Shared Control/Autonomy: A Historical Perspective, Current Trends, and the Role of Generative AI

Michael Hagenow, Mario Selvaggio, Xuehui Yu, Yanwei Wang, Yiannis Demiris, Andreea Bobu, Yilun Du, Harold Soh, Dylan Losey, and Julie Shah

***Abstract*—In shared control and shared autonomy systems, humans collaborate with robot agents to achieve common goals. Research in this area dates back over 40 years, with numerous applications, such as in manufacturing, robot surgery, and assistive technologies. Shared control approaches have even seen some commercialization efforts in areas like semi-autonomous driving and automotive assembly. Recently, shared control and shared autonomy approaches have gained significant traction, with hundreds of new methods published in scientific papers each year. In this paper, we examine recent approaches and trends in these methods, investigating several crucial aspects that are underexplored in previous surveys. First, we provide descriptive statistics and trends related to human input methods, technical approaches, and applications. Second, we examine the growing role of generative artificial intelligence approaches in shared control and autonomy. Based on these insights, we offer updated recommendations for future approaches.**

***Index Terms*—Shared control, shared autonomy, generative artificial intelligence**

I. Introduction

ROBOTS offer the potential to support humans across a wide range of domains, from factories to homes. While fully autonomous robots offer the allure of completing tasks independently, many scenarios benefit from human-in-the-loop systems, where skilled humans and robots team together to leverage their respective strengths. This setup is particularly desirable in tasks that are under-defined, safety critical, or require human judgment. Human involvement in such systems can vary dramatically, but one popular class of approaches are shared control or shared autonomy (SC/SA) methods, where a human provides input to an intelligent robot, and the actions of both agents are combined together to achieve shared goals. In this survey, we examine the growing literature of shared control/autonomy systems to provide a broad look at the most recent trends and opportunities in the field.

Michael Hagenow is with the Department of Computer Sciences, University of Wisconsin–Madison, Madison, WI 53706 USA (e-mail: hagenow@cs.wisc.edu). Mario Selvaggio is with the Department of Electrical Engineering and Information Technology, University of Naples Federico II, Naples, Italy (e-mail: mario.selvaggio@unina.it). Xuehui Yu and Harold Soh are with the Department of Computer Science, National University of Singapore, Singapore (e-mail: yuxuehui@nus.edu.sg; harold@comp.nus.edu.sg). Yanwei Wang is with Generalist AI (e-mail: felix@generalistai.com). Yiannis Demiris is with the Department of Electrical and Electronic Engineering, Imperial College London, London, UK (e-mail: y.demiris@imperial.ac.uk). Andreea Bobu and Julie Shah are with the Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA 02139 USA (e-mail: abobu@mit.edu; julie_a_shah@csail.mit.edu). Yilun Du is with the School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138 USA (e-mail: ydu@seas.harvard.edu). Dylan Losey is with the Department of Mechanical Engineering, Virginia Tech, Blacksburg, VA 24061 USA (e-mail: losey@vt.edu).

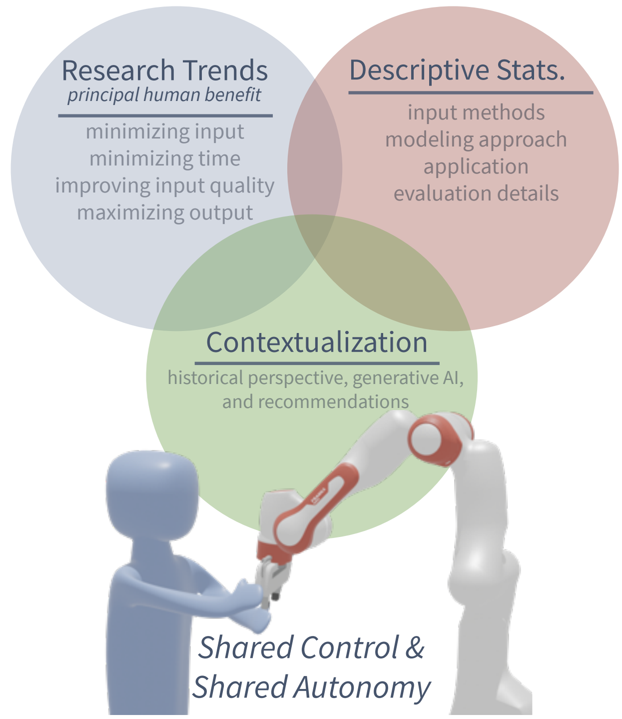

Fig. 1. Overview of the key elements of shared control and autonomy investigated in this survey. Our main review includes a historical perspective on the terminology and origins of shared control/autonomy, a review of recent trends in the past five years, discussion of shared control/autonomy with generative AI, and recommendations for future research.

Shared control and autonomy systems provide an intermediate between manual robot teleoperation and full autonomy, in terms of the robot's level of autonomy. A successful implementation often requires a number of critical design decisions related to the human interface and the robot system. A typical taxonomy requires specifying the form of user input, specification of robot autonomy (e.g., control laws, an autonomous policy), and an arbitration law that dictates how the input from the human and the autonomous agent can be combined. Introduced initially for domains where human access was impractical and robust robot autonomy was impossible (e.g., space robotics), shared control/autonomy has seen success in many areas, including assistive robots, surgical applications, and general robotic manipulation tasks.

Given the growing popularity of shared control/autonomy approaches, previous surveys have developed taxonomies and provided some analysis of past literature, but have not provided a structured review of the literature, including both a quantitative analysis of current trends and an overview of modern aspects, such as the role of generative artificial intelligence approaches. Abbink et al. [1] provide design and evaluation guidelines for shared control systems and a review of techniques in common domains, such as automotive, surgery, and brain-machine interfaces. Losey et al. [2] provide a review of three key elements of shared control systems: intent estimation, arbitration, and communication mechanisms. Selvaggio et al. [3] provide a categorization of different shared control/autonomy arbitration approaches and discuss the role of haptics, human models, and environment information in their implementations. Li et al. [4] propose an alternative taxonomy for telerobotic shared control approaches and a review of learning-approaches and adaptive-autonomy approaches. Other surveys focus on specific application domains, such as semi-autonomous driving [5], [6], [7].

Despite these prior surveys, key questions remain: What approaches are most common in modeling how humans and robots contribute in shared control systems? What are the most popular applications of the technology? What is the impact of new generative AI approaches on shared control/autonomy systems? Our survey addresses these gaps through two primary contributions. First, we provide a broader and structured review of recent literature that allows us to quantify recent trends. We survey the most recent five years in several general robotics publication venues to provide descriptive statistics related to key design and evaluation choices for SC/SA approaches, including human input, modeling, applications/tasks, and evaluation criteria. We further use the same broad review to identify recent trends. Second, we analyze the role of emergent generative AI techniques (e.g., language models, diffusion, vision-language-action models), which have been transformational in robot learning, in accelerating the capabilities of SC/SA approaches and systems. Through these two key contributions, we are able to provide an updated discussion and recommendations. For researchers developing new shared control/autonomy approaches, we hope that our structured review and analysis of shared control/autonomy techniques will identify recent progress in the area and aid in design choices, such as inputs, modeling approaches, choice of application, implementation, and study design.

In the remaining sections of this survey, we provide a brief historical perspective on the definitions and use of shared control and shared autonomy (Section II), we describe our literature review process and paper selection criteria (Section III), we discuss the main results and trends (Section IV), we highlight recent work incorporating generative artificial intelligence in shared control and autonomy systems (Section V), and we conclude with a general discussion and recommendations for future work (Section VI).

II. A Historical Perspective on Shared Control and Shared Autonomy

This section provides a brief historical review of early shared control and shared autonomy systems, drawing particular attention to the origin of the two terms and the automation landscape at the time of their introduction. We also aim to shed light on the initial motivations for shared control and shared autonomy systems, and to highlight the interchangeable use of the terms in early approaches.

Both *shared control* and *shared autonomy* emerged to describe robot control schemes that lie between manual teleoperation and full autonomy. Prior to their introduction, Ferrell and Sheridan proposed *supervisory control* [8] as a human-autonomy teaming paradigm for settings where direct control was infeasible, such as for assistive applications or scenarios with large time delays. While the initial intent of supervisory control was for the operator to issue high-level commands (e.g., goals) to a lower-level autonomous routine, in practice less strict definitions of supervisory control served as an umbrella for many teleoperation systems, including those with some aspects of autonomy [9].

New terminology emerged to offer more precise distinctions across the expanding range of human-in-the-loop control strategies. *Shared control* appeared first in the early 1970s during the development of the autonomous control subsystem at NASA Jet Propulsion Laboratory. Differentiated from supervisory control, the first shared control systems were designed for lower-level human-computer interactions in space station operations and involved observing user inputs, inferring the desired tasks, and taking appropriate control actions [10], [11]. These systems, which augmented human input to conform to a desired task plan, were categorized as subsets of supervisory control (alongside *traded control* where the human and machine alternate periods of control) [9], [12]. Notably, many of the methods studied at the time were applied to remote robot space operations, where reliable autonomy was not possible and latency and a lack of proper perception precluded more direct control approaches. Beyond space applications, other early approaches included Nagata et al.'s conversational iterative method where a robot learns and executes commands from a human teacher and Madni et al.'s underwater manipulation interface that allocated subtasks between the operator and robot manipulator [13], [14]. While neither method was originally introduced as shared control, Khatib's Artificial Potential Fields [15] and Rosenberg's Virtual Fixtures [16] both became popular formalisms used in shared control systems [17]. Such approaches often define shared control objectives based on desiderata in the robot's configuration space (e.g., collision avoidance) or task space (e.g., goals or constraints).

Shared autonomy did not emerge in the robotics literature until nearly twenty years later. The earliest examples include the development of the DLR Robot Technology Experiment (ROTEX, shown in Figure 2) in the early 1990s, where the role of shared autonomy was to create local sensory feedback control, such as for shaft-turning tasks [18]. Michelman et al. developed another early approach where primitive autonomous actions controlled the fingers of a robot hand that were commanded by simplified human input [20]. Notably, early approaches were also described as TeleSensor Programming (TSP), and used the terms *shared control* and *shared autonomy* interchangeably [21]. While the majority of work from this time focused on space robotics technology, Taylor et al. discussed opportunities for shared autonomy for computer-aided robot surgery, where partial autonomy would aid in functions such as instrument positioning and readjustments for patient positioning [22]. Around the same time, Hirai provided an early framework for shared autonomy systems by comparing

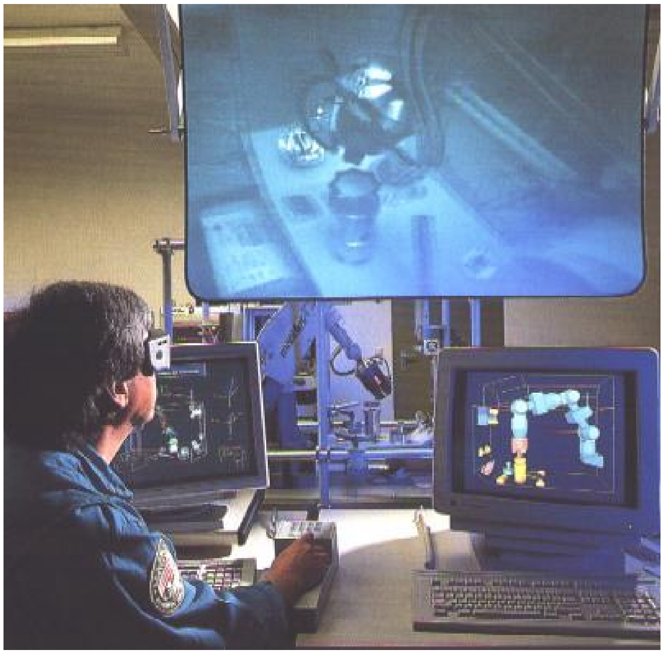

Fig. 2. Robot Technology Experiment (ROTEX) was an early shared autonomy approach, where the robot operated with partial autonomy to complete low-level sensor-based feedback control tasks [18]. Reprinted from [19], with permission from Springer Nature.

previous approaches [23]. In an early survey on distributed autonomous robotic systems, Asama defined shared autonomy as a cooperative system between machines and humans and draws attention to design of the human interface, telepresence, and virtual reality technologies [24].

As shared human-robot systems have matured and further diversified, researchers have increasingly revisited distinctions between the two terms. *Shared control* has been the prevalent terminology used to describe human-robot systems with low-level interaction or intervention from the human, likely due to its earlier introduction in the literature. However, *shared autonomy* has seen increasing use in recent years. Previous surveys, methods, and taxonomies have attempted to establish clearer definitions within the broader automation landscape. Levels of automation curves, such as in Endlsey and Kaber, place shared control as an intermediate between manual control and supervisory control [25]. Selvaggio et al. differentiate *shared control* as where the human manually tunes the level of autonomy and *shared autonomy* as where the system automatically adjusts the level of autonomy based on sensing, inference, and modeling [3]. Li et al. adopt a new set of terminology: *semi-autonomous control, state-guidance shared control, and state-fusion shared control* to re-categorize recent control-sharing approaches [4]. However, given similar conceptual foundations and practical overlap in the literature, we argue both *shared control* and *shared autonomy* will likely remain popular, and thus use the terms interchangeably in conducting our survey of recent trends.

III. Literature Review Approach

Our review required two main efforts. First, we conducted a structured literature review of shared control/autonomy papers from the last five years in general robotics venues. We then separately conducted a review of emergent methods that leverage generative artificial intelligence techniques (e.g., transformers, diffusion policies) as part of shared autonomy systems to aid our discussion around future SC/SA systems.

For the structured review, our goal was to provide a clear and tractable snapshot of recent trends in the shared control/autonomy literature. We chose to focus on the three general robotics venues with highest h5-index and to target the last five full years of published papers (between 2020 and 2024). We conducted our search on March 18, 2025. At this time, the three venues with the highest h5-index were the IEEE Robotics and Automation Letters (RA-L), the IEEE International Conference on Robotics and Automation (ICRA), and Science Robotics. We cut off our selected venues and inclusion years to yield a quantity of papers that could be discussed and categorized within a single survey. With the given venues and years, our initial search yielded 405 papers. We acknowledge that there are other general robotics venues where shared control and shared autonomy are regularly published—such as the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), the ACM/IEEE International Conference on Human-Robot Interaction (HRI), and IEEE Transactions on Robotics (T-RO) (in addition to specialized domain-specific venues). While we were unable to exhaustively survey publication venues in our review, we believe the high-level trends provide useful data to researchers trying to understanding shared control/autonomy research.

