

A multidimensional taxonomy for human-robot interaction in construction

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ABSTRACT

Despite the increased interest in construction robotics both in academia and the industry, insufficient attention has been given to aspects related to Human-Robot Interaction (HRI). Characterizing HRI for construction tasks can help researchers organize knowledge in a structured manner that allows for classifying construction robotics applications and comparing and benchmarking different studies. This paper builds upon existing taxonomies and empirical studies in HRI in various industries (e.g., construction, manufacturing, and military, among others) to propose a multidimensional taxonomy to characterize HRI applications in the construction industry. The taxonomy design followed a systematic literature review in which common themes were identified and grouped into 16 categories. The proposed taxonomy can be used as a foundation for systematic reviews and meta-analyses of HRI applications in construction and can benefit the construction industry by informing the design of collaborative tasks performed by human-robot teams.

1. Introduction

Especially in the last two decades, robots have become more common in supporting on-site and off-site construction tasks. Many studies focus on the development of construction robotics applications, focusing primarily on the technical aspects of the development of robots or the impacts of their applications on productivity, quality, and safety (e.g., [1–3]). However, these studies put less emphasis on the interactions between humans and robots during task execution. Understanding and properly designing robots and tasks in construction with an emphasis on Human-Robot Interaction (HRI) is important because it can promote a safer, healthier, and more productive task environment. Furthermore, deploying collaborative robotics on work sites has the potential to take advantage of the strengths of humans (e.g., creativity, decision-making capabilities, flexibility, adaptability) and robots (e.g., precision, power, tirelessness) to reduce or eliminate specific health and safety risks associated with a task while potentially increasing the productivity and quality of work [4,5].

However, the experience from more automated industries such as manufacturing and aerospace shows that proper consideration must be given to the various aspects of the interaction, especially when

collaborative robotics is implemented. For example, human factors such as trust in automation, situation awareness, and mental workload were shown to have major implications during the implementation of intelligent systems on the performances of the humans involved in the tasks [6,7]. The same is true about task design since the implementation of technology changes the way a task is performed [8]. Given its unstructured and dynamic nature, at least for the near future, the construction industry is likely to rely more heavily on collaborative teams of humans and robots rather than on full automation, and, for that, properly designing robots and tasks to support HRI is key. For example, existing research on robotic applications in earth-moving and mining operations shows that before fully autonomous machines can be deployed on-site, incremental improvements must be made to the machines and their control mechanisms [9]. In these applications, the commonly used operation methods are manual operation, remote operation, teleoperation, assisted teleoperation, and fully autonomous operation, all of which require some level of human intervention [9].

Significant variability is found in the development and deployment of robotic systems in construction, both in terms of the used terminology and system design approaches, which hinders the standardization and comparison of HRI studies in construction. Therefore, a unifying

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taxonomy for the construction industry is important for several reasons. First, standard terminology may support improved communications between designers and developers [10]. Second, the lack of a knowledge structure capable of classifying existing studies may complicate the comparability and generalizability of research results. A taxonomy may support the design of human-robot systems by helping researchers and engineers to identify key factors that influence the behavior of these systems [11]. The proposition of taxonomies in the field of HRI is not new, and, to date, many examples exist in the literature [12–15]; however, currently, there is no unifying multidimensional taxonomy readily available for HRI applications in the construction industry.

Many recent studies have reviewed and categorized specific aspects of HRI applications in the construction industry. Examples exist in the classification of the levels of human-robot collaboration [16] and the types of robot-environment interaction [17], reviews of robotic applications in construction [18,19], and robot learning modalities [20], among others. However, although these studies make important contributions to the body of knowledge of construction robotics, they tend to categorize each application according to only the selected feature reviewed in the study. Alternatively, many multidimensional HRI taxonomies are available in applications from other industries [12–15]; however, their direct applicability in construction contexts may be limited due to the lack of specific task and environmental characterizations of construction. By revisiting these classifications and organizing this knowledge into a multidimensional taxonomy that also draws from results in other industries, it is possible to categorize a given application using a variety of factors and identify relationships among them. It can also support understanding how certain classes of applications address specific issues in construction. For example, one can look at which safety mechanisms are usually deployed for robots with a given level of autonomy for a specific task type or which traits are needed for a particular team composition in a given environment.

This paper proposes a comprehensive multidimensional HRI taxonomy focusing on construction tasks. The proposed taxonomy, structured around three dimensions (i.e., team, task, and environment), is based on a systematic literature review of HRI applications in various industries (e.g., construction, manufacturing, military, aerospace, among others) and includes both taxonomic categories from existing taxonomies and proposed new categories from the results of the literature review. The proposed taxonomy aims to (1) identify the main factors that affect the interactions between humans and robots in the completion of a physical task in a team context, (2) identify how other fields conceptualize and enact HRI and which characteristics of HRI can be adapted to the construction industry to improve current practices, and (3) develop a taxonomy that can assist researchers in considering relevant factors related to the individual and shared characteristics of humans and robots, tasks, and environments, for the design and operation of construction robotics. The proposed taxonomy also aims to serve as a foundation for reviews and meta-analyses focusing on HRI in construction applications and may allow the comparison of different studies in the field and the identification of current research gaps and trends.

2. Literature review - existing taxonomies in HRI

Existing taxonomies in HRI cover a broad range of topics in various fields. In some cases, the taxonomy discusses HRI on a higher level that considers a wide range of categories and factors (multidimensional taxonomies) that characterize the agents, the task, and the environment and that may be applied in diverse fields [12–14]. Commonly, these multidimensional taxonomies use the results of one-dimensional taxonomies that focus on specific aspects of the interaction, including technological factors [21], psychosocial factors [22], safety [23], task allocation [24], and training [25], among others.

2.1. One-dimensional taxonomies and factors influencing their designs

2.1.1. Technical factors

Various studies have proposed architectures, algorithms, user interfaces (UI), control mechanisms, sensors, and end-effectors that expand the current capabilities of existing robots and, therefore, have the potential to support the development of new robots. Relative to the design of UI, existing studies have proposed taxonomies focusing on usability guidelines for teleoperated systems [26]. Other applications have focused on developing kinematics, robot mobility, and end-effectors. For example, taxonomies exist on the use of individual robot motion to shape the collective behavior (motion and path planning) of groups of robots [27]. Researchers often study how humans perform specific tasks to propose taxonomies upon which robot motion can be based. Robot grasping is a field that has benefitted a lot from this approach, and several taxonomies have been proposed using human grasping as a starting point (e.g., [28]). Other examples include whole-body pose taxonomies for humanoid robots in which human body pose is used as a reference to enhance humanoid stability (e.g., [29]). Next, the main functions of collaborative robots used to ensure human physical and psychological safety in HRI have also been organized in a taxonomy [23]. Finally, regarding robot social traits and communication skills, which make the interaction more natural for the human interacting with the robot, existing taxonomies have considered the robot's social awareness through the robot's social sensitivity, social insight, and communication [30].

2.1.2. Human factors

The automation research community tends to criticize technology-centered taxonomies due to their diminished consideration of the human factors involved in the interaction because a more human-centered design can better inform the system's overall design [31]. Taking human factors into consideration allows the design of intelligent systems that effectively execute their assigned tasks without creating health and safety risks to the humans directly involved in the task or to the humans who may be near the robots. Existing reviews show a variety of human factors that are commonly studied in human-robot collaboration applications, which involve both physical (e.g., fatigue, ergonomics, and workload) and psychosocial factors (e.g., trust, cognitive workload, risk cognition, perceived safety, and emotions) [32]. Many studies have assessed the effects of the levels of robot automation on human performance, situation awareness, and mental workload [7], and the influence of individual, team, system, task, and environmental factors on human situation awareness, decision-making, and action [33]. Well-being and performance have been characterized based on the evaluation metrics used to assess human factors, including trust, anxiety, workload, and ergonomics [34]. Finally, trust in the robots has also been studied, with existing taxonomies focusing on trust failures and mitigation strategies to repair trust in HRI applications [22].

2.1.3. Team factors

Many studies have focused on the aspects that directly influence team dynamics in HRI, including team composition, communication strategies, safety, control sharing, and collaboration levels during task execution (e.g., [35,36]). Team composition has been studied from various perspectives that consider a wide range of possible human-robot team configurations (e.g., [12–14]). Team composition and the levels of collaboration among humans and robots have also been used to specify the safety layers required in collaborative tasks involving teams of humans and robots [15]. Finally, control-sharing mechanisms and the levels of robot autonomy have been commonly used as a basis for taxonomy development. For example, in the construction industry, the characterization of human-robot collaborative teams has been approached through the consideration of the level of robot autonomy and human effort [16] and, in the automotive industry, the roles of users (humans) and the driving automated system have been used to describe

the levels of driving automation [37].

2.1.4. Task factors

On many occasions, aspects related to the task are used in the designs of taxonomies and human-robot systems. Most commonly, these taxonomies characterize different task types and, in some cases, define degrees of task criticality (e.g., [12–14]). In some cases, task types and their requirements, difficulty, and speed have been used in taxonomies related to robot-assisted training [25]. Other taxonomies have focused on subtask allocation in multi-robot teams [24]. Finally, task classifications (i.e., divisible vs. interactive, agonistic vs. antagonistic) have been used to characterize interactive behaviors in human-robot teams, which include cooperation, collaboration, and competition [38].

2.1.5. Environmental factors

Finally, some studies focused on the interactions of the agents, humans or robots, with the environment where the tasks occur. The environmental difficulty, mission complexity, and human interface have been used in the military domain to characterize the autonomy levels of unmanned systems [39]. This study recognizes the challenges associated with the characterization of environmental difficulty, which is a result of the influence of other factors in the models, and the interdependencies among them, as is the case with the dynamics of the environment, weather, mobility, navigation, and operational factors [39]. Attempts to characterize the interaction between robots and the environment also exist, which accounts for different robot-environment configurations that include single or multiple robots (working as a team or independently) and single or multiple environments [17].

2.2. The development of multidimensional HRI taxonomies

The first attempt to organize the state of the art in the fields of Human-Computer Interaction (HCI), Human-Machine Interaction (HMI), and Human-Robot Interaction (HRI) into a multidimensional taxonomy dates to 2000 and aimed to classify existing studies in these fields based on application, research approach, system autonomy, interaction distance, and interaction media [40]. Although this first taxonomy listed a series of applications in various fields, it was intended to be a research taxonomy. Therefore, its application to inform the design of HRI systems was limited. Next, a more comprehensive taxonomy based on the current state of research (meta-survey) in the field of HRI was proposed [35] and extended two years later to reflect the changes that occurred during this timeframe [12]. These taxonomies [12,35] focused heavily on the level of interaction among teams, as well as some aspects of the task and its social nature, the team, and the robot.

