Human-Cobot Energy Feedback for Closed-Loop Sustainable Design for Disassembly: A Taxonomy

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Abstract. This paper presents a focused analysis and taxonomy of energy feedback from human-cobot collaboration within a closed-loop sustainable design framework. Current research areas, including energy-efficient planning, design for disassembly, closed-loop design in product lifecycle management, and human-cobot collaboration, remain fragmented. Planning methods typically optimize production around a fixed product architecture, while design for disassembly relies primarily on static metrics. Studies on collaborative disassembly and robot energy modeling show that task-level energy, intervention rates, and failure or rerouting events can be measured. However, these data are rarely integrated in the early stages of product and process design. To address this gap, the proposed taxonomy is divided into eight dimensions: the type of energy feedback, the human-robot interaction modality, energy metrics, closed-loop control logic, system architecture, industrial application, time scale, and sustainability indicators. Two cross-classifications are then introduced: an ontological structure for integrating product lifecycle management, knowledge graph, and digital twin, and a multi-criteria analysis to balance energy, ergonomics, safety, quality, productivity, and circularity.

Keywords: Human-cobot collaboration; Energy-aware scheduling; Design for disassembly; Product Lifecycle Management; Sustainable manufacturing.

1 Industrial context and motivation

Industry accounts for close to 30% of the world's final energy consumption and about a quarter (24%) of direct anthropogenic GHG emissions, a share that rises to 34% once indirect emissions from electricity and heat are included [1,2]. The EU Circular Economy Action Plan and the upcoming Ecodesign for Sustainable Products Regulation emphasize designing products for durability, repairability, reuse, and disassembly. Two research communities have independently tackled these issues: operations research has developed advanced energy-efficient scheduling models for flow-shops, job-shops, and reconfigurable manufacturing systems (RMS) [3–8], while engineering-design research has developed proactive eco-design, design-for-disassembly (DfD), and design for X (DfX) methods, which are largely disconnected from real operational data [9–13]. Industry 4.0 has produced an unprecedented amount of shop-floor data via the industrial internet of things, digital twins, and cyber-physical systems [14–18]; however, most of this data is still used downstream for purposes like monitoring and predictive maintenance, rather than upstream, where it could influence product and line design decisions. Industry 5.0, as defined by the European Commission, introduces a normative requirement: Artificial intelligence (AI) systems used in manufacturing should be human-centric, aiming to augment rather than replace designers and production planners [19,20]. A missing element concerns the human-cobot workstation. Human-robot collaboration in disassembly and assembly combines human dexterity, contextual judgment, and fallback capability with the repeatability and endurance of robots/cobots [21–23]. The collaborative robotics industry is no longer limited to ensuring safety during human-machine interaction. Recently, attention has shifted towards adaptive systems that account for posture, effort, fatigue, cognitive load, safety, and performance. The goal is no longer simply for the robot to be tolerated in the workspace, but for it to actively help improve production and working conditions. This evolution indicates the transition from Industry 4.0 to Industry 5.0, in which performance is no longer measured solely by productivity but by a balance among human-centricity, sustainability, and resilience. In this context, it is necessary to redefine the term "Human-Cobot Energy Feedback". The literature uses the word "energy" to refer variously to the robot's electrical or mechanical energy, the concepts of passivity and "energy tanks" in control, or, more marginally, to the human physiological cost estimated via biosignals, posture, or muscular effort. The segmentation is clear: research in energy robotics focuses on motion/control efficiency; collaborative ergonomics addresses comfort, safety, and workload; while sustainability encompasses the circular economy, disassembly, and environmental KPIs. The key question, therefore, is: how can we define a unified framework that enables closed-loop use of energy, human, and robotic feedback to design more sustainable collaboration?

2 Contributions

This work does not consider the robot or the human in isolation but rather their interaction within the production environment. This environment must be treated as a sociotechnical system, which entails several costs. The main hypothesis is that the objective is not only to reduce the robot's energy consumption but also to account for the human's energy consumption and workload, adaptation to the context, and long-term impacts. This justifies the proposed classification, which is based on studies showing, on the one hand, energy savings thanks to the cobot, and, on the other hand, ergonomic or cognitive gains when the robot adjusts its paths, roles, or assistance based on the human's condition.