Each paper from our search was subsequently screened for exclusion. Exclusion criteria included workshop papers, surveys, and papers where shared control/autonomy were only mentioned in related or future work. In total, 210 papers were excluded, leading to a final list of 195 papers for our review. We were encouraged that 21 of the excluded papers cited shared control/autonomy implementations as future work. The final list included 101 papers from RA-L, 92 papers from ICRA, and two papers from Science Robotics. For each paper, we categorized key components of the shared control/autonomy approach, including the input method, modeling approach, and application area. Additional details regarding our search criteria and categorization methodology can be found in Appendix A.

Given the fast rate of change in shared autonomy approaches using generative artificial intelligence methods, instead of a structured review, we more broadly searched for and identified papers representing different key technologies and applications in shared control/autonomy. In total, we surveyed 34 papers. These papers include both shared autonomy methods and generative AI background that contextualizes shared autonomy research directions. The work is split across Sections V and VI (as part of the recommendations). We hope that as shared control/autonomy with generative models matures, we will see future structured reviews of this literature.

IV. Trends in Shared Control and Shared Autonomy

From our structured review, we conducted two primary analyzes that are detailed below. The first analysis computed

TABLE I
DECOMPOSITION OF SA/SC APPROACHES BY INPUT METHOD, MODELING APPROACH, AND APPLICATION DOMAIN.

Input Method	**Paper Count**
Direct Control Interfaces	54
Haptic	44
Kinesthetic Control	30
Physiological Signal	23
Gesture/Hand Tracking	18
GUI	14
VR/AR	9
Simulation/Dataset	4
Language Controller	4
No Actual Interaction	2
Implicit Cues	2
Modeling Approach	**Paper Count**
Optimization	41
Input Blending	32
Compliance Control	24
Intent / Goal Inference	22
Reinforcement Learning	20
Filtering	18
Input Mapping	16
Planning	14
Supervisory Control	14
Templates	14
Virtual Fixtures	14
Classical ML	13
Traded Control	12
Prob. Graphical Model	12
Imitation Learning	11
Generative Modeling	10
Divisible Control	10
Prob. Modeling	10
Multi-Robot Control	10
Deep Learning Models	5
LLM-based Approaches	3
Application Domain	**Paper Count**
Assistive Robotics	49
General Manipulation	46
Medical Robotics	35
Navigation Robotics	20
UAV	11
HRC	10
Industrial Robotics	9
Space Robotics	8
Multi-Robot Systems	7
Emergency Response Robotics	3

descriptive statistics about the prevalence of different key design decisions for shared autonomy systems. The second analysis identified key trends and used these trends to organize a discussion of the survey literature.

A. Descriptive Statistics

To better understand the landscape of shared autonomy research, we characterize the distribution of key design decisions and application domains in recent methods. Specifically, we assessed shared autonomy work based on the method of human input, the underlying modeling approach, and the application where the resulting system was applied. We also analyzed evaluation details, such as user study population and metrics.

We provide a broad overview of our descriptive statistics in Table I, including the categories identified for the key shared autonomy design decisions. For input method (Table IIa), modeling approach (Table III), and application (Table IIb), we report both total counts to show prevalence as well as five-year trends to highlight areas of potential growth or decline. The trend directions are determined using linear regression, where the sign and magnitude of the fitted regression line's slope indicate whether a category is *increasing* (slope $> +0.5$), *stable* ($-0.5 \leq$ slope $\leq +0.5$), or *decreasing* (slope < -0.5). Given that these trends are estimated from five annual data points (2020–2024), they should be interpreted as descriptive rather than strongly inferential. For input methods, we note a few high-level trends. Overall, we see a general increase of all input types across the five-year period, with direct control devices (e.g., joysticks, joypads, keyboard, teleoperation interfaces) remaining prevalent. Language-driven interfaces have emerged in the past few years, fueled by advances in language models. Though not shown in the table, we also see increases in multi-modal inputs (e.g., combining manual and physiological inputs) to capture more rich measures of user intention. For modeling approaches, we see the largest diversity across categories. Optimization continues to dominate, likely due to its flexibility in modeling desired shared control objectives (e.g., task performance, safety, and comfort). In the last year, reinforcement learning has also seen sharp growth, perhaps due to the flexibility afforded by the reward function and the success of human-in-the-loop reinforcement learning methods [26], [27]. With advances in large language models, LLM-based approaches began to appear in shared autonomy in 2024, most commonly for specifying high-level tasks or inferring user intent from language. Applications are dominated by assistive robotics, which tend to have an emphasis on human-robot interaction and thus relevance for shared control. The second most popular area is general manipulation (e.g., pick and place) which is often used to study foundational questions in shared autonomy. Across categories, we did not see many areas of decline. We hypothesize a few possible reasons. First, we are still seeing large general growth in shared autonomy which may mask declines through the volume effects. Second, many of the specific categories are complementary, serving different problem settings and thus may continue to experience growth in the long term.

In addition to *input, modeling, and application*, a critical piece of shared autonomy is evaluation. We analyzed the size of user evaluations and common evaluation metrics in our surveyed papers. First, we looked at number of participants (shown in Figure 3). Out of 195 papers, we found that 41 papers had fewer than two participants, typically meaning they did not run a user evaluation or had an informal user evaluation (e.g., system demonstrations by the authors). Of the studies with more than two participants, the median value was 10. Often, studies with small number of participants leveraged expert populations (e.g., surgeons). Regarding metrics, the most common evaluative tool was the NASA task load index (TLX) [28]. Other common metrics (as relevant) included tracking error, effort, success rate, and task completion time. Many papers also introduced non-standardized, task-specific, highlighting both the diversity of shared autonomy scenarios and the lack of current unified evaluation benchmarks.

TABLE II
YEARLY EVOLUTION OF (LEFT) INPUT METHODS AND (RIGHT) APPLICATION DOMAINS IN SHARED AUTONOMY AND SHARED CONTROL RESEARCH (2020–2024). ARROWS INDICATE TREND DIRECTION: ↑ INCREASING, ↔ STABLE, ↓ DECREASING.

(a) Input Method

Input Method	2020	2021	2022	2023	2024	Total	Slope	Trend
Direct Control Interfaces	7	12	12	8	15	54	1.2	↑
Haptic	10	13	3	7	11	44	-0.4	↔
Kinesthetic Control	2	8	4	9	7	30	1.1	↑
Physiological Signal	3	6	4	4	6	23	0.4	↔
Gesture/Hand Tracking	2	3	2	5	6	18	1.0	↑
GUI	2	1	4	3	4	14	0.6	↑
VR/AR	1	2	2	0	4	9	0.4	↔
Language Controller	0	0	0	1	3	4	0.7	↑
Simulation/Dataset	0	1	2	0	1	4	0.1	↔
No Actual Interaction	0	2	0	0	0	2	-0.2	↔
Implicit Cues	0	2	0	0	0	2	-0.2	↔

(b) Application Domain

Application Domain	2020	2021	2022	2023	2024	Total	Slope	Trend
Assistive Robotics	5	11	12	8	13	49	1.3	↑
General Manipulation	7	6	7	11	15	46	2.1	↑
Medical Robotics	5	8	7	7	8	35	0.5	↔
Navigation Robotics	3	7	1	1	8	20	0.4	↔
UAV	2	5	1	0	3	11	-0.3	↔
HRC	1	5	1	3	0	10	-0.4	↔
Industrial Robotics	1	4	2	1	1	9	-0.3	↔
Multi-Robot Systems	1	2	1	0	3	7	0.2	↔
Space Robotics	1	1	1	1	4	8	0.6	↑
Emergency Response	0	2	0	0	1	3	0.0	↔

B. Research Trends

As indicated by the proceeding section, shared control/autonomy approaches span diverse input modalities, modeling approaches, and application domains. Motivated by this breadth, we introduce a new taxonomy for categorizing approaches for shared control/autonomy. Our taxonomy is human-centered and divides approaches based on the principal benefit that the approach offers to the human teammate. Given that shared control systems have long existed to help humans in work that would be completed manually otherwise (e.g., in person or through teleoperation), we argue this human-centered categorization is appropriate and will hopefully encourage future researchers to consider the principal human benefit when developing new algorithmic or applied approaches. From our review, we identified four main categories for the principal human benefit for shared control/autonomy: *minimizing human time (31 papers)*, *minimizing human input (43 papers)*, *improving human input quality (111 papers)*, and *maximizing human output (10 papers)*. In cases where a method is designed for multiple human benefits (they are not mutually exclusive), we chose the category that best aligned with the technical approach. We explain these categories in greater detail in the following sections and use the categories to structure our review of recent trends.

1) Minimizing Human Time: These methods are designed for tasks with periods that do not require human oversight and input, allowing the human to temporarily focus on a different task. A common approach is *traded control*, where a robot and human take turns completing sequences within the overall task [29]. Typically, it is assumed that the human has deeper knowledge of the task than the robot, and thus is prompted to takeover at key points throughout the task. The key to enabling such approaches is a *trigger* where the robot system recognizes the need for human input and can elicit help. Common approaches to developing trigger-based approaches to minimize human time include explicit role modeling based on task phase or context, and confidence-based approaches for the autonomous robot system to monitor when help is needed.

Many approaches to minimize human time explicitly model the task times when human input is needed. For example, several approaches elicit human input upfront to aid in downstream autonomous execution. These requests include asking the human to identify key manipulation parameters (e.g., grasp pose) [30], [31], [32], [33], [34], [35], [36] or register task trajectories under environment uncertainty [37]. Other upfront input approaches aim to understand the high-level plan or objectives of the human before the robot takes over, either through preference queries [38], [39], task sequences [40], or language clarifications [41]. In addition to upfront human input, it is also common to model and allocate subtasks to either the human or the robot. Several surgical robot shared control approaches study task variability and complexity to identify what surgical subtasks require human takeover [42], [43], [44], [45]. In manufacturing, Hopko et al. design a collaborative polishing task where the human provides input on challenging trajectory segments to study the impact of operator fatigue and characteristics in such takeover settings [46]. Finally, some approaches determine sub-task allocation (and thus, transitions of control) for humans and robots based on reinforcement learning approaches [47], [48]. Approaches leveraging explicit modeling of control handovers offer the benefit of knowing when human input will be requested, which can enable the person to better allocate and plan their time. However, these methods require explicit modeling of when human input is needed which is not always possible or possibly can lead to very conservative takeover requests. For example, there may be a suturing step in a medical operation that occasionally requires human intervention. In this case, explicit modeling

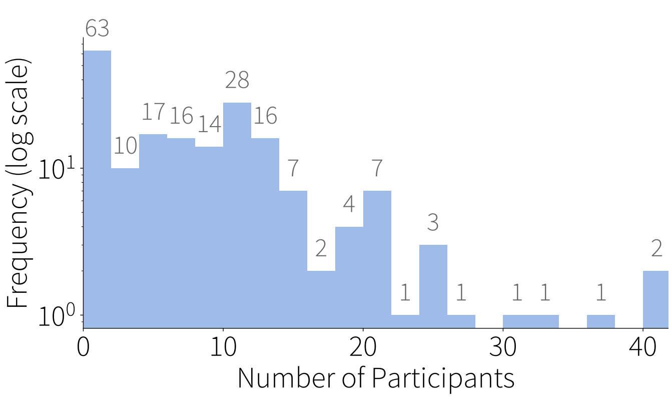

Fig. 3. Histogram of SC/SA evaluation participant count (bin size of two).

approaches will always hand over control to the person for the suturing though help is infrequently needed.

The second common class of trigger-based methods for minimizing human time develops confidence-based triggers on the robot side to indicate when the robot needs help. Triggers include identifying when the system deviates from the intended path [49], identifying when the automated system fails to generate a quality solution [50], [51], and explicit features measuring the likelihood of robot success on a task [52], [53]. The trigger can also be based on factors related to the human. This includes estimating the user's desired trajectory, such as in Huang et al. where confidence over the driver's desired trajectory is used in semi-autonomous driving and in Kizilkaya et al. where deep reinforcement learning is used to model mode-switching based on user trajectory intent [53], [54]. Li et al. [55] also show how human trust measures can be used to estimate confidence for takeover requests. In confidence-based approaches, the control can be frequently traded as the robot experiences intervals of varying confidence throughout the task. Several systems instead focus on mediating a single handover of control through a robot *autocomplete* where the robot observes the human inputs and takes over when it is confident it can complete the remainder of the task autonomously [56], [57], [58], [59]. In addition to confidence requests based on robot uncertainty, Owan et al. trade control based on robot *certainty* where the robot takes over when it is certain it can perform confined-space manufacturing tasks faster than human teleoperation based on a learned model from user demonstrations [60]. Finally, recent work by Liu et al. demonstrates how large language models can be leveraged in mediating takeovers by consulting an LLM that has been prompted with example scenarios where human input should be elicited [61].

TABLE III
YEARLY EVOLUTION OF MODELING APPROACHES IN SHARED AUTONOMY AND SHARED CONTROL STUDIES (2020–2024). ARROWS INDICATE TREND DIRECTION: ↑ INCREASING, ↔ STABLE, ↓ DECREASING.

Modeling Approach	2020	2021	2022	2023	2024	Total	Slope	Trend
Optimization	5	14	5	6	11	41	0.4	↔
Input Blending	4	8	6	7	7	32	0.5	↔
Compliance Control	1	9	6	2	6	24	0.3	↔
Intent / Goal Inference	1	6	4	4	7	22	1.0	↑
Reinforcement Learning	3	4	3	2	8	20	0.8	↑
Filtering	2	3	6	2	5	18	0.5	↔
Input Mapping	3	5	3	1	4	16	-0.2	↔
Planning	3	5	3	0	3	14	-0.5	↔
Supervisory Control	2	2	4	4	2	14	0.2	↔
Templates	2	1	5	1	5	14	0.6	↑
Virtual Fixtures	4	2	2	2	4	14	0.0	↔
Classical ML	2	6	1	1	3	13	-0.3	↔
Traded Control	4	2	1	2	3	12	-0.2	↔
Prob. Graphical Model	2	4	0	3	3	12	0.1	↔
Imitation Learning	1	3	4	1	2	11	0.0	↔
Generative Modeling	2	3	1	2	2	10	-0.1	↔
Prob. Modeling	1	3	2	2	2	10	0.1	↔
Divisible Control	1	3	2	1	3	10	0.2	↔
Multi-Robot Control	2	5	2	1	0	10	-0.8	↓
Deep Learning Models	0	1	0	2	2	5	0.5	↔
LLM-based Approaches	0	0	0	0	3	3	0.6	↑

2) Minimizing Human Input: These methods are designed for tasks where it is infeasible, undesirable, or unnecessary for the human to fully control the robot system, and thus the shared control approach focuses on minimizing the total input needed from the human to complete the task. Differentiated from *minimizing human time*, which can also minimize input by reducing intervention time, we categorize approaches that *minimize human input* as those assuming that the human is actively monitoring or giving continuous input as needed for the robot to succeed. These approaches typically rely on techniques to reduce the dimension of human control input. Common approaches include dimensionality reduction techniques, divisible shared control, and interfaces to provide sparse corrective or supervisory input.