Although this updated taxonomy [12] is comprehensive in that it considers a relatively broad range of factors involved in various types of interactions between humans and robots, some limitations to its applicability exist. Among the main criticisms of this taxonomy is the fact that it lacks a structure showing the relationships among the categories because some of the categories refer to context-level variables (e.g., task type) while others refer to local dynamics (e.g., interaction types), which is important given that context level variables affect many of the local dynamics [14]. To model these relationships, a taxonomy with three levels of depth: context model, local dynamics model, and effects, was proposed [14]. These levels were used to describe the three components of HRI: *task*, *team*, and *environment*, and included the contributions of various existing taxonomies in the field, along with proposed new categories. As presented by the authors, limitations of this taxonomy include the fact that some categories are not completely developed due to the paper's length and scope restrictions, and a more extensive characterization is needed [14].

Similarly, another recent taxonomy is structured in a hierarchical (top-down) approach that starts at a macroscopic level, defined as the interaction context, goes through the robot's characterization, and ends at the microscopic level defined by the team classification [13].

Although straightforward and simple to use, this taxonomy is too general to appropriately characterize collaborative construction tasks in a construction site. The reason is that it includes various fields of applications, and, for robot task specifications and morphology, it considers categories that are rare or unlikely to be found on construction sites. For example, cognitive and emotional stimulation are listed under robot task specification, and it puts too much emphasis on robot morphology.

2.3. Gap analysis

Although we presented several taxonomies that consider HRI more generally or by focusing on specific aspects of the interaction, except for the works of [16,17], none of the listed taxonomies consider the specificities of construction sites and, for that, a direct application of these existing taxonomies in HRI studies in construction may be limited. As presented, construction sites are dynamic and unconstrained environments, with multiple crews simultaneously working around a fixed product, which still poses several challenges to deploying robots and automation on-site. Each of the two existing taxonomies proposed for the construction industry focuses on a single aspect of the interaction, namely the level of robot autonomy and human effort in Liang et al. [16] and the robot-environment interaction in Tan et al. [17]. As a result, although these taxonomies can characterize well the aspects of the interaction they reviewed, they cannot be used to characterize other aspects of the interaction that are not included in their designs. For example, it is not possible to completely characterize aspects related to team composition and safety mechanisms if these taxonomies are used alone.

Directly applying existing multidimensional taxonomies from other industries (e.g., [12–15]) may also be insufficient due to the lack of a complete characterization of tasks and environments in the construction context in these taxonomies. For example, Yanco and Drury [12] included task type in their proposed taxonomy but did not include any specific category related to the environment. For task type, although the authors provided some examples of what a task type could be, they did not include a list of task type options, which was left to the user of the taxonomy depending on the specific application. The authors mentioned, however, that the description of the task type must be done to characterize the system's design and use, which may also allow an implicit representation of the robot's environment [12]. The taxonomy in Onnasch and Roesler [13], on the other hand, included some task types that exist in construction applications (i.e., transportation, manipulation, precision, and physical load reduction) but also included physical, emotional, and cognitive stimulation, which may not be useful in construction contexts. The taxonomy also included a categorization of the setting in which the interaction takes place, but it only included two options, namely field and laboratory. Although these two classes provide some generic categorization, it oversees some other potential settings where construction may take place, including, for example, on-site, offsite, and outer space settings. Finally, Parashar et al. [14] listed "construction" as a task type, but it is too generic to describe any specific application in construction. For the characterization of the environment, the authors did not include a classification of the task setting but rather only described the spatial distribution of the team (i.e., proximal, remote, or hybrid).

By revisiting existing taxonomies and reviewing key developments in the field of HRI in various industries, this study proposes a new HRI taxonomy specific to construction applications. This taxonomy is expected to provide a common terminology that can be used to classify HRI applications, allow for a more direct comparison of different HRI studies, and inform the design of human-robot systems with a focus on construction applications.

3. Methods

This section describes the methods used for paper retrieval, selection,

and classification during the development of the taxonomy proposed in this paper.

3.1. Database choice

The research approach used in this paper is qualitative, and the paper's structure follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist [41]. Two search engines were used, Web of Science™ and SCOPUS, and the selection of the included papers followed a predefined inclusion criteria flowchart. These two search engines were selected because they index millions of journal and conference papers from major publishers in the fields of interest in this study, including Elsevier, Springer, IEEE, Taylor & Francis, ACM, and Sage.

3.2. Paper retrieval process

A group of 12 combinations of keywords, frequently used in the field of HRI, was used in the retrieval processes. Other than “human-robot”, the keywords “teams”, “multiple”, “interaction”, “collaboration”, “coordination”, “cooperation”, “communication”, and “interface” were combined and used. The selection of the keywords was based on the findings of an initial search on papers in the HRI field, where it was identified that common relationships between humans and robots were described as “interaction”, “collaboration”, “coordination”, “cooperation”, “communication”, and “interfaces”. To include studies that considered the relationships between humans and robots in a team or multi-agent context, which is likely to be found in construction applications, the research team narrowed down the search criteria by including the keywords “team” and “multi”. The search was based on the combined keywords in the titles, abstracts, and keywords of the studies indexed in the databases. Table 1 lists the combinations of keywords used in the search engines.

The search criteria did not include any restriction on a specific industry or a time frame; therefore, the retrieved papers ranged from 1985 to 2022 and were from different industries (e.g., construction, manufacturing, healthcare, military, aerospace, transportation, entertainment, and education). Only the papers in English were included. The results from both search engines were merged, and duplicates were removed both automatically and manually. Initially, 7794 papers were retrieved from the two search engines, out of which 2471 were duplicates, resulting in a final set of 5323 papers.

3.3. Inclusion criteria and paper selection

The study's inclusion and exclusion criteria were developed and refined based on the proposed taxonomy aims and the PRISMA guidelines. The inclusion criteria considered whether the papers: (a)

presented an empirical study, (b) described a physical task, and (c) involved the interaction between human(s) and embodied robot(s) and excluded papers that did not follow these criteria and proposed studies with no validation. These criteria were important because the construction industry is task-oriented, and the transition phase from the current mostly non-automated to the future fully automated construction operations is likely to be characterized by high levels of collaboration between humans and robots [9,42,43]. Based on the criteria, out of the 5323 papers from the initial search, 4209 papers were excluded solely based on the information presented in their titles and abstracts, which resulted in 1114 papers to be included for further review and identification of common themes in HRI in various industries. For this set of papers (1114), the raters read the abstracts, methods, and discussion sections of each paper, as well as analyzed figures and graphs, to evaluate whether enough information about the team, the task, and the environment could be extracted to allow for subsequent characterization of the paper using the proposed taxonomy. For example, we excluded papers in which the scope was to test or validate a new control algorithm or end-effector, and only limited information about the team or the task could be extracted. We also excluded studies that may have oversimplified the robot or the task to study a specific human factor (e.g., trust in the robot) in a way that only limited information could be extracted about the robot or the task. For each paper, two raters voted to either include or exclude it. If both raters agreed on including or excluding the paper, that decision was final; when one rater voted to include the paper and the other to exclude it, both raters would present the reasons for their decisions and make a final decision about including or excluding the paper. By using this process, we narrowed down the set of papers to 326 papers for full review and validation of the proposed taxonomy through interrater agreement.

3.4. Taxonomy development

3.4.1. Information gathering

While reviewing the set of 1114 papers, the five raters involved in the process (three Ph.D. students in civil engineering, one postdoctoral researcher in education, and one undergraduate student in civil engineering) listed some of the key terms that were included in the reviewed papers in existing HRI applications in various domains. For each of these terms, the raters also included an accepted definition encountered in the literature (for example, “*Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*” (p. 792) [44]). These definitions were used to characterize the identified terms' scopes, create a shared understanding among the raters, and reduce duplicity when multiple terms were used to define the same concept. Also, these definitions were used to group the key terms by considering the similarities of their contents.

3.4.2. Taxonomy design

The taxonomy design followed both a bottom-up and a top-down approach. In the bottom-up approach, the list of key terms identified by the raters was grouped around major themes in HRI based on their definitions and the relationships the key terms had with each other. The taxonomy design also followed a faceted approach, in which more flexibility is given to include new factors and future adaptations of the taxonomy [45]. In a broader sense, hierarchical relationships were identified to reduce the number of categories in the initial versions of the taxonomy.

The raters identified the categories, factors, and levels included in the proposed taxonomy based on the selected key terms and the reviewed papers' contents. For the taxonomy presented in this study, a *category* is defined as a set of related factors or levels that characterize one dimension of the human-robot interaction (e.g., human traits, level of robot autonomy); a *factor* is an element of a category that may, or may not, be exclusive (e.g., the human traits category includes the non-

Table 1
Combination of keywords used in the searches.

Combination of keywords
human-robot* AND team* AND interact*
human-robot* AND team* AND collab*
human-robot* AND team* AND coordinat*
human-robot* AND team* AND cooperat*
human-robot* AND team* AND communicat*
human-robot* AND team* AND interface
multi* AND human-robot* AND interact*
multi* AND human-robot* AND collab*
multi* AND human-robot* AND coordinat*
multi* AND human-robot* AND cooperat*
multi* AND human-robot* AND communicat*
multi* AND human-robot* AND interface

Note: The wildcard character (*) is used to replace characters in the search terms in the search engines; e.g., robot* will retrieve results that include the terms robots, robotics, among others.

exclusive elements *mental workload*, *situation awareness*, *ergonomics*, and *trust in automation*, and the setting category includes the exclusive factors *on-site*, *off-site*, *outer space*, *laboratory*, and *simulation*); and a *level* is a value in a continuum of possible states within a category (e.g., in the level of robot autonomy category, the autonomy of a robot ranges from *teleoperated* to *fully autonomous*). In addition, these categories were grouped according to the three components of an interaction: *team*, *task*, and *environment*, as in the model proposed by Parashar et al. [14]. Team, task, and environment are commonly defined as the three components of the interaction in human-robot interaction [8], and in Parashar et al. [14], this definition is represented explicitly in the taxonomy structure.

In the top-down approach, existing HRI, HCI, and HMI taxonomies were reviewed and compared to the initial draft of the proposed taxonomy to refine it. In this process, some categories were adapted to reflect well-accepted classifications identified in the literature review. Such adaptations included changing the names of certain categories, adding new categories, adding or deleting factors under certain categories, and reorganizing categories and factors to better reflect the state of the art in existing HRI taxonomies.