This article presents an initial review and classification linking energy-efficient planning, design for disassembly, human-robot collaboration, and closed-loop design. The classification organizes existing research according to: (i) the level of operation, from simple tasks to production planning; (ii) sustainability indicators, such as energy consumption, dismantling effort, and recyclability; (iii) the roles of humans, cobots, and AI in decision-making; and (iv) the use of shop floor data as feedback for product and process design. Its main purpose is to link measured data, such as energy consumption or intervention rate, to upstream design choices, such as fasteners, modularity, accessibility, and disassembly operations.

3 PRISMA-oriented mapping method

The strategy adopted consists of a preliminary review conducted in accordance with the PRISMA 2020 methodology [25], supplemented by the PRISMA-S recommendations to improve the traceability of the literature search (see Figure 1). PRISMA 2020 requires a clear description of sources, search terms, eligibility criteria, the selection process, and reasons for exclusion, while PRISMA-S aims to enhance the reproducibility of queries and documentation. The protocol review includes a search of Scopus, Web of Science, IEEE, ScienceDirect, ACM, and Springer to identify key conferences and chapters. The search period extends from 2010 to 2026. The documents included are: original articles, systematic reviews, relevant conferences in robotics, human-robot interaction, and human-computer interaction, as well as work on control, ergonomics, sustainable development, or digital twins. Patents, non-peer-reviewed industrial articles, and purely marketing articles are excluded, except for contextual discussion. The search combines four groups: HRC/HRI ("human-robot collaboration," "cobot," "pHRI," "physical human robot interaction," "collaborative assembly," "ergonomics"), energy ("energy consumption," "energy-aware," "power," "physiological workload," "fatigue," "electromyography (EMG)," "heart rate variability (HRV)," "electrodermal activity (EDA),", closed loop ("closed loop," "adaptive control," "role allocation," "trajectory adaptation," "digital twin"), and sustainability ("sustainable production," "circular economy," "dismantling," "LCA," "CO_2," "Industry 5.0"). This structure allows for the inclusion of articles in which the word "energy" is not explicitly mentioned but in which the measurement of human cost through fatigue, posture, or cognitive workload is present. The inclusion criteria are as follows: work involving human-robot/cobot interaction; the presence of measured or estimated feedback on energy, physiological state, ergonomics, or performance; logic of adaptation, control, allocation, planning, or decision support; industrial or equivalent application; results described in such a way as to allow the extraction of variables/concepts for modeling the taxonomy. Exclusion criteria are: fully autonomous robotics without significant human interaction; studies focused solely on safety without actionable feedback; simulation work without operational indicators; articles where sustainability is neither addressed nor inferred from energy, environmental, or circular economy indicators. The selection process illustrated in Figure 1 identified 16 representative studies for the taxonomy (Table 1). Given this deliberately targeted approach, this mapping should be viewed as a structured and reproducible basis for a comprehensive systematic review.