In cases where the appropriate robot actions can be inferred by low-dimensional human input, dimensionality reduction techniques are often used in shared autonomy to reduce the input burden for humans. A common approach leverages *shared control templates* (SCTs) that define low-dimensional control spaces for particular tasks [62], [63], [64], [65]. In addition to minimizing human input, SCTs have also been shown to benefit traded control approaches [66] and robot learning [67]. Often, including some SCT methods, the approach to dimensionality reduction is data-driven. Losey et al. use a variational autoencoder to learn a low-dimensional mapping for manipulation tasks from task demonstrations [68], [69]. Variants have also been proposed to eliminate the need for demonstrations [70], learn a linear control mapping [71], present discrete options to the user [72], and to use facial movements as the low-dimensional input [73]. Instead of directly mapping inputs to robot commands, other methods use demonstration variance to extract low-dimensional human corrective interfaces to adjust the robot's behavior [74], [75], [73]. A similar corrective approach is used in Chang et al. to correct the robot optimization objective rather than the current robot behavior [76]. Cognetti et al. also employ a corrective mechanism for robot navigation tasks where users can adjust the properties of the trajectory represented by a B-spline [77].

Another common approach to reducing human input involves *divisible shared control*, where the human controls a subset of the robot's output and the remaining dimensions are controlled by the robot. One possible allocation is where the human remotely teleoperates a robot manipulator and the shared control automatically controls the view of a camera [78], [79]. Other typical allocations include where the robot controls only force or alignment [80], [81], the distal robot joints [82], the vehicle the robot arm is attached to [83], and a second robot arm during bimanual surgical operations [84]. While most approaches rely on the robot inferring control outputs that complement the partial human input, several approaches instead divide the robot control across several human users [85], [86]. Finally, some divisible approaches are designed for the robot to provide assistance during physical human-robot collaborations [87], [88]. Here the task is divided across the human and robot rather than dividing robot control dimensions. For example, Tao et al. learn a cooperative robot policy for multi-agent object manipulation by iteratively refining a model of the human's goal [89].

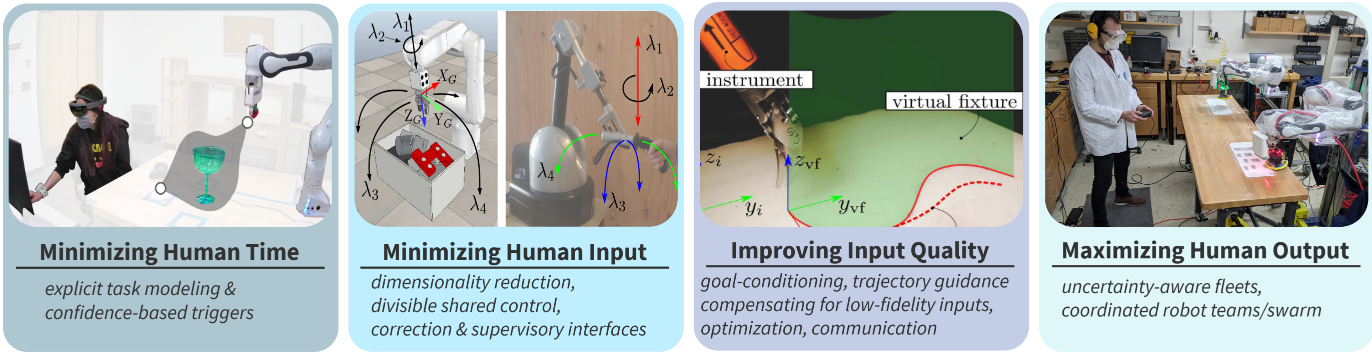

Fig. 4. Summary of the high-level trends (*including a representative approach*) of the shared control/autonomy survey, categorized by the principal benefit offered to the human. *(Left to right)* A representative approach for *minimizing human time* has a human completing a secondary task until they receive haptic feedback that the robot requires assistance (Reprinted from [103], © 2021 IEEE. Reprinted with permission). A representative approach for *minimizing human input* has the human provide four-degree-of-freedom input and the robot infers the remaining degrees of orientation during grasping (Reprinted from [104], © 2018 IEEE. Reprinted with permission). A representative approach for *improving input quality* involves virtual fixtures during remote teleoperation to aid in tracking dissection splines during a surgical procedure (Reprinted from [105], © 2018 IEEE. Reprinted with permission). Finally, a representative approach for *maximizing human output* involves a human assisting multiple robots sequenced around uncertainty (Reprinted from [106], © 2023 IEEE.).

The final common approach to *minimize human input* has the person actively monitor and provide sparse intervention to the robot as it works. Several methods rely on physical interventions where the person interrupts and physically guides the robot through the correct actions [90], [91], [92], [93], such that the robot can learn desired behavior for future task instances. Instead of applying physical input directly to the robot, Shen et al. provide a physical coupling through a haptic input device that uses a control barrier function to enforce that only safe changes are made to the robot task model [94]. Outside of physical intervention, other recent work has investigated sparse input using head control [95], Electroencephalography (EEG) [96], [97], a laser pointer [98], natural language [99], and user preference queries [100], [101]. Lin et al. investigate the impact of unreliable autonomy on systems employing sparse user inputs and correlations to the desired level of robot autonomy [102].

3) Improving Input Quality: These are methods where the primary purpose of the interaction is to take user input, which is often imperfect or coarse, and to refine it toward successful task completion. Such setups are the most popular in recent shared control/autonomy literature and tend to focus on settings where it is possible for the robot to, at least, partially model the task (e.g., user intent) and fuse its task knowledge with the provided human input to achieve more accurate or efficient task outcomes. Common motivations and approaches to improve input quality involve blending input based on online human goal/intent prediction, explicit methods to compensate for low-fidelity human input, trajectory guidance methods, and optimization approaches.

A popular shared control approach was introduced by Dragan et al. [17] where a robot uses the past human trajectory to infer the most plausible goal object location and provide assistance toward an optimal trajectory to the desired goal. Since that time, goal-conditioned or intent-predict based methods have remained popular in shared control/autonomy. Many recent methods similarly infer user goals [107], [108], [109], [110], [111] or desired future actions [112], [113], [114], [115], [116], [117], [118], [119] to provide appropriate assistance. Cai et al. propose a hierarchical framework that infers both high-level goals and low-level actions. When blending inputs based on inferred goals, communication is critical for successful teaming [120]. Haptic feedback is commonly used to indicate robot desired assistance [121]. Mullen et al. additionally investigate augmented reality for communicating the planned assistance and uncertainty over intent [103]. While past human inputs are the most common signal to detect intent, gaze is also often used as an additional signal that can indicate intent [122], [123]. Often the input blending in these systems directly combines the human input and robot estimated action (e.g., as a weighted combination), but Bowman et al. investigated different blending coefficients for each robot control dimension [124]. Beyond input blending, goal-inference approaches can also be applied to close-proximity human-robot collaboration where intent inference is used to plan collaborative actions or avoid collisions with the human [125], [126].

A second common motivation for systems that improve input quality is for settings where human input is low-fidelity or coarse. In contrast to goal inference, where assistance improves efficiency but the person could complete the task on their own, in low-fidelity settings the raw human input is typically insufficient for task success. Commonly, these systems use Electromyography (EMG) input [127], [128], [129], [130], [131], [132], [133], [134], [135], inertial measurement units (IMUs) [136], [130], [137], and brain machine interfaces (BMIs) [138]. In the case of EMG or BMI input, the motivation is typically for assistive shared control/autonomy setups where these signals can aid users who might not be able to provide input through another means. IMUs are leveraged for their affordability and setups often aim to exploit their use for mobile input devices that are accessible to a wider range of users. Beyond these coarse human inputs, Sanchez et al. explore the use of foot control for laparoscopic surgery [139], Panzirsch et al. explore force interactions using virtual reality interactions [140], and Laghi et al. use vision to improve human inputs using a virtual reality controller for high precision bimanual manipulation tasks [141]. While it is typically assumed that the physical interface is the source of coarse or lower-fidelity input, Cho et al. use a similar formulation to study how novice remote driving can be improved by modeling the novices as experts corrupted by noise [142].

When tasks can be modeled more explicitly, including safe regions of operation, methods often employ explicit trajectory guidance. Such methods frequently leverage *virtual fixtures* (VFs) [16] that constrain the actions that the person can execute. VFs typically provide either haptic guidance or input overrides through blending to ensure users control the robot safely and efficiently. Several recent methods focus on surgical or medical applications where the virtual fixtures provide trajectory guidance toward safer behaviors [143], [144], [145], [146], [147], [148]. For example, Marinho et al. use virtual fixtures during suturing to guide the surgeon toward higher-performing needle passes [146]. Outside of surgery, other approaches employ virtual fixtures for explicit trajectory modeling in periodic tasks [149], [150] and for path following applications [151], [152], [153], [154], [155], [156]. It is also common to derive virtual fixture trajectories based on prior human demonstrations [157], [158]. Dynamic movement primitives (DMPs) and other movement primitives are used to learn stable trajectories from a small number of demonstrations that can later be used for trajectory assistance [159], [160], [161], [162], [163]. Gaussian processes and Gaussian mixture models are also commonly used to encode demonstrations for use in virtual fixtures and can vary assistance based on the model variance [164], [165], [166], [167]. Human demonstrations can also be used to formulate primitive geometric constraints in shared control/autonomy systems [168], [169], [170]. Several recent approaches leveraging virtual fixtures also aim to provide a more interactive experience with the user. Poignonec et al. develop an approach where the fixtures adjust over time for cases with incorrect guidance or a shifting desired trajectory [171]. Pruks et al. provide an interactive framework where users can specify features, primitives, and constraints to build fixtures for challenging contact tasks [172].

The third major category of approaches *improving input quality* leverage optimization approaches. Dating back to early work on potential fields [15], many methods leverage optimization to avoid robot collisions. Modern approaches still aim to create effective optimizations that preserve human input as possible while effectively calculating and avoiding collisions [173], [174], [175], [176]. Often collision information is conveyed to the user through haptics [177], [178], [179], though Chen et al. leverage augmented reality during surgical applications for the human to visualize difficult-to-see anatomy [180]. Zhong et al. [181] propose a haptic feedback approach to collision avoidance that further measures human attention to allow for closer passes to collision geometry when the person is highly engaged. Beyond collisions, optimization is also used for broader notions of safety and stability. Several methods filter user inputs to preserve the overall robot system stability [182], [183], [184]. Other methods filter inputs to preserve additional safety measures, such as in safety-critical applications like semi-autonomous vehicles [185], high-speed drones [186], and an assistive wheelchair [187].

Given the flexibility of optimization formulations in shared control/autonomy, other approaches more broadly use optimization to preserve desirable motion properties. For example, in surgical applications, optimization can be used to minimize force and damp surgeon tremor [188], [189] and in general applications, optimization helps create desirable (e.g., smooth) motion outputs [190], [191], [192], [193]. Backman et al. use optimization in drone landing to optimize the inputs of less-experienced pilots to better match expert inputs [194]. In shared control/autonomy systems involving physical human-robot interaction (pHRI), optimization is often used to adjust the impedance or admittance of an interaction [195], [196], [197], [198], [199], [200], [201]. For example, Pezeshki et al. propose a game-theoretic approach to set the gains and stiffness of a variable impedance rehabilitation robot [197]. In pHRI interactions, the optimization of the shared controller often also prioritizes minimizing physical human effort [202], [203], [204], [205], [206], [207], [208] or improving ergonomics [209], [210], [211]. For example, Mitra et al. design an approach to optimize ergonomics during object handovers between a robot and human [209].

Work on improving input quality also extends beyond technical formulations for input blending. Recent work investigates practical concerns such as how to communicate with the human and the impacts of unreliable autonomy. Regarding communication, Zhang et al. show how haptic feedback can be used to signal the level of robot autonomy and can improve the user's experience [212]. Jonnavittula et al. show how the robot can change its task movements to communicate how it is interpreting human inputs [213]. Concerning the reliability of autonomy, systems that improve the human's inputs are only useful when the system can determine required modifications to the human input. Balachandran et al. learn an adaptive policy that shifts back control authority to the human as vision measurements of the robot system degrade [214]. Other works show how reliability can be assessed implicitly by measuring human trust of the robot in the shared control/autonomy system [215], [216]. For more successful deployments of future shared autonomy systems, we hope to see increased work investigating practical considerations for system deployment, including bidirectional communication and methods assessing and improving the robustness of autonomy.

4) Maximizing Human Output: These approaches typically rely on scaling a person's output across supervision of a small fleet or coordinated set of robots. Differentiated from approaches to shared control that *minimize human time* as the primary objective, these settings often heavily utilize the worker (i.e., the worker remains in the loop) while distributing their input across several robots.

A common approach involves fleet supervision, where one person oversees multiple robots and the individual robots request human input during periods of uncertainty. Papallas et al. propose a multi-robot shared control approach where human supervision is requested when mobile robots are unable to effectively plan through trajectory optimization [217]. Hagenow et al. propose a multi-robot shared autonomy approach that learns times of task uncertainty from expert demonstrations and develops a scheduling optimization such that a single operator can intervene across robot executions that offset periods of variability [106]. Swamy et al. propose a fleet supervision method that shifts recognition of uncertainty to the human and estimates the likelihood that human assistance will be given to robots in a mobile robot fleet [218]. The trends of intervention are empirically learned from small-scale supervision experiments. Finally, Chandan et al. show how augmented reality can provide passive guidance during multi-robot supervision so the person can visualize robot plans and plan intervention accordingly [219].

Instead of individual intervention, several methods use human input to coordinate the efforts of a robot fleet toward a centralized task. Miyuachi et al. develop a multi-operator, multi-robot strategy where a swarm of robots balance task completion and maintaining communication lines under physical constraints [220]. Dai et al. propose a brain-computer interface that estimates human intent and uses the estimated intention field to focus the efforts of a swarm of robots in foraging [221] and firefighting [222] applications. Macchini et al. propose a shared control method where human gestures control a leader drone that coordinates a collective swarm behavior of drones via Reynold's algorithm [223]. Focusing instead on manipulators, Ozdamar et al. propose a control architecture where a person can control multiple arms, including groups of coordinated arms, during general manipulation [224] . Finally, Yang et al. investigate multi-robot conflict resolution when the input to the fleet is shared across several users [225].