3.4.3. Taxonomy testing and validation

Nine rounds of the interrater agreement were completed to produce the final version of the taxonomy proposed in this paper. In each round, randomly selected sets of 10 to 50 papers from the 326 papers included in the review were coded individually by each of the five raters and the kappa coefficient of agreement (K), more specifically, the Randolph's free-marginal multi-rater kappa [46], was used to compute the interrater agreement. The Randolph's free-marginal multi-rater kappa was selected because it does not require the raters to assign a predetermined number of cases to each category. In the proposed taxonomy, some categories included non-exclusive factors, and some reviewed papers did not provide enough information about all the categories included in the proposed taxonomy. Thus, not defining how many factors needed to be selected from each category in the proposed taxonomy was necessary. As five raters were involved in this process, there was a need to ensure that their agreement on the classification of the papers was consistent. This was meant to ensure that the meaning of each of the categories, factors, and levels was clear to all the raters and to identify potential problems with any of the proposed categories, factors, and levels, which resulted in modifications to the taxonomy between rounds of interrater agreement. After nine rounds of interrater agreement, the K values for all the included categories were considered appropriate (see Section 5.1), and the interrater agreement iterations stopped. Next, to validate the final version of the proposed taxonomy, 97 construction papers were randomly selected and classified using the proposed taxonomy. These papers represented a variety of construction robotics applications that were used to illustrate each of the factors and levels included in the proposed taxonomy.

3.4.4. Taxonomy usage and comparison to existing taxonomies

Finally, the raters coded and compared two recently published HRI studies in the construction domain to illustrate (1) the shortcomings of current taxonomies in completely characterizing HRI applications in the construction industry; (2) how the proposed taxonomy could be used in practice; and (3) the strengths of using the proposed taxonomy, such as identifying essential aspects of robot deployment in the construction industry. The selected studies [47,48] represented recent applications of HRI in the construction industry and were selected to illustrate all categories included in the proposed taxonomy, as well as variations in the classifications within these categories. Four existing taxonomies were also selected to characterize one of the selected studies [47]; two of the existing taxonomies focused on construction applications [16,17], and the other two were recent multidimensional HRI taxonomies [13,14]. The selection of the two taxonomies in construction was because, to the best of the authors' knowledge, these were the only two taxonomies purposefully developed for HRI applications in construction, and the

two general taxonomies selected represented the efforts of recent studies in the field of HRI and resulted from an in-depth review of existing taxonomies.

4. A taxonomy for human-robot interactions in construction

Following the process explained in the Methods section, the authors developed the proposed taxonomy for human-robot interaction in construction applications. The taxonomy is structured around three dimensions: *Team*, *Task*, and *Environment*, which are representative of interactions between humans and robots [14]. Each of these dimensions is further subdivided into the categories that compose them, and, for the case of the Team dimension, there are three major groups for the identified categories: Human, Robot, and Shared Characteristics among them, which characterizes the agents of the interaction at the individual and group levels. The selected dimensions represent the components included in the definition of physical human-robot interaction, in which human(s), robot(s), and the environment(s) interact to create a dynamic system that can accomplish a task [49]. A more detailed description of each category and its factors or levels is presented in the following sections. Fig. 1 presents the proposed taxonomy's structure and examples of construction applications for each of its factors and levels.

4.1. Team

In the context of HRI, a team can be defined as humans and robots collaborating to complete a common task [50]. The team dimension aims to identify individual and shared characteristics among agents (robots) and experts (humans) during HRI. Individual characteristics include human traits and robot traits, and shared characteristics include team traits that cannot be analyzed at the individual level.

Human

4.1.1. Human traits

HRI research largely considers four human traits: mental workload, situation awareness, trust in automation, and ergonomics. *Mental workload* can be described as an individual's amount of cognitive work required to complete a task [51]. It can be perceived as the operator's performance or physiological activity to fulfill the environmental demand [52]. *Situation awareness* (SA) is defined as a person's ability to perceive, comprehend, and project the conditions of the elements in the environment in a given time and space [44]. *Trust in automation* can be defined as the belief that an agent will assist a human in accomplishing his/her goals in an uncertain situation [53]. This factor includes several variations, including rapport building, i.e., behaviors and social cues that help develop harmonious team relationships and establish trust and confidence [54]. Finally, (physical) *ergonomics* focuses on the design of the tasks and the robots to minimize the negative effects of inappropriate postures and loads during task execution on the workers' safety and health.

In construction applications, *mental workload* has been used to assess cognitive task demand in situations characterized by adverse conditions [55] and to adjust the robot's behavior dynamically to reduce the cognitive demand of the humans involved in the task [47]. *Situation awareness* has been commonly studied to improve operators' safety and task performance levels, especially by deploying new technologies that increase operators' situation awareness levels [56–58]. Given that working alongside a robot may be a new experience for most construction workers, *trust in automation* has also been the object of interest in many studies in construction. It has been studied from the perspective of being influenced by the worker's perceived safety when working with a robot [59] and from the perspective that sensors can provide real-time measurements of the levels of trust of the human in the robot [60]. *Ergonomics* has been approached from the design and planning of human-robot collaborative tasks that minimize the physical load that the human is exposed to [61] and from the design of collaborative robots that adapt

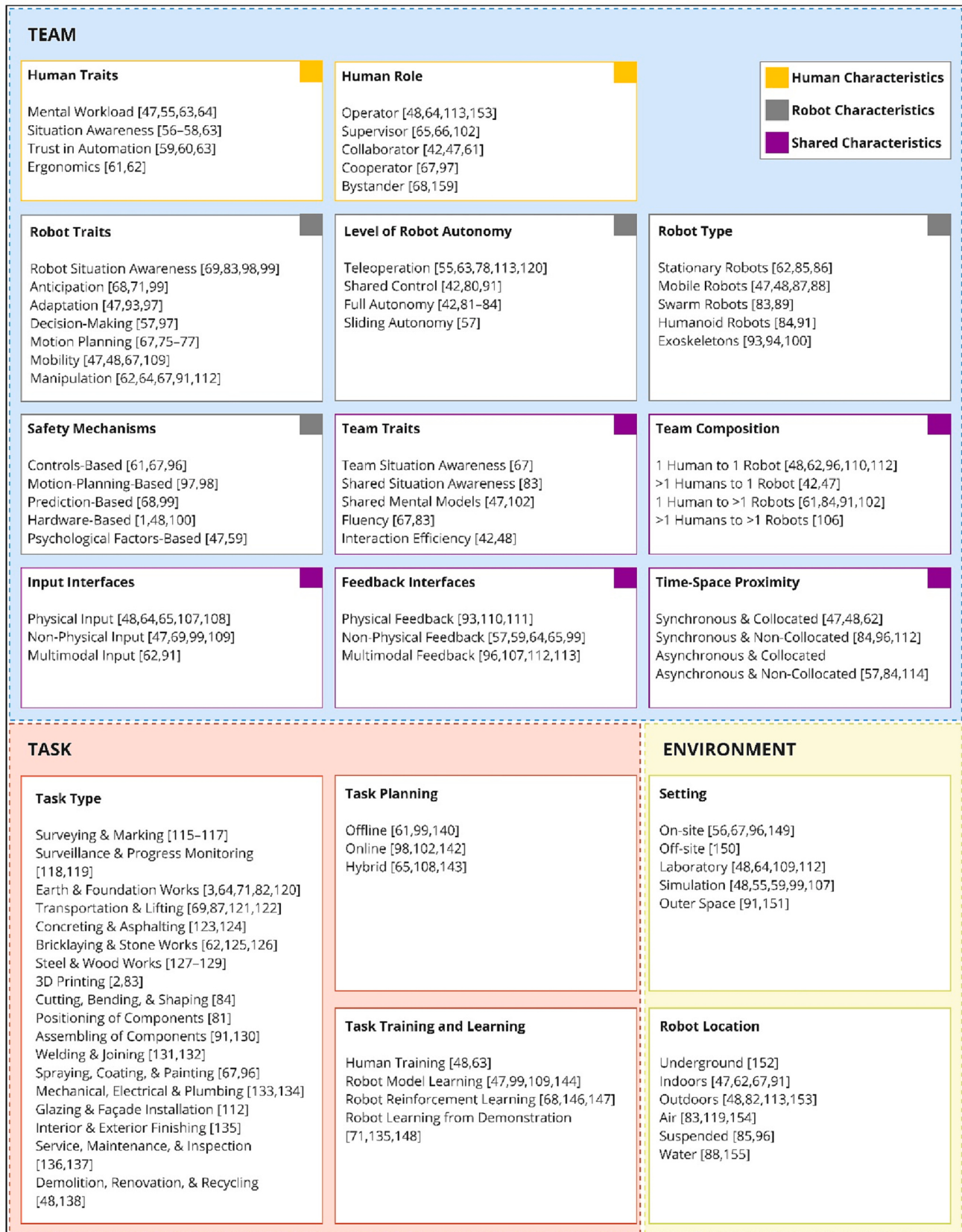


Fig. 1. Proposed taxonomy for Human-Robot Interaction in construction.

their behaviors to minimize the effects of worker's fatigue during task execution [62]. Finally, mental workload, situation awareness, trust in automation, and self-efficacy have been studied during training sessions for construction workers interacting with robots [63]. It is important to mention that the purpose of this category is not to include all possible human factors but rather to include the main factors of interest in HRI studies identified during the review process.

4.1.2. Human role

This category describes the roles that humans assume in different contexts. Five possible human roles based on the definitions presented by Onnasch and Roesler [13] were considered, i.e., *operator*, *supervisor*, *collaborator*, *cooperator*, and *bystander*. In the *operator* role, the human directly controls what the robot does during the task (e.g., [48,64]). In the *supervisor* role, the human monitors and instructs the robot but does not directly control every action of the robot (e.g., [65,66]). Putting the robot and human on the same hierarchical level, a human *collaborator* works alongside the robot to complete a task in a way that the actions of one team member depend on the other team member's actions (e.g., [47]). Alternatively, a human *cooperator* also works alongside the robot to complete a task, but the actions of the human and the robot do not depend on each other as they work on independent aspects of the task (e.g., [67]). Finally, the human *bystander* role does not involve direct interaction between the human and the robot to complete a task, but because they share the same space, the human needs to consider the robot's actions to avoid collisions (e.g., [68]).

Robot

4.1.3. Robot traits

Designing the robot with the appropriate capabilities required by the application is key to promoting a more fluid interaction and achieving task goals. In tasks characterized by higher levels of collaboration, for example, the abilities to perceive and comprehend the environment, communicate intentions, make decisions, plan, and learn can promote joint actions [50]. The purpose of this category is not to include all possible capabilities a robot can have but rather to include the main traits that can be used to promote a smoother interaction between humans and robots. The traits considered here are the ones that somehow mimic human-like cognitive and physical abilities and, thus, may resemble a more natural interaction that is likely to take place in tasks developed by teams of humans only. Five cognitive abilities and two physical abilities as robot traits were included in the proposed taxonomy.