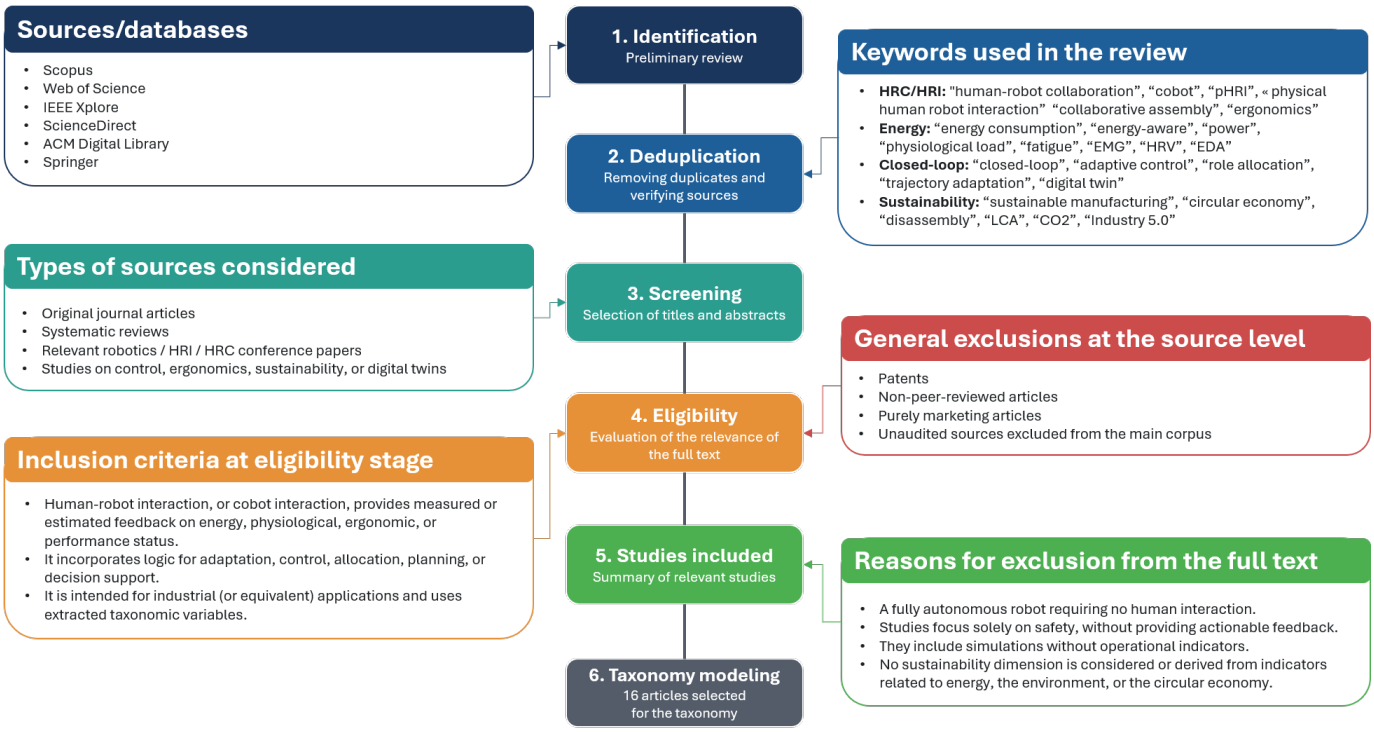


Figure 1. PRISMA-oriented systematic mapping protocol used to define the review's scope

4 State of the art

The state of the art can be grouped into four research areas that directly support the proposed taxonomy. The first section of the literature concerns energy efficiency on the robot side. Energy-aware scheduling and sustainable operations provide the planning vocabulary for decisions on energy costs, peak demand, total energy, and reconfigurable manufacturing [4,6]. A second section concerns sustainable, DfD/DfX, and circular applications, particularly disassembly. DfD/DfX and circular design provide upstream design variables such as fastener choice, accessibility, material separation, and recovery potential [9–11]. The third section of the literature on digital twins and Industry 5.0 architectures shows that real-time, bidirectional connectivity between

physical systems, simulations, cognitive assistance, and environmental indicators is becoming feasible. Implementing digital twins aligned with ISO 23247 and integrating VR and IoT provides a credible basis for moving from a descriptive taxonomy to an operational architecture. Closed-loop product lifecycle management (PLM) and digital twin research formalize the ways in which lifecycle, service, and end-of-life information can feed back into design and process planning [12–17]. Finally, the last section of the literature concerns physical and cognitive ergonomics in human-robot communication (HRC). Human-robot collaboration and robot energy modeling demonstrate that collaborative disassembly, task allocation, and task-level robot energy signatures can be measured or estimated [22–27]. Each line of Table 1 allows for positioning a research axis in relation to the proposed conversion of data on human-cobot tasks into feedback for sustainable design.

4.1Energy-aware scheduling and sustainable operations

The most robust studies show that robot energy consumption is highly dependent on trajectory, execution time, waiting postures, and instruction parameters [24,28]. On the UR10e cobot, simple programming and posture strategies can reduce energy consumption by 3% to 37% [24]. Other recent work highlights that trajectory optimization based on simplified models remains industrially relevant, with typical gains of approximately 15% for fixed start and end points, and that energy savings above 50% are achievable in favorable operating scenarios when freely programmable parameters are jointly tuned [27,28]. This line of research is mature in the "robot electricity/mechanics" component, but has very little connection to the human state. Energy-aware scheduling provides the most mature mathematical foundation for the operational side of the taxonomy. Giret et al. [3] establish sustainable manufacturing scheduling as a field that must integrate energy and environmental criteria with production objectives. Gahm et al. [5] structure the problem around energy cost, peak power, and energy-efficient decision levels, while Masmoudi et al. [4] and Delorme et al. [5] show how energy considerations can be formalized in job-shop and reconfigurable manufacturing contexts. However, these works usually optimize operations after the product architecture and process alternatives have already been fixed. For closed-loop sustainable design, this is limiting. A high-energy operation may result from a poor connector, inaccessible screw, inappropriate tool path, insufficient fixture support, or unnecessary module coupling. A scheduling algorithm can allocate the operation differently, but it cannot, by itself, explain that the product architecture should be modified.

4.2DfD, DfX, and circular design

Research on collaborative disassembly, repair, and recycling of electric vehicle batteries [29,30] shows that human-robot collaboration is especially relevant when product variability, uncertainty, safety, and the need for human judgment make full automation unreliable. This is an ideal application for the proposed taxonomy, as it simultaneously encompasses human effort, robot consumption, safety, quality, cycle time, and recovered circular value. DfD and DfX approaches address the upstream side of the problem. Favi et al. [9] propose a design-for-disassembly tool for the demanufacturing and recycling of mechatronic products, while Vanegas et al. [11] formalize ease-of-disassembly indicators for circular economy strategies. Sassanelli et al. [10] show that DfX approaches are central for circular economy implementation, and Kerin and Pham [13] connect Industry 4.0 technologies to remanufacturing. Formentini et al. [31] organize DfD information at the component, product, subsystem, system, and system-of-systems levels through disassembly systems engineering. These studies provide a solid foundation for planning and systems, but none convert measured robotic energy and human workload into traceable feedback that can be used to update upstream product design and PLM (Product Lifecycle Management) knowledge. It is precisely this conversion that the taxonomy seeks to bridge. The remaining weakness is that most indicators are static or expert-driven and are rarely updated by real evidence from human-cobot workstations. This creates an opportunity for a new type of DfD indicator: not only an estimate of whether a component can be disassembled, but also an evidence-based measure of how the human-cobot system actually operates and how it varies. Energy, failure, and intervention data can refine DfD scores and expose hidden design-induced effort.

4.3Closed-loop PLM, digital twins, and digital thread

Closed-loop PLM introduced the idea that information generated during use or service, or at the end of life, should be returned to design [32,33]. Digital twin research extends this logic by linking products, processes, and services through data-driven models [14,15]. At the same time, studies on IoT-enabled reverse supply chains and cyber-physical manufacturing demonstrate that end-of-life and reconfiguration data can be captured at scale [17,18,29]. These contributions are essential for the proposed taxonomy. Still, they rarely encode task-level human-cobot energy, intervention, or failure data as reusable DfX knowledge linked to computer-aided design (CAD), bill of materials (BOM), process planning, or PLM attributes. A human-cobot workstation can make closed-loop PLM more concrete. Each problematic operation can be traced to a product structure, a connector, a fixture, a route, a tool, or an operator decision. This traceability is a precondition for transforming a measurement into a design recommendation.

4.4 Human-cobot collaboration and robot energy modeling

Human-robot collaboration in disassembly has been studied to combine human flexibility and robotic repeatability [22,23], and broader HRC reviews emphasize safety, shared autonomy, perception, adaptability, and human-aware control [34]. Here, the goal is not to reduce the robot's power output (Wh), but to minimize the human cost: unfavorable postures, unnecessary range of motion, mental workload, fatigue, frustration, or decreased confidence. Vision-based monitoring studies show that online assessment of cognitive load and posture is possible using stereo cameras, head pose estimation, and skeleton tracking; others demonstrate that adapting robot trajectories or anticipating human joint overloading through whole-body ergonomic models [35,36] can simultaneously improve productivity and cognitive comfort. More recently, architectures integrating visual perception, dynamic ergonomics, and adaptive decision-making demonstrate real-time classification of ergonomic risk with sub-second latency, making

closed-loop control of robotic assistance a realistic possibility [36]. The section focuses on biosignals and multimodal physiology. Recent HRC datasets include EEG, ECG, EDA, respiration, EMG, voice, and facial cues; they show that psychophysiological state can be captured more comprehensively than posture alone, and that robot behavior can be adapted online to the estimated co-worker fatigue [37]. A particularly important point for future research is that some studies show a dissociation between observable performance and latent physiological cost: operators can maintain performance levels while increasing their physiological effort, for example, under thermal stress. For sustainable design, this changes the target variable: a system that is "efficient" in terms of throughput can remain unsustainable if it shifts the cost from the robot to the human. Also, the section connects HRC to safety, passivity, and energy control. Energy tank frameworks and energy-aware impedance controllers are particularly interesting because they place energy at the heart of interaction safety [38]. In collaborative disassembly, an energy-aware Cartesian impedance controller limits the power flow to the robot and improves behavior on unintended contacts. Along the same lines, an ISO/TS 15066-oriented energy-tank framework enables direct satisfaction of safety energy constraints, preventing excessively conservative assumptions; passivity-based variable-admittance strategies pursue the same objective of ensuring stable physical interaction while preserving transparency [38]. This work provides a strong semantic definition of the word "energy," but it remains largely disconnected from broader sustainability metrics. Parsa and Saadat [39] enrich their planning approach by integrating component prioritization with the PROMETHEE II method, AND/OR product modeling, task allocation, and a modified genetic algorithm that accounts for time criteria, non-targeted components, and operator changes. In parallel, robot energy modeling shows that energy can be estimated from robot instructions, joint variables, trajectories, and experimental measurements [24–27]. These studies prove that task-level energy signatures are technically measurable, but they do not yet close the loop toward upstream product-process redesign. The unresolved issue is therefore not measurement alone, but conversion. Robot energy models rarely feed product design decisions, while HRC studies rarely convert intervention, rerouting, or failure events into PLM knowledge. The proposed taxonomy addresses this missing conversion layer by explicitly linking measured task evidence to redesignable product-process variables. Table 1 summarises peer-reviewed journal articles and selected high-quality reviews used in the state-of-the-art. Preprints and non-audited sources were excluded from the corpus used for the table.

Table 1. Representative studies used to position the taxonomy

Reference	Main object of study	Feedback used	Closed loop	Key result for the taxonomy
Giret et al. (2015) [3]	Sustainable manufacturing scheduling	Energy and sustainability objectives	Planning level	Basis for energy-aware manufacturing scheduling.
Gahm et al. (2016). [5]	Energy-efficient scheduling review	Energy cost, peak power, operational energy	Planning level	Research framework for energy-aware production planning.
Masmoudi et al. (2019). [6]	Job-shop scheduling	Energy-aware job-shop objectives	Planning level	Integrates energy into scheduling objectives.
Delorme et al. (2023). [7]	RMS planning	Energy cost and uncertain demand	Line/system planning	Connects energy to reconfigurable manufacturing decisions.
Favi et al. (2019). [9]	DfD tool	Disassembly sequence, accessibility, recycling	Design level	Links product variables to disassembly performance.
Vanegas et al. (2018). [11]	Ease-of-disassembly assessment	Disassembly effort and circularity indicators	Design level	Robust DfD reference for circular design.
Formentini et al. (2025) [31]	Disassembly systems for circular product design	DfD parameters across five system levels	Lifecycle/system framework	Multi-level DSE structure linking disassembly information to circular design.
Liu et al. (2019). [22]	HRC in disassembly	Task allocation, human flexibility, and robot assistance	Workstation level	HRC as a strategy for sustainable disassembly.
Hjorth and Chrysostomou (2022). [23]	HRC review for non-destructive disassembly	Safety, allocation, and collaboration modes	Review level	Consolidates HRC challenges for disassembly.
Heredia et al. (2021). [24]	Instruction-level cobot energy estimation	Robot instruction, power, energy	Task/program level	Supports task-level cobot energy modeling.
Zhang and Yan (2021). [26]	Robot energy optimization	Operational robot energy data	Optimisation level	Supports AI-based robot energy optimization.
Jiang et al. (2023). [25]	Robot energy prediction with Long Short-Term Memory	Time-series energy prediction	Prediction level	AI layer for energy-aware operation.
Parsa and Saadat (2021) [39]	HRC disassembly planning	Remanufacturability, task time, operator change	Planning/optimisation level	PROMETHEE II method and a modified genetic algorithm for allocation and sequence planning.
Kiritsis (2011). [32]	Closed-loop PLM	Lifecycle information feedback	PLM level	Foundational loop from lifecycle data to design.

5 Human-Cobot Energy Feedback Taxonomy

The definition of "Human-Cobot Energy Feedback for Closed-Loop Sustainable Design" is as follows: any measured, estimated, or inferred signal related to the energy, effort, workload, or interaction state of the human-cobot pair and used to adapt, in a closed loop, the design, operation, or reconfiguration of a collaborative system to improve its environmental, ergonomic, safety, and

productivity performance. This definition is intentionally broader than that of "robot energy efficiency" because it combines electrical energy and human physiological workload within a single design framework. It draws on research on energy-efficient control, cognitive load, fatigue, posture, biosignals, and adaptive digital twins. The taxonomy classifies the literature along eight dimensions (Table 2, Figure 2). The feedback pipeline itself, in contrast, unfolds over five successive levels that any concrete instantiation of the taxonomy must implement (Figure 3). I. Capture the task phenomenon: the real execution episode in which a human and a cobot interact with a product, tool, fixture, and environment. II. Extract the energy signature: active energy, standby allocation, peak power, torque peak, motion duration, restart, and rerouting cost. III. Introduces human-AI interpretation: segmentation, anomaly detection, causal explanation, and operator validation. IV. Converts the evidence into product-process feedback. V. Governs the feedback through PLM, digital twins, or knowledge graphs. The central principle is that energy feedback is useful for design only when it is attached to a modifiable design variable. A high-energy unscrewing task is not yet a design insight. It becomes a design insight when the evidence can be linked to screw type, access angle, module packaging, fixture stability, torque requirement, surface degradation, or route choice. This link should be explicit, traceable, and reviewable by human experts.

Table 2. Dimensions of the taxonomy

Dimension	Main classes	Related research question
Energy feedback	electric/mechanical robot; human physiological energy, environmental feedback; hybrid feedback	What is actually being measured as “energy”?
HRI modality	physical, visual, auditory, haptic, AR/XR, multimodal	Through which channel is collaboration organized?
Energy metrics	Wh, power, current, energy tank; electroencephalography (EEG), heart rate variability (HRV), and electrodermal activity (EDA); Ovako Working Posture Analysis System (OWAS), Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), and Ergonomic Assessment Work-Sheet (EAWS); cycle time; CO2e	What costs and benefits are quantified?
Closed-loop control	monitoring, estimation, decision-making, adaptation, replanning	Does feedback actually change the system?
System architecture	edge sensors, programmable logic controller/Robot Operating System, AI and optimization, digital twin, ontology, knowledge graph	Where is feedback transformed into a decision?
Industrial application	assembly, co-transport, disassembly, inspection, maintenance	In which scenario is the taxonomy instantiated?
Time scale	real-time, workstation, batch, line, product lifecycle	How quickly does action occur, and at what scale is learning taking place?
Sustainability indicators	energy, safety, ergonomics, quality, circularity, resilience, carbon	What “sustainable” design is actually being pursued?



Figure 2. Eight-dimensional taxonomy for human-cobot energy feedback

Table 3 presents the first cross-classification based on an HRC ontology augmented by sustainability. Existing work on core ontologies for robotics and automation, initiated by the IEEE ORA standardization effort [40], already describes humans, robots, tasks, critical situations, and safeguards. This framework can be extended into five class families: Agent, Task, Signal, Adaptation,

and Outcome. Energy and physiological signals then become first-order entities, interoperable with a PLM, a digital twin, or a knowledge graph.

Table 3. Ontological cross-classification for PLM, digital twin, and knowledge graph integration

Ontological class	Recommended subclasses	Example instance
Agent	Human, cobot, supervisor, sensor, digital twin	operator_A, UR10e_1
Task	Assembly, screwing, transport, disassembly	unscrewing_EOL_module
Signal	Power, current, EMG, HRV, EDA, posture, ergonomic risk	HRV_worker_A
Adaptation	Speed, trajectory, role allocation, feedback modality, safe mode	reduce_speed_if_HRV_drop
Outcome	Energy, quality, safety, time, fatigue, circularity, CO2e	CO2e_per_task, EAWS_score

Such an ontology has two decisive advantages. First, it enables explainable reasoning about the sustainability-ergonomics-performance trade-off; second, it facilitates alignment with digital twin architectures and industrial knowledge. This is probably the most credible way to transform this taxonomy into a lasting, original contribution rather than a simple descriptive classification. The second cross-classification relies on a multi-criteria analysis inspired by the PHRI frameworks (Table 4), where several conflicting objectives must be balanced. The literature already shows that Pareto-type or multi-criteria optimization approaches are relevant for balancing stability, transparency, safety, and performance in physical interaction. Here, the same logic must be extended to environmental and circular dimensions.

Table 4. Criteria to select depending on metrics

Criteria	Candidate Metrics	Direction of Optimization
Robot energy	Wh/task, average power, peaks, dissipation	minimize
Human workload	EMG, HRV, EDA, ergonomic score, subjective fatigue	minimize
Productivity	Cycle time, unproductive time, throughput	maximize or minimize according to the metric
Quality	Defects, repeats, precision	maximize
Safety	Collisions, ISO constraints, near misses, protection distance	maximize safety / minimize risk
Extended sustainability	CO2e, reparability, disassembly, material recovery rate	maximize

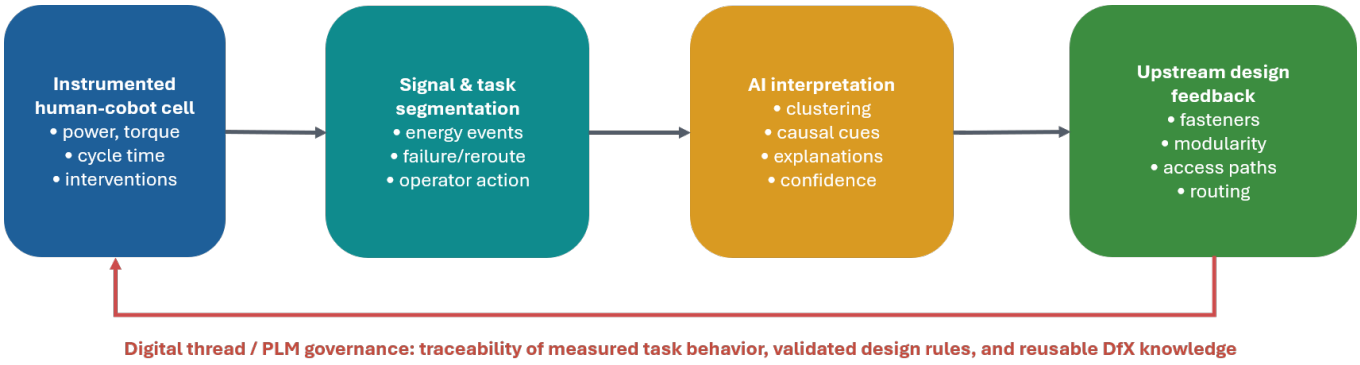


Figure 3. A closed-loop conceptual framework that converts observed human-cobot interactions into feedback to inform upstream design

The methodological advantage is that future work can compare HRC architectures (Figure 3) not only in terms of robotic performance but also in terms of sustainable Pareto surface area. A collaborative cell is better not because it consumes the least possible electricity, but because it simultaneously improves energy efficiency, operator health and safety, and circular value.

6 Discussion: scientific locks and research opportunities

The taxonomy reveals four scientific locks. The first is data granularity. Energy measured at the cell level is too coarse to support redesign; the signal must be segmented into task episodes and attributed to product/process variables. The second is causality. A high-energy event may be caused by product design, product condition, operator strategy, tool wear, robot program, or fixture quality. Closed-loop design requires methods that can separate these causes with human validation. The third is semantic interoperability. Feedback should be linked to CAD/BOM, process plans, and PLM objects rather than stored as detached time series. The fourth is human-centered explainability. Operators and designers must be able to challenge and validate AI recommendations before they become design rules. The next step involves an instrumented study of a disassembly robotic cell using a cobot and a human. This study links power, torque, cycle time, interventions, failures, and human workload indicators to product and process variables from a closed-loop design perspective.

Table 5. Research agenda derived from the taxonomy

Research question	Required method	Expected contribution
How to segment human-cobot task energy?	Power/torque/time-series segmentation with operator-labeled events	Validated dataset and task-energy signatures.
How to distinguish design-induced from condition-induced energy?	Causal modeling, ablation tests, and repeated product variants	Explainable feedback rules.

How to update DfD indicators with measured energy?	Multi-criteria indicator combining energy, intervention, failure, and recovery value	Energy-enhanced DfD score.
How to store feedback in PLM?	Mapping to CAD/BOM/process objects and knowledge graph rules	Traceable closed-loop DfX knowledge.
How to validate sustainability gains?	Before/after redesign, LCA sensitivity, and scheduling simulation	Evidence of energy and circularity improvement.

7 Conclusion

This paper introduced human-cobot energy feedback as a missing link between sustainable operations and upstream product-process design. The proposed taxonomy connects task phenomena, energy signatures, human-AI interpretation, design feedback, and PLM governance. Its originality lies in treating measured workstation behavior not as an end-of-line monitoring signal but as design evidence that can inform fasteners, modularity, access, fixtures, routing, and task allocation. The next step is empirical. The taxonomy should be tested on an instrumented assembly/disassembly cell, with controlled product variants and human-cobot task logs. Such validation would enable quantification of whether feedback-informed redesign improves energy efficiency, circularity, and robustness while preserving human expertise in the loop. Different research perspectives emerge from the state of the art. For instance, production lines are subjected to different constraints (e.g., energy and human constraints). Therefore, various optimization methodologies (e.g., decision-aiding methods and metaheuristics) could be proposed to address the human-robot collaboration problem. The taxonomy is not designed as a validated optimization approach. It defines the variables and feedback loops for the next empirical phase in the product-process design: the construction of a model based on metaheuristic algorithms, coupled with machine learning/deep learning approaches, to filter data from the robotic cell and operator information during disassembly. This model will also verify that the design's production context is compliant with the proposed taxonomic structure, represented as knowledge graphs, to optimize the delivery of relevant information to the designer and assist them in their multi-criteria decision-making. This model will aim to maximize production efficiency and circular value within a given framework, and minimize robot energy consumption and human workload. The method will be based on the work of Parsa and Saadat [39] and will then be analyzed from the perspective of the Disassembly Systems Engineering of Formentini et al. [31].

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