Given the practical constraint that these methods require fleets of robots, there has been relatively less work in shared autonomy. We expect that as robot hardware becomes more accessible, we will see growth in this category. Early work mostly demonstrates how to direct the operator's attention across multiple robots or to coordinate the actions of robots toward a central goal. There are many unanswered questions including how to enable effective fleet communication for coordinated efforts (i.e., tasking a leader robot and effectively delegating to the fleet) and how to scale human intervention methods to larger fleets of robots where it becomes challenging to maintain situation awareness [226]. Furthermore, we see opportunities to bridge the two main approaches, where agents can both coordinate and conduct individual work under the supervision of a human.

V. Generative Artificial Intelligence in Shared Control/Autonomy

Like in many robotics areas, the rapid growth of generative model capabilities has created new opportunities in shared control and shared autonomy. While work in this area is not yet mature, we expect to see significant growth in the coming years. In this section, we overview emerging shared autonomy with generative artificial intelligence (AI), including models for input dimensionality reduction (Sec. V-A), opportunities with large generative imitation models (Sec. V-B), and recent shared autonomy interfaces with generative robot policies (Sec. V-C). Based on the trends, we also provide recommendations for pertinent work for generative AI and shared autonomy in Section VI.

A. Simplifying Human Input with Generative AI

Before generative models were capable of modeling complex long-horizon task behavior, their initial use in shared autonomy was as part of *lower level-of-autonomy* systems that simplify user input by learning a low-dimensional action mapping through a generative model. Typically contextualized in teleoperation, the goal of these systems is to develop latent low-DoF control spaces that allow users to "turn simplified knobs" to guide robots through task completion without the high physical and cognitive burden associated with high-DOF teleoperation. Here, the use of a generative model affords learning from and reproducing multi-modal action distributions. Early work learned fixed one or two-DoF latent actions from demonstrations for smooth assistive teleoperation, for example using a conditional variational autoencoder (CVAE) [68]. Subsequent formulations build on the core latent space formulation. For example, it is possible to adapt latent mappings online based on the user's inferred intent, so that the same joystick input can change meaning as goals become clearer [227]. Language was also explored as a higher-level interface to manage different latent mappings. For example, LILA binds language to latent spaces [228], and LAMS uses LLMs to auto-switch latent mappings so that users can provide simple two-DoF inputs without a need to toggle mappings [229]. While language is employed in several methods, the core motivation of latent action methods is to ground user inputs to continuous robot actions, which is a complementary capability to language, which typically serves higher-level task communication. This dichotomy is also reflected in recent work with generative robot policies, described below. Summarizing, these early generative model shared autonomy works let humans shape rich robot behaviors from generative models with heavily simplified user input.

B. Generative AI Robot Policies and Opportunities

With recent efforts toward robot foundation models, new opportunities are emerging for shared autonomy, particularly focusing on targeted human interactions with generative robot policies. To better understand this context, we first provide a high-level overview of recent advances in generative policies and the corresponding impact on shared autonomy. Behavior cloning (BC) remains a common approach for modeling and learning robot behaviors, and most recent methods model action distributions generatively [230]. While early BC struggled with coverage of the state space and multi-modal data, newer approaches—autoregressive policies (e.g., ACT/ALOHA and generalist visuomotor models) [231], [232], diffusion policies [233], [234], [235], and flow-matching policies [236], [237]—learn richer, multi-modal action distributions with much stronger capabilities in modeling long-horizon behavior. Given that shared autonomy systems rely on some amount of robot autonomy and task modeling, more capable models have opened the doors for more versatile shared autonomy approaches. Most of these models are trained via human data, and thus scalable data-collection interfaces have seen increased attention [231], [238], [239], [240]. By developing effective human demonstration interfaces, generative models are able to learn both to more robustly perform and assist in contact-rich manipulation robot behaviors [241], [235]. Given the importance of high-quality data, recent work has investigated how to apply shared autonomy methods for better data collection [242].

Despite growing data and more capable policies, autonomy with generative models remains brittle. For example, π_0 highlights challenges in generalizing to open-world settings. A lack of robust autonomy limits the utility of these models in safety or performance-critical domains [232], [236], [230]. Moreover, while generative policies are capable of modeling multi-modal behaviors, it is not clear whether multiple trajectories are always equally desirable or if human input is needed to disambiguate between them [243]. Thus, there are many opportunities for shared autonomy with these frontier models: from data collection, to uncertainty-aware methods where shared autonomy helps improve overall robustness. Next, we discuss early works tackling such challenges, for example through interactive language and policy steering methods.

C. Shared Autonomy with Generative Robot Policies

Shared autonomy interfaces for interacting with generative robot policies can be generally separated into two categories: interfaces leveraging language and interfaces leveraging lower-level interactions (e.g., to the robot state or actions). Starting with language, many modern policies are language-conditioned, making language a natural interface for shared autonomy. Several system architectures support basic human interaction by accepting a single initial language prompt and then executing the robot behavior open-loop (e.g., OpenVLA, Octo, π_0) [232], [234], [236]. Recent work enables more real-time language guidance. Language interventions have been shown to support real-time behavior changes and to improve long-horizon manipulation [244], [245]. Recent work has also shown that iterative human-in-the-loop pipelines (e.g., language model question-asking paradigms) improve LLM-conditioned manipulation [61]. In addition to helping in the moment, Zha et al. show how language corrections can be distilled into policy knowledge to reduce future interventions [99]. Language can also be combined with low-DoF input (e.g., through a joystick) or robot queries for language assistance to create more capable shared autonomy loops [246], [41]. Language thus provides a convenient and flexible interface for shared autonomy, but assumes that human feedback can be grounded in the robot's control space.

Because language may not always be sufficiently grounded in robot actions, several recent generative shared autonomy methods let users intervene directly in the policy's action or trajectory space. The majority of these methods leverage diffusion policies for their capabilities in representing multi-modal task behavior. One of the earliest approaches, Diffusion for Shared Autonomy, casts the input-blending assistance problem as denoising in the policy action space [247]. Diffusion shared autonomy policies have also investigated safe handovers of control [248], causal low-level edits of behavior during execution [249], physical human-robot collaboration [250], and methods to circumvent the latency associated with diffusion model inference [251]. Promoting further flexibility, Inference-Time Policy Steering (ITPS) uses human input (e.g., keypoints, trajectory sketches, or small physical perturbations) to bias sampling in a frozen generative policy—balancing human alignment with the policy's distribution of learned behavior [243]. Complementary to language shared autonomy interfaces, these lower-level interfaces enable human input grounded directly in robot actions.

VI. General Discussion

In this section we summarize the findings of our survey. First, we provide recommendations for future work in shared autonomy, considering the five-year trends and recent methods involving generative AI. We end with a discussion about the limitations of our survey (and corresponding opportunities for future work) and broad conclusions.

A. Recommendations

Based on the trends identified throughout our review, we identified five core recommendations for future research in shared control and shared autonomy systems. Our recommendations include both broad recommendations for shared autonomy (recommendations 1, 2, 3, and 5) informed by our analysis of recent literature as well as specific efforts that are needed for future generative AI systems (recommendation 4).

1) Improving the Breadth and Richness of Human Interaction in Shared Control/Autonomy Systems: From our review, we find that current systems primarily focus on fundamental technical questions in shared control/autonomy—such as when to request help, how to give input, and how to blend inputs in a safe and effective way—while comparatively little research addresses how to create high-quality, user-centered interactions. A key concern is that technologies developed without intentional efforts to optimize the human experience may hinder adoption if the shared autonomy system is not engaging or aligned with the human's interaction preferences.

While most shared autonomy systems rely on a fixed type of human input, a promising direction is in developing systems that accept flexible human input. Recent work has investigated this in two main areas: *interactive learning* and *real-time corrective feedback*. Interactive learning is designed for more flexible human input [252], including systems where the human selects the appropriate feedback to provide [253], [254], [255] and systems that define fixed interaction sequences [256], [257], [258]—for instance, beginning with demonstrations and switching to preferences as the model improves. For real-time interactions, Wang et al. explore how multiple human inputs (e.g., physical intervention, keypoints, sketches) can be used to steer a generative policy [243]. Finally, toward more rich *robot-initiated* interactions in shared autonomy, INQUIRE and REALM are two recent approaches that reason about the value of different human inputs and elicit the most informative feedback in offline interactive learning and real-time control settings, respectively [259], [260]. Given the nascency of flexible input shared autonomy approaches, we view this direction as an important open area.

More rich interaction in shared autonomy also requires further efforts in how robots communicate and ask for feedback in shared autonomy. With emerging generative AI capabilities, we will see new frontiers of interaction in shared autonomy. For example, new generative predictive visual models could present options to the user in the form of video synopses for how the robot wants to proceed [261], [262]. We expect that human-centered shared autonomy systems that integrate flexible input and expressive communication with lead to more natural, conversational, and engaging collaboration.

2) Performance and Safety Guarantees for Learning-Based Shared Autonomy: An important issue is how to provide meaningful safety assurances during learning. Learning often involves exploration, and in shared autonomy, that exploration occurs while humans and robots jointly control the system. Safety must therefore be guaranteed both during the learning process and in the resulting learned behavior. Safe exploration methods, such as those based on control barrier functions or uncertainty-aware arbitration, can help ensure that learning proceeds within safe boundaries [263]. Overly restrictive safety measures, however, can also inhibit learning and adaptation. Balancing safety with the need for progress remains an open research challenge.

These questions take on urgency in high-risk domains such as assistive robotics, surgical systems, and physical rehabilitation, where the consequences of unsafe learning are immediate and severe [264]. In these settings, shared autonomy may act as a safety buffer that limits the robot's autonomy while leveraging human oversight. However, as systems become increasingly learning-driven, the field needs methods that maintain safety envelopes while allowing robots to adapt to user-specific needs, physical limitations, or changing contexts. For example, an assistive robot that learns from user demonstrations must ensure safety even when the human provides an incomplete or suboptimal example. This tension between personalization and protection is a key challenge for future work.

One promising direction is to couple learning with formal safety frameworks and human-centered communication mechanisms. Natural language input and output could allow humans to define safety constraints, clarify intentions, or authorize specific actions. At the same time, the robot could communicate its uncertainty, reasoning, or safety status in human-understandable terms. This approach connects closely to the previous recommendation, which emphasizes richer multi-modal interaction. Treating language as both a safety and learning channel could enable safer and more transparent shared autonomy systems. Moving ahead, open questions remain. How can we formalize and measure safety during interactive learning? How can we design learning objectives that adapt to human feedback without exceeding risk thresholds? And how can we ensure that safety mechanisms remain interpretable and trusted by the human collaborator? Addressing these questions will require joint progress in control theory, interactive learning, and human-robot communication.

3) Toward Open World Shared Autonomy: Existing work on shared autonomy often focuses on carefully controlled environments. This is a natural first step; but for real-world impact, we need to relax this strong domain knowledge and move towards open-ended conditions. Overall, open world shared autonomy faces challenges from both the *robot's perspective* and the *human's perspective*.

From the robot's perspective, the key issue is robustness to out-of-distribution contexts. The designers cannot anticipate every way in which the robot will need to assist the human user; accordingly, the robot will need to learn how to share autonomy for previously unseen scenarios. Early works on shared autonomy often assumed a nominal trajectory or a fixed number of goals, and modulated that trajectory or goal based on the human's inputs [17]. For unstructured tasks, future works on shared autonomy will need to learn new trajectories (or identify previously unspecified goals). This could be achieved through the intersection of shared autonomy and imitation learning: for example, the human user might guide the robot through the entire task, and then—the next time the human faces that task—the robot extrapolates from the previous example to provide assistance [265], [116]. Of course, if the robot's shared autonomy adapts over time, then the performance of that assistance also fluctuates. Within unstructured environments the robot will therefore need to identify when it can and cannot provide meaningful assistance. Here we need robots that are able to recognize what they do not know, and to defer to the human when uncertain.

From the human's perspective, the key issue for open world shared autonomy is how everyday users interface with partially automated systems. It is not clear when and how humans expect robots to provide assistance. Part of the solution here focuses on educating users (for example, through augmented reality interfaces [266]) so that they can build mental models of their robotic partners (i.e., training users on how to operate shared autonomy robots). But another side is making shared autonomy algorithms that are inherently intuitive so that users can seamlessly integrate with them. Here we envision algorithms with controls-grounded formulations, uniting the open-ended assistance of shared autonomy with clearly understood and predictable patterns of control systems. This could more generally take the form of visualizing the robot's plan, notifying the human when the robot is going to take or return control, having safety barriers to prevent catastrophic disagreements, and asking for the human's feedback to improve future experiences.

Beyond robot and human aspects, there is also a temporal challenge to open world shared autonomy. Most experiments surveyed in this paper take place in a less than a one hour period. But when we rollout these shared autonomy robots in the real world, people will be interacting with these robots for days, months, and years. This means that challenges that arise in short user studies may no longer be significant over longer periods (i.e., as users get more familiar with the system). Conversely, new issues may arise that we have not perviously encountered. For example, as the robot adapts to the person (and the person adapts to the robot), the person might change their habits to select tasks that the robot can efficiently assist for. For example, if the robot is really good at making coffee, but terrible at making tea, the user might settle for coffee more frequently. This sort of social and behavioral impact is not well understood, and should be considered in future works.

4) Adapting and Developing Generative Models for Shared Autonomy Interactions: Going forward, we see two emerging ways that shared autonomy interacts with frontier generative models: approaches that add human interfaces to existing generative models, and new generative models where interaction is developed as a part of the robot's model architecture.

Integrating shared autonomy with existing models requires understanding the available signals from models that can be used to request and structure human input. There is a long history in shared autonomy of using confidence measures to inform when human interventions are needed for the robot system (i.e., *minimizing human time* in Section IV). A key challenge with emergent models is determining how to represent robot uncertainty. Several recent methods propose entropy and loss metrics for diffusion trained policies to understand when they are encountering out-of-distribution states or have ambiguity over multiple actions that may be taken (i.e., multimodal behavior) [267], [268]. A similar process has also been used for vision-language-action models where token-level uncertainty is used to trigger human assistance [269]. More broadly, we are also starting to see more work proposing metrics to assess the confidence of VLA models [270]. While these papers are promising starting points, more work is needed for reliable assistance triggers that consider the many sources of model uncertainty. If assistance can be reliably triggered, an open question is how the person should provide feedback to the robot, for example through language or by taking over on the task until robot confidence is restored. As mentioned above, this is tightly coupled with communication where the policy should be able to indicate the information needed to address its uncertainty. As open-source generative robot models continue to advance, we hope to see more end-to-end SC/SA systems addressing these key interface elements.