To perceive the environment, the robot may use different sensors that can detect the locations of humans and objects, temperature changes, harmful substances, and vibrations, among other things. Thus, *robot situation awareness* (e.g., [69]) is included as the ability of the robot to perceive, understand, and predict the status of elements in the environment in the future [70]. Other factors related to cognition include the ability to anticipate human intentions, which is accomplished through understanding explicit and implicit cues as it occurs in human-human interactions. *Anticipation* (e.g., [71]), defined as the ability to understand non-verbal visual cues to anticipate human action, can promote a more natural interaction between humans and robots by enabling the robot to anticipate human intention and behave in a way that humans can predict its intentions [72]. *Adaptation* (e.g., [47]), i.e., the ability of a robot to adjust its behavior in response to changes in the task state, human physiological state, or human non-verbal cues, is required to work efficiently as a team. Adaptation is an important trait in collaborative robotics applications because it can adjust the robot's behavior to reduce human physical and psychological discomforts during task execution.

Next, *decision-making* (e.g., [57]) is the robot's ability to use information from its internal memory and the current states of the environment as detected by its sensors to change its representation of the world and make decisions [73]. The ability to make decisions can enable the

robot to plan its motions (i.e., *motion planning*, also known as path planning), which is defined as the ability to generate a path between two robots' configurations while avoiding collisions with objects in the environment [74]. In construction, existing applications involve finding paths between two distinct locations in the environment (e.g., [75]) and determining the motion sequences of the robot's end-effectors (e.g., [76,77]). Finally, *mobility* and *manipulation* are two key physical robot traits for construction applications. In on-site construction applications, the robot will likely need to move to perform its tasks around the building and need manipulators to handle materials and tools. *Mobility* (e.g., [47,48]) refers to the ability of a robot to change its location in the environment. Alternatively, *manipulation* refers to the ability of a robot to manipulate objects and materials using its arms and end-effectors, which can have an end fixed in the environment [62] or be attached to a mobile platform [64].

4.1.4. Level of robot autonomy

Robots can have different levels of autonomy depending on the design of the robot itself and the task at hand. The category of Level of Robot Autonomy (LoRA) is commonly used in existing HRI taxonomies, and its importance derives from the fact that it relates to the amount of required user intervention during task execution [35]. Despite the existence of a variety of LoRA classifications in the literature, in which the number of possible levels may vary from two to ten [7,12,16,21,40], the proposed taxonomy adopted Yanco and Drury's [12] four levels of robot autonomy. Thus, in the present taxonomy, the four possible levels of robot autonomy include *teleoperation*, *shared control*, *full autonomy*, and *sliding autonomy*. The decision to select Yanco and Drury's [12] levels of autonomy was that it provides a balance between a too-general classification that would not provide enough information about the level of robot autonomy (e.g., "without autonomy" vs. "with some autonomy" [40]) and a too detailed classification (e.g., with ten possible levels [7,21]) that could make it harder for the users of the taxonomy to characterize the robots correctly.

In *teleoperation* applications (e.g., [55,78,79]), the robot is controlled by a human operator through a cord or wirelessly [18] to assist the human during the task [21]. In such applications, the human operator is responsible for sensing the environment (with or without the help of the robot) and planning the tasks [21], which can occur with the robot being operated in direct line-of-sight (remote control) or not (teleoperation) [18]. It is important to note that although there is a distinction between remote control and teleoperation, the same term (*teleoperation*) is used to describe both modes of operation in the taxonomy. In *shared control*, the robots (e.g., [42,80]) possess certain degrees of autonomy and share control of the task with the human involved in the interaction in a way that the robot performs some tasks while the humans perform other tasks [35]. Next, robots with *full autonomy* (e.g., [81–83]) are robots that do not require human intervention to sense the environment, plan, and implement the task [21]. Finally, *sliding autonomy* (e.g., [57]), also called adjustable autonomy or mixed-initiative [12], represents the situations in which the level of autonomy of the system varies during task execution because of the dynamic conditions of the task or the environment. The main difference between semiautonomous robots and robots that can vary their autonomy levels is that while the former systems operate at a fixed level of autonomy, the latter can vary their autonomy levels during task execution [12].

4.1.5. Robot type

Given the variety of applications in construction, a wide range of construction robots exist. In most cases, these robots are specialized in a single task, i.e., Single-Task Construction Robots (STCR) [19], but examples exist of construction robots that can perform more than a single task, which can be accomplished by changing the robot's end effectors or by using a more flexible robot such a humanoid or robotic arm that can perform multiple tasks (e.g., [84]). The proposed taxonomy classifies construction robots into five types: *stationary robots*, *mobile robots*,

swarm robots, humanoid robots, and exoskeletons. The first type, *stationary robots*, also known as industrial robots, include robots connected to fixed base structures. Examples include robotic arms fixed to the floor or other structures, robots connected to rails and gantry cranes, cable robots, and additive manufacturing robots (e.g., [62,85,86]). Although off-site applications of stationary robots are more common in construction, on-site applications also exist, e.g., on-site factories. Alternatively, *mobile robots* are robotic systems capable of moving around the environment, which can be achieved through driving on wheels or tracks (e.g., [47,48]), walking (e.g., [84]), flying (e.g., [87]), or swimming/floating (e.g., [88]). Given the nature of on-site tasks, usually characterized by a fixed product (e.g., building, bridge) on which moving crews perform their tasks, mobile robots find a wide range of applications in construction sites.

Next, *swarm robots* are multi-robot systems (composed of mobile robots such as drones) that perform tasks at high levels of collaboration and coordination (e.g., [83,89]). Although these systems are composed of many mobile robots, the proposed taxonomy classifies robot swarms as a different robot type because the robots in these systems are organized to function as a unity. *Humanoid robots*, defined as robots that resemble the human body in terms of their appearance, function, and motion capabilities [90], are robots that usually possess a high number of joints and degrees of freedom that make them flexible enough to execute a variety of tasks (e.g., [84,91]). Humanoid robots, although still rare in construction applications, have the potential to reduce the need and associated costs of employing a different STCR for each task that is automated in construction robotics applications. Finally, *exo-skeletons* are wearable robots that increase human physical strength and endurance, thus allowing their wearers to lift and carry heavy loads [92]. In most cases, they are employed to increase the weight a human can safely handle and improve the worker's body postures during task performance (e.g., [92–94]).

4.1.6. Safety mechanisms

Given that in many construction robotics applications humans and robots share the same workspace or work in relative proximity, human safety considerations must be included in the design of the robots and the tasks. In this category, safety is considered from two perspectives: physical safety, which focuses on eliminating or minimizing the adverse effects of physical contact between humans and robots, and psychological safety, which focuses on minimizing the psychological discomforts caused by interactions between humans and robots [95]. Although safety is sometimes studied as a human factor (e.g., [32]), in which cases it is approached from the perspective of [human] perceived safety, this taxonomy included safety mechanisms as a category of the robot. This is because the safety mechanisms described in this category focused more heavily on adjustments of the robot's behavior to minimize both physical and psychological safety risks that can negatively affect the human involved in the interaction. The safety features included in the proposed taxonomy are based on the survey of safety methods in HRI presented by Lasota et al. [95] and the 5-categories taxonomy described in Zacharaki et al. [23].

The first category, *controls-based safety mechanisms*, includes mechanisms that monitor the human or the robot and change the robot's motions through low-level controls prior to (pre-collision methods) or after (post-collision methods) a collision has been detected [95]. Pre-collision methods are usually based on setting limits to the robot's operational parameters (e.g., velocity, acceleration, and force), monitoring speed and separation between humans and robots, or using the potential field approach in which repulsive vectors change the robot's motions when a potential collision is detected [95] (e.g., [61,67,96]). Alternatively, post-collision methods detect and localize collisions after they happen, which is usually done by onboard sensing. Then, the system reacts by moving the robot away from the collision or by reasoning whether the collision was intentional before reacting [95] (e.g., [67]). Next, *motion-planning-based safety mechanisms* use motion planners to

change the robot's motions in response to changes in task conditions [95]. These changes may involve the robot navigating in an area in which humans are located (i.e., human-aware navigation) or an area with static or moving objects (e.g., other robots, equipment, furniture, walls) (e.g., [97,98]). Motion-planning-based safety mechanisms usually work well in quasi-static task conditions in which using the current state of the task provides enough information that the robot can base its decisions; however, in more dynamic task conditions, this approach may not be sufficient [95].

In *prediction-based safety mechanisms*, humans and robots anticipate the motions and actions of other team members to dynamically adjust their behaviors and ensure safety during task execution [95] (e.g., [68,99]). Next, *Hardware-based safety mechanisms* include selecting user-friendly materials for the robots, using force-torque sensors in the robots' joints and end-effectors, and using panic buttons to minimize the physical safety risks associated with the interaction [23]. In construction applications, the use of lightweight materials for exoskeletons (e.g., [100]) and the inclusion of emergency stops buttons in robotic cells, control boxes, and robot's bodies are some examples (e.g., [48]). Finally, given that recent developments in collaborative robotics have emphasized the importance of psychological safety in the design and deployment of robots, the proposed taxonomy also included *psychological factors-based safety mechanisms*. In most cases, the applications are based on adjusting the robot's behavior to reduce human psychological discomfort and stress during human-robot interaction [95]. It can be accomplished through training the robot to perceive and interpret human non-physical cues that may indicate discomfort during the interaction or adjust the robot's behavior during task execution to reduce the mental workloads imposed on the humans based on physiological measurements (e.g., [47,59]).

Shared characteristics

4.1.7. Team traits

At the team level, shared characteristics such as team traits include factors that cannot be completely characterized if only one of the parties (human(s) or robot(s)) is included. As with robots, some of these traits belong to the realm of cognition, while others include observable effects during task execution. In the discussion of shared traits related to cognition, *team situation awareness*, *shared situation awareness*, and *shared mental models* (SMM) are included. At the team level, SA can be viewed from two perspectives: Team and Shared SA. As presented by Endsley et al. [101], *team situation awareness* (e.g., [67]) relates to each team member possessing the required levels of SA to fulfill their tasks, while *shared situation awareness* relates to the team members possessing the same levels of SA that are needed for shared responsibilities (e.g., [83]). Next, the concept of *shared mental models* (e.g., [102]) refers to the mechanisms by which team members share an understanding of the task requirements, which, in turn, helps them to predict their teammates' actions and needs, thus facilitating action coordination [103]. Besides the cognition-based traits, other team traits included in this taxonomy are *fluency* and *interaction efficiency*. *Fluency* (e.g., [67]) is defined as the ability of a team to work together at high levels of coordination and adaptation [104]. Finally, it is possible to use a variety of metrics to assess the *interaction efficiency* in HRI tasks (e.g., [67]), which is typically measured in terms of the time required to complete a task, productivity, performance, number of errors during task execution, among others [105]. Again, the purpose of this category is not to include all possible team traits but rather to include the most relevant traits identified following our methodology.

4.1.8. Team composition

Team composition is another team trait influencing HRI and has been approached from various perspectives in many taxonomies. Examples include the use of the "ratio of people to robots" and the "level of shared interaction among teams", which represents the combinations of humans and robots and how these combinations relate to controlling the

robots [35], the “composition of robot teams”, which indicates whether a team of multiple robots is homogeneous or heterogeneous [12], and team composition as a direct comparison between the number of humans and the number of robots involved in the interaction [13]. In the present taxonomy, a simplification of the team composition classification presented in Parashar et al. [14] is used. Put simply, four classifications are possible: *single human to single robot* (e.g., [48]), *multiple humans to single robot* (e.g., [47]), *single human to multiple robots* (e.g., [84,102]), and *multiple humans to multiple robots* (e.g., [106]).

4.1.9. Input interfaces

In the proposed taxonomy, the category *input interfaces* describe the mechanisms and devices that humans use to communicate intentions or control the robots. These can be done through three modalities: *physical input*, *non-physical input*, and *multimodal input*. *Physical input*, which is characterized by the direct contact of humans with the robot or its controllers through the sense touch, includes the use of robots' control boxes, joysticks, levers, computer keyboards and mice, tablets, haptic devices, hand guidance, among others (e.g., [48,64,65,107,108]). *Non-physical input*, characterized by non-physical communications from the human to the robot, usually includes speech commands, gesture recognition, and the interpretation of physiological signals by the robots (e.g., [47,69,99,109]). Finally, *multimodal input* is characterized by using multiple input interfaces, which can be accomplished by combining multiple physical interfaces, multiple non-physical interfaces, or a blend of physical and non-physical interfaces to communicate the intentions of the human to the robot (e.g., [62,91]).

4.1.10. Feedback interfaces

In the proposed taxonomy, the category *feedback interfaces* describe the mechanisms and devices that humans use to receive feedback from the robot, which can also be done through three modalities: *physical feedback*, *non-physical feedback*, and *multimodal feedback*. *Physical feedback*, which is characterized by mechanisms and devices that provide feedback information from the robot to the human through haptic sensation (tactile or kinesthetic), includes force, torque, vibration, and tilt mechanisms, among others (e.g., [93,110,111]). *Non-physical feedback*, which is characterized by non-physical communications from the robot to the human, includes the use of computer screens and head-mounted displays that provide visual information from the robot or site in the form of images (photographs and videos), text, and graphs, speakers and headphones that provide sound feedback in the forms sounds, beeps, and alarms, among others (e.g., [57,59,64,65,99]). Finally, *multimodal feedback* is characterized by using multiple feedback interfaces, which can be accomplished by combining multiple physical interfaces, multiple non-physical interfaces, or a blend of physical and non-physical interfaces to provide information about the robot, the task, and the environment to the human (e.g., [96,107,112,113]).

4.1.11. Time-space proximity

The definition of time-space proximity in the proposed taxonomy considers how close the interaction takes place in terms of time and space and uses the classifications provided by Yanco and Drury [35]. In terms of physical location, the interaction is classified under collocated, when humans and robots are in the same place, or non-collocated, when they are not. Alternatively, temporal proximity considers whether humans and robots use computing resources simultaneously, which makes the interaction synchronous when they do and asynchronous when they do not. In the proposed taxonomy, physical and temporal proximity are combined into four possible classes: *synchronous and collocated* (e.g., [47,48,62]), *synchronous and non-collocated* (e.g., [96,112]), *asynchronous and collocated*, and *asynchronous and non-collocated* (e.g., [57,84,114]).

4.2. Task

The task dimension includes the characteristics of the developed task considering its type, planning, and the mechanisms used to teach it to humans and robots.

4.2.1. Task type

The *task type* is a high-level representation of a task [12,25]. Task type identification is an essential part of HRI studies because it supports determining the outline of a study, which includes steps such as determining system requirements and creating a design roadmap [13]. For the proposed taxonomy, 18 task types are included, namely *surveying and marking* [115–117], *surveillance and progress monitoring* [118,119], *earth and foundation works* [3,64,71,82,120], *transportation and lifting* [69,87,121,122], *concreting and asphaltting* [123,124], *bricklaying and stone works* [62,125,126], *steel and wood works* [127–129], *3D printing* [2,83], *cutting, bending, and, shaping* [84], *positioning of components* [81], *assembling of components* [91,130], *welding & joining* [131,132], *spraying, coating, and painting* [67,96] *mechanical, electrical & plumbing* [133,134], *glazing and façade installation* [112], *interior and exterior finishing* [135], *service, maintenance, and inspection* [136,137], and *demolition, renovation, and recycling* [48,138]. These task types were selected based on existing reviews of robotic construction task types [16,18,19,43] and the raters' literature review results.

4.2.2. Task planning

In the context of HRI, *task planning* refers to the processes of task breakdown and task allocation between the team members. Task planning has been a topic of interest in HRI research, especially as part of the efforts to increase the coordination of the actions of multi-agent teams during task execution. Unfortunately, no single task planning approach works well in all cases since task planning depends on several factors, such as task type, robot design, and the dynamics of the environment. Considering existing HRI approaches in the literature related to task planning and design (e.g., [24,139]), this taxonomy uses the classification presented in Parashar et al. [14], in which task planning is classified under three possible types: *offline*, *online*, and *hybrid*. In general, when the environment is deterministic and known, *offline* task planning (e.g., [99,140]) generates a static task sequence that can be implemented by the agents [141]. Alternatively, when dynamic and unknown conditions are present in the environment, *online* planning (e.g., [98,142]) can be used to change the agents' actions because of new information being provided to the team. Finally, *hybrid* task planning (e.g., [143]) is a mix of offline and online task planning in which an initial task sequence is defined (offline), but if the system realizes it will lead to task failure during task execution, it replans the task sequence (online) [141].

4.2.3. Task training and learning

In HRI research, task training represents a key component of the development of autonomous robots and collaborative human-robot teams [8]. The present taxonomy approaches training and learning from two perspectives: *human training* and *robot learning*. In *human training*, the application focuses on mechanisms and best practices for the development of skills and knowledge for humans operating or collaborating with robots, which can employ lecture-based, hands-on demonstrations or computer-based methods such as Virtual Reality (VR) and Augmented Reality (AR) (e.g., [48,63]). Alternatively, in *robot learning*, the application focuses on teaching the robots how to plan or perform tasks and how to respond to the stimuli from the environment in which it is located. In the proposed taxonomy, robot learning is classified into three main types: *model learning*, *reinforcement learning*, and *learning from demonstration*. In *model learning* (e.g., [47,99,109,144]), the robot learns a model from measured data and uses this model to predict information about the environment or its effects on the environment [145]. In *reinforcement learning* (e.g., [68,146,147]), the robot interacts with its environment using a trial-and-error approach that

allows it to learn optimal behaviors that are associated with a policy that aims to maximize a given reward function [145]. Finally, in *learning from demonstration* (LfD) (e.g., [71,135,148]), instead of being pre-programmed to learn how to perform a given task, the robot learns a task from human demonstration, which can be given by kinesthetic teaching, teleoperation, or passive observation [20].

4.3. Environment

In the proposed taxonomy, the environment dimension characterizes the location and setting where the construction tasks are performed.

4.3.1. Task setting

Focusing specifically on HRI applications within the construction industry, the *task setting* was divided into five general categories. *On-site* studies involve applications of robots and automated systems at operating job sites (e.g., [56,149]). *Off-site* investigations focus on applications in which automated or robotic systems are employed in factories and warehouses in locations other than the final installed location of the built structures (e.g., [150]). Next, a *laboratory* represents a highly controlled environment that limits the influence of naturally occurring phenomena (i.e., environmental noise, weather, non-participant human interaction) (e.g., [64,109]). Due to advancements in visualization and simulation technologies, researchers can also use *simulations* to study the interactions between workers and the proposed robots in virtual environments (e.g., [55,59]). Finally, given the increasing research interest in construction on the surfaces of the Moon and Mars, the proposed taxonomy lists outer space as another environment. However, current studies focusing on outer space applications are usually done in laboratories [91] or simulations [151].

4.3.2. Robot location

Although the category *task setting* characterizes the general setting where the task takes place, more information is needed to completely characterize the relationships between the team, task, and environment. *Robot location* characterizes with more detail where the task takes place (setting) and may define some of the requirements for the robot and the task. The category considers six possible robot locations that may happen in each setting: *underground*, *indoors*, *outdoors*, *air*, *suspended*, and *water*. A robot is located *underground* when it is performing tasks such as tunneling or foundation works below ground (e.g., [152]). A robot is *indoors* when performing building construction tasks, e.g., bricklaying [62] or painting [67], in an enclosed space protected from weather conditions. A robot is located *outdoors* when it is performing tasks such as excavation and transportation (e.g., [82,153]), in which cases it is exposed to the weather. A robot is in the *air* when it is a flying robot (e.g., drone), for which most applications involve progress monitoring and surveillance (e.g., [83,119,154]). A robot is *suspended* when it is lifted by a crane, cables, or other lifting equipment to perform tasks such as 3D printing, demolition, façade cleaning, or inspection (e.g., [85,96]). Finally, a robot is in/on the *water* when it is a swimming or floating robot that perform tasks underwater, on the water's surface, or inside wet pipes (e.g., [88,155]).

5. Results and discussion

5.1. Interrater agreement of the categories in the proposed taxonomy

Table 2 presents the results of the interrater agreement calculated using Randolph's kappa (K) for each of the categories in the proposed taxonomy during the interrater agreement process described in Section 3.4.3.

Table 2 shows that the interrater agreement for all categories in the taxonomy was in the range of $0.62 \leq K \leq 0.92$. Kappa values range between -1 and 1, with -1 indicating complete disagreement, 0 indicating agreement not higher than chance, and 1 indicating perfect

Table 2

Interrater Agreement for the Taxonomy Categories.

Category	Randolph's Kappa (K)
Task Setting	0.92
Task Type	0.91
Robot Location	0.88*
Robot Type	0.87
Team Composition	0.87
Human Traits	0.80
Input Interfaces	0.80
Feedback Interfaces	0.78
Time-Space Proximity	0.77
Human Role	0.76
Level of Robot Autonomy	0.76
Task Training and Learning	0.70
Safety Mechanisms	0.68*
Task Planning	0.67
Team Traits	0.64
Robot Traits	0.62

* These K values were computed for the interrater agreement among three raters instead of the five raters mentioned in Section 3.4.3 because these categories were added after a subsequent update of the taxonomy.

agreement among raters. According to Fleiss et al. [156], values of $K < 0.40$ are poor, values in the range of $0.40 \leq K \leq 0.75$ are intermediate to good, and values of $K > 0.75$ are excellent. Table 2 shows that the categories with the lowest interrater agreement were some of the categories with non-exclusive factors, i.e., *robot traits* and *team traits*, for which $K = 0.62$ and $K = 0.64$, respectively. The other non-exclusive category, *human traits*, obtained a higher interrater agreement value, $K = 0.80$. The explanation for this result is twofold. First, the number of factors in each of these three categories is different, with *human traits* having a smaller number of factors than both *team traits* and *robot traits*. While *human traits* has four factors, *team traits* has five factors, and *robot traits* has seven factors. Second, another possible explanation is related to the fact that studies that consider the effects of the human factors included in the *human traits* category usually refer to these factors explicitly in the body of the texts and usually measure them subjectively or objectively (e.g., mental workload, trust, situation awareness). Alternatively, the factors included in the *team traits* and *robot traits* categories were usually inferred by the raters using the information provided in the paper, which was not necessarily based on variables being measured in the studies. For example, in each application, it was possible that a robot had none to all the factors listed under *robot traits*. On some occasions, one rater could select a given factor while another rater would not, thus reducing the interrater agreement. Alternatively, for categories that included exclusive factors or levels, the interrater agreement values were usually higher, e.g., $K = 0.91$ and $K = 0.92$ for *task type* and *task setting*, respectively, and $K = 0.87$ and $K = 0.88$ for *team composition* and *robot location*, respectively, which can be explained by the limit imposed on the number of factors or levels to be selected, i.e., 1, in studies that only describe one experiment.

Many reasons can be listed to explain the source of disagreement among the raters during the paper classification process. First, classifying the papers using the proposed taxonomy is a subjective process based on the interpretation of each rater of the information provided in each paper. Each study presented the information with different levels of detail, and, on many occasions, the raters based their classifications on information extracted from figures and tables and not directly mentioned in the text. The classification process was also based on the interpretation of each rater of the definitions for each factor/level included in the taxonomy. As presented, the authors created a document in which each factor/level was defined using an accepted definition found in the literature. However, even then, the understanding of these definitions may have varied among raters during the classification process. Finally, another source of disagreement came from studies in which more than a robot or task is described. In such cases, a rater might

have emphasized a robot or task more than another, which was also a source of disagreement among the raters.

5.2. Classification of construction applications using existing taxonomies

As mentioned, to the best of the authors' knowledge, there are only two HRI taxonomies tailored for the construction industry. In both cases, the proposed taxonomies focus on a single aspect of the interaction: the level of robot autonomy and human effort in Liang et al. [16] and the robot-environment interaction in Tan et al. [17]. To illustrate their applicability in the construction industry, we classified the study presented by Liu et al. [47], in which the authors proposed a system that uses the worker's electroencephalogram (EEG) signals to evaluate task-related cognitive loads and adjust the robots' behavior to respond to these loads during task execution in a bricklaying context using an unmanned ground vehicle (UGV) (Husky A 200). Fig. 2 (a) shows this study's classification using the taxonomy proposed by Liang et al. [16], and Fig. 2 (b) shows the classification of the same study using the taxonomy proposed by Tan et al. [17]. The factors shown in red in Fig. 2 (a) and (b) represent the selected classifications of the paper using the taxonomies.

Given the specific focus of both taxonomies, shown in Fig. 2 (a) and (b), it is easy to see that neither one of them can completely characterize HRI applications in construction, which is not necessarily a drawback of the studies, but just a consequence of the fact that these studies focused on a single aspect of the interaction. Next, to illustrate why existing general taxonomies in HRI are limited in completely characterizing applications in the construction industry, two general-purpose taxonomies in HRI were selected to classify the study presented in Liu et al. [47]. Fig. 3 shows the classification of [47] using the taxonomy proposed by Onnasch and Roesler [13], and Fig. 4 shows the classification of [47] using the taxonomy proposed by Parashar et al. [14]. The factors shown in red in Fig. 3 and Fig. 4 represent the selected classifications of the paper using the taxonomies.

Overall, although the taxonomy proposed in Onnasch and Roesler [13] (Fig. 3) correctly classified the robot task specification, i.e., transport, it did so because "transport" is listed as one of the general task types for robots, not necessarily because it includes a variety of construction task types. For example, if the robot used in the task performed such tasks as 3D printing, assembly, or site monitoring, it would not be possible to find an appropriate match to characterize the robot task type. In terms of the field of application, there is no option that appropriately characterizes the application other than describing any given construction task as a "service". In terms of task setting, although this specific study takes place in a laboratory, it would not be possible to describe whether the application is on-site or off-site in case one of these settings was being used. The characterization of the robot morphology as "technical", as opposed to anthropomorphic and zoomorphic, also does not add much to the description of the robot in the context of construction application since most robots in construction are machine-like robots that would be classified as "technical" under the possible

options in this taxonomy. For the remaining categories, some of which are included in the proposed taxonomy in this paper, there are not any criticisms; however, categories such as *human, robot, and team traits, task training and learning*, and *safety mechanisms* are not included in [13], which may also limit a complete characterization of some of the key aspects of the interaction in a construction context.

The classification of the study presented by Liu et al. [47] using the taxonomy proposed by Parashar et al. [14] (Fig. 4) also has some shortcomings due to the taxonomy's focus on HRI applications in any industry. Although this taxonomy includes the three components of HRI: team, task, and environment, there is not much characterization of the team members, human(s) and robot(s), at the individual level. Characterizing the team members is key because it informs the traits needed for more effective collaboration in a given context or application. Also, the application type, classified as "construction", is too generic to characterize any specific application in construction appropriately. The setting and the safety mechanisms associated with the task are not characterized under any of the included categories in this taxonomy, which are shortcomings of this taxonomy in characterizing construction applications because these categories influence many aspects of the interaction and the overall requirements of the task. This taxonomy provides, however, a more detailed characterization of the dynamics of the interaction, both in terms of taskwork and teamwork, and proposes interesting relationships among some categories of the taxonomy under the "effects" of the interaction, although, as mentioned by the authors in the text, they could not be extended due to limitations in the length and scope of the paper.

5.3. Classification of existing construction applications using the proposed taxonomy

Next, two studies were selected to demonstrate the usage of our proposed taxonomy to summarize various aspects of a given application and compare different studies. Fig. 5 and Fig. 6 present the classifications of the selected studies presented in Liu et al. [47] (the same study used in Section 5.2) and Adami et al. [48], respectively. Adami et al. [48] investigated the effectiveness of Virtual Reality- (VR) based training on construction workers' knowledge acquisition, operational skills, and safety behavior when operating a remote-controlled demolition robot (Brokk 110) as compared to traditional hands-on training with an experienced trainer. The study by Liu et al. [47] was summarized in Section 5.2. The factors shown in red in Fig. 5 and Fig. 6 represent the selected classifications of the paper using the taxonomies.

Fig. 5 and Fig. 6 show that the proposed taxonomy could be used to classify both studies, even though the objectives and contexts of the studies were different. Liu et al. [47] developed and validated new methods to control the robot's behavior during task performance. Alternatively, Adami et al. [48] made no modifications to the robot, and the emphasis of the study was on how different construction workers' training modalities affect the overall performance of the workers when dealing with the actual robot on-site.

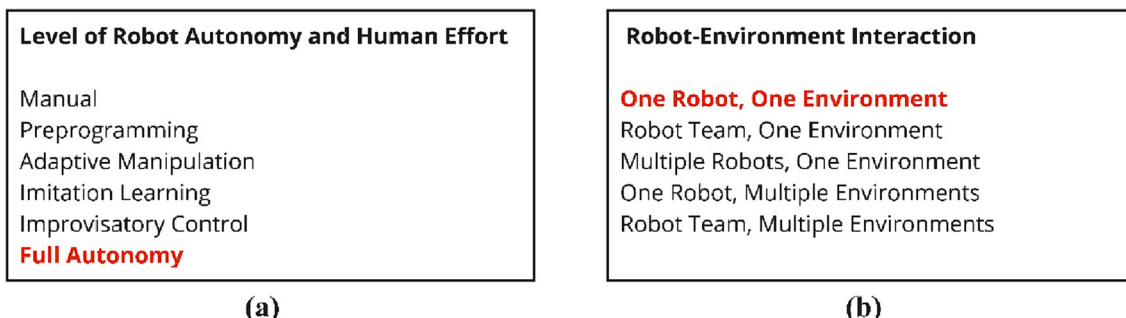


Fig. 2. Classification of Liu et al. [47] using the taxonomy proposed by (a) Liang et al. [16] and (b) Tan et al. [17].

Interaction Context Classification		Robot Classification		
Field of Application Industry Service Military & Police Space Expedition Therapy Education Entertainment None	Exposure to Robot: Embodied Depicted Setting: Field Laboratory	Robot Task Specification Information Exchange Precision Physical Load Reduction Transport Manipulation Cognitive Stimulation Emotional Stimulation Physical Stimulation	Robot Morphology Appearance ☐ a ☐ z ☒ t Communication ☐ ☐ ☒ Movement ☐ ☐ ☒ Context ☐ ☐ ☒ a: anthropomorphic z: zoomorphic t: technical	Degree of Robot Autonomy - ☐ ☐ ☒ + Information Acquisition ☐ ☐ ☒ Information Analysis ☐ ☐ ☒ Decision-Making ☐ ☐ ☒ Action Implementation ☐ ☐ ☒

Team Classification			
Human Role Supervisor Operator Collaborator Cooperator Bystander	Team Composition NH = NR NH > NR NH < NR NH: number of humans NR: number of robots	Communication Channel Input: Electronic Mechanical Acoustic Optic Output: Tactile Acoustic Visual	Proximity Temporal: Synchronous Asynchronous Physical: Following Touching Approaching Passing Avoidance None

Fig. 3. Classification of Liu et al. [47] using the taxonomy proposed by Onnasch and Roesler [13].

A few notes about the study presented in Fig. 5 (classification of Liu et al. [47]) include selecting *fluency* as a team trait due to the coordination of the actions of humans and robots during the task and selecting *shared mental models* because the robot kept a mental model of the human during task performance to adjust the frequency of blocks that are delivered to the worker in response to changes in the workers' cognitive load levels. *Human traits* only included *mental workload* because the study specifically addressed this trait. As the robot was fully *autonomous*, multiple traits were included, namely the ability to move (*mobility*), to make decisions (*decision-making*), and to increase or decrease its speed as the workers' cognitive load levels changed during task execution (*adaptation*). The *input interface* was *non-physical* because the robot received the EEG signals wirelessly and without any human intervention, and the *feedback interface* was *multimodal* because the worker could directly see the robot and pick blocks from the robot. The human role was *collaborator* because both human and robot had a single goal, and the actions of the human depended on the robot's actions. The selected *safety mechanism* was *psychological-factors-based* because the adjustment of the robot's behavior aimed at minimizing the adverse effects of cognitive loads, which can be associated with the development of stress, for example. *Bricklaying* was selected as the task type because the team's common goal was to build the wall. Finally, *model learning* was selected for *task training and learning* because the authors described the training and testing of a classification model used by the robot in the study.

Alternatively, in Fig. 6 (classification of Adami et al. [48]), *interaction efficiency* was selected as a *team trait* because the study assessed how well the workers could control the robot. The other team traits were not selected because the robot had no sensors that allowed it to perceive the environment or teammate. As for *human traits*, *situation awareness* was selected because some of the performance metrics in the study involved assessing how well the worker conducted the safety checks in the machine before and during operation. The selected *robot traits* were *mobility* and *manipulation* because the robot could move using its tracks (*mobile robot*) and use its end-effectors to break objects. The *input interface* was

considered *physical* because the workers used a control box with buttons and levers to control the robot (*operator* role for the human), and the *feedback interface* was considered *multimodal* because the *operator* was close to the robot and was able to see, touch, and hear it. The control box had an emergency stop button, and thus, the *safety mechanism* of the task was considered *hardware-based*. *Human training* was selected under *task training and learning* because the focus of the study was to assess the effectiveness of human training modalities in the selected task type, i.e., *demolition*. Finally, two *task settings* were selected, i.e., *simulation* and *laboratory*, because the VR-based training was done in a simulated environment, and the hands-on training was conducted *outside* the laboratory.

5.4. Discussion of results

When compared to the taxonomies presented in Fig. 3 and Fig. 4, the proposed taxonomy, as shown in Fig. 5 and Fig. 6, more appropriately defined the *task settings*, *robot locations*, *robot types*, and *task types* because the proposed taxonomy in this study focuses specifically on construction applications. The proposed taxonomy also includes some categories not included in the other two [13,14], as is the case with *safety mechanisms*, for example. For the two taxonomies that were developed in the construction context (Fig. 2 (a) and (b)), although they characterize well the aspect of HRI they selected to study, neither of them can be used to characterize an HRI study more generally because they only considered a single aspect of the interaction, i.e., level of robot autonomy and robot-environment interaction, respectively. Also, the proposed taxonomy emphasizes the characteristics of the agents involved in the interaction both at an individual level (*robot and human*) and at the *team* level. The results presented in Fig. 5 and Fig. 6 show that the proposed taxonomy allowed for a succinct description of different applications that can be used to characterize a given study or to compare different studies. Additionally, by providing a summarized classification of many studies, the taxonomy can inform researchers and professionals during the design of robots and tasks by listing commonly used *human*,

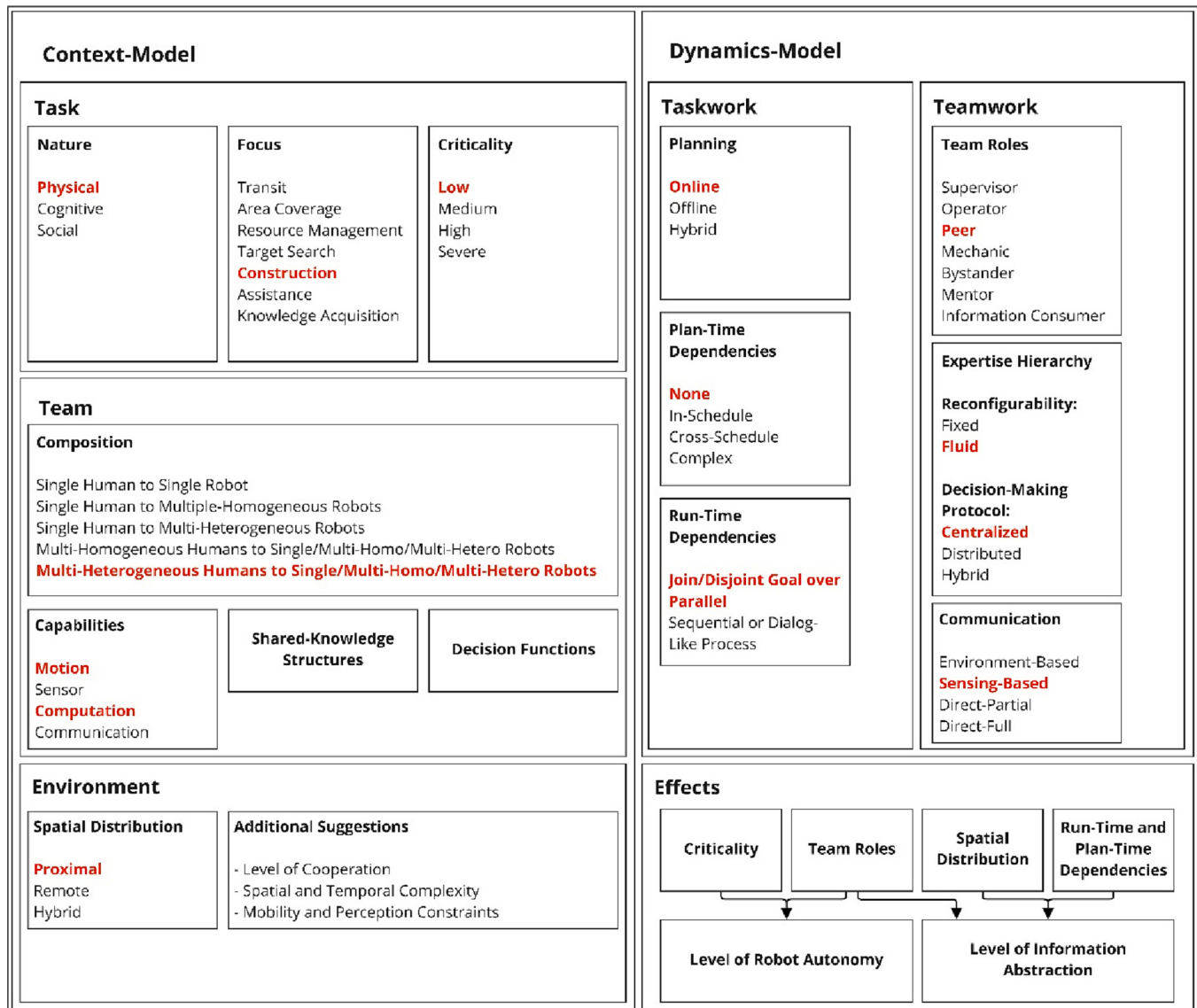


Fig. 4. Classification of Liu et al. [47] using the taxonomy proposed by Parashar et al. [14].

robot, team, and task traits associated with a given application. In this sense, the designers can get insights from similar or not-so-similar applications and propose modifications that improve the interaction. Finally, this succinct characterization of studies may allow researchers and professionals to identify relationships among the categories included in the taxonomy from the results of the classified studies.

The proposed taxonomy is the product of a review effort that included results from taxonomies, classifications, and literature reviews of HRI applications in various industries, including construction, manufacturing, military, aerospace, and healthcare. As presented, many classifications and taxonomies in HRI currently exist; however, they may not be able to characterize HRI applications in construction completely. First, the identified taxonomies focusing on construction applications are unidimensional [16,17]. Although they provide an in-depth characterization of the categories they describe, they cannot be used to characterize other aspects of the interaction. A potential solution would be to use many unidimensional taxonomies, each focusing on a different aspect of the interaction, to characterize the interaction in a construction application completely. This solution, however, has some shortcomings. For example, although reviews of the use of robotics in construction exist [18,19,43], none of these reviews were intended to be used as a taxonomy for robot types or construction task types because

these studies may have focused on a specific class of robots (e.g., single-task construction robots [19]) or may have selected some applications while intentionally leaving others out [18,43]. The proposed taxonomy reviewed these studies and compiled their results and others to propose new categorizations for both robot types and task types that were not readily available in the literature. Additionally, directly drawing from the results of unidimensional taxonomies from other industries for the categories that are still not available in construction would not solve the problem because the application's nature and conditions might be different for some categories, thus requiring adaptations for construction applications. For example, the characterization of the task environment is the object of research in the military domain [39]; however, directly applying these results in construction applications would not suffice simply because the characterization of the environment in the military domain needs to consider the elements that influence the safety of operations in the face of the existence of the enemy. Alternatively, although a characterization of the environment in the construction domain also needs to consider the safety of operations, this is done because many construction tasks are intrinsically risky and may be unsafe to operators, not because there are enemies around.

Second, for multidimensional taxonomies in HRI, although they are available to virtually any HRI application in various industries [12–15],

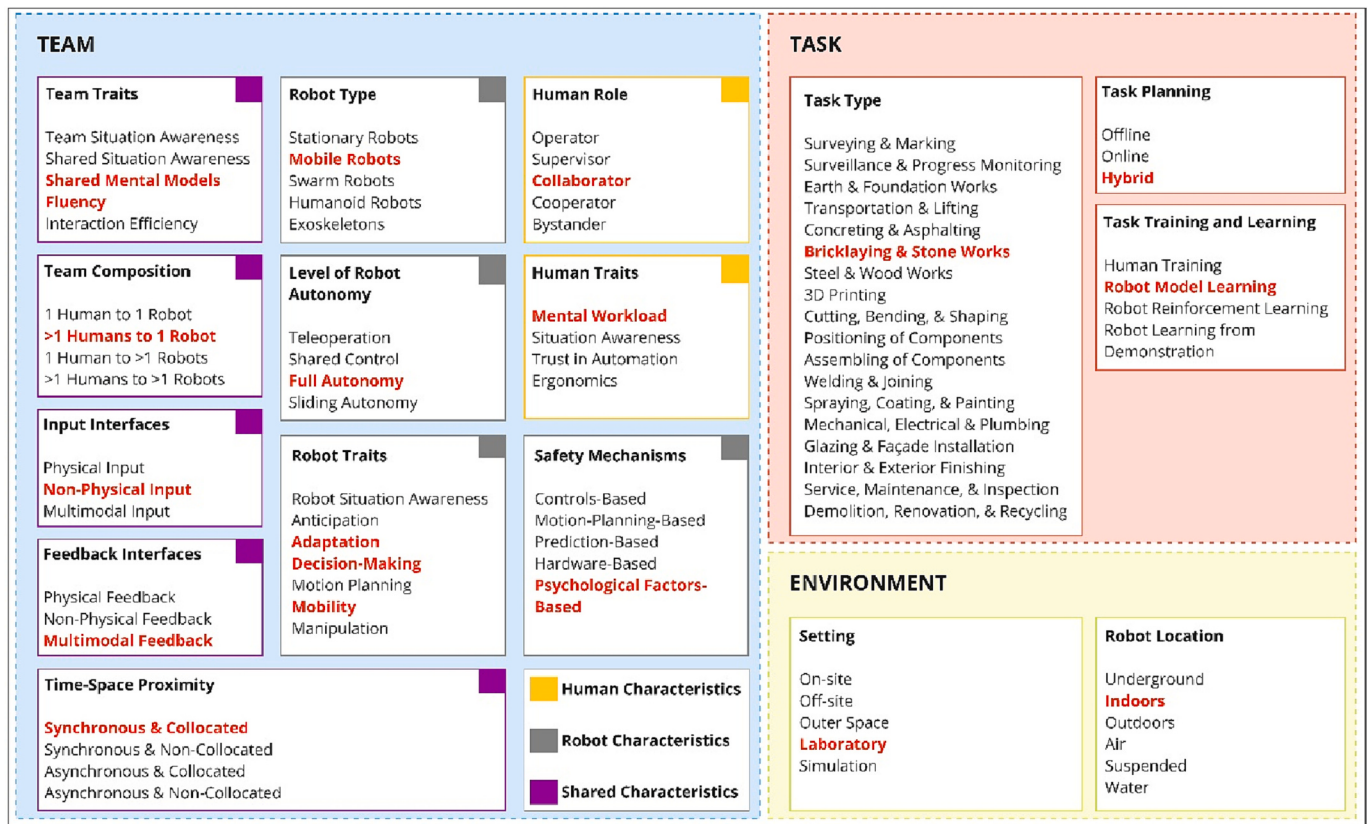


Fig. 5. Classification of Liu et al. [47] using the proposed taxonomy.

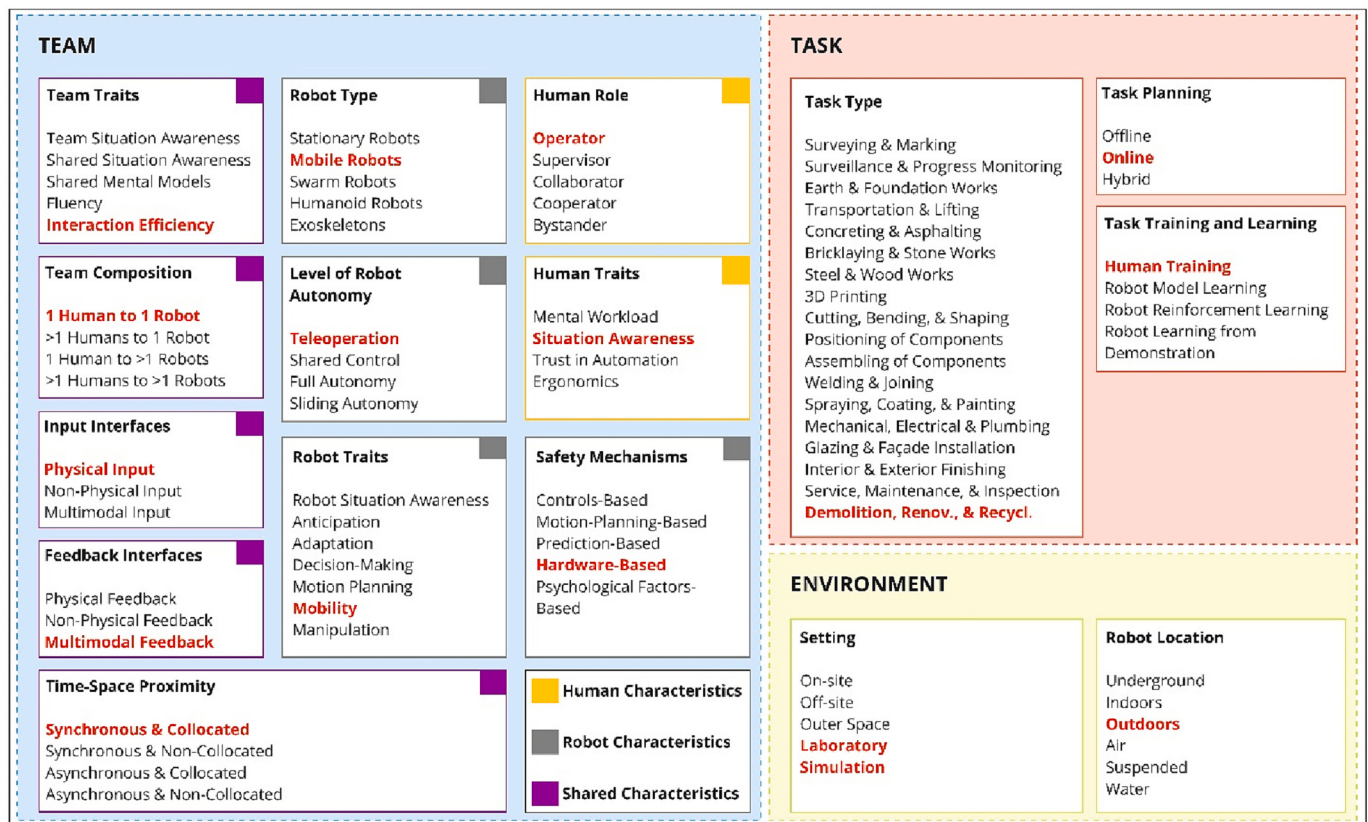


Fig. 6. Classification of Adami et al. [48] using the proposed taxonomy.

they may not be able to completely characterize construction applications unless additions and modifications are made to the categories of the taxonomies. For example, for task specification, Onnasch and Roesler [13] included tasks that may be found in construction (e.g., transportation, manipulation, precision, and physical load reduction) but also included physical, emotional, and cognitive stimulation, which may not be relevant for construction tasks. Parashar et al. [14] listed “construction” as a potential task focus, but that characterization is not enough in a construction-specific classification. Malik and Bilberg [15] used the ISO 15066 definitions to categorize safety implications in applications involving collaborative industrial robots, but a direct application of this categorization to some construction robots is not possible because the included safety mechanisms only consider collaborative industrial robots. Some categories, however, can be directly applied from one industry to another, and the proposed taxonomy benefited from this fact for some of the included categories (e.g., team composition, human roles, and time-space proximity).

5.5. Limitations

Even though an attempt was made to make the proposed taxonomy as comprehensive as possible by drawing relevant results from existing HRI, HCI, and HMI studies and taxonomies, some aspects of HRI in construction may have been intentionally or unintentionally overlooked in the proposed taxonomy. During the design of the proposed taxonomy, the categories that were considered more relevant and thus included in the taxonomy’s final design were the ones that more strongly related to the three dimensions of HRI (i.e., team, task, and environment). Thus, the proposed taxonomy purposefully did not include technical aspects such as the types of sensors, end-effectors, and control mechanisms that the robots may use, for example. Depending on the needs of the user of the taxonomy, these categories and others may be necessary, in which cases the taxonomy will need to be adapted before it can be used. As presented, since the taxonomy was structured using a faceted approach, it is easy to include new categories and factors depending on the needs of a specific study. Future adaptations and new versions of the proposed taxonomy are also easy to produce, which can result from the need to include some of the overlooked categories or new developments in construction robotics.

In addition, it is possible that some studies may not be entirely or appropriately characterized by the proposed taxonomy, given their scopes and objectives. For example, applications that focus exclusively on developing new control algorithms or end-effectors (e.g., [1–3]) may not describe some aspects of the team and task organization in enough detail that would make using the proposed taxonomy informative. In such cases, it is better to apply the proposed taxonomy only after the new algorithm or end-effector has been tested (either virtually or physically) in a context that allows the proper characterization of all the dimensions of HRI (i.e., team, task, and environment). It should be noted that, for the design of such tests, the proposed taxonomy may be used to inform the designers about relevant features that may be included and analyzed in the tests. For example, one can look at how the new control algorithm or end-effector affects the human factors included in the taxonomy or how they impact the decision-making dynamics in the team and the roles humans and robots may assume in the task.

Differences may exist in some of the definitions and assumptions made in the taxonomy compared to other studies in the literature. For example, the definition of what is considered a robot may vary between different studies. Some researchers consider robots only equipment that have a minimum level of autonomy, referring to remotely operated and teleoperated equipment as machines (e.g., [113,120]). Other studies consider that remotely operated and teleoperated equipment without autonomy is a class of robots (e.g., [48,111]). The proposed taxonomy followed the latter school of thought and included remotely operated and teleoperated equipment without autonomy as robots. The same is true for exoskeletons and drones, which may be referred to as tools or

machines in some applications (e.g., [157,158]) and as robots in other applications (e.g., [83,93,100,159]) based on their levels of autonomy. During the review process, there were also cases in which the same term was used to refer to two different concepts, as was the case with the term “teleoperated” being used to refer to remotely controlled (i.e., operated in the operator’s direct line-of-sight) (e.g., [48,64]) and teleoperated robots (i.e., controlled with the help of a screen or display) (e.g., [84,99,120]). The proposed taxonomy differentiated between the two terms when describing the *level of robot autonomy* but referred to both cases as “teleoperated” to simplify the overall structure of the taxonomy. To reduce the likelihood that a definition or concept may be misinterpreted when using the proposed taxonomy, the description of the categories and their associated factors include an accepted definition of the term as found in the literature. Finally, the proposed taxonomy received input from civil engineers, architects, and HCI/HRI professionals during its design but did not receive input from professionals such as roboticists or industrial engineers, for example.

6. Conclusions

This paper presented the development of a multidimensional HRI taxonomy tailored for construction tasks. The proposed taxonomy draws from existing results in HRI, HMI, and HCI in various industries and is structured under three dimensions: team, task, and environment. Its development was based on the premise that, in collaborative robotics applications, humans and robots work together as a team and interact with their environment to perform a given task. Due to the specificities of the construction industry, it was deemed necessary to propose a taxonomy focusing on key aspects of construction tasks, which was not readily available in existing HRI taxonomies proposed for other industries. As presented, the proposed taxonomy can support the comparison of existing HRI applications in the construction industry, as well as support informed decisions in the design of construction robots or construction tasks that involve teams of humans and robots. Finally, the taxonomy is also expected to serve as a guide for comparing HRI studies in the construction domain.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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