revision process started in 2017, also aim to cover the emerging aspects related to HRC. A detailed overview of the information provided by standards and relevant from the perspective of this review is reported in Appendix A. Within the scientific community, some efforts were devoted to providing online tools to support robot developers and researchers in such an evolving landscape [23].

These robotic standards also describe the safety-related guidelines and instructions, which stipulate that collaborative operations should incorporate one or more of the following four collaborative operation modes [20]:

- Safety-Rated Monitored Stop (SRMS)—no longer addressed as a collaborative mode in the latest versions but as a safety function called "monitored standstill".
- Hand Guiding (HG).
- Speed and Separation Monitoring (SSM).
- Power and Force Limiting (PFL).

Physical interactions—whether intended or accidental—between the two humans and robots play a crucial role when assessing safety in HRC. Among the various operation modes, PFL envisages direct physical contact between humans and robots, underscoring the necessity for rigorous safety measures (i.e., an inherently safe robot system or a specific safety-related control system) and the requirement to ensure, in the risk assessment phase, that any forces exchanged will not overcome pre-defined safe boundaries.

As robotics technology progresses, incorporating physical human–robot interaction (pHRI) into diverse applications has gained substantial importance in the scientific landscape. This growing emphasis is driven by the need to harness the complementary strengths of humans and robots—merging human cognitive abilities, such as adaptability, creativity, and decision-making, with the precision, strength, and consistency of robotic systems [24]. This synergy enables the automation of complex tasks that require a delicate balance of human intuition and robotic efficiency and broadens the scope of robotics applications across industries.

A first overview of the basic concept and principles of pHRI was provided in [25]; at that time, the authors noted the use of safety indexes typical of the automotive sector to assess human–robot impacts, envisaging specific indexes related to the impact forces or the transmitted energy. An overview of compliance control strategies from the perspective of pHRI is provided in [26], in which the authors emphasise the need for both active and intrinsic compliance. The topic of "shared control" in pHRI, as a likely option when humans and robots work together, has been reviewed in [27], with a particular focus on the subdivision of control between humans and robots and how the two entities can communicate among them. Another survey [28] discusses the increased flexibility of shared control when integrating machine learning-based approaches. In [29], the different approaches for sensing and multi-modal fusion methods to improve the perception of humans and robots are explored. A recent review [30] aims to comprehensively recap all the relevant developments in pHRI, also including an analysis of safety-related aspects, namely robot design, human detection and motion prediction, motion planning and control, and providing insights for future development. In [31], a review of the last advancements in HRI is reported, with a particular focus on safety in collaborative operations characterised by SSM and/or PFL. The review reported in [32] focusses on the occupational and health concerns and solutions in HRC reported in the available scientific literature, claiming that future studies should focus on real implementations, rather than laboratory study cases, and promoting safety as a driver rather than a limitation for the full performance of the systems. The systematic review reported in [33] collects all the studies related to safety and ergonomics in HRC, identifying four main paper thematic clusters: contact detection and mitigation, contact avoidance, physical ergonomics, and cognitive ergonomics.

Although the listed surveys deal with safety in pHRI, none of them provide an overview of the developments related to assessing human–robot contacts, which deserve primary importance in ensuring safety in working environments, especially in factories. Based on data collected adopting a systematic approach, this review aims to fill this gap by focusing on and providing a detailed analysis of the existing physical human–robot impact and collision models, as well as the methodologies for measuring these impacts in the industrial domain. Within these two main topics, covering the fundamentals of assessing and validating safety in pHRI, the collected papers are classified into several subfields; in particular, papers related to physical human–robot contact models are further classified based on the specific element modelled (i.e., the human body, the robot, or the impact), while those dealing with safety evaluation through experimental impact assessment cover three main aspects: determining limits for safe pHRI, approaches for evaluating human–robot contacts and the "biofidelic" sensors, commonly used to mimic the human body in those tests.

The paper is organised as follows. In Section 2, the systematic review methodology is described; in Section 3, the results of paper search are reported, describing the collected papers subdivided in thematic categories. The Conclusion is reported in Section 4. In Appendix A, an overview of the information provided by ISO deliverables particularly relevant for the purposes of this review is presented, whereas in Appendix B the tables collecting all the analysed papers are provided.

2. Systematic Literature Review Method

This research employs a systematic literature review methodology, in accordance with the Preferred Reporting Item for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, in order to comprehensively search, critically appraise, synthesise, and analyse all pertinent studies within a particular research domain.

In the initial phase of this study, we delineated the following sequential steps, described in the following paragraphs:

1. Rationale and research objectives: establish the aims and goals of the review.
2. Eligibility criteria, information sources, and search strategy: outlining the scope and limits of the research to ensure focused inquiry; defining the sources used for the search and the strategy adopted.
3. Selection process: developing criteria for inclusion and exclusion to guide the data collection process.

2.1. Rationale and Research Objectives

The primary objective of this systematic literature review is to comprehensively assess the state of research on the modelling and measurement of pHRI in industrial environments, as primary approaches to assess safety in human–robot contacts. This review reports on the contributions over the last 15 years in the fields of human body modelling during contact scenarios, robot modelling, and collision analysis (Section 3.1), as well as efforts to establish adequate safety thresholds, assess possible human–robot collisions, and develop biofidelic sensors for accurate impact characterisation (Section 3.2). By categorising and critically analysing these studies, this review aims to elucidate current methodologies, enabling the identification of existing gaps in pHRI models and testing. Furthermore, it highlights trends, limitations, and emerging directions, providing a roadmap for future research to ensure safer and more effective human–robot collaboration in dynamic industrial environments.

2.2. Eligibility Criteria, Information Sources, and Search Strategy

As a primary driver, the search design was oriented to select a wide set of keywords (reported in Table 1), aiming at encompassing all the aspects of safety assessment in industrial pHRI. To manage such an articulated search, the search source selection was focused on those considered more relevant for the engineering (mainly robotics/electronics) field and enabling advanced search and keyword combination options. The selection considered several databases and citation indexes for academic research, both publisher-proprietary and open access. As a publisher-proprietary primary source, IEEE Xplore was selected as the main reference publisher for the engineering and technology community. In addition, Scopus was selected as a database encompassing a broader range of sources and disciplines. Despite representing a fundamental source for studies, Google Scholar was discarded as generating a large number of results, not providing the option of restricting the keyword search to the significant record fields (i.e., title, abstract, and keywords).

Table 1. Keywords used for the systematic literature review.

Levels	Description	Keywords	
Level 1	Finding research papers on human–robot collaboration	▪ "human-robot collaborat*" ▪ "HRC" ▪ "cobot" ▪ "cobotic" ▪ "collaborative robot operation*" ▪ "collaborative operation*" ▪ "cooperative robot*" ▪ "HRI" ▪ "human-robot interactions" ▪ "robot safety"	▪ "human-robot cooperat*" ▪ "collaborative robot*" ▪ "cobots" ▪ "cobotics" ▪ "human-robot coexist*" ▪ "robot coexist*" ▪ "robotic collaboration*" ▪ "human-robot interaction" ▪ "human-robot collaborative interaction"
Level 2	Extracting research papers on human–robot physical contacts	▪ "physical human-robot*" ▪ "power and force limit*" ▪ "physical interact*" ▪ "collision*" ▪ "dynamic contact*" ▪ "human-robot impact*"	▪ "human-robot physical*" ▪ "pHRI" ▪ "physical impact*" ▪ "physical contact*" ▪ "dynamic impact*"
Sub-level 1 (SL1)	Specific research on contact or impact modelling	▪ "transient contact*" ▪ "quasi-static contact*" ▪ "transient physical contact" ▪ "contact model*" ▪ "collision model*" ▪ "dynamic model*" ▪ "dynamic impact model" ▪ "dynamic collision model*"	▪ "finite element" ▪ "impact model*" ▪ "equivalent mass" ▪ "effective mass" ▪ "apparent mass" ▪ "clamp*" ▪ "body model"
Sub-level 2 (SL2)	Specific research on impact-measuring sensors and devices	▪ "biofidel*" ▪ "contact force*" ▪ "collision measur*" ▪ "power and force measur*" ▪ "PFMD" ▪ "collision force" ▪ "impact test*" ▪ "pressure sensor" ▪ "biomechanical limit*" ▪ "pain threshold" ▪ "pain onset threshold" ▪ "impact stud*" ▪ "risk assessment"	▪ "collision sensor" ▪ "impact measur*" ▪ "bio-simulant" ▪ "force sensor*" ▪ "virtual force sensor" ▪ "virtual sensor" ▪ "pressure sensors" ▪ "biomechanical threshold" ▪ "biomechanical thresholds" ▪ "pain thresholds" ▪ "pain onset thresholds" ▪ "collision evaluat*" ▪ "risk assessments"

The initial boundary keyword selection (Level 1) was centred around the term "collaborative robotics" and its related terminologies, which depict various HRC aspects.

The focus of this review was mainly on pHRI, leading to the second boundary selection level (Level 2). This was based on the term "physical human-robot interaction" and its analogous derivatives, which are commonly used in the field to describe these interactions.

Following the establishment of the primary two layers, two sub-levels were created to concentrate on the primary objectives. To refine the search and direct it towards the modelling of physical human–robot impacts, the first sub-level (SL1) was focused on "contact modelling" and its related derivations. Simultaneously, the second sub-level (SL2) was focused on "measuring the impacts" and their similar variations. The literature search included the papers published in the period January 2010–December 2024, utilising the Scopus and IEEE Xplore databases. A detailed summary of all the keywords considered for each stage of the search strings is presented in Table 1. The combination of the reported keywords (KW) allowed for two search strings to be obtained, as follows:

$$STRING_i = (\text{“}KW_1\text{”}\ \mathbf{OR}\ \text{“}KW_2\text{”}\ \mathbf{OR}\ldots)_{Level\ 1}\ \mathbf{AND}\ (\text{“}KW_1\text{”}\ \mathbf{OR}\ \text{“}KW_2\text{”}\ \mathbf{OR}\ldots)_{Level\ 2}\ \mathbf{AND}\ (\text{“}KW_1\text{”}\ \mathbf{OR}\ \text{“}KW_2\text{”}\ \mathbf{OR}\ldots)_{Sub-Level\ i}$$

2.3. Selection Process

Figure 1 illustrates the number of research papers on human–robot collaboration published in SCOPUS and IEEE Xplore from 2000 to 2024 (December). Notably, there has been a substantial increase in publications starting around 2010, indicating a significant rise in research activity and interest in this field. This trend reflects the burgeoning advancements and growing importance of HRC over the past decade. Consequently, to ensure our systematic literature review captures the most relevant and impactful studies, we focused on papers published from 2010 to December 2024 (last search performed on 25 January 2025). This period represents the most prolific era in HRC research, providing a comprehensive view of contemporary developments and innovations in the field. Furthermore, only the papers authored in English were selected. Additionally, the selection process excluded review papers by setting the appropriate parameters in the advanced search engines of Scopus and IEEE Xplore. Hence, only conference papers, journal articles, book chapters, and magazines were chosen for the literature review.

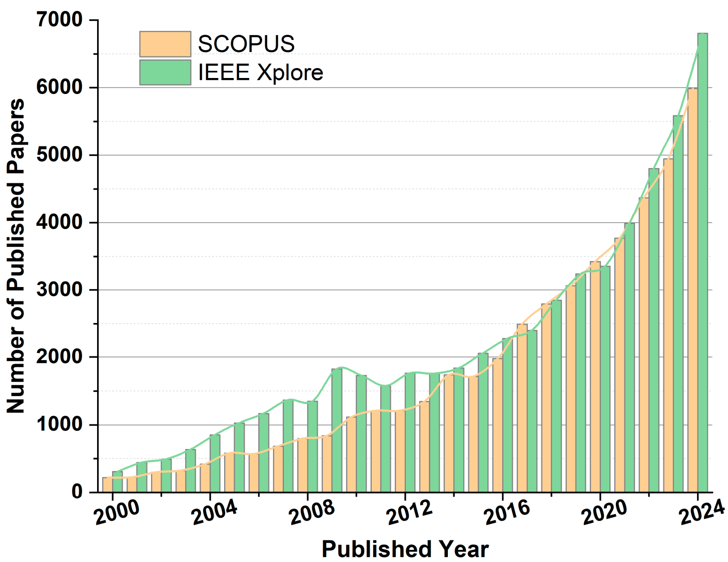

Figure 1. Number of publications on human–robot collaboration in SCOPUS and IEEE Xplore (Year 2000 to 2024).

A database was set on purpose, made of four main datasheets, each one containing the records collected from a single search source (i.e., Scopus or IEEE Xplore), in relation to one sub-level. This approach enabled us to perform a comparison of the datasheets, based on the Digital Object Identifier (DOI) associated with each paper, in order to exclude the repetitions within each sub-level, and even those collected in both the sub-levels. The records without DOIs were compared based on the title.

Afterwards, the analysis was performed by two researchers, working independently, considering the criteria hereafter reported. First, by checking the title and abstract of each paper, the selection was focused on papers dealing with pHRI only in relation to industrial applications, as per the concept of HRC; this limitation was necessary to ensure the consistency of the grouped results, besides allowing for a clear identification of a solid base of standards to consider as a reference, which is particularly relevant dealing with safety topics. Afterwards, the remaining papers were screened in order to select those addressing the assessment of safety in pHRI from both the contact simulation and validation perspectives, thus excluding all the records dealing with the improvement of safety in relation to specific functions or applications. The final task concerned the classification of the papers in appropriate categories and subcategories, as detailed in the following Section.

3. Results and Discussion

The quantity of papers identified at each search stage is depicted in the flow diagram reported in Figure 2. The initial search (Level 1) targeted broad terms related to HRC and related keywords. This search yielded 41,161 papers from SCOPUS and 46,036 papers from IEEE Xplore. The Level 2 search string is incorporated with related terms for pHRI to refine the focus on physical interactions between humans and robots. This narrowed the results to 3829 papers from SCOPUS and 7429 papers from IEEE Xplore, which can be seen in Figure 2. From the initial Level 1 search, a total of 87,197 papers were identified. After refining the focus to physical human–robot interactions (Level 2), the total number of papers was reduced to 11,258, representing approximately 12.9% of the original search results.

In the initial search design, we expected the papers selected within SL1 focusing on pHRI modelling and those found within SL2 focusing on safety evaluation and impact assessment; the two related categories were formalised as follows:

- Category 1—Physical human–robot contact models;
- Category 2—Safety evaluation and impact assessment.

However, the analysis highlighted a relevant number of papers within the two SLs, addressing topics related to pHRI in the industrial domain but going beyond the established primary focuses. Accordingly, two main thematic categories were identified in order to filter the results and exclude the papers not dealing with safety assessment, as reported here:

- Improving inherent safety in HRC (including control strategies, compliance-oriented designs and devices, means for contact detection, etc.);
- Contact avoidance and path planning.

The number of papers collected in the SL1 group resulted in 237 papers from SCOPUS and 863 papers from IEEE Xplore, totalling 1100 papers. The total number of duplicate records removed in this level was 106. By cross-checking, a total of 550 duplicate records were found, which were removed in equal amount from each SL. Title and abstract screening led to the removal of 547 papers; those were excluded if their focus was outside the scope of pHRI in industrial environments or if they primarily addressed unrelated fields or methodologies. By analysing the remaining 172 papers (~15.6% of the total found for SL1), 125 papers were assessed as referring to “Improving inherent safety”, while 21 addressed “Collision avoidance and path planning”. Consequently, 26 papers were selected for the actual purposes of this review. Two of these papers were assessed to be more appropriately categorised within the "Safety evaluation and impact assessment" group, while the other twenty-four properly fit "Physical human-robot contact models".

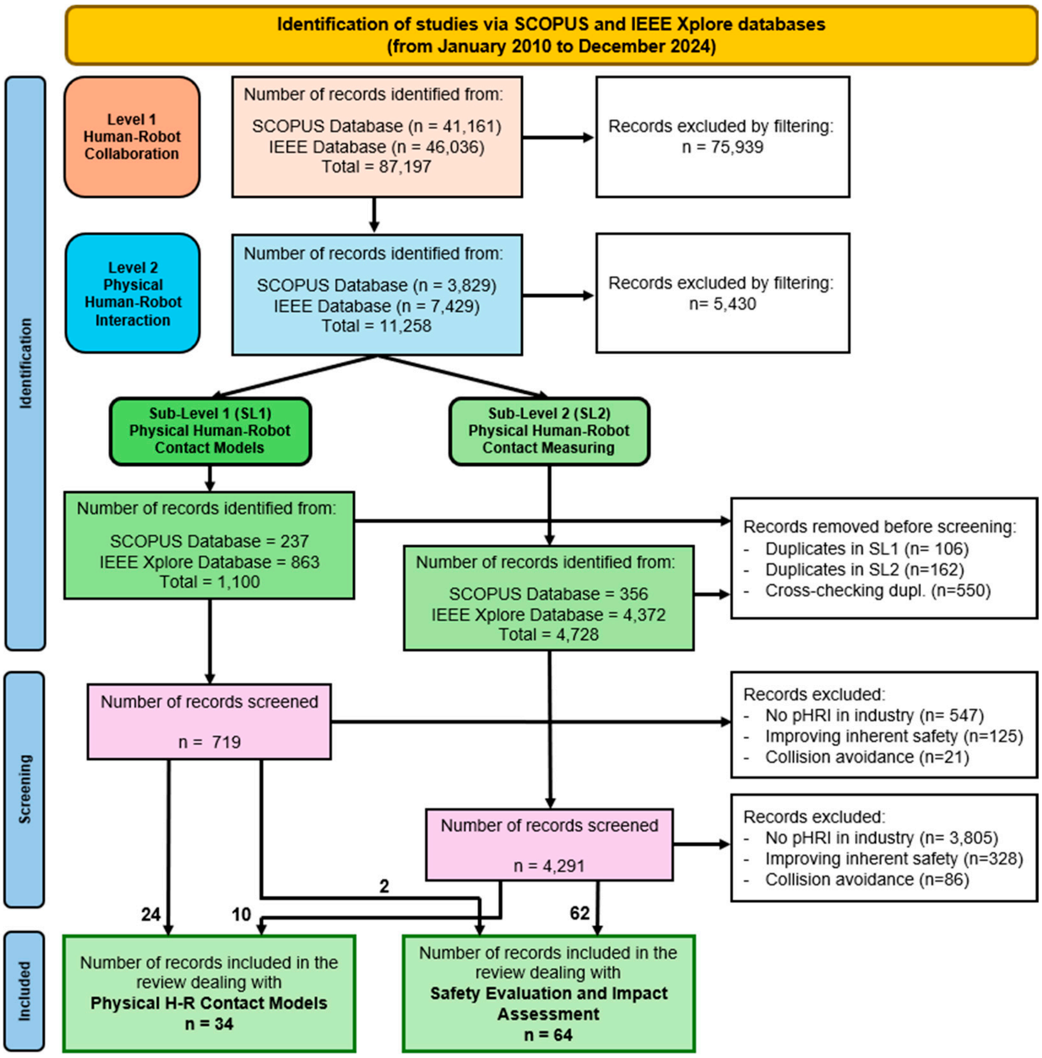

Figure 2. Flow diagram of the paper search performed.

An analogue approach was used for SL2. The terms and keywords yielded 356 papers from SCOPUS and 4372 from IEEE Xplore, totalling 4728. The number of duplicate records removed was 162, while 275 duplicate records were removed due to cross-checking, as previously discussed. Title and abstract screening led to remove 3805 papers; from the resulting 486 papers (~10.3% of the SL2 total), 328 were assessed as dealing with "Improving inherent safety", while 86 addressed "Collision avoidance and path planning". The remaining 72 papers were assessed as relevant for this review, with 62 of them actually dealing with "Safety evaluation and impact assessment" and 10 falling within "Physical human-robot contact models".

As reasonably expected considering paper search design, the category "Physical human-robot contact models", characterised by a theoretical and foundational focus, is primarily fed by SL1, with 24 papers out of 34 (~70.6%); this is even more significant considering that the total amount of papers collected (and selected) in SL2 is significantly higher than the number of papers provided in SL1. On the other hand, the category "Safety evaluation and impact assessment" is mainly populated by SL2-provided documents, with 62 out of 64 papers (~96.9%). It is worth observing that, despite the accurate selection of keywords, the papers removed as dealing with "Improving inherent safety in pHRI", which is actually out of the scope of this paper, represented a significant amount of all the collected papers dealing with safety in pHRI (453 out of 658, ~68.8%). This category is mainly characterised by control strategies to improve safety, compliance-oriented designs and devices, and contact detection by means of soft skins, sensors, and indirect approaches. This aspect firmly supports the consideration that research related to safety in HRC widely focuses on practical implementations aimed at improving safety in HRC rather than theoretical and procedural studies to assess and validate safety, which may instead benefit from research efforts to fill the gap of knowledge between users and the regulatory framework [34]. The number of papers discarded as dealing with "Contact avoidance and path planning" is considerably lower, as these topics are hardly relevant from the viewpoint of pHRI.

To enhance comprehensiveness and perform a more detailed analysis, the two main categories are further subdivided as follows:

- Physical human–robot contact models (Section 3.1):
    1. Human body modelling in contact scenarios (Section 3.1.1).
    2. Robot modelling (Section 3.1.2).
    3. Collision modelling and analysis (Section 3.1.3).
- Safety evaluation and impact assessment (Section 3.2):
    1. Determining limits for safe pHRI (Section 3.2.1).
    2. Approaches for evaluating human–robot contacts (Section 3.2.2).
    3. Biofidelic sensors (Section 3.2.3).

Figure 3 illustrates the distribution of research papers across the subcategories under Physical Human–Robot Contact Models (Section 3.1) and Safety Evaluation and Impact Assessment (Section 3.2). The distribution of research papers across subsections, as depicted in the figure, highlights that subsections Sections 3.2.1 and 3.2.2 exhibit the highest number of studies, with 27 and 27 papers, respectively, collectively accounting for 56% of the total reviewed papers. Conversely, Sections 3.1.1 and 3.1.2 have the least representation, with only 17 papers combined (10% and 7%, respectively). The subsection Section 3.1.3 also displays relatively low research activity, with a total of 10 papers representing 10% of the reviewed studies.

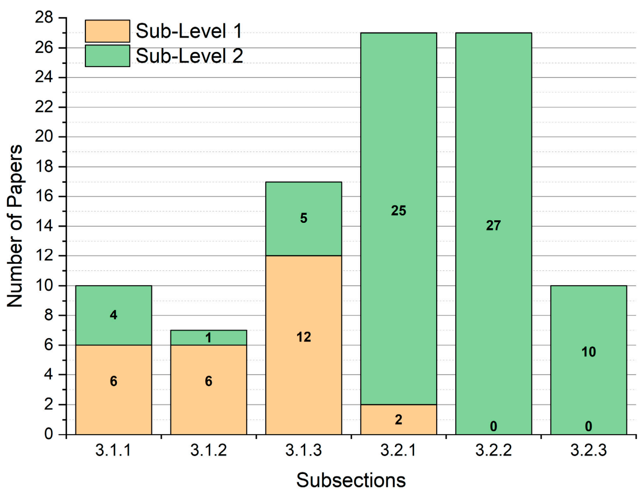

Figure 3. Number of research papers within each subcategory.

This uneven distribution indicates a notable research gap in understanding and developing fundamental models (human and robot) and technologies like biofidelic sensors that underpin accurate and reliable analyses of human–robot contact scenarios. While significant progress has been made in setting safe interaction limits and evaluating contact, the foundational elements for such analyses remain underexplored. Addressing these underrepresented areas is essential to advance the field comprehensively and foster a robust, interdisciplinary approach to improving physical human–robot collaboration.

3.1. Physical Human–Robot Contact Models

Physical human–robot contact models are crucial for ensuring safe and efficient interactions between humans and robots in collaborative environments. These models are designed to predict and control the forces exerted during contact to prevent injury and improve robot performance in tasks that require close human–robot interaction. Most papers focused on developing biomechanical models and the representation of human body parts and on collision analysis, while very few addressed robot modelling. In Figure 4, a graphical representation of the identified subcategories is reported.

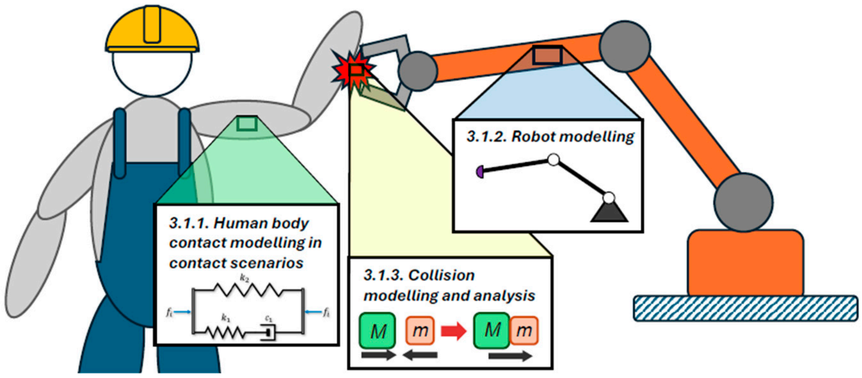

Figure 4. Graphical representation of the "Physical human-robot contact models" subcategories.

3.1.1. Human Body Modelling in Contact Scenarios

Understanding the mechanical properties of human body parts is fundamental to predicting and mitigating the impacts of physical interactions with robots. This category includes studies that model various human body parts using mass–spring–damper systems, viscoelastic properties, and other biomechanical representations to ensure accurate simulation of contact scenarios.

The reviewed studies summarised in Table A1 cover various body models and highlight specialised approaches for assessing interaction dynamics across multiple human body parts. For the upper limbs, Shin et al. [35] examined skin and tissue responses using nonlinear collision models incorporating layered contact dynamics, also considering pressure distribution effects due to the impactor shape to assess the effects of impacts. Rajaei et al. [36] explored upper arm soft tissue behaviour under constrained impacts, introducing nonlinear force-displacement models; using a pendulum device with different impactor shapes, the deformation of the tissues at the contact with the impactor is compared to the deformation affecting the opposite part of the body (i.e., the constrained surface). For the lower arm, Povse et al. [37] developed a mechanical model simulating passive motion for impact studies, comparing the impact energy density with the measurements acquired with volunteers. Vemula et al. [38] introduced a safety design metric based on power flux density, quantifying injury severity for upper and lower arm collisions in industrial robotic applications. Lee et al. [39,40] further refined hand impedance models, employing linear mass–spring–damper systems to enhance interaction stability and transparency. In this context, hand impedance refers to the resulting deformation or motion of the hand when a force is applied; it encompasses the mechanical properties of the hand, such as stiffness, damping, and inertia.

Focusing on broader body regions, Courreges et al. [41] validated the log-linearized Hunt–Crossley model for abdominal contact via an in vivo experiment; later on, they proposed the use of such an approach as an empirical model of soft biological tissue, validating the results by an experimental comparison with the original Hunt–Crossley model [42]. Dong et al. [43] developed a mass–spring–damper model for the thorax, also considering human height and weight information and improving a previous model by integrating elasticity and damping characteristics of the ribs. Attention to the dorsal region is reflected in Lacerda et al. [44], who developed a simulated model composed of nine different zones to characterise stiffness distribution to inform robotic manipulator interactions.

While these studies offer valuable insight into human–robot interaction safety, several limitations warrant attention. Most models focus on the upper limb (e.g., upper arm, lower arm, shoulder, etc.), with fewer studies addressing the dorsal region and abdomen. One reason for this emphasis is the functional relevance and frequency of interaction between robotic systems and the upper limbs in collaborative tasks. Upper limbs are the primary contact points in many physical human–robot interactions. The relative complexity of modelling the dorsal region and abdomen also presents a challenge. These areas exhibit greater variability in tissue properties, shape, and movement due to the involvement of multiple muscle groups, complex skeletal structures, and the presence of internal organs. Soft tissues in these regions are also less frequently engaged in direct physical interaction during collaborative tasks, reducing their perceived priority for modelling in many applications.

Many models adopt simplified biomechanical representations, such as linear spring–damper systems or single-degree-of-freedom systems, which inadequately capture the complexity of the human body's nonlinear, anisotropic, and viscoelastic properties. These simplifications often disregard the heterogeneity of soft tissue stiffness, variability across anatomical regions, and the dynamic effects of muscle activation and posture. Furthermore, most studies rely on averaged biomechanical properties derived from small, demographically homogeneous samples, failing to account for inter-individual variability due to age and gender. Measurement methods, such as indentation devices, are often limited by their localised scope and lack of granularity, which restricts the generalizability of results to other body parts or dynamic scenarios. Additionally, certain models may lack comprehensive validation across diverse scenarios, limiting their applicability in dynamic and multi-contact interactions typical of collaborative robotic environments.

To address the limitations of existing human body models in human–robot interaction research, future work should focus on developing more comprehensive and adaptive models that better reflect the complexity of human biomechanics. These models must incorporate soft tissues' nonlinear, viscoelastic, and anisotropic properties while accounting for dynamic variations due to posture, muscle activation, and multi-contact interactions. Advanced modelling approaches leveraging techniques such as finite element analysis (FEA), and machine learning could enable the development of individualised models that account for variations in age, gender, and anthropometric diversity. Using real-time data acquisition systems, such as wearable sensors, could facilitate adaptive models that dynamically adjust based on a user's physiological state and environmental conditions.

Also, exploring new measurement technologies, such as magnetic resonance elastography and ultrasound elastography, could provide richer datasets for enhancing model accuracy and granularity. These techniques could also help in the real-time monitoring and validation of human–robot interactions in practical settings. Furthermore, future advancements in modelling must prioritise ethical and safety considerations.

3.1.2. Robot Modelling

In physical human–robot interactions, accurately representing the effective or reflected mass of the robot at the contact point is crucial for ensuring safety and understanding impact dynamics. This effective mass, defined as the apparent mass of the robot observed at the point of interaction, varies significantly based on the robot's configuration and the direction of the impact [45]. Consequently, precise modelling of this parameter is necessary to predict and control the robot's behaviour during accidental or intended contact with a human. The research papers hereafter reported summarise key contributions in this area, emphasising methodologies for calculating or approximating the effective mass under various operational conditions.

The reviewed literature on robot modelling in human–robot contact scenarios demonstrates a progression of methodologies for calculating and utilising robots' effective or reflected mass to enhance safety during physical interactions, as summarised in Table A2. Lee and Song [46] introduced an approach leveraging the inertia matrix and Jacobian determinants to calculate an effective mass for collision safety, focusing on a planar robot arm model. This was further expanded by Lee et al. [47], who optimised the link lengths of a 3 DOF planar manipulator by incorporating effective mass into design safety criteria. In subsequent work, Lee et al. [48] integrated manipulability and effective mass to refine collision modelling, establishing a connection between these parameters and spatial manipulator design optimisation.

Kirschner et al. [49] critiqued the simplified, effective mass approximations in ISO/TS 15066, advocating for configuration- and direction-dependent calculations, which provide more precise collision force predictions. Steinecker et al. [50] proposed the Mean Reflected Mass metric, which averages reflected mass across all directions, offering a physically interpretable and versatile tool for safety assessments and robot posture optimisation. Jeanneau et al. [51] developed a reduced mass–spring–mass model that decouples the actuator-side inertia from the contact point, simplifying impact force evaluation while maintaining accuracy. Finally, Stuhlenmiller et al. [52] applied configuration- and direction-dependent effective mass in motion planning, optimising robot trajectories to regulate energy transfer during contact, thus enhancing both safety and motion efficiency.

Collectively, these works illustrate the evolution of effective mass modelling from basic formulations to advanced metrics and applications, enabling safer and more effective human–robot collaboration. However, the proposed models for determining the robot's effective mass at the contact point exhibit some limitations. Many rely on simplifications, such as assuming a constant or configuration-independent effective mass, which fails to capture the dynamic variations caused by the robot's changing posture and motion direction. This can result in non-conservative estimates, particularly in scenarios involving complex trajectories or multi-directional interactions. Additionally, these models often idealise collisions as inelastic and static, overlooking quasi-static or elastic interactions that occur in real-world applications. While computationally efficient, such simplifications reduce the accuracy and adaptability of these models, limiting their reliability in diverse and dynamic human–robot contact scenarios.

So, future research should focus on dynamic and real-time modelling of effective mass, enabling adaptation to change robot configurations and trajectories. Integrating multi-contact dynamics and detailed biomechanical models of human anatomy can enhance safety and reliability in diverse scenarios. Experimentally validating models across a range of collision conditions and developing compliance-focused designs will further improve robustness. Standardised methodologies and modular, application-specific approaches are also needed to bridge the gap between theoretical models and industrial applications. Expanding energy-based metrics and leveraging machine learning for predictive capabilities can provide a more comprehensive understanding of human–robot interactions, advancing safety and performance.

3.1.3. Collision Modelling and Analysis

This category focuses on developing and validating models that describe the mechanics of collisions, including Hertz contact theory, Hunt–Crossley models, and nonlinear dynamic models. These studies provide insights into the factors influencing impact severity, allowing to assess the risks and dynamics of impacts.

As summarised in Table A3, foundational work by Park et al. [53] advanced this work by optimising robot surface properties to reduce stress on human tissue via controlled compliance. Later on, Park et al. [54] further refined collision analysis with a frontal impact model, considering head, neck, and chest impacted at various speeds and validating the simulation results with experimental limits available in the literature. Based on an equivalent spring–mass model and on Hertz contact dynamics, Liang et al. [55] addressed head collisions with a flexible joint robot, simulating multiple configurations and optimising stiffness to minimise the exchanged force. Vemula et al. [56] developed a "compliant contact force" model to represent the impact between non-homogeneous elastic bodies (i.e., neglecting viscoelastic and damping properties), validated in comparison with FE-based approaches. Focusing on specific safety zones, Kim et al. [57] evaluated head-collision safety across various manipulator configurations to optimise force mitigation by integrating such information in trajectory generation. In pursuit of dynamic safety, Shin et al. [58] integrated a skin-layered collision model, also considering impactor shape, in the calculation of safety separation distance during robot operation in order to optimise robot velocity while ensuring safety; in the advanced study reported in [59], they developed a real-time framework to adjust collaborative robot speeds based on collision proximity. Liu et al. [60] contributed by quantifying energy dissipation during impacts, providing insights into injury threshold calculations. Higuchi et al. [61] developed a hyper-elastic FE model using CT data of porcine thighs, validated with quasi-static and dynamic compression tests. Popov et al. [62] proposed an analytical model based on De Luca and Haddadin's algorithm, including covariance analysis for noise reduction.

Addressing tight-contact situations, Byner et al. [63] presented a two-mass model tailored to clamping hazards, defining permissible speeds to reduce risk. Herbster et al. [64] continued this trajectory by focusing on constrained collisions, developing a model to predict contact forces based on feedback to refine control strategies. Clever et al. [65] proposed innovative criteria for assessing physical contact, using energy and power flux density to evaluate collision severity more robustly than traditional peak force metrics. Complementing these efforts, Samarathunga et al. [66] utilised a pendulum-based experimental setup to simulate human body segments. They conducted an experimental analysis to determine how impact forces vary with changes in impact velocity and different equivalent masses during transient contact. Mujica et al. [67] developed a simulated framework for evaluating co-manipulation scenarios, using a spring–damper model to simulate the interaction with the human hand. Yang et al. [68] considered quasi-static human–robot contacts to model and identify robot parameters using a Physics-Informed Neural Network. Liping et al. [69] propose a theoretical analysis aimed at establishing a vibration model representing an interconnected human–robot systems in order to simulate force transmission during impacts. While Mohammad et al. [70] developed advanced reaction strategies for parallel robots in human–robot collaboration, focusing on collision and clamping scenarios. These integrate a proprioceptive dynamics-based collision model with neural network classification. Using Cartesian impedance control and a disturbance observer, the system detects contact events and employs neural networks for clamping classification and response. This approach aims to enhance safety and efficiency in human–robot interactions.

Together, these studies demonstrate a progression from fundamental collision assessment to sophisticated modelling and control strategies, enhancing both safety and operational flexibility in human–robot collaboration. However, these studies are limited to models that oversimplify human tissue dynamics and robot surface properties, failing to capture human tissues' nonlinear, layered, and viscoelastic behaviour. While finite element (FE) simulations provide accuracy, they are computationally intensive and impractical for real-time use. Real-time mathematical models, although efficient, often lack biomechanical fidelity and omit factors like anisotropy and internal damping. Additionally, limited experimental validation leads to discrepancies between modelled and observed outcomes, particularly in complex scenarios. Most models are specific to certain robots or collisions, reducing generalizability across diverse applications. These issues highlight the need for validated, efficient models that balance realism with computational feasibility.

Future research should focus on expanding the scope of current models to encompass a wider range of body parts and interaction scenarios. For example, refining models to account for dynamic interactions at higher velocities and incorporating more complex biomechanical properties of human tissues will enhance the accuracy and reliability of safety assessments. Extending studies to include different body regions and dynamic conditions would provide more comprehensive safety guidelines.

Integrating real-time collision detection and mitigation, supported by machine learning and artificial intelligence, could significantly improve the adaptability and safety of collaborative robots. Advanced real-time data processing and decision-making algorithms could further enhance real-time assessment methods.

Additionally, greater emphasis on experimental validation using diverse datasets is essential to enhance model reliability and applicability. Multilayered simulations that capture the sequential deformation of human tissues and robot coverings should be expanded to consider complex interactions, such as dynamic changes in contact geometry and multi-point impacts. Developing standardised testing protocols, incorporating variable robot configurations and environmental factors, will improve cross-platform applicability. Furthermore, advancements in sensor technology can provide real-time data on impact forces and tissue deformation, enabling models to refine predictions and improve accuracy iteratively. By addressing these directions, future research can bridge the gap between theoretical modelling and practical implementation, ensuring safer and more adaptive human–robot collaborations.

3.2. Safety Evaluation and Impact Assessment

Safety evaluation and impact assessment become essential to rigorously assess the potential risks and impacts of human–robot contact. This process involves defining safety limits that align with biomechanical thresholds, developing methodologies for evaluating various forms of human–robot interactions, and employing advanced sensing technologies to accurately measure and monitor contact forces. By integrating these approaches, robotic application designers can optimise both safety and performance, reducing the risks of injury while maintaining the efficiency of collaborative robots.

The following sections will explore key aspects of safety evaluation, including determining safe limits for pHRI, approaches for assessing human–robot contacts, and the use of biofidelic sensors in monitoring and evaluating safety in real-world applications. In Figure 5, a graphical representation of the identified subcategories is reported.

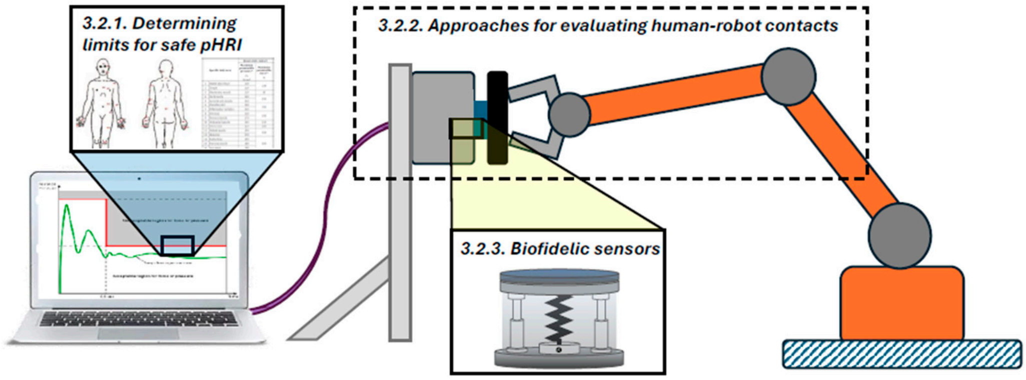

Figure 5. Graphical representation of the "Safety evaluation and impact assessment" subcategories.

3.2.1. Determining Limits for Safe pHRI

Safely integrating robots into environments shared with humans requires establishing strict limits for pHRI. Based on ISO/TS 15066, ISO 10218-2:2025 considers 29 body regions, each with specific biomechanical thresholds for permissible force and pressure. For instance, more sensitive areas like the head have lower limits, while more robust areas like the arms or legs can tolerate higher impact forces. The standard outlines an essential safety mode, power and force limiting (PFL), which restricts the energy a robot can transfer during contact.

The limits in ISO/TS 15066 are based on human subject studies, where 100 healthy adult participants underwent controlled impact tests. These tests measured the force and pressure at which subjects reported slight pain, helping researchers define safe thresholds. The study accounted for male and female participants, recognising that pain thresholds differ across genders and body regions. In this section, we will explore research and methodologies aimed at establishing biomechanical limits, including those contributing to the limits provided by ISO/TS 15066. In studies summarised in Table A4, several approaches have been taken to address the limits and thresholds for safe physical human–robot interaction (pHRI), particularly in terms of force, pressure, and energy limitations during contact.

Some studies prior to ISO/TS 15066 comprehensively explored biomechanical thresholds for safe physical human–robot contact using diverse methodologies to establish injury limit values. Haddadin et al. provided valuable contribution in the field; they analysed the safety characteristics of the DLR Lightweight Robot III (LWR-III) for safe human–robot interaction [71] and systematically evaluated safety in human–robot interaction, analysing impact forces, clamping scenarios, and soft-tissue injuries, providing contact force thresholds, and soft-tissue tolerance values for dynamic and quasi-static impacts in relation to the region of the head [72]. They also conducted seminal research employing crash-test dummies and porcine tissue analogues to analyse collision impacts [73,74]. They emphasised key variables such as velocity, mass, and contact area, finding that higher velocities and rigid structures amplified injury severity, thus suggesting dynamic adjustments to robot parameters during contact to mitigate injury risks. Povše et al. [75] correlated impact energy density with perceived pain thresholds during robot–human collisions, using live-subject experiments to identify pain tolerance as a critical parameter for defining safe robot velocities and configurations. Ito et al. [76] extended this analysis to sharp mechanical hazards, particularly focusing on the eye. Through mechanical simulations, they estimated severity indices and highlighted the necessity of region-specific safety standards for sensitive body areas. Fujikawa et al. [77] applied automotive crash-test principles to evaluate paediatric injury risks during robot collisions, using child dummies to derive mechanical injury parameters such as the Head Injury Criterion (HIC), Neck Injury Criterion (NIC), and

Maximum Chest Deflection. Their results underscored the vulnerability in collaborative environments and emphasised the importance of lighter, slower-moving robots. Behrens and Elkmann [78] refined thresholds for blunt impacts through live-subject collision tests. Their innovative approach incorporating pain perception and tolerable contusions as acceptable outcomes, provided data-driven recommendations for safe robot operations. These studies collectively leveraged experimental rigour and biofidelic metrics to define actionable safety thresholds, forming the scientific foundation for ISO/TS 15066 deliverable.

Most studies examined build on the ISO/TS 15066 and earlier foundational research to refine and expand biomechanical thresholds and safe operational practices for collaborative robotics. Behrens et al. [79] introduced a framework for managing the complexity of contact hazards in collaborative robotics, emphasising the need for robust dynamic models that incorporate biomechanical thresholds. Behrens et al. [80] further developed statistical models to generalise biomechanical limit values, making them adaptable across diverse collaborative environments. Kirschner et al. [81] presented Contact Sensitivity Maps (CSMs), a benchmarking tool for assessing collision handling systems, offering insights into robot joint configurations and their impact mitigation capacities. Han et al. [82] expanded the understanding of human pain thresholds in physical human–robot interactions, suggesting a nuanced approach to modelling transient and quasi-static contacts. Relano et al. [83] contributed a Generalised Impact Absorption Factor (GIAF) that bridges the gap between floating and fixed-base robots, highlighting actuator inertia's role in mitigating collision forces. Cordero et al. [84] proposed the New Index for Robots (NIR) as a safety criterion for human–robot collision and compared it with the HIC via experiments; the NIR exhibited analogue trends but requiring simpler calculations.

Han et al. [85] conducted collision tests with mini-pig skin specimens using a free-drop system and histological analysis to measure tissue damage depth, finding a linear relationship between impact force and skin injury depth, with contact force $\leq$100 N preventing injury propagation to the dermis. Sugiura et al. [86] conducted impact tests using live pigs as human analogues and measured transferred energy and peak contact pressure across chest and extremity impacts. Staab et al. [87] designed a pendulum-based setup, mimicking body parts by using adjustable weights and viscoelastic elements, and conducted experiments measuring energy transfer, force, and pendulum deflection. In [88], Fujikawa et al. conducted vertical and horizontal impact tests using live pigs as human analogues measuring contact forces, velocities, and tissue damage and obtaining energy and pressure thresholds to avoid injuries. In [89], they based their study on experiments on rabbit forearms to develop a rabbit model to determine skin injury thresholds.

Hüising et al. [90] investigated the effectiveness of rounded edges and chamfers in reducing collision forces and pressures during quasi-static contact events. Park et al. [91] explored pressure pain thresholds in collisions, providing empirical evidence for region-specific thresholds to enhance safety measures in human–robot interactions. Virgala et al. [92] reviewed power-and-force limiting (PFL) techniques, correlating their performance with ISO/TS 15066 standards and emphasising the biomechanical considerations required for transient and quasi-static contacts. Hamad et al. [93] investigated upper extremity injury biomechanics during robotic interactions, aligning their findings with force tolerance and injury criteria outlined in ISO standards. Han et al. [94,95] advanced this field by detailing pain onset thresholds and evaluating pain–force correlations in various contact scenarios, enriching the database of biomechanical limits. Behrens et al. [96] refined biomechanical response curves for biofidelic calibration, promoting accurate and reproducible safety evaluations. Expanding the safety framework, Kirschner et al. [97] created a human hand injury protection database using surrogate models to document injury severity for pointed and edged contact scenarios, setting clear limits on effective mass and velocity for safe pHRI applications. The research contributions outlined collectively highlight the interdisciplinary efforts to advance pHRI safety through biomechanics, sensor integration, and adaptive control strategies, forming a robust foundation for developing collaborative robots prioritising human well-being.

While the thresholds and biomechanical limits proposed in these studies provide critical safety benchmarks for collaborative robotics, several limitations persist. The variability in human tolerance due to factors such as age, gender, and individual physical condition is insufficiently addressed, leading to generalised thresholds that may not adequately protect vulnerable populations. Additionally, the reliance on controlled experimental conditions, such as those simulating transient and quasi-static contacts, does not fully account for dynamic, real-world scenarios where unpredictable human behaviour and environmental factors can amplify risks. Furthermore, many studies focus on specific body regions or contact scenarios, limiting their applicability to broader, whole-body safety considerations. The challenge of balancing safety with robot efficiency and functionality also remains unresolved, as stricter limits often reduce robot speed, payload, and operational effectiveness, which can hinder industrial adoption. Finally, the absence of comprehensive long-term validation in real-world collaborative environments constrains the translation of these thresholds into universally applicable safety standards.

In conclusion, determining safe limits for pHRI requires balancing safety and performance. While current standards like ISO/TS 15066 provide foundational safety guidelines, future advancements should focus on refining these limits to optimise robot efficiency without compromising human safety. Customising safety standards for specific applications and environments is crucial, as different sectors (e.g., healthcare vs. manufacturing) may require varying thresholds. Future research in collaborative robotics safety should focus on developing adaptive and individualised safety thresholds that account for human variability, such as differences in age, gender, and health conditions, to enhance inclusivity and protection. Advanced biofidelic sensors and real-time biomechanical modelling could enable robots to dynamically assess and respond to human tolerance during the interaction, improving safety and operational efficiency. Expanding studies to address whole-body interactions and cumulative effects of repeated contacts will provide a more comprehensive understanding of safety requirements. Integrating machine learning and AI-driven predictive analytics could refine robot behaviour, allowing proactive adjustments to mitigate risks in unpredictable environments. Additionally, long-term validation of thresholds in diverse real-world settings, particularly in high-risk industries, is essential to establish globally harmonised and practically viable safety standards. Besides providing further inputs for the development of appropriate standards, these advancements will ensure that collaborative robotics becomes safer, more reliable, and widely adoptable across industries.

3.2.2. Approaches for Evaluating Human–Robot Contacts

Ensuring the safety of human–robot interactions requires evaluation and assessment of potential impacts. Papers in this category propose various methods and metrics for assessing contact scenarios, such as power flux density, biomechanical limits, and pain thresholds. These studies are essential for developing safety standards and guidelines to protect human users in collaborative environments.

Foundational work by Haddadin et al. [98,99] and Matthias et al. [100] has defined early injury metrics, leveraging controlled experiments with anthropomorphic dummies to simulate blunt-force trauma during robot collisions. These injury-centric models align closely with ISO/TS 15066 guidelines, establishing contact force and pressure standards for collaborative operations and setting a baseline for safety metrics in human-friendly robots. Povše et al. [101] developed a passive mechanical lower arm to simulate human arm characteristics, validated by the comparison with tests with human volunteers. In [102], Treitz et al. conducted crash tests using a KUKA robot and a side impact dummy, measuring head accelerations and neck forces with various damping materials; in [103], they developed models for assessing collision risks and parameterised models using a collision testbed.

To refine these metrics, recent studies incorporate sensorless collision detection and adaptive power-and-force limiting (PFL) strategies, as illustrated by Dombrowski et al. [104], which used inverse dynamics and neural networks to predict and manage collision responses in real-time. Fischer et al. [105,106] extended this with experimental testbeds that simulated transient contact forces, highlighting the influence of impact parameters like velocity, effective mass, and sensor positioning. Their findings suggest that safety metrics should consider body-part-specific tolerance levels.

Matthias et al. [107] and Rosenstrauch et al. [108] provided foundational insights into the application of ISO/TS 15066 for risk assessment in collaborative robotics, highlighting the limitations of static force thresholds and the need for scenario-specific parameter tuning. Expanding on this, Mansfeld et al. [109] and Schlotzhauer et al. [110] introduced collision force mapping techniques, demonstrating how robot mass, velocity, and workspace positioning significantly influence impact forces. Their findings advocate for real-time force prediction models and adaptive safety optimisations beyond standardised force limits.

Moreover, interlaboratory studies, such as Scibilia et al. [111], reveal the critical need for standardised testing procedures to ensure reproducibility across HRC safety assessments, stressing variations in sensor stiffness, robot controllers, and test setups as primary sources of measurement discrepancies. Schneider et al. [112] and Kirschner et al. [113] proposed speed- and trajectory-optimisation models, offering preliminary guidelines for quasi-static and dynamic contact scenarios. These approaches are complemented by Fischer et al. [106], who introduced power flux density as an alternative metric, evaluating the energy transfer rate during impacts, which has shown promise in assessing injury potential beyond static force limits. Furthermore, they proposed an equivalent mass model for the robot, which includes the joint position of the robot and the impact direction.

Ponikelský et al. [114] introduced an asymmetric collision measurement approach that highlights how spatial positioning and speed significantly affect force distributions in collaborative settings, providing critical insights into optimised safety zones. The studies [115–117] furthered these efforts by developing a biofidelic finite element model (FEM) of the human hand to predict and assess impact forces in transient contact scenarios, laying the groundwork for bio-realistic contact simulations in HRI.

To ensure compliance with safety standards, Rathmair et al. [118] proposed formal verification methods using model checking, while Sohail et al. [119] presented an automated standard conformance testing framework, identifying inconsistencies in traditional certification processes. Meanwhile, simulation-based approaches have gained traction, as demonstrated by Huck et al. [120], who utilised digital twins and motion capture to predict hazardous interactions before deployment. Similarly, Zhu et al. [121] addressed inconsistencies in collision measurement methodologies, refining transient contact models and force measurement calibration techniques.

Kirschner et al. [122] and Svarny et al. [123] extended these safety assessments by proposing constrained and 3D collision-force maps, respectively, offering data-driven, robot-specific safety benchmarks that improve predictive accuracy for impact risk assessment. In contrast, Hu [124] adopted a design-centric approach, integrating stiffness modulation and lightweight structures to enhance cobot safety without sacrificing performance. Collectively, these studies illustrate a shift toward integrated, data-driven safety frameworks, where biomechanical modelling, force prediction, and adaptive control strategies converge to optimise human–robot collaboration in dynamic environments.

These works form a robust framework for evaluating human–robot contacts by integrating biomechanical injury data, real-time impact prediction, and rigorous experimental validation. The alignment of injury metrics with dynamic safety control mechanisms offers a multidimensional approach, enhancing safety in collaborative environments and setting a high standard for future HRC safety research and industrial applications.

Despite advancements in evaluating human–robot contacts, several limitations persist. The lack of standardised experimental setups and metrics reduces the generalizability of results, and existing methods often fail to adapt to dynamic environments. Current approaches emphasise quasi-static and transient contact scenarios but overlook intermediate interaction types common in real-world applications. The reliance on static biomechanical thresholds does not account for individual variability in pain tolerance or injury susceptibility. Computational simulations are hindered by oversimplified human anatomical models, resulting in gaps between predictions and actual outcomes. Moreover, the interplay between robot control parameters and environmental variability remains inadequately addressed, and isolated testing methodologies fail to consider holistic factors like ergonomics and task-specific interactions. Practical implementation challenges, particularly in cost-sensitive industrial settings, further constrain the adoption of advanced evaluation systems. Addressing these issues will require more adaptive, context-aware frameworks and interdisciplinary collaboration to improve safety and efficiency in human–robot interactions.

Future research should explore advanced adaptive sensing technologies that can dynamically adjust to varying interaction scenarios, enabling real-time evaluation of human–robot contact forces and pressures. The development of more comprehensive biomechanical models, incorporating detailed anatomical variability and tissue properties, will enhance the accuracy of simulations and assessments. Machine learning approaches can be employed to predict impact outcomes under diverse scenarios, bridging the gap between simulations and real-world interactions. Additionally, research into hybrid evaluation frameworks that combine quasi-static, transient, and intermediate contact scenarios will better reflect the complexities of human–robot interactions. Standardising experimental setups and metrics across industries could foster global collaboration and the comparability of findings. Innovations in cost-effective, modular testing systems would make advanced evaluation technologies accessible to any industry. Lastly, integrating ergonomic, cognitive, and task-specific considerations into evaluation frameworks could improve collaborative robotics' overall safety, comfort, and usability in dynamic and diverse environments.

3.2.3. Biofidelic Sensors

Unlike traditional sensors focusing solely on force or pressure, biofidelic sensors provide a more comprehensive understanding of how human tissue would respond in different collision or contact scenarios. Indeed, these sensors are designed to replicate the behaviour of various body parts, such as skin, muscle, and bone, allowing for more accurate measurements of forces and pressures exerted during human–robot contact.

By simulating human-like responses, biofidelic sensors enable researchers and engineers to evaluate the safety of robotic systems more effectively, ensuring that robots operate within the biomechanical limits that are safe for humans. They are particularly useful in testing collaborative robots in both controlled and real-world environments, as they provide data on transient and quasi-static contacts, which are critical for assessing the risk of injury.

These sensors are integral to perform safety validation procedures, such as the methodology reported in Annex N of ISO 10218-2:2025. By providing realistic feedback, biofidelic sensors help ensure that robots comply with these safety regulations, thus enhancing their design and control systems to mitigate risks in pHRI. These sensors are designed to assess impact forces and contact dynamics, in some cases incorporating innovative methodologies to ensure accuracy, repeatability, and sensitivity to diverse contact scenarios.

For instance, Shi et al. [125] developed a biosimulant artefact system integrating calcium alginate bead sensors, which deform under impact. These beads visually indicate injury thresholds and enable consistent measurement of transient forces due to their uniform fabrication process, ensuring reproducibility and cost-effectiveness. Active measures such as using ballistic gelatine layers to simulate tissue compression added sensitivity to stress distributions within the artefact. Expanding on this, Dagalakis et al. [126] introduced disposable biofidelic artefacts embedded with dynamic impact sensors, emphasising their reliability in calibrating force measurements under various collision conditions. These artefacts leveraged layered designs of ballistic gelatine and artificial leather to replicate the mechanical response of human tissue and achieved high sensitivity by accurately detecting transient forces during robot impacts.

Hirata et al. [127] focused on creating artificial safety dummies with simplified structures that maintain reliability through rigorous biomechanical calibration. The biofidelic properties of the dummies were validated through their active responses to varying forces, demonstrating precision in replicating human tissue deformation. Iki et al. [128] extended these efforts by designing dummy skins tailored for robot end-effector contact analysis. The sensors demonstrated exceptional reproducibility in emulating the deformation characteristics of human hands, ensuring reliability across repeated tests. Li et al. [129] developed a dummy finger embedded with PVDF film sensors to measure both shear strain and vibration during robot contact, providing reliable data on strain energy and enabling real-time safety assessments for collaborative environments. This design highlights the potential of using built-in sensor systems within human-like dummies to offer precise, quantitative feedback on contact forces. Liu et al. [130] advanced the sensitivity of biofidelic dummies by integrating nonlinear viscoelastic models to reflect human tissue impedance properties. This approach enabled the sensors to provide adaptive and reliable force measurements in dynamic interactions. Nguyen et al. [131] introduced a neural network-based compensation method to mitigate sensor drift, which significantly enhanced the reliability of biofidelic test devices during prolonged use. By calibrating sensor outputs against transient and sustained forces, this approach ensured accurate force and deformation measurements, furthering the applicability of biofidelic devices in human–robot collaboration. Case et al. [132] worked on the design and fabrication of a soft pressure sensor, with particular focus on the biofidelic response of the material, aimed at the integration in a dummy arm.

The characterisation of commercially available biofidelic sensors provides critical insights into their capabilities and limitations in human–robot interaction safety assessments. Zimmermann et al. [133] systematically compared three widely used biofidelic force-measuring devices under dynamic and static load conditions. By employing a linear motor test machine and pendulum setups, the study highlighted key performance metrics, such as force range, compression element properties, and fixation stiffness. The results revealed an average peak force variation of 5% among devices, with softer compression elements and less rigid fixations amplifying discrepancies. This variability underscores the need for standardised testing protocols to enhance reliability. The dynamic behaviour of the devices also showed significant dependence on factors like the mass of the moving plate and geometry, emphasising the importance of design considerations in replicating human tissue properties. Samarathunga et al. [134] extended this analysis by focusing on the dynamic characteristics of a biofidelic measuring device using a physical pendulum setup. Through experimental and theoretical approaches, this study identified key parameters, including natural frequency, damping coefficient, and bandwidth. The findings revealed that the sensor's response is heavily influenced by its damping characteristics and the addition of viscoelastic damping materials, which mimic human tissue behaviour. A critical limitation highlighted was the sensor's inability to accurately measure forces with impact durations shorter than its time constant, leading to peak force underestimations in transient contact scenarios. The research also emphasised the need for precise calibration and characterisation to ensure the sensor's fidelity to human biomechanics in various collaborative scenarios. These studies underscore the advancements in commercially available biofidelic sensors while addressing the need for consistent performance, adaptability, and improved standards. These sensors remain indispensable for evaluating power-and-force-limiting capabilities in collaborative robotics, but ongoing refinements are essential to enhance their accuracy and application in diverse human–robot interaction environments.

The proposed biofidelic sensors, despite their innovations, face limitations that warrant further attention. High biofidelity materials, such as ballistic gelatine and calcium alginate beads, often require precise fabrication and environmental controls, limiting scalability and applicability in dynamic, real-world settings. Many designs, such as disposable sensors, lack durability, raising concerns about cost-effectiveness and sustainability. While advanced compensation methods like neural networks improve reliability, they depend on high-quality data and computational resources, which may not always be accessible.

Reproducibility is another challenge, as fabrication inconsistencies can affect sensor performance and limit their use for universal safety standards. Furthermore, many sensors excel at detecting transient forces but struggle with prolonged or quasi-static forces, which is critical in collaborative environments. Lastly, these sensors often replicate specific body parts, limiting their generalizability to diverse human–robot interactions. Overcoming these challenges will require innovations in materials, cost-effective manufacturing, adaptable designs, multi-modal sensing technologies, and computational modelling to enhance their practicality, reliability, accuracy, scalability, and robustness.

4. Conclusions

The review on pHRI, with a particular emphasis on physical human–robot contact modelling, and safety evaluation by impact measuring, offered a thorough exploration of the advancements and challenges in this rapidly evolving field.

This systematic literature review provided a detailed analysis of six critical subcategories in physical human–robot interaction (pHRI): human body modelling, robot modelling, collision modelling, determining safe limits, approaches for evaluating human–robot contacts, and the development and application of biofidelic sensors. The findings highlight significant progress in understanding and improving safety in human–robot collaboration while also revealing persistent challenges and gaps that need to be addressed for more comprehensive and reliable safety assurance.

Human body modelling has primarily focused on the upper limbs, reflecting their frequent interaction with robots. However, these models often oversimplify human anatomy by relying on linear, homogeneous, and static representations that fail to capture human tissues' anisotropic, nonlinear, and viscoelastic properties. Moreover, limited validation across diverse body regions, such as the abdomen or dorsal area, reduces the generalizability of findings. Similarly, robot modelling has progressed from static to configuration- and direction-dependent approaches for estimating effective or reflected mass, significantly enhancing impact dynamics' accuracy. However, these models often neglect multi-directional interactions and dynamic robot postures, limiting their reliability in complex real-world scenarios.

In collision modelling, quasi-static contact scenarios have received the most attention due to their ease of testing and the higher perceived risk of severe injuries. While quasi-static impacts provide critical insights, the limited exploration of transient and dynamic interactions oversimplifies the complexity of real-world human–robot collisions. Developing models encompassing transient dynamics, higher-velocity impacts, and multilayered human tissue responses remains an essential future direction. Biomechanical thresholds established through standards like ISO/TS 15066 for determining safe limits, finally co-opted in ISO 10218-2:2025, provide a foundational framework. However, these thresholds often rely on data from narrow demographic groups, typically healthy adults, failing to account for the variability introduced by age, gender, health conditions, and physical abilities. This lack of inclusivity undermines the applicability of these limits, particularly for vulnerable populations such as elderly workers or those with disabilities.

Approaches for evaluating human–robot contacts have predominantly relied on experimental setups and simplified metrics such as peak force or pressure. While these methods are practical, they frequently overlook critical parameters like contact duration, force distribution, and the cumulative effects of repeated impacts, which can be relevant for understanding and mitigating contact severity. Biofidelic sensors have significantly improved the fidelity of impact assessments, yet challenges persist in ensuring their reproducibility, sensitivity, and adaptability across diverse body regions and interaction scenarios. As a futuristic outlook, integrating real-time sensing with predictive analytics could significantly enhance the utility of these sensors in dynamic environments.

Addressing these gaps requires interdisciplinary efforts to develop comprehensive, validated models requiring advanced computational techniques and robust experimental frameworks. Expanding demographic diversity in safety assessments and incorporating adaptive technologies based on machine learning and artificial intelligence would enhance the reliability and inclusivity of safety standards. By prioritising these areas, future research can establish a holistic and scientifically robust framework for ensuring safety in human–robot collaboration and fostering innovation while safeguarding human well-being, primarily in the industrial practice, likely impacting other robotic application fields, like healthcare and service applications.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

As already mentioned in the Introduction, ISO/TS 15066 represented, from its publication in 2016 until 2025, the up-to-date pre-standardisation document for HRC applications, playing a pivotal role in shaping the design of human–robot contact models by providing comprehensive guidelines that aim to ensure safety during collaborative operations.

At the moment of writing this review, the updated versions of ISO 10218-1 and 10218-2 have just been released, including several prescriptions and information related to HRC applications. As an important innovation, in 10218-1, robots are classified as Class I or Class II, characterised by different safety performance levels; a robot with a mass, maximum force transmitted and maximum speed values below predefined limits can be classified as

Class I. To determine the maximum force transmitted, a test methodology is prescribed in Annex E.

ISO 10218-2 reports a specific procedure for the risk assessment of HRC applications, with a focus on the possible human–robot contacts. Those need to be identified and evaluated, in order to design the application minimising the risk of occurrence and applying the necessary risk reduction measures. The following information are provided in Annexes, particularly relevant for the purposes of this review paper:

- **Biomechanical Limits:** borrowed from ISO/TS 15066, Annex M defines specific biomechanical thresholds for different body regions, defined as pain onset limits, which can be used as safety limits in the evaluation of both quasi-static and transient contact types. To prevent harm, pressure limits are also provided.
- **Fully inelastic contact model:** building on ISO/TS 15066, Annex M also suggests the use of a two-body model to replicate human–robot impacts. This model enables the calculation of the transmitted elastic energy, thus the exchanged force, to be compared to the limits. For the application of the model, the document provides (i) reference values of effective mass and elastic constant for several parts of the human body and (ii) a simplified model for the calculation of the robot mass involved in the impact.
- **Contact validation procedure:** Annex N reports information about the validation methodology for contact scenarios identified in the risk assessment, analogue to those provided by the German Institute for Occupational Safety and Health (IFA) [135] and ANSI RIA TR 15.806 [136]. The procedure consists of reproducing each contact scenario, substituting human body parts with biofidelic sensors, tuned in stiffness and damping properties to replicate the human body's different parts, whose properties are, in turn, reported in the Annex.

The deliverable ISO/PAS 5672 [137] provides a deeper guidance for testing human–robot contacts, providing in particular the following information:

- A further characterisation of contact types, based on load profile (quasi-static or dynamic) and spatial configuration (constrained or unconstrained);
- Design specifications, calibration and requirements for biofidelic sensors;
- Measurement methods, including a conversion-based approach to deal with the measurement of unconstrained contacts;
- Measurement procedure.

Appendix B

In this appendix, the tables summarising the papers collected and selected for each category and subcategory are reported.

Table A1. Summary of research papers on human body modelling in contact scenarios for safe human–robot interaction.

Paper	Objective	Human-Body Part	Modelling Approach	Validation Method
Povse et al., (2012) [37]	Develop a mechanical lower arm dummy for impact studies.	Lower arm	Mathematical model based on antagonistic muscle pairs and passive elbow properties.	Experimental: impact force and energy density compared with human volunteers.
Courrèges et al., (2016) [41]	Assess the validity of the log-linearized Hunt–Crossley (LLHC) model.	Abdomen tissue	LLHC model for contact force.	Experimental: experiment with probe on human abdomen and comparison with standard Hunt-Crossley (HC) model.
Shin et al., (2017) [35]	Estimate physical safety considering impactor shape and effective inertia.	Hand and other parts	Nonlinear collision model with layered skin contact, Hertz theory for pressure distribution.	Simulation: comparison peak contact force and pressure with ISO/TS 15066.
Lee et al., (2017) [39]	Estimate the impedance of the hand.	Hand	Linear mass–spring–damper system; impedance estimation based on drop tests.	Experimental: comparison of force-displacement data with simulated values.
Lee et al., (2018) [40]	Improve transparency in pHRI using impedance compensation.	Hand	Linear mass–spring–damper system integrated with admittance control.	Experimental: comparison of energy and interaction force with/without impedance compensation.
Vemula et al., (2018) [38]	Develop a safety design metric based on power flux density to assess impact severity.	Upper and lower arm	Linear spring–damper model.	Comparison with experimental data in [78] of peak force and contact duration.
Courrèges et al., (2019) [42]	Compare LLHC and HC models.	Biological tissues	LLHC model for contact force.	Experimental: impact tests on bovine articular cartilage and in vivo human abdomen indentation tests.
Lacerda et al., (2021) [44]	Analyse the physical interaction of the robotic manipulator and human dorsal regions for safety.	Dorsal region (back, upper and lower)	2D stiffness map of dorsal muscles and spine, integrated with impedance control.	Simulation: calibrate stiffness based on displacement-force relationships to approximate dorsal stiffness distribution.
Rajaei et al., (2021) [36]	Investigate human upper arm soft tissue behaviour during contact to develop safety devices.	Upper arm soft tissue	Nonlinear force-displacement, based on dynamic and quasi-static impact tests.	Experimental: validation with pendulum device and ultrasound, comparing tissue deformation at the opposite sides.
Dong et al., (2022) [43]	Develop an accurate thorax model for calculation of robot speed limits.	Thorax	Mass–spring–damper, adding a mass–spring layer between the striker and the ribs.	Simulation: comparison of the force–deflection simulated curve with tests on a cadaver.

Table A2. Summary of key approaches in robot modelling for effective mass estimation at the contact point in human–robot interactions.

Paper	Modelling Approach	Equivalent Mass Calculation Method	Verification of the Model
Lee & Song, (2011) [46]	Collision safety evaluation using a 3 DOF planar robot arm model.	Inertia and Jacobian matrices to determine effective mass based on configuration.	Simulation: estimate collision forces, meeting safety criteria.
Lee et al., (2012) [47]	Collision safety evaluation with a focus on link length for a 3 DOF planar manipulator.	Inertia and Jacobian matrices to determine effective mass based on configuration.	Simulation: optimising link length to meet safety criteria with practical modifications.
Lee et al., (2013) [48]	Development of a collision model linking effective mass and manipulability to design parameters.	Inertia and Jacobian matrices to represent configuration-dependent inertial properties; manipulability to estimate collision velocity.	Simulation of a three-DOF manipulator to evaluate collision forces and adjust design parameters for safety compliance.
Kirschner et al., (2021) [49]	Comparison of effective mass calculation methods in ISO/TS 15066 vs. traditional dynamic models for collision safety.	Simplified ISO/TS 15066 vs. detailed dynamic models, including joint and link parameters.	Experimental: pendulum collision setup. Result: significant differences in results, favouring the detailed model for accuracy and safety.
Steinecker et al., (2022) [50]	Development of Mean Reflected Mass metric to assess safety in pHRI.	Calculated as an average of reflected masses in all directions, independent of specific impact direction.	Simulations and physical collision tests.
Jeanneau et al., (2024) [51]	Development of a reduced mass–spring–mass model for compliant robots in impact scenarios.	Calculated projecting robot dynamics into a translational mass–spring–mass system, decoupling inertia at contact from the actuator side.	Simulation: comparison of reduced and full models for various impact scenarios.
Stuhlenmiller et al., (2024) [52]	Optimal motion planning considering power and force limiting for human–robot collaboration.	Configuration- and direction-dependent effective mass to optimise transferred energy during contact.	Simulation: comparison of motion time and energy transfer with and without effective mass adjustments.

Table A3. Summary of research papers on collision modelling and analysis.

Paper	Objective	Collision Model Used	Modelling Approach	Validation Method
Park et al., (2011) [53]	Minimise stress in human–robot collisions by designing a safe robot surface cover.	Hertz Contact Theory.	Theoretical modelling of impact stress and material properties of head and robot arm with soft covering.	Comparison with cadaver data from biomechanics literature and crash-test data.
Park et al., (2015) [54]	Analyse safety and reduce injury risk in frontal collisions, focusing on head, neck, and chest injury potentials.	5-DOF mass–spring–damper System.	Dynamic collision model of head, neck, chest, and torso; force analysis for blunt impacts based on severity indices.	Comparison with experimental crash data from Hybrid III dummy and EuroNCAP injury tolerances.
Kim et al., (2016) [57]	Evaluate head-collision safety for a 7-DOF manipulator using posture adjustments to reduce injury.	Two-mass linear collision model with spring interface.	Analytical model: MSI (manipulator safety index) to estimate head injury based on manipulator properties.	Simulations of various postures and trajectories and analysis of MSI.

Table A3. *Cont.*

Paper	Objective	Collision Model Used	Modelling Approach	Validation Method
Liang et al., (2017) [55]	Ensure safe head collisions with a flexible joint robot by optimising effective mass and stiffness to minimise impact force.	Equivalent spring–mass model, Hertz contact dynamics.	Analytical calculation of effective mass and stiffness; optimisation to minimise force.	Simulation-based validation across multiple configurations and collision directions.
Vemula et al., (2017) [56]	Develop a compliant contact force (CCF) model for simulating.	Compliant Contact Force (CCF) Model.	CCF to evaluate collision characteristics of non-homogeneous, layered elastic bodies.	Simulation: comparison of finite element (FE) model with theoretical existing models.
Shin et al., (2018) [58]	Enhance both productivity and safety by controlling the allowable maximum safe velocity.	Skin-layered collision model with impactor shape consideration.	Calculates collision force applying nonlinear elastic properties for human skin.	Simulation: velocity control under varying distances; validation with ISO/TS 15066 thresholds.
Shin et al., (2019) [59]	Develop a real-time evaluation method for predicting collision peak pressure and force.	One-layered nonlinear contact model.	Mathematical model for estimating contact force and pressure, incorporating skin deformation and impactor shape.	Experimental: indentation tests using silicone rubber and comparison with FE simulations.
Liu et al., (2021) [60]	Propose a method for calculating the supplied energy in collisions.	Three-element Maxwell viscoelastic model.	Analytical energy calculation using viscoelastic properties for four collision types (free-bumping, clamping, etc.).	Simulation: comparison of analytical results with simulation outcomes using different collision modes.
Higuchi et al., (2021) [61]	Develop a finite element (FE) model of a porcine thigh for evaluating bruise tolerance and injury metrics in blunt impacts.	Hyper-elastic FE model incorporating strain-based injury metrics.	Model developed using CT data of porcine thighs.	Experimental: force-displacement and strain compared with histological findings of erythrocyte leakage.
Popov et al., (2022) [62]	Enhance the accuracy of interaction parameters identification (force and application point) using torque sensors.	Analytical model based on De Luca and Haddadin's algorithm.	Improved the conventional two-step identification technique with covariance matrix optimisation for noise reduction.	Experimental: simulated and real data to test noise robustness and accuracy improvement.
Byner et al., (2022) [63]	Extend the ISO/TS 15066 model for accurately estimating peak forces and permissible speeds in constrained clamping.	Extended two-mass model.	Combines inertial forces from the robot with actuation forces and system reaction time for accurate force prediction.	Experimental: comparison of peak forces across different robot configurations and velocities.
Clever et al., (2022) [65]	Propose and validate energy and power flux densities as integral criteria for assessing physical contact severity.	Lumped parameter model with viscoelastic and spring elements.	Energy and power flux densities to smooth measurement peaks and assess contact severity.	Experimental: pendulum impact tests on a manipulator with different configurations and impact velocities.
Mujica et al., (2022) [67]	Develop a simulated framework for evaluating co-manipulation scenarios focusing on interaction forces.	Spring–damper model for human hand interaction.	Simulation to model a robot with a rigidly attached payload; interaction forces modelled using a spring–damper system.	Experimental: real robot equipped with force/torque sensors to compare simulated and real interaction forces.

Table A3. *Cont.*

Paper	Objective	Collision Model Used	Modelling Approach	Validation Method
Yang et al., (2023) [68]	Model and identify the cobot parameters during pHRI using a hybrid Physics-Informed Neural Network (PINN).	Quasi-static (QS) contact model with flexible joint dynamics.	Combines joint and task space modelling for pHRI using Lagrange dynamics; utilises PINN for parameter identification.	Experimental: comparison between simulation results and experimental data for torque estimation accuracy.
Mohammad et al., (2023) [70]	Develop reaction strategies for parallel robots during HRC, focusing on collisions and clamping scenarios.	Collision model with neural network classification.	Cartesian impedance control and a disturbance observer to detect contact; neural networks for clamping classification.	Experimental: comparison of reaction times and forces with a planar parallel robot.
Herbster et al., (2023) [64]	Develop a model for predicting contact forces during constrained collisions.	Pinching collision model using stiffness and braking distance.	Contact force-deformation curve combined with robot reaction and braking distances to estimate contact forces.	Experimental: comparison between model predictions and measured data in different configurations.
Liping et al., (2023) [69]	Analyse the force absorption and impact dynamics in HRC, focusing on vibration and collision mechanics.	Mass–spring–damper vibration model.	Vibration model of humans and robots as interconnected systems to simulate force transmission during impact.	Theoretical analysis using equations of motion; comparison of force calculations under various conditions.
Samarathunga et al., (2024) [66]	Analyse transient contact dynamics using a pendulum setup to simulate brief, dynamic impacts.	Equivalent mass models for the physical pendulum and the robot.	Pendulum setup to simulate various human body masses and impact velocities, focusing on transient dynamics.	Experimental: impact force measurements on a robot and the pendulum to simulate the forearm.

Table A4. Summary of selected studies on biomechanical limits and safety thresholds for pHRI.

Paper	Objective	Biomechanical Limit	Methodology	Key Findings
Haddadin et al., (2010) [71]	Analyse the safety of the DLR Lightweight Robot III in human–robot interaction.	EuroNCAP standard criteria	Crash tests with dummy models, injury severity indices measured by biomechanical protocols, tissue injuries using swine tests.	Soft-tissue injuries depend heavily on sharp violence, mitigated with rapid collision detection.
Povse et al., (2010) [75]	Investigate the relationship between impact energy density and pain intensity during collisions.	Impact energy density thresholds.	Experiments with human volunteers using different robot end-effectors to assess pain intensity and measure impact energy density.	Correlation between impact energy density and pain intensity. 2.52 J/cm^2 was confirmed as safe energy density threshold.
Haddadin et al., (2010) [73]	Investigate the severity of soft-tissue injuries caused by sharp robotic tools.	Penetration force, deflection, and injury types.	Experiments using a robot with various sharp tools on silicone, pig tissue, and volunteers to assess collision detection and reactions.	Identified effective injury thresholds and demonstrated that rapid collision reactions significantly reduce injury severity.

Table A4. *Cont.*

Paper	Objective	Biomechanical Limit	Methodology	Key Findings
Haddadin et al., (2010) [72]	Systematically evaluate safety in pHRI analysing impact forces, clamping scenarios, injuries.	Head Injury Criterion (HIC), contact force, soft-tissue tolerance	Experiments with industrial robots analysing free impacts, clamping, near-singular configurations; simulated, real-world crash tests.	Impact severity depends more on velocity, while HIC saturates with mass; proposed thresholds based on impact forces.
Haddadin et al., (2011) [74]	Evaluate the severity of soft-tissue injuries caused by robotic tools.	Penetration force, skin deflection, organ depth measurements.	Tests with sharp tools using pig models, silicone blocks, volunteers; assessed the effectiveness of collision detection and reaction.	Rapid collision detection significantly reduces injury severity, with penetration depths minimised to safe levels.
Ito et al., (2012) [76]	Estimate the injury severity of eye collisions involving sharp mechanical hazards in HRC.	Eyelid state, considering collision position and collision angle.	Static and dynamic collision experiments with dummy eyes (porcine and artificial) using a robotic end effector at varying conditions.	Eye injury severity depends on collision configuration; eyelid closure provides protection, eyeball motion can worsen.
Fujikawa et al., (2013) [77]	Assess collision injury risks for children in HRC using automotive accident data.	HIC, Neck Injury Criterion, Maximum Chest Deflection.	Performed mobile robot and crash dummy collision tests while using automotive accident criteria procedures for data analysis.	Robot mass and speed are critical factors in head injuries, while neck and chest injuries are low under controlled conditions.
Behrens et al., (2014) [78]	Establish verified thresholds for human–robot safety by conducting tests with live subjects.	Pain tolerance, mild contusions, blunt impact traumas.	Ultrasound-based diagnostics to evaluate pain, contusions, other injuries using a pendulum system for live subject collision tests.	Mild contusions are admissible for pHRI verification; pain threshold testing suggests the ideal robot speed and mass.
Cordero et al., (2014) [84]	Validate the New Index for Robots integrated with HRI safety criteria, comparison with HIC.	HIC, impact force/acceleration thresholds for head and arm.	Computed NIR with HIC whilst a SCARA robot with head/arm models was put through tests at varying speeds and impact locations.	NIR followed the HIC trend, providing a more simplistic calculation based on robot mass, velocity, and stiffness.
Fujikawa et al., (2017) [88]	Determine safety criteria for robot design by quantifying injury tolerance under blunt impacts.	Peak mean contact pressure and transferred energy.	Vertical and horizontal impact tests using live pigs to gather data for force, velocity, tissue damage, and histological changes.	The injuries are unlikely with contact pressure < 1.3 MPa or energy < 87 kJ/m^2; proposed model for injury estimation.
Han et al., (2018) [85]	Establish safety conditions for HRC based on an analysis of skin injuries caused by impacts.	Contact force, injury depth for minor skin injuries.	Drop test on mini-pig skin while determining the tissue damage depth.	Contact force < 100 N did not cause damage to the dermis, proving a linear link between impact force and injury depth.
Sugiura et al., (2019) [86]	Investigate mechanical tolerance for bruising, focusing on differences chest/extremities.	Minimum transferred energy per unit area, contact pressure.	Impact tests using live pigs, measuring transferred energy and peak contact pressure across chest and extremity impacts.	The extremities have lower bruise tolerance compared to the chest; recommended body-part-specific criteria for robot design.

Table A4. *Cont.*

Paper	Objective	Biomechanical Limit	Methodology	Key Findings
Park et al., (2019) [91]	Determine the pressure pain thresholds for collisions to inform safety standards.	Pressure pain at 15 body sites, including neck, forehead, hand.	Experimented with 90 males using a system to measure pressure thresholds at various body sites while considering age and BMI.	The range of pain thresholds found is 65.1 to 196.1 N/cm^2, depending on age and BMI, useful also for safety standards.
Staab et al., (2020) [87]	Develop a pendulum apparatus to assess transient (TR) contact in unconstrained scenarios.	Effective mass, peak contact force, energy transfer.	Designed a pendulum device with movable weights and viscoelastic components to measure the energy, force and deflection.	Linear relationships: robot speed, contact force, energy transfer; models in [20] are conservative, to be adjusted for TR contact.
Virgala et al., (2021) [92]	Discuss the PFL application technique in collaborative workplaces based on ISO/TS 15066.	TR and QS force and pressure limits for various body regions.	Guidelines for using PFL robots in assembly tasks, explained TR and QS contact scenarios with force measurements.	PFL robots must comply with force and pressure limits; design modifications (padding, speed limits) minimise injury risk.
Han et al., (2021) [82]	Determine biomechanical limits for PFL by measuring pain onset thresholds.	Pain onset for TR contact at the forehead, deltoid, and thigh.	Clinical trials with 37 subjects using a pendulum collision system, measuring impact force and pressure on different body areas.	Identifies the force limits for pain perception and suggests calculation for real-time safety-oriented adjustments.
Behrens et al., (2021) [79]	Propose an updated framework for managing contact hazards that expands the ISO/TS 15066.	Pain onset and injury onset, with new severity category (S0).	Developed a stress tolerance level and risk assessment model combining biomechanics and statistics for body region and impact limits.	Enhanced the PFL method with three subdivisions for accurate risk assessment and limit evaluation, facilitating application.
Kirschner et al., (2021) [81]	Develop a benchmarking protocol using Contact Sensitivity Maps (CSM) to assess collisions.	Effective mass and velocity; contact sensitivity.	Developed a pendulum-based setup to test various robots in dynamic collision, comparing force and torque thresholds.	Demonstrated the effectiveness of CSMs for collision sensitivity evaluation; differences between robots and configurations.
Hamad et al., (2021) [93]	Summarise injury biomechanics data for upper extremities and develop a digital database.	Force thresholds for fractures, contusions, bending moments.	Classified upper limb impact configurations through data-based approaches that correlate robot and human side parameters of injuries.	Developed a digital database of injuries/safety records focused on safety limits for pHRI with arms and hands.
Han et al., (2022) [94]	Establish biomechanical limits based on pain onset and bearable pain thresholds in QS contacts.	Pain onset and maximum bearable pain (29 body parts).	Measured pain onset and tolerance by region in 40 males using a custom algometric device under a quasi-static force.	Using maximum bearable pain thresholds instead of pain onset values may improve robot productivity while ensuring safety.
Behrens et al., (2022) [80]	Develop a statistical model providing biomechanical limits, focusing on impact/pinching loads.	Pain onset; gender-specific differences (28 body locations).	Conducted algometry and pendulum impact to test 112 subjects while analysing the data using a regression model based on gender.	Developed a statistical model that defined biomechanical limits by gender.

Table A4. *Cont.*

Paper	Objective	Biomechanical Limit	Methodology	Key Findings
Relano et al., (2023) [83]	Develop and validate the Generalised Impact Absorption Factor (GIAF).	Impact parameters (e.g., back-driveability and inertia).	Developed a mathematical model for GIAF; validated with various robot configurations to measure impact response, back-driveability.	GIAF measures impact absorption for different robots, improving their configuration to lower collision forces.
Hüsing et al., (2023) [90]	Investigate the effectiveness of rounded edges and chamfers for QS collisions to reduce forces.	Collision force and pressure for the humerus based on [22].	Used 20 impactors to test a robot while changing edge radii and chamfers, measuring force and pressure using a biofidelic sensor.	Rounded edges reduced collision forces more effectively compared to chamfers; decreasing returns beyond certain sizes.
Fujikawa et al., (2023) [89]	Develop an in vivo rabbit model for determining injury thresholds in dynamic pinching scenarios.	Peak contact force for skin opening and bruising.	Used the rabbit forearm and leg (in place of a human finger) to analyse the injuries from dynamic impacts with different impactor shapes.	Established rabbit models for skin injury threshold validation; openings above 184 N, bruising occurred with lower forces.
Han et al., (2024) [95]	Determine force pain thresholds for transient and quasi-static collisions in cobots operations.	Pain onset, deltoid and thigh (different impactor shapes).	Applied forces with different impactors for deltoid and thigh on 37 subjects with a pendulum device to measure the resulting pain.	Defined pain thresholds by body location and contact geometry, emphasising on adjustment of robot parameters.
Behrens et al., (2024) [96]	Develop biomechanical curves for calibrating biofidelic devices, ensuring accurate measurements.	Force-deformation characteristics across 24 body locations.	Constructed curves based on 75th percentiles using statistical modelling methods to normalise force data, improve their biofidelity.	Created specific curves for device calibration, which allow for standardised tests in relation to latest safety regulations.
Kirschner et al., (2024) [97]	Develop a human hand injury protection database for safely using robots with edged tools.	Injury severity based on impactor shape, effective mass, velocity.	Conducted impact drop tests using different types of pig and chicken hand models and analysed skin, muscle, and bone injuries.	Established safe limits of impact velocity and mass for edged tools for the purpose of Injury Protection databases.

Table A5. Summary of selected research papers on approaches for evaluating human–robot contact.

Paper	Objective	Methodology/Approach	Validation Method
Povše et al., (2010) [101]	Evaluate safe physical human–robot interaction in industrial tasks, focusing on lower arm collision with small robots.	Development a passive mechanical lower arm (PMLA) to simulate human arm characteristics, validating it against human volunteers.	Validated PMLA accuracy by comparing its responses to human volunteers under various impact conditions.
Haddadin et al., (2010) [98]	Develop and validate safety measures and reactive motion control methods for injury prevention in human-friendly robots.	Standardised crash-testing for soft-tissue injury and developed reactive control for impact mitigation.	Validated with crash tests, soft-tissue drop tests, and LWR-III simulations to assess injury severity and control effectiveness.
Treitz et al., (2010) [102]	Evaluated safety requirements in industrial robot collisions for human–robot cooperation work to improve safety practices.	Carried out a crash test with a side impact dummy to measure head accelerations, neck forces. Created a soft and hard tissue injury assessment testbed.	Validated with high-speed cameras and sensors, measuring forces; evaluated the effectiveness of damping materials, control strategies.

Table A5. *Cont.*

Paper	Objective	Methodology/Approach	Validation Method
Treitz et al., (2013) [103]	Assessed human–robot systems through injury thresholds and productivity to devise passive safety measures.	Developed a testbed for collisions at Fraunhofer IPA to measure impact forces, torques, and pressures between robots and humans and risk modelling.	Models were verified through experiments in collision testbeds; injuries were measured and compared with predefined thresholds.
Matthias et al., (2014) [100]	Robot collisions were characterised, and the mechanical loading criteria of safety were defined.	A collision test setup was developed to perform impact scenarios; forces, pressures and momentums were measured using an ABB DAC robot.	Validated experimental collision data with FEM and calibrated simulations for accuracy.
Haddadin et al., (2016) [99]	Developed a safety framework for pHRI focusing on the scope of injury biomechanics and impact prevention measures.	Classified injury scenarios biomechanically and proposed control algorithms for risk reduction, validated through crash tests and human trials.	Injury risk strategies were tested via impact collisions and human subject experiments, comparing forces with theoretical models.
Matthias et al., (2016) [107]	Utilised ISO/TS 15066 in risk assessment for the PFL of collaborative robots in assembly scenarios.	Used ISO/TS 15066 on ABB YuMi robot to evaluate quasi-static and transient contact risk, enabling force measurement and defining protective measures.	Adjusting the robot's speed and torque within biomechanical limits to lower the risk in the scenario that was tested.
Rosenstrauch et al., (2017) [108]	Evaluated the use of ISO/TS 15066 application in HRC and highlighted residual safety risks.	Tested with a six-DOF robot in pick and place actions under the ISO/TS 15066 limit of force and speed to minimise chances of injury.	Measuring forces on a pork belly sample. Despite compliance with ISO/TS 15066, significant penetrations highlighted limitations of the TS.
Mansfeld et al., (2018) [109]	Integrated biomechanics and robot dynamics in developing an injury risk assessment safety map.	Created a safety map based on biomechanics and robot mass/velocity data to set injury thresholds and assess risks.	Verified by mapping biomechanical injury data against PUMA 560 and KUKA LWR IV+ robot performance to mark safety limits.
Dombrowski et al., (2018) [104]	Simulated HRC with power and force limiting for improved safety in manufacturing.	Implemented impact force and pressure assessment by developing a digital tool for HRC simulation, integrating ISO/TS 15066 for preliminary risk analysis.	Refining parameters of risk with collision data and simulation data were validated through parameter studies and real-world cases.
Schlotzhauer et al., (2019) [110]	Used 2D collision-force mapping to evaluate the safety of collaborative robots for sensitive manipulators to assess sensitivity.	Tested UR10 and UR10e while performing pick and place tasks using a biofidel device to map forces and model collisions for speed regulation.	Validated by statistically analysing the reliability of modelled collision force measurement throughout positions and velocities.
Kirschner et al., (2021) [113]	Ran experiments using CCFM to analyse constrained human–robot collisions under ISO/TS 15066.	Developed CCFMs for the UR10e, UR5e, and Franka Emika Panda robots while assessing peak impact forces with a Pilz PRMS device.	Comparison of measured impact forces with ISO/TS 15066 predictions, with significant discrepancies; need for robot-specific assessments.
Scibilia et al., (2021) [111]	Assessing the PFL safety procedure's consistency and accuracy was achieved through interlaboratory comparison.	Conducted standardised PFL experiments in four European laboratories, measuring and comparing force and pressure in different configurations.	Interlaboratory comparison validation; sensor fixtures, robot settings, and alignment were determined to be critical factors for repeatability.
Rathmair et al., (2021) [118]	Formally verification of safety in collaborative robotics, accounting for variability and adaptive behaviour.	Utilised symbolic model checking with the nuXmv tool, incorporating spatial risk models, behaviour trees to verify mechanical hazards, e.g., clamping.	The laboratory demonstrator validated using nuXmv for clamping hazards verification and ensured compliance with safety standards.

Table A5. *Cont.*

Paper	Objective	Methodology/Approach	Validation Method
Kirschner et al., (2021) [122]	Establish a standardised framework for tactile robot performance and safety benchmarking.	Metrics for F/T sensing, control precision, and collision response were developed and tested on the UR10e, UR5e, and Franka Emika Panda robots.	Trilateral experimental validation of force resolution, accuracy, and response times was conducted on the three tested robots.
Svarny et al., (2021) [123]	Create a 3D Collision-Force Map (CFM) with integrated height, distance, and velocity for a safe predictive force estimation.	Built a data-driven impact force model by measuring collision forces of UR10e and KUKA LBR iiwa at different velocities, heights, and distances.	Validated by comparing model predictions to experiments, outperforming ISO/TS 15066 and 2D CFMs, optimising safety and efficiency.
Fischer et al., (2022) [105]	Compare measurement approaches for transient human–robot collisions to identify the best setup for collaborative robots.	Investigated impact force measurement systems with fixed, linear, and pendulum setups using UR3e and GTE CBSF-35 PFMD for evaluation.	Validated by comparing experiments with models, showing the highest impact forces in fixed setup, aligning with ISO/TS 15066.
Huck et al., (2022) [120]	Create a pre-deployment hazard identification tool for HRC using risk assessment simulation techniques.	Created a proof-of-concept in CoppeliaSim where motion capture and force estimation were integrated for unsafe HRC scenario identification.	Used ABB GoFa for validation in simulated industrial tasks, evaluating hazard detection in relation to the risk criteria defined previously.
Schneider et al., (2023) [112]	Formulate reference values and approximation techniques for maximum allowed collaborative operating speeds (MACS).	Measured forces and pressures during clamping and transient contact with Yaskawa HC10 DT IP67 lathe tending machining.	Proposed an equation for defining MACS in the quasi-static scenario with validation of measured forces by comparison with ISO/TS 15066.
Hu (2023) [124]	Develope a safety design and optimisation approach for cobots intended to balance performance with safe pHRI.	Developed a safety model integrating biomechanical limits and performance indices, resulting in an HRI safety diagram for a 7-DOF cobot.	Validated through simulations with the 7-DOF cobot while ensuring compliance with ISO/TS 15066 and biomechanical thresholds.
Fischer et al., (2023) [106]	Studied the effect that human–robot collisions have on safety while varying the geometry and material hardness of the impactor.	Tested various impact setups, geometries, and hardness levels, assessing force and pressure against ISO/TS 15066 limits.	Compared experimental findings with IS0 standards for validation, using PFMD measurements to apply force and pressure throughout the different impact scenarios.
Sohail et al., (2023) [119]	Develop an automated robot standard compliance testing procedure to fulfil ISO standards reducing manual testing.	Used Robot test definition language together with property-based testing to create automated testing for compliance with ISO 23482-1, ISO 10218.	Validated across five robotic platforms, using Husky and Unitree B1, for undetected bugs and testified efficacy of the methodology.
Hornung et al., (2024) [115]	Developed a Finite Element Model of the human hand to analyse the impact force in HRI.	Constructed a FEM using a biofidel device along with parameter optimisation for prediction of hand impact force.	Validated by simulation and measurement comparison with known collision speeds of 70 to 115 mm/s.
Ponikelský et al., (2024) [114]	Create a technique to determine the collision force and pressure distribution with different speeds and varying positions.	Developed a spatial collision model, with force and pressure in different positions and speeds up to 400 mm/s are measured using CoboSafe.	Validated against ISO/TS 15066, determining speed as a critical variable for collision forces, which increased towards the base of the robot.

Table A5. *Cont.*

Paper	Objective	Methodology/Approach	Validation Method
Zhu et al., (2024) [121]	Examine discrepancies in measurement of human–robot collision and suggest methods for easier safety evaluation in cobots.	Examined factors influencing the evaluation of safety and suggested optimisation of PFMD, models of transient contacts, and human kinematics.	Validated by means of PFMD configuration study and calibration test, improving consistency against ISO/TS 15066 benchmarks.
He et al., (2024) [117]	Create a digital twin framework for HRC testing that improves current standards.	Created a simulated framework integrating AI for human behaviour modelling, stochastic movement, and hybrid testing for risks and ergonomics.	Validated with Jaka Zu 7 robot in bolt tensioning while conducting risk assessment and compliance checks with ISO/TS 15066.
Zhang et al., (2024) [116]	Design a safety evaluation procedure for pHRI in heavy-duty assembly through human model simulation.	Developed a safety assessment based on human activity recognition using upper limb motion data, neural network mapping, fuzzy logic evaluation.	Validated on a heavy-duty assembly robot and proved the model accuracy in posture recognition and safety risk estimation.

Table A6. Summary of studies utilising biofidelic sensors for safety assessment in HRC.

Paper	Sensor Type/Technology	Application	Key Findings
Shi & Dagalakis (2015) [125]	Calcium alginate bead embedded in biosimulant	Robot impact safety testing.	With calcium alginate beads, a disposable system of bio-simulants was developed that helps visualise severe injuries during robot impact testing.
Dagalakis et al., (2016) [126]	Biosimulant artefacts with embedded sensors.	Dynamic impact testing for HRC safety.	Developed the DITCI instrument, a biosimulant testing device with adjustable settings for measuring tissue deformation and injury grade.
Iki et al., (2020) [128]	Urethane-based dummy skin with viscoelastic modelling.	Safety validation for collaborative robot systems.	Using the 3-element Maxwell model, a biofidelic dummy skin was created and experimentally validated under static and dynamic conditions for risk assessment purposes.
Hirata et al., (2021) [127]	Upper arm dummy with flexible pressure array sensors.	Safety evaluation for collaborative robots.	Developed a biofidelic dummy that simulates human pain perception under quasi-static and dynamic conditions, showing the ability to replicate the force-displacement characteristic for safety assessment.
Nguyen et al., (2022) [131]	Soft capacitive sensor embedded in a biofidelic forearm device.	Compensation for electrical current drift in human–robot collision.	Designed a neural network controller in a biofidelic device mimicking human forearm structure and function to correct for sensor drift to lessen the impact and deformation of the collision for safer human–robot interaction.
Zimmermann et al.(2022) [133]	Biofidel force-pressure measuring devices.	Validation of collaborative robotics applications.	For cobot safety verification, three biofidel devices were compared and a maximum variance of 5% peak force was achieved, which indicates the need for standardisation.

Table A6. *Cont.*

Paper	Sensor Type/Technology	Application	Key Findings
Liu et al., (2023) [130]	Polyurethane-based dummy with nonlinear viscoelastic modelling.	Safety validation for physical human–robot interaction (pHRI).	A five-element model was used to construct a viscoelastic hand dummy, which showed high biofidelity at steady state forces above 5 N and was validated with dynamic impact testing.
Samarathunga et al., (2024) [134]	Biofidelic force sensor with a customised damping material.	Human–robot impact assessment dynamics.	Developed a biofidelic sensor model with a custom system built with a physical pendulum, revealing the impact on the measurement due to the natural frequency and damping. Suggested better modelling to improve accuracy in assessing human–robot collisions.
Li et al., (2024) [129]	Dummy finger with built-in film sensor.	Safety assessment for human–robot contact.	Designed a dummy finger integrated with a PVDF sensor to detect shear strain and vibration, thus validating real-time safety assessment in a potential scenario.
Case et al., (2021) [132]	Soft capacitive pressure sensor	Measuring human–robot collision forces	Engineered a biofidelic soft capacitive pressure sensor matching the human's forearm tissues with a linear capacitance response up to 50 N.

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