Rather than building shared autonomy around existing generative robot policies, there are also opportunities to make shared autonomy and general human interaction a more fundamental part of future large generative models. Currently, this is not done for large models, and shared autonomy approaches instead adapt pretrained policies for interactions [243], [271] or train policies that accept limited human feedback during execution [244], [245]. While these capabilities are useful, future robot foundation models should integrate shared control interactions directly within the model architecture. For example, future models may have action heads that expose steerable subspaces, explicit "ask-for-help" tokens, calibrated confidence estimates, and sampling strategies designed for human-in-the-loop operation. By considering shared autonomy architecture in large models, we can encourage human interaction as a core foundation-model capability to be designed and evaluated when building new models [272]. Beyond interfaces for shared autonomy input, an open question is how interactive models can serve as adaptive teammates that personalize over longitudinal use by people.

5) Developing Benchmarks to Standardize Evaluations, Tasks, and Metrics: Our survey indicates that the experimental metrics, tasks, and study design vary greatly across shared control/autonomy literature. Following the popularity in other areas of robotics (e.g., manipulation [273], reinforcement learning [274], planning [275]), ideally benchmarks could be developed to define standard tasks and experimental protocols for shared autonomy. One critical difference in shared autonomy is the human, which can make it challenging to design benchmarks that meaningfully assess shared autonomy systems. Furthermore, given differing goals and assumptions of shared autonomy systems, it can be difficult to establish reasonable baselines from existing literature when designing experiments. Thus, there has been limited benchmarking work in shared autonomy, and the few shared autonomy benchmarks typically focus on specialized domains. Pan et al. propose a Fitt's law benchmark for target-reaching tasks using shared autonomy [276]. For assistive applications, Stolen et al. propose a shared control benchmark consisting of system modeling, metrics, and practices for benchmarking [277]. Assistive Gym further provides modeled tasks and pretrained baseline policies to encourage benchmarking of assistive policies [278].

To expand work in benchmarking for shared autonomy, there are critical questions remaining. How can we design benchmarks with sufficiently-general tasks to promote adoption by the research community? We also believe that defining key metrics and baselines for shared autonomy benchmarking are still open questions. One promising direction is to define subproblems within shared control/autonomy to establish benchmarks. We believe that our categorization in Section IV might provide an appropriate starting point to scope such future benchmarks. For example, a benchmark focused on *minimizing human time* could standardize secondary tasks, baselines, and metrics related to worker utilization and situation awareness. Whereas, for systems focused on *maximizing human output*, we might focus on fleet tasks and metrics related to switching and robot fan-out [279]. While inevitably, shared autonomy systems require domain-specific assumptions, which makes development of meaningful benchmarks challenging, we believe there exists a taxonomy of benchmarks (such as a benchmark for every principal human benefit) that strikes an appropriate middle ground and will move the field toward better standardization in metrics and evaluation.

B. Survey Limitations

For tractability, we conducted our survey over a five-year window with three general robotics publication venues. Future work could look at longer time periods or more inclusive publication venues, but may limit how thoroughly trends can be identified. Additionally, we provided descriptive statistics related to input method, modeling, and application. Because some areas (e.g., surgical robotics) have specialized conferences, we acknowledge that this trend reporting specifically considers publication rates in general venues. Finally, our evaluation of generative AI focused on identifying popular and promising emergent approaches. Once there is a larger body of mature literature, it would be interesting to conduct a systematic review of generative AI and shared control/autonomy.

C. Conclusions

We present an updated survey on shared control/autonomy that focuses on areas under or unexplored in past survey literature, including the historical perspective of shared control and shared autonomy, recent descriptive trends of methods, and the growing role of generative AI. As part of our investigation, we provided an updated look at trends including a new taxonomy for categorizing approaches based on their principal human benefit: *minimizing human time*, *minimizing human input*, *improving human input quality*, and *maximizing human output*. We also provide a look at emergent literature leveraging generative artificial intelligence for shared autonomy. Based on our identified trends, we provide updated recommendations for future research.

Acknowledgment

The authors would like to thank Thomas Sheridan for reviewing the historical section.

References

[1] D. A. Abbink, T. Carlson, M. Mulder, J. C. De Winter, F. Aminravan, T. L. Gibo, and E. R. Boer, "A topology of shared control systems—finding common ground in diversity," *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 5, pp. 509–525, 2018.

[2] D. P. Losey, C. G. McDonald, E. Battaglia, and M. K. O'Malley, "A review of intent detection, arbitration, and communication aspects of shared control for physical human–robot interaction," *Applied Mechanics Reviews*, vol. 70, no. 1, p. 010804, 2018.

[3] M. Selvaggio, M. Cognetti, S. Nikolaidis, S. Ivaldi, and B. Siciliano, "Autonomy in physical human-robot interaction: A brief survey," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7989–7996, 2021.

[4] G. Li, Q. Li, C. Yang, Y. Su, Z. Yuan, and X. Wu, "The classification and new trends of shared control strategies in telerobotic systems: A survey," *IEEE Transactions on Haptics*, vol. 16, no. 2, pp. 118–133, 2023.

[5] Y. Xing, C. Huang, and C. Lv, "Driver-automation collaboration for automated vehicles: a review of human-centered shared control," in *2020 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2020, pp. 1964–1971.

[6] M. Marcano, S. Díaz, J. Pérez, and E. Irigoyen, "A review of shared control for automated vehicles: Theory and applications," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 6, pp. 475–491, 2020.

[7] W. Wang, X. Na, D. Cao, J. Gong, J. Xi, Y. Xing, and F.-Y. Wang, "Decision-making in driver-automation shared control: A review and perspectives," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 5, pp. 1289–1307, 2020.

[8] W. R. Ferrell and T. B. Sheridan, "Supervisory control of remote manipulation," *IEEE spectrum*, vol. 4, no. 10, pp. 81–88, 1967.

[9] T. B. Sheridan, *Telerobotics, automation, and human supervisory control*. MIT press, 1992.

[10] A. Freedy, G. Weltman, and J. Lyman, "Learning control systems using computer with application to remote manipulation," in *Proceedings of the 1972 IEEE Conference on Decision and Control and 11th Symposium on Adaptive Processes*. IEEE, 1972, pp. 326–327.

[11] A. Freedy, F. C. Hull, L. F. Lucaccini, and J. Lyman, "A computer-based learning system for remote manipulator control," *IEEE Transactions on Systems, Man, and Cybernetics*, no. 4, pp. 356–363, 1971.

[12] D. L. Akin, R. D. Howard, and J. Oliveria, "Human factors in space telepresence," Tech. Rep., 1983.

[13] T. NAGATA, M. MUKAIDONO, and R. MUROI, "A method of computer control for an industrial robot with conversational mode," *Transactions of the Society of Instrument and Control Engineers*, vol. 6, no. 6, pp. 570–578, 1970.

[14] A. Madni, Y.-y. Chu, and A. Freedy, "Intelligent interface for remote supervision and control of underwater manipulation," in *Proceedings OCEANS'83*. IEEE, 1983, pp. 106–110.

[15] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," *The international journal of robotics research*, vol. 5, no. 1, pp. 90–98, 1986.

[16] L. B. Rosenberg, "Virtual fixtures: Perceptual tools for telerobotic manipulation," in *Proceedings of IEEE virtual reality annual international symposium*. Ieee, 1993, pp. 76–82.

[17] A. D. Dragan and S. S. Srinivasa, "A policy-blending formalism for shared control," *The International Journal of Robotics Research*, vol. 32, no. 7, pp. 790–805, 2013.

[18] G. Hirzinger, J. Heindl, K. Landzettel, and B. Brunner, "Multisensory shared autonomy-a key issue in the space robot technology experiment rotex," in *Proc. IEEE Conf.*, 1992.

[19] G. Hirzinger, N. Sporer, M. Schedl, J. Butterfaß, and M. Grebenstein, "Torque-controlled lightweight arms and articulated hands: Do we reach technological limits now?" *The International Journal of Robotics Research*, vol. 23, no. 4-5, pp. 331–340, 2004.

[20] P. Michelman and P. Allen, "Shared autonomy in a robot hand teleoperation system," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'94)*, vol. 1. IEEE, 1994, pp. 253–259.

[21] K. Landzettel, B. Brunner, and G. Hirzinger, "The telerobotic concepts for ess," in *IARP Workshop on Space Robotics, Montreal*, 1994.

[22] R. H. Taylor, C. B. Cutting, Y.-y. Kim, A. D. Kalvin, D. Larose, B. Haddad, D. Khoramabadi, M. Noz, R. Olyha, N. Bruun *et al.*, "A model-based optimal planning and execution system with active sensing and passive manipulation for augmentation of human precision in computer-integrated surgery," in *Experimental Robotics II: The 2nd International Symposium, Toulouse, France, June 25–27 1991*. Springer, 1993, pp. 177–195.

[23] S. HIRAI, "A theoretical view of shared autonomy," *Journal of the Robotics Society of Japan*, vol. 11, no. 6, pp. 788–793, 1993.

[24] H. Asama, "Trends of distributed autonomous robotic systems," in *Distributed Autonomous Robotic Systems*. Springer, 1994, pp. 3–8.

[25] M. R. Endsley and D. B. Kaber, "Level of automation effects on performance, situation awareness and workload in a dynamic control task," *Ergonomics*, vol. 42, no. 3, pp. 462–492, 1999.

[26] J. Luo, C. Xu, J. Wu, and S. Levine, "Precise and dexterous robotic manipulation via human-in-the-loop reinforcement learning," *Science Robotics*, vol. 10, no. 105, p. eads5033, 2025.

[27] C. O. Retzlaff, S. Das, C. Wayllace, P. Mousavi, M. Afshari, T. Yang, A. Saranti, A. Angerschmid, M. E. Taylor, and A. Holzinger, "Human-in-the-loop reinforcement learning: A survey and position on requirements, challenges, and opportunities," *Journal of Artificial Intelligence Research*, vol. 79, pp. 359–415, 2024.

[28] S. G. Hart, "Nasa-task load index (nasa-tlx); 20 years later," in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 50, no. 9. Sage publications Sage CA: Los Angeles, CA, 2006, pp. 904–908.

[29] D. Kortenkamp, R. P. Bonasso, D. Ryan, and D. Schreckenghost, "Traded control with autonomous robots as mixed initiative interaction," in *AAAI Symposium on Mixed Initiative Interaction*, vol. 97, no. 4, 1997, pp. 89–94.

[30] C. M. Heunis, B. Silva, G. Sereni, M. C. Lam, B. Belakhal, A. Gaborit, B. Wermelink, B. R. Geelkerken, and S. Misra, "The flux one magnetic navigation system: a preliminary assessment for stent implantation," *IEEE Robotics and Automation Letters*, vol. 8, no. 9, pp. 5640–5647, 2023.

[31] S. Park, Y. Chai, S. Park, J. Park, K. Lee, and S. Choi, "Semi-autonomous teleoperation via learning non-prehensile manipulation skills," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 9295–9301.

[32] L. Zhu, J. Shen, S. Yang, and A. Song, "Robot-assisted retraction for transoral surgery," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 12 102–12 109, 2022.

[33] C. Peng, D. Yang, D. Zhao, M. Cheng, J. Dai, and L. Jiang, "Viiat-hand: a reach-and-grasp restoration system integrating voice interaction, computer vision, auditory and tactile feedback for blind amputees," *IEEE Robotics and Automation Letters*, 2024.

[34] R. Buchanan, A. Röfer, J. Moura, A. Valada, and S. Vijayakumar, "Online estimation of articulated objects with factor graphs using vision and proprioceptive sensing," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 16 111–16 117.

[35] S. Hart, A. H. Quispe, M. W. Lanighan, and S. Gee, "Generalized affordance templates for mobile manipulation," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 6240–6246.

[36] E. Miller, M. Durner, M. Humt, G. Quere, W. Boerdijk, A. M. Sundaram, F. Stulp, and J. Vogel, "Unknown object grasping for assistive robotics," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 18 157–18 163.

[37] R. Zhang, J. Chen, Z. Wang, Z. Yang, Y. Ren, P. Shi, J. Calo, K. Lam, S. Purkayastha, and B. Lo, "A step towards conditional autonomy-robotic appendectomy," *IEEE Robotics and Automation Letters*, vol. 8, no. 5, pp. 2429–2436, 2023.

[38] V. Myers, E. Bıyık, and D. Sadigh, "Active reward learning from online preferences," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 7511–7518.

[39] D. Schitz, S. Bao, D. Rieth, and H. Aschemann, "Shared autonomy for teleoperated driving: A real-time interactive path planning approach," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 999–1004.

[40] R. Papallas and M. R. Dogar, "Non-prehensile manipulation in clutter with human-in-the-loop," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 6723–6729.

[41] Y. Dai, R. Peng, S. Li, and J. Chai, "Think, act, and ask: Open-world interactive personalized robot navigation," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 3296–3303.

[42] Z. J. Hu, Z. Wang, Y. Huang, A. Sena, F. R. y Baena, and E. Burdet, "Towards human-robot collaborative surgery: Trajectory and strategy learning in bimanual peg transfer," *IEEE Robotics and Automation Letters*, vol. 8, no. 8, pp. 4553–4560, 2023.

[43] H. Saeidi, J. D. Opfermann, M. Kam, S. Wei, S. Léonard, M. H. Hsieh, J. U. Kang, and A. Krieger, "Autonomous robotic laparoscopic surgery for intestinal anastomosis," *Science robotics*, vol. 7, no. 62, p. eabj2908, 2022.

[44] D. Zhang, Z. Wu, J. Chen, R. Zhu, A. Munawar, B. Xiao, Y. Guan, H. Su, W. Hong, Y. Guo *et al.*, "Human-robot shared control for surgical robot based on context-aware sim-to-real adaptation," in *2022 International conference on robotics and automation (ICRA)*. IEEE, 2022, pp. 7694–7700.

[45] W. Chi, G. Dagnino, T. M. Kwok, A. Nguyen, D. Kundrat, M. E. Abdelaziz, C. Riga, C. Bicknell, and G.-Z. Yang, "Collaborative robot-assisted endovascular catheterization with generative adversarial imitation learning," in *2020 IEEE International conference on robotics and automation (ICRA)*. IEEE, 2020, pp. 2414–2420.

[46] S. K. Hopko, R. Khurana, R. K. Mehta, and P. R. Pagilla, "Effect of cognitive fatigue, operator sex, and robot assistance on task performance metrics, workload, and situation awareness in human-robot collaboration," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 3049–3056, 2021.

[47] R. Wang, D. Zhao, A. Gupte, and B.-C. Min, "Initial task allocation in multi-human multi-robot teams: An attention-enhanced hierarchical reinforcement learning approach," *IEEE Robotics and Automation Letters*, 2024.

[48] M. Rigter, B. Lacerda, and N. Hawes, "A framework for learning from demonstration with minimal human effort," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2023–2030, 2020.

[49] H. Zheng, Z. J. Hu, Y. Huang, X. Cheng, Z. Wang, and E. Burdet, "A user-centered shared control scheme with learning from demonstration for robotic surgery," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 195–15 201.

[50] J. DelPreto, J. I. Lipton, L. Sanneman, A. J. Fay, C. Fourie, C. Choi, and D. Rus, "Helping robots learn: a human-robot master-apprentice model using demonstrations via virtual reality teleoperation," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 10 226–10 233.

[51] A. Sidaoui, N. Daher, and D. Asmar, "Robot grasping through a joint-initiative supervised autonomy framework," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 7868–7874.

[52] M. Kam, H. Saeidi, M. H. Hsieh, J. U. Kang, and A. Krieger, "A confidence-based supervised-autonomous control strategy for robotic vaginal cuff closure," in *2021 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2021, pp. 12 261–12 267.

[53] X. Huang, S. G. McGill, J. A. DeCastro, L. Fletcher, J. J. Leonard, B. C. Williams, and G. Rosman, "Carpal: Confidence-aware intent recognition for parallel autonomy," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 4433–4440, 2021.

[54] B. Kizilkaya, C. She, G. Zhao, and M. A. Imran, "Intelligent mode-switching framework for teleoperation," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 692–15 698.

[55] Y. Li, R. Cui, W. Yan, S. Zhang, and C. Yang, "Reconciling conflicting intents: Bidirectional trust-based variable autonomy for mobile robots," *IEEE Robotics and Automation Letters*, 2024.

[56] M. K. Zein, A. Sidaoui, D. Asmar, and I. H. Elhajj, "Enhanced teleoperation using autocomplete," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 9178–9184.

[57] M. K. Zein, M. Al Aawar, D. Asmar, and I. H. Elhajj, "Deep learning and mixed reality to autocomplete teleoperation," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 4523–4529.

[58] B. Ibrahim, I. H. Elhajj, and D. Asmar, "3d autocomplete: Enhancing uav teleoperation with ai in the loop," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 17 829–17 835.

[59] T.-C. Lin, A. U. Krishnan, and Z. Li, "Shared autonomous interface for reducing physical effort in robot teleoperation via human motion mapping," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 9157–9163.

[60] P. Owan, J. Garbini, and S. Devasia, "Faster confined space manufacturing teleoperation through dynamic autonomy with task dynamics imitation learning," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2357–2364, 2020.

[61] H. Liu, Y. Zhu, K. Kato, A. Tsukahara, I. Kondo, T. Aoyama, and Y. Hasegawa, "Enhancing the llm-based robot manipulation through human-robot collaboration," *IEEE Robotics and Automation Letters*, 2024.

[62] S. Bustamante, G. Quere, K. Hagmann, X. Wu, P. Schmaus, J. Vogel, F. Stulp, and D. Leidner, "Toward seamless transitions between shared control and supervised autonomy in robotic assistance," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 3833–3840, 2021.

[63] G. Quere, A. Hagengruber, M. Iskandar, S. Bustamante, D. Leidner, F. Stulp, and J. Vogel, "Shared control templates for assistive robotics," in *2020 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2020, pp. 1956–1962.

[64] S. Bustamante, I. Rodríguez, G. Quere, P. Lehner, M. Iskandar, D. Leidner, A. Dömel, A. Albu-Schäffer, J. Vogel, and F. Stulp, "Feasibility checking and constraint refinement for shared control in assistive robotics," *IEEE Robotics and Automation Letters*, 2024.

[65] G. Quere, F. Stulp, D. Filliat, and J. Silverio, "A probabilistic approach for learning and adapting shared control skills with the human in the loop," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 728–15 734.

[66] S. Bustamante, G. Quere, D. Leidner, J. Vogel, and F. Stulp, "Cats: Task planning for shared control of assistive robots with variable autonomy," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 3775–3782.

[67] A. Padalkar, G. Quere, F. Steinmetz, A. Raffin, M. Nieuwenhuisen, J. Silvério, and F. Stulp, "Guiding reinforcement learning with shared control templates," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 11 531–11 537.

[68] D. P. Losey, K. Srinivasan, A. Mandlekar, A. Garg, and D. Sadigh, "Controlling assistive robots with learned latent actions," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 378–384.

[69] D. P. Losey, H. J. Jeon, M. Li, K. Srinivasan, A. Mandlekar, A. Garg, J. Bohg, and D. Sadigh, "Learning latent actions to control assistive robots," *Autonomous robots*, vol. 46, no. 1, pp. 115–147, 2022.

[70] S. A. Mehta, S. Parekh, and D. P. Losey, "Learning latent actions without human demonstrations," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 7437–7443.

[71] M. Przystupa, K. Johnstonbaugh, Z. Zhang, L. Petrich, M. Dehghan, F. Haghverd, and M. Jagersand, "Learning state conditioned linear mappings for low-dimensional control of robotic manipulators," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 857–863.

[72] P. Naughton and K. Hauser, "Structured action prediction for teleoperation in open worlds," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 3099–3105, 2022.

[73] B. Zhu, D. Zhang, Y. Chu, and X. Zhao, "A novel limbs-free variable structure wheelchair based on face-computer interface (fci) with shared control," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 5480–5486.

[74] M. Hagenow, E. Senft, R. Radwin, M. Gleicher, B. Mutlu, and M. Zinn, "Corrective shared autonomy for addressing task variability," *IEEE robotics and automation letters*, vol. 6, no. 2, pp. 3720–3727, 2021.

[75] ——, "Informing real-time corrections in corrective shared autonomy through expert demonstrations," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 6442–6449, 2021.

[76] C. T. Chang, M. P. Stull, B. Crockett, E. Jensen, C. Lohrmann, M. Hebert, and B. Hayes, "Iteratively adding latent human knowledge within trajectory optimization specifications improves learning and task outcomes," *IEEE Robotics and Automation Letters*, 2024.

[77] M. Cognetti, M. Aggravi, C. Pacchierotti, P. Salaris, and P. R. Giordano, "Perception-aware human-assisted navigation of mobile robots on

persistent trajectories," *IEEE Robotics and Automation Letters*, vol. 5, no. 3, pp. 4711–4718, 2020.
[78] X. Ma, C. Song, P. W. Chiu, and Z. Li, "Visual servo of a 6-dof robotic stereo flexible endoscope based on da vinci research kit (dvrk) system," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 820–827, 2020.
[79] L. Chen, A. Naceri, A. Swikir, S. Hirche, and S. Haddadin, "Autonomous and teleoperation control of a drawing robot avatar," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 714–15 720.
[80] X. Ma, W.-Y. Kuo, K. Yang, A. Rahaman, and H. K. Zhang, "A-see: active-sensing end-effector enabled probe self-normal-positioning for robotic ultrasound imaging applications," *IEEE robotics and automation letters*, vol. 7, no. 4, pp. 12 475–12 482, 2022.
[81] H. Tian, M. Huber, C. E. Mower, Z. Han, C. Li, X. Duan, and C. Bergeles, "Excitation trajectory optimization for dynamic parameter identification using virtual constraints in hands-on robotic system," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 11 605–11 611.
[82] M. Khoramshahi, G. Morel, and N. Jarrasse, "Intent-aware control in kinematically redundant systems: Towards collaborative wearable robots," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 10 453–10 460.
[83] H. Mishra, R. Balachandran, M. De Stefano, and C. Ott, "A compliant partitioned shared control strategy for an orbital robot," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7317–7324, 2021.
[84] N. A. Strohmeyer, J. H. Park, B. P. Murphy, and F. Alambeigi, "A semi-autonomous data-driven shared control framework for robotic manipulation and cutting of an unknown deformable tissue," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 9881–9886.
[85] Y. Tanaka, T. Katagiri, H. Yukawa, T. Nishimura, R. Tanada, I. Ogura, T. Hagiwara, and K. Minamizawa, "Sensorimotor control sharing with vibrotactile feedback for body integration through avatar robot," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 9509–9516, 2022.
[86] A. Munawar, J. Y. Wu, R. H. Taylor, P. Kazanzides, and G. S. Fischer, "A framework for customizable multi-user teleoperated control," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 3256–3263, 2021.
[87] P. Chang, R. Luo, M. Dorostian, and T. Padır, "A shared control method for collaborative human-robot plug task," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7429–7436, 2021.
[88] Y. Liu, R. Leib, and D. W. Franklin, "Follow the force: Haptic communication enhances coordination in physical human-robot interaction when humans are followers," *IEEE Robotics and Automation Letters*, vol. 8, no. 10, pp. 6459–6466, 2023.
[89] L. Tao, M. Bowman, J. Zhang, and X. Zhang, "Forming real-world human-robot cooperation for tasks with general goal," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 762–769, 2021.
[90] M. Li, A. Canberk, D. P. Losey, and D. Sadigh, "Learning human objectives from sequences of physical corrections," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 2877–2883.
[91] K. Shi and G. Hu, "Dual-mode human-robot collaboration with guaranteed safety using time-varying zeroing control barrier functions and quadratic program," *IEEE Robotics and Automation Letters*, vol. 8, no. 9, pp. 5902–5909, 2023.
[92] S. A. Mehta, F. Meng, A. Bajcsy, and D. P. Losey, "Strol: Stabilized and robust online learning from humans," *IEEE Robotics and Automation Letters*, vol. 9, no. 3, pp. 2303–2310, 2024.
[93] J. Hoegerman and D. Losey, "Reward learning with intractable normalizing functions," *IEEE Robotics and Automation Letters*, vol. 8, no. 11, pp. 7511–7518, 2023.
[94] Z. Shen, M. Saveriano, F. J. Abu-Dakka, and S. Haddadin, "Safe execution of learned orientation skills with conic control barrier functions," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 13 376–13 382.
[95] C. Zhang, C. Lin, Y. Leng, Z. Fu, Y. Cheng, and C. Fu, "An effective head-based hri for 6d robotic grasping using mixed reality," *IEEE Robotics and Automation Letters*, vol. 8, no. 5, pp. 2796–2803, 2023.
[96] I. Akinola, Z. Wang, J. Shi, X. He, P. Lapborisuth, J. Xu, D. Watkins-Valls, P. Sajda, and P. Allen, "Accelerated robot learning via human brain signals," in *2020 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2020, pp. 3799–3805.
[97] H. J. Choi, S. Das, S. Peng, R. Bajcsy, and N. Figueroa, "On the feasibility of eeg-based motor intention detection for real-time robot assistive control," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 5592–5599.
[98] D. Torielli, L. Bertoni, L. Muratore, and N. Tsagarakis, "A laser-guided interaction interface for providing effective robot assistance to people with upper limbs impairments," *IEEE Robotics and Automation Letters*, 2024.
[99] L. Zha, Y. Cui, L.-H. Lin, M. Kwon, M. G. Arenas, A. Zeng, F. Xia, and D. Sadigh, "Distilling and retrieving generalizable knowledge for robot manipulation via language corrections," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 172–15 179.
[100] S. Holk, D. Marta, and I. Leite, "Polite: Preferences combined with highlights in reinforcement learning," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 2288–2295.
[101] N. Wilde, A. Sadeghi, and S. L. Smith, "Learning submodular objectives for team environmental monitoring," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 960–967, 2021.
[102] T.-C. Lin, A. U. Krishnan, and Z. Li, "The impacts of unreliable autonomy in human-robot collaboration on shared and supervisory control for remote manipulation," *IEEE Robotics and Automation Letters*, vol. 8, no. 8, pp. 4641–4648, 2023.
[103] J. F. Mullen, J. Mosier, S. Chakrabarti, A. Chen, T. White, and D. P. Losey, "Communicating inferred goals with passive augmented reality and active haptic feedback," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 8522–8529, 2021.
[104] M. Selvaggio, F. Abi-Farraj, C. Pacchierotti, P. R. Giordano, and B. Siciliano, "Haptic-based shared-control methods for a dual-arm system," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 4249–4256, 2018.
[105] M. Selvaggio, G. A. Fontanelli, F. Ficuciello, L. Villani, and B. Siciliano, "Passive virtual fixtures adaptation in minimally invasive robotic surgery," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3129–3136, 2018.
[106] M. Hagenow, E. Senft, N. Orr, R. Radwin, M. Gleicher, B. Mutlu, D. P. Losey, and M. Zinn, "Coordinated multi-robot shared autonomy based on scheduling and demonstrations," *IEEE Robotics and Automation Letters*, vol. 8, no. 12, pp. 8335–8342, 2023.
[107] P. Naughton, J. S. Nam, A. Stratton, and K. Hauser, "Integrating open-world shared control in immersive avatars," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 17 807–17 813.
[108] Z. Lei, B. Y. Tan, N. P. Garg, L. Li, A. Sidarta, and W. T. Ang, "An intention prediction based shared control system for point-to-point navigation of a robotic wheelchair," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 8893–8900, 2022.
[109] E. Yousefi, D. P. Losey, and I. Sharf, "Assisting operators of articulated machinery with optimal planning and goal inference," in *2022 international conference on robotics and automation (ICRA)*. IEEE, 2022, pp. 2832–2838.
[110] R. Tian, N. Li, A. Girard, I. Kolmanovsky, and M. Tomizuka, "Cost-effective sensing for goal inference: A model predictive approach," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 6451–6457.
[111] H. Nemlekar, J. Modi, S. K. Gupta, and S. Nikolaidis, "Two-stage clustering of human preferences for action prediction in assembly tasks," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 3487–3494.
[112] G. Li, Z. Li, and Z. Kan, "Assimilation control of a robotic exoskeleton for physical human-robot interaction," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 2977–2984, 2022.
[113] P. Song, P. Li, E. Aertbeliën, and R. Detry, "Robot trajectron: Trajectory prediction-based shared control for robot manipulation," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 5585–5591.
[114] H.-S. Moon and J. Seo, "Fast user adaptation for human motion prediction in physical human–robot interaction," *IEEE Robotics and Automation Letters*, vol. 7, no. 1, pp. 120–127, 2021.
[115] D. Gopinath, M. N. Javaremi, and B. Argall, "Customized handling of unintended interface operation in assistive robots," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 10 406–10 412.
[116] M. Zurek, A. Bobu, D. S. Brown, and A. D. Dragan, "Situational confidence assistance for lifelong shared autonomy," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 2783–2789.
[117] K. Katuwandeniya, S. H. Kiss, L. Shi, and J. V. Miro, "Exact-likelihood user intention estimation for scene-compliant shared-control naviga-

tion," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 6437–6443.

[118] Y. Li, R. Cui, W. Yan, C. Feng, and S. Zhang, "Mitigating over-assistance in teleoperated mobile robots via human-centered shared autonomy: Leveraging suboptimal rationality insights," *IEEE Robotics and Automation Letters*, 2024.

[119] Y. Li, J. Eden, G. Carboni, and E. Burdet, "Improving tracking through human-robot sensory augmentation," *IEEE Robotics and Automation Letters*, vol. 5, no. 3, pp. 4399–4406, 2020.

[120] M. Cai, K. Patel, S. Iba, and S. Li, "Hierarchical deep learning for intention estimation of teleoperation manipulation in assembly tasks," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 17 814–17 820.

[121] T. Hara, T. Sato, T. Ogata, and H. Awano, "Uncertainty-aware haptic shared control with humanoid robots for flexible object manipulation," *IEEE Robotics and Automation Letters*, vol. 8, no. 10, pp. 6435–6442, 2023.

[122] S. Chen, J. Gao, S. Reddy, G. Berseth, A. D. Dragan, and S. Levine, "Asha: Assistive teleoperation via human-in-the-loop reinforcement learning," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 7505–7512.

[123] C. Wang, S. Huber, S. Coros, and R. Poranne, "Task autocorrection for immersive teleoperation," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 3949–3955.

[124] M. Bowman and X. Zhang, "Dimension-specific shared autonomy for handling disagreement in telemanipulation," *IEEE Robotics and Automation Letters*, vol. 8, no. 3, pp. 1415–1422, 2023.

[125] M. Wells, Z. Kingston, M. Lahijanian, L. E. Kavraki, and M. Y. Vardi, "Finite-horizon synthesis for probabilistic manipulation domains," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 6336–6342.

[126] Z. Huang, Y.-J. Mun, X. Li, Y. Xie, N. Zhong, W. Liang, J. Geng, T. Chen, and K. Driggs-Campbell, "Hierarchical intention tracking for robust human-robot collaboration in industrial assembly tasks," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 9821–9828.

[127] A. Dwivedi, D. Shieff, A. Turner, G. Gorjup, Y. Kwon, and M. Liarokapis, "A shared control framework for robotic telemanipulation combining electromyography based motion estimation and compliance control," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 9467–9473.

[128] A. Menon, L. I. G. Olascoaga, V. Balanaga, A. Natarajan, J. Ruffing, R. Ardalan, and J. M. Rabaey, "Shared control of assistive robots through user-intent prediction and hyperdimensional recall of reactive behavior," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 12 638–12 644.

[129] P. Sedighi, X. Li, and M. Tavakoli, "Emg-based intention detection using deep learning for shared control in upper-limb assistive exoskeletons," *IEEE Robotics and Automation Letters*, vol. 9, no. 1, pp. 41–48, 2023.

[130] Y. Du, H. B. Amor, J. Jin, Q. Wang, and A. Ajoudani, "Learning-based multimodal control for a supernumerary robotic system in human-robot collaborative sorting," *IEEE Robotics and Automation Letters*, 2024.

[131] N. Yang, R. Sha, R. Sankaranarayanan, Q. Sun, and G. Weinberg, "Drumming arm: an upper-limb prosthetic system to restore grip control for a transradial amputee drummer," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 10 317–10 323.

[132] L. Meng, L. Yang, and E. Zheng, "Hierarchical human motion intention prediction for increasing efficacy of human-robot collaboration," *IEEE Robotics and Automation Letters*, 2024.

[133] R. Wen, K. Yuan, Q. Wang, S. Heng, and Z. Li, "Force-guided high-precision grasping control of fragile and deformable objects using semg-based force prediction," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2762–2769, 2020.

[134] X. Shi, W. Guo, W. Xu, Z. Yang, and X. Sheng, "Semi-autonomous grasping control of prosthetic hand and wrist based on motion prior field," *IEEE Robotics and Automation Letters*, 2024.

[135] X. Peng, S. Li, and L. Stirling, "Improving complex task performance in powered upper limb exoskeletons with adaptive proportional myoelectric control for user motor strategy tracking," *IEEE Robotics and Automation Letters*, 2024.

[136] R. Garcia-Rosas, T. Yu, D. Oetomo, C. Manzie, Y. Tan, and P. Choong, "Exploiting inherent human motor behaviour in the online personalisation of human-prosthetic interfaces," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 1973–1980, 2021.

[137] M. A. Perozo, E. Niddam, S. Durand, L. Cuvillon, and J. Gangloff, "Teleoperation of a suspended aerial manipulator using a handheld camera with an imu," *IEEE Robotics and Automation Letters*, 2024.

[138] H. Shi, L. Bi, Z. Yang, H. Ge, W. Fei, and L. Wang, "Adaptive model prediction control framework with game theory for brain-controlled air-ground collaborative unmanned system," *IEEE Robotics and Automation Letters*, 2024.

[139] J. H. Sanchez, W. Amanhoud, A. Billard, and M. Bouri, "Foot control of a surgical laparoscopic gripper via 5dof haptic robotic platform: Design, dynamics and haptic shared control," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 12 559–12 566.

[140] M. Panzirsch, A. Pereira, H. Singh, B. Weber, E. Ferreira, A. Gherghescu, L. Hann, E. den Exter, F. van der Hulst, L. Gerdes *et al.*, "Exploring planet geology through force-feedback telemanipulation from orbit," *Science robotics*, vol. 7, no. 65, p. eabl6307, 2022.

[141] M. Laghi, L. Raiano, F. Amadio, F. Rollo, A. Zunino, and A. Ajoudani, "A target-guided telemanipulation architecture for assisted grasping," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 8759–8766, 2022.

[142] Y. Cho, H. Yun, J. Lee, A. Ha, and J. Yun, "Goondae: denoising-based driver assistance for off-road teleoperation," *IEEE Robotics and Automation Letters*, vol. 8, no. 4, pp. 2405–2412, 2023.

[143] X. Xiao, X. Li, Y. Shi, J. Fang, L. Li, P. He, and H. Mo, "An integrated position-velocity-force method for safety-enhanced shared control in robot-assisted surgical cutting," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 3533–3539.

[144] C. Lauretti, F. Cordella, C. Tamantini, C. Gentile, F. S. di Luzio, and L. Zollo, "A surgeon-robot shared control for ergonomic pedicle screw fixation," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2554–2561, 2020.

[145] P. Baksic, H. Courtecuisse, and B. Bayle, "Shared control strategy for needle insertion into deformable tissue using inverse finite element simulation," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 12 442–12 448.

[146] M. M. Marinho, H. Ishida, K. Harada, K. Deie, and M. Mitsuishi, "Virtual fixture assistance for suturing in robot-aided pediatric endoscopic surgery," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 524–531, 2020.

[147] M. Aggravi, D. A. Estima, A. Krupa, S. Misra, and C. Pacchierotti, "Haptic teleoperation of flexible needles combining 3d ultrasound guidance and needle tip force feedback," *IEEE Robotics and automation letters*, vol. 6, no. 3, pp. 4859–4866, 2021.

[148] R. Mieling, M. Neidhardt, S. Latus, C. Stapper, S. Gerlach, I. Kniep, A. Heinemann, B. Ondruschka, and A. Schlaefer, "Collaborative robotic biopsy with trajectory guidance and needle tip force feedback," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 6893–6900.

[149] S. Oliver, L. Pecly, and K. Hashtrudi-Zaad, "Uncoupled stability dynamic range for hunt-crossley modeled virtual environments," *IEEE Robotics and Automation Letters*, vol. 8, no. 9, pp. 5751–5758, 2023.

[150] A. Kalinowska, M. Schlafly, K. Rudy, J. P. Dewald, and T. D. Murphey, "Measuring interaction bandwidth during physical human-robot collaboration," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 12 467–12 474, 2022.

[151] Z. Liao, J. V. S. Luces, A. A. Ravankar, and Y. Hirata, "Running guidance for visually impaired people using sensory augmentation technology based robotic system," *IEEE Robotics and Automation Letters*, vol. 8, no. 9, pp. 5323–5330, 2023.

[152] C. A. Braun, L. Haide, L. Fischer, S. Kille, B. Varga, S. Rothfuss, and S. Hohmann, "Using a collaborative robotic arm as human-machine interface: System setup and application to pose control tasks," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 12 464–12 470.

[153] S. D. Sierra, M. F. Jimenez, M. Munera, C. A. Cifuentes, and A. Frizera-Neto, "Haptic human-robot collaboration for walker-assisted navigation based on admittance controllers," *IEEE Robotics and Automation Letters*, vol. 8, no. 5, pp. 2622–2628, 2023.

[154] J. M. Walker and A. M. Okamura, "Continuous closed-loop 4-degree-of-freedom holdable haptic guidance," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6853–6860, 2020.

[155] J. Pan, J. Eden, D. Oetomo, and W. Johal, "Effects of shared control on cognitive load and trust in teleoperated trajectory tracking," *IEEE Robotics and Automation Letters*, 2024.

[156] Z. Rysbek, S. Li, A. M. Shervedani, and M. Žefran, "Proactive robot control for collaborative manipulation using human intent," in *2024*

IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2024, pp. 3176–3182.
[157] M. Fennel, A. Zea, and U. D. Hanebeck, "Haptic-guided path generation for remote car-like vehicles," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 4087–4094, 2021.
[158] L. Chen, Z. J. Hu, Y. Huang, E. Burdet, and F. R. y Baena, "Human robot shared control in surgery: A performance assessment," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 165–15 171.
[159] G. Maeda, "Blending primitive policies in shared control for assisted teleoperation," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 9332–9338.
[160] R. Liu, T. Ma, N. Yao, H. Li, X. Zhao, Y. Wang, H. Pan, and Q. Song, "Adaptive symmetry reference trajectory generation in shared autonomy for active knee orthosis," *IEEE Robotics and Automation Letters*, vol. 8, no. 6, pp. 3118–3125, 2023.
[161] C. Z. Qiao, M. Sakr, K. Muelling, and H. Admoni, "Learning from demonstration for real-time user goal prediction and shared assistive control," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 3270–3275.
[162] L. Penco, K. Momose, S. McCrory, D. Anderson, N. Kitchel, D. Calvert, and R. J. Griffin, "Mixed reality teleoperation assistance for direct control of humanoids," *IEEE Robotics and Automation Letters*, vol. 9, no. 2, pp. 1937–1944, 2024.
[163] C. Tamantini, F. Cordella, C. Lauretti, F. S. di Luzio, M. Bravi, F. Bressi, F. Draicchio, S. Sterzi, and L. Zollo, "Patient-tailored adaptive control for robot-aided orthopaedic rehabilitation," in *2022 international conference on robotics and automation (ICRA)*. IEEE, 2022, pp. 5434–5440.
[164] Y. Michel, R. Rahal, C. Pacchierotti, P. R. Giordano, and D. Lee, "Bilateral teleoperation with adaptive impedance control for contact tasks," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 5429–5436, 2021.
[165] Y. Michel, Z. Li, and D. Lee, "A learning-based shared control approach for contact tasks," *IEEE Robotics and Automation Letters*, vol. 8, no. 12, pp. 8002–8009, 2023.
[166] V. Schettino and Y. Demiris, "Improving generalisation in learning assistance by demonstration for smart wheelchairs," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 5474–5480.
[167] M. Mühlbauer, T. Hulin, B. Weber, S. Calinon, F. Stulp, A. Albu-Schäffer, and J. Silvério, "A probabilistic approach to multi-modal adaptive virtual fixtures," *IEEE Robotics and Automation Letters*, 2024.
[168] C. Cai, Y. S. Liang, N. Somani, and W. Yan, "Inferring the geometric nullspace of robot skills from human demonstrations," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 7668–7675.
[169] S. Iregui, J. De Schutter, and E. Aertbeliën, "Reconfigurable constraint-based reactive framework for assistive robotics with adaptable levels of autonomy," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7397–7405, 2021.
[170] D. Torielli, L. Franco, M. Pozzi, L. Muratore, M. Malvezzi, N. Tsagarakis, and D. Prattichizzo, "Wearable haptics for a marionette-inspired teleoperation of highly redundant robotic systems," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 670–15 676.
[171] T. Poignonec, F. Nageotte, N. Zemiti, and B. Bayle, "Simultaneous haptic guidance and learning of task parameters during robotic teleoperation–a geometrical approach," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 3619–3625.
[172] V. Pruks and J.-H. Ryu, "A framework for interactive virtual fixture generation for shared teleoperation in unstructured environments," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 10 234–10 241.
[173] L. Huber, J.-J. Slotine, and A. Billard, "Fast obstacle avoidance based on real-time sensing," *IEEE Robotics and Automation Letters*, vol. 8, no. 3, pp. 1375–1382, 2022.
[174] H. Zhang, L. Zhu, J. Shen, and A. Song, "Implicit neural field guidance for teleoperated robot-assisted surgery," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 6866–6872.
[175] L. van der Spaa, G. Franzese, J. Kober, and M. Gienger, "Disagreement-aware variable impedance control for online learning of physical human-robot cooperation tasks," in *ICRA 2022 full day workshop–shared autonomy in physical human-robot interaction: Adaptability and trust*, 2022.
[176] R. Moccia, C. Iacono, B. Siciliano, and F. Ficuciello, "Vision-based dynamic virtual fixtures for tools collision avoidance in robotic surgery," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1650–1655, 2020.
[177] D. Baek, Y.-C. Chang, and J. Ramos, "A study of shared-control with bilateral feedback for obstacle avoidance in whole-body telelocomotion of a wheeled humanoid," *IEEE Robotics and Automation Letters*, vol. 8, no. 11, pp. 6979–6986, 2023.
[178] M. Macchini, T. Havy, A. Weber, F. Schiano, and D. Floreano, "Hand-worn haptic interface for drone teleoperation," in *2020 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2020, pp. 10 212–10 218.
[179] X. Cheng, X. Geng, Y. Huang, and E. Burdet, "Haptic feedback of front vehicle motion may improve driving control," *IEEE Robotics and Automation Letters*, 2024.
[180] Z. Chen, K. Fan, L. Cruciani, M. Fontana, L. Muraglia, F. Ceci, L. Travaini, G. Ferrigno, and E. De Momi, "Toward a framework integrating augmented reality and virtual fixtures for safer robot-assisted lymphadenectomy," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 3602–3608.
[181] N. Zhong and K. Hauser, "Attentiveness map estimation for haptic teleoperation of mobile robot obstacle avoidance and approach," *IEEE Robotics and Automation Letters*, vol. 9, no. 3, pp. 2152–2159, 2024.
[182] A. Pokhrel, M. Nazeri, A. Datar, and X. Xiao, "Cahsor: Competence-aware high-speed off-road ground navigation in SE(3)," *IEEE Robotics and Automation Letters*, 2024.
[183] S. Wang and J. Ramos, "Dynamic locomotion teleoperation of a reduced model of a wheeled humanoid robot using a whole-body human-machine interface," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 1872–1879, 2021.
[184] B. B. Carlos, A. Franchi, and G. Oriolo, "Towards safe human-quadrotor interaction: Mixed-initiative control via real-time nmpc," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7611–7618, 2021.
[185] B. Rivière, J. Lathrop, and S.-J. Chung, "Monte carlo tree search with spectral expansion for planning with dynamical systems," *Science Robotics*, vol. 9, no. 97, p. eado1010, 2024.
[186] A. Singletary, A. Swann, Y. Chen, and A. D. Ames, "Onboard safety guarantees for racing drones: High-speed geofencing with control barrier functions," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 2897–2904, 2022.
[187] S. A. Tafrishi, A. A. Ravankar, J. V. S. Luces, and Y. Hirata, "A novel assistive controller based on differential geometry for users of the differential-drive wheeled mobile robots," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 5755–5761.
[188] E. Kim, I. Choi, and S. Yang, "Design and control of fully handheld microsurgical robot for active tremor cancellation," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 12 289–12 295.
[189] P.-L. Yen and T.-H. Ho, "Shared control for a handheld orthopedic surgical robot," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 8394–8400, 2021.
[190] P. Jiang, W. Li, Y. Li, and D. Zhang, "Adaptive motion scaling for robot-assisted microsurgery based on hybrid offline reinforcement learning and damping control," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 8216–8222.
[191] A. Christou, A. J. Del-Ama, J. C. Moreno, and S. Vijayakumar, "Adaptive control for triadic human-robot-fes collaboration in gait rehabilitation: A pilot study," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 5561–5568.
[192] X. Gao, J. Silvério, E. Pignat, S. Calinon, M. Li, and X. Xiao, "Motion mappings for continuous bilateral teleoperation," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 5048–5055, 2021.
[193] M. Bowman and X. Zhang, "We-filter: adaptive acceptance criteria for filter-based shared autonomy," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 12 528–12 534.
[194] K. Backman, D. Kulić, and H. Chung, "Learning to assist drone landings," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 3192–3199, 2021.
[195] G. J. Lahr, H. B. Garcia, A. Ajoudani, T. Boaventura, and G. A. Caurin, "A hybrid model-based evolutionary optimization with passive boundaries for physical human-robot interaction," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 1426–1432.
[196] F. Benzi and C. Secchi, "Unified power and admittance adaptation for safe and effective physical interaction with unmodelled dynamic

environments," *IEEE Robotics and Automation Letters*, vol. 8, no. 12, pp. 8279–8286, 2023.
[197] L. Pezeshki, H. Sadeghian, M. Keshmiri, X. Chen, and S. Haddadin, "Cooperative assist-as-needed control for robotic rehabilitation: A two-player game approach," *IEEE Robotics and Automation Letters*, vol. 8, no. 5, pp. 2852–2859, 2023.
[198] Y. Cho, M. Lorenzini, A. Fortuna, M. Leonori, and A. Ajoudani, "A user-and slope-adaptive control framework for a walking aid robot," *IEEE Robotics and Automation Letters*, 2024.
[199] S. Jadav, J. Heidersberger, C. Ott, and D. Lee, "Shared autonomy via variable impedance control and virtual potential fields for encoding human demonstrations," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 15 151–15 157.
[200] P. Franceschi, N. Pedrocchi, and M. Beschi, "Adaptive impedance controller for human-robot arbitration based on cooperative differential game theory," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 7881–7887.
[201] C. Zhang, S. Liu, C. Zeng, Y. Jiang, and J. Luo, "A robot humanoid control framework through human arm active endpoint stiffness and direction adaptive compensation," *IEEE Robotics and Automation Letters*, 2024.
[202] R. J. Ansari and Y. Karayiannidis, "Task-based role adaptation for human-robot cooperative object handling," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 3592–3598, 2021.
[203] X. Tu, M. Li, M. Liu, J. Si, and H. H. Huang, "A data-driven reinforcement learning solution framework for optimal and adaptive personalization of a hip exoskeleton," in *2021 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2021, pp. 10 610–10 616.
[204] Q. Zhang, V. Nalam, X. Tu, M. Li, J. Si, M. D. Lewek, and H. H. Huang, "Imposing healthy hip motion pattern and range by exoskeleton control for individualized assistance," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11 126–11 133, 2022.
[205] E. M. Van Zoelen, H. Veldman-Loopik, K. van den Bosch, M. Neerincx, D. A. Abbink, and L. Peternel, "Enabling embodied human-robot co-learning: Requirements, method, and test with handover task," *IEEE Robotics and Automation Letters*, 2024.
[206] M. Shushtari, R. Nasiri, and A. Arami, "Online reference trajectory adaptation: A personalized control strategy for lower limb exoskeletons," *IEEE Robotics and Automation Letters*, vol. 7, no. 1, pp. 128–134, 2021.
[207] F. M. Escalante, L. F. dos Santos, Y. Moreno, A. A. Siqueira, M. H. Terra, and T. Boaventura, "Markovian transparency control of an exoskeleton robot," *IEEE Robotics and Automation Letters*, vol. 8, no. 2, pp. 544–551, 2022.
[208] J. K. Mehr, M. Sharifi, V. K. Mushahwar, and M. Tavakoli, "Intelligent locomotion planning with enhanced postural stability for lower-limb exoskeletons," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7588–7595, 2021.
[209] M. Mitra, G. Kumar, P. P. Chakrabarti, and P. Biswas, "Enhanced human-robot collaboration with intent prediction using deep inverse reinforcement learning," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 7880–7887.
[210] L. Rapetti, C. Sartore, M. Elobaid, Y. Tirupachuri, F. Draicchio, T. Kawakami, T. Yoshiike, and D. Pucci, "A control approach for human-robot ergonomic payload lifting," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 7504–7510.
[211] H. Yan, J. Li, H. Liu, Z. Tu, P. Yang, M. Pang, Y. Leng, and C. Fu, "Locomotion control on human-centaur system with spherical joint interaction," *IEEE Robotics and Automation Letters*, 2024.
[212] D. Zhang, R. Tron, and R. P. Khurshid, "Haptic feedback improves human-robot agreement and user satisfaction in shared-autonomy teleoperation," in *2021 ieee international conference on robotics and automation (icra)*. IEEE, 2021, pp. 3306–3312.
[213] A. Jonnavittula and D. P. Losey, "Communicating robot conventions through shared autonomy," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 7423–7429.
[214] R. Balachandran, H. Mishra, M. Cappelli, B. Weber, C. Secchi, C. Ott, and A. Albu-Schaeffer, "Adaptive authority allocation in shared control of robots using bayesian filters," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 11 298–11 304.
[215] Y. Li and F. Zhang, "Trust-preserved human-robot shared autonomy enabled by bayesian relational event modeling," *IEEE Robotics and Automation Letters*, 2024.
[216] Q. Wang, D. Liu, M. G. Carmichael, and C.-T. Lin, "Robot trust and self-confidence based role arbitration method for physical human-robot collaboration," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 9896–9902.
[217] R. Papallas, A. G. Cohn, and M. R. Dogar, "Online replanning with human-in-the-loop for non-prehensile manipulation in clutter—a trajectory optimization based approach," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 5377–5384, 2020.
[218] G. Swamy, S. Reddy, S. Levine, and A. D. Dragan, "Scaled autonomy: Enabling human operators to control robot fleets," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 5942–5948.
[219] K. Chandan, V. Kudalkar, X. Li, and S. Zhang, "Arroch: Augmented reality for robots collaborating with a human," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 3787–3793.
[220] G. Miyauchi, Y. K. Lopes, and R. Groß, "Multi-operator control of connectivity-preserving robot swarms using supervisory control theory," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 6889–6895.
[221] W. Dai, Y. Liu, H. Lu, Z. Zheng, and Z. Zhou, "A shared control framework for human-multirobot foraging with brain-computer interface," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 6305–6312, 2021.
[222] W. Dai, Y. Liu, H. Lu, Z. Zhou, and Z. Zhen, "Shared control based on a brain-computer interface for human-multirobot cooperation," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 6123–6130, 2021.
[223] M. Macchini, L. De Matteïs, F. Schiano, and D. Floreano, "Personalized human-swarm interaction through hand motion," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 8341–8348, 2021.
[224] I. Ozdamar, M. Laghi, G. Grioli, A. Ajoudani, M. G. Catalano, and A. Bicchi, "A shared autonomy reconfigurable control framework for telemanipulation of multi-arm systems," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 9937–9944, 2022.
[225] Y. Yang, D. Constantinescu, and Y. Shi, "Proportional and reachable cluster teleoperation of a distributed multi-robot system," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021, pp. 8984–8990.
[226] M. R. Endsley, D. J. Garland *et al.*, "Theoretical underpinnings of situation awareness: A critical review," *Situation awareness analysis and measurement*, vol. 1, no. 1, pp. 3–21, 2000.
[227] H. J. Jeon, D. P. Losey, and D. Sadigh, "Shared autonomy with learned latent actions," *arXiv preprint arXiv:2005.03210*, 2020.
[228] S. Karamcheti, M. Srivastava, P. Liang, and D. Sadigh, "Lila: Language-informed latent actions," in *Conference on robot learning*. PMLR, 2022, pp. 1379–1390.
[229] Y. Tao, J. Yang, D. Ding, and Z. Erickson, "Lams: Llm-driven automatic mode switching for assistive teleoperation," in *2025 20th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2025, pp. 242–251.
[230] J. Urain, A. Mandlekar, Y. Du, M. Shafiullah, D. Xu, K. Fragkiadaki, G. Chalvatzaki, and J. Peters, "Deep generative models in robotics: A survey on learning from multimodal demonstrations," *arXiv preprint arXiv:2408.04380*, 2024.
[231] T. Z. Zhao, V. Kumar, S. Levine, and C. Finn, "Learning fine-grained bimanual manipulation with low-cost hardware," *arXiv preprint arXiv:2304.13705*, 2023.
[232] M. J. Kim, K. Pertsch, S. Karamcheti, T. Xiao, A. Balakrishna, S. Nair, R. Rafailov, E. Foster, G. Lam, P. Sanketi *et al.*, "Openvla: An open-source vision-language-action model," *arXiv preprint arXiv:2406.09246*, 2024.
[233] C. Chi, Z. Xu, S. Feng, E. Cousineau, Y. Du, B. Burchfiel, R. Tedrake, and S. Song, "Diffusion policy: Visuomotor policy learning via action diffusion," *The International Journal of Robotics Research*, vol. 44, no. 10-11, pp. 1684–1704, 2025.
[234] O. M. Team, D. Ghosh, H. Walke, K. Pertsch, K. Black, O. Mees, S. Dasari, J. Hejna, T. Kreiman, C. Xu *et al.*, "Octo: An open-source generalist robot policy," *arXiv preprint arXiv:2405.12213*, 2024.
[235] J. Barreiros, A. Beaulieu, A. Bhat, R. Cory, E. Cousineau, H. Dai, C.-H. Fang, K. Hashimoto, M. Z. Irshad, M. Itkina *et al.*, "A careful examination of large behavior models for multitask dexterous manipulation," *arXiv preprint arXiv:2507.05331*, 2025.
[236] K. Black, N. Brown, D. Driess, A. Esmail, M. Equi, C. Finn, N. Fusai, L. Groom, K. Hausman, B. Ichter *et al.*, "
$backslash$
pi_0: A vision-language-action flow model for general robot control," *arXiv preprint arXiv:2410.24164*, 2024.

[237] Q. Rouxel, A. Ferrari, S. Ivaldi, and J.-B. Mouret, "Flow matching imitation learning for multi-support manipulation," in *2024 IEEE-RAS 23rd International Conference on Humanoid Robots (Humanoids)*. IEEE, 2024, pp. 528–535.

[238] P. Wu, Y. Shentu, Z. Yi, X. Lin, and P. Abbeel, "Gello: A general, low-cost, and intuitive teleoperation framework for robot manipulators," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2024, pp. 12 156–12 163.

[239] C. Chi, Z. Xu, C. Pan, E. Cousineau, B. Burchfiel, S. Feng, R. Tedrake, and S. Song, "Universal manipulation interface: In-the-wild robot teaching without in-the-wild robots," *arXiv preprint arXiv:2402.10329*, 2024.

[240] M. Hagenow, D. Kontogiorgos, Y. Wang, and J. Shah, "Versatile demonstration interface: Toward more flexible robot demonstration collection," *arXiv preprint arXiv:2410.19141*, 2024.

[241] G. R. Team, S. Abeyruwan, J. Ainslie, J.-B. Alayrac, M. G. Arenas, T. Armstrong, A. Balakrishna, R. Baruch, M. Bauza, M. Blokzijl *et al.*, "Gemini robotics: Bringing ai into the physical world," *arXiv preprint arXiv:2503.20020*, 2025.

[242] Y. Wu, X. Chen, Y. Chen, H. Sadeghian, F. Wu, Z. Bing, S. Haddadin, A. König, and A. Knoll, "Sharedassembly: A data collection approach via shared tele-assembly," *arXiv preprint arXiv:2503.12287*, 2025.

[243] Y. Wang, L. Wang, Y. Du, B. Sundaralingam, X. Yang, Y.-W. Chao, C. Pérez-D'Arpino, D. Fox, and J. Shah, "Inference-time policy steering through human interactions," in *2025 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2025, pp. 15 626–15 633.

[244] C. Lynch, A. Wahid, J. Tompson, T. Ding, J. Betker, R. Baruch, T. Armstrong, and P. Florence, "Interactive language: Talking to robots in real time," *IEEE Robotics and Automation Letters*, 2023.

[245] L. X. Shi, Z. Hu, T. Z. Zhao, A. Sharma, K. Pertsch, J. Luo, S. Levine, and C. Finn, "Yell at your robot: Improving on-the-fly from language corrections," *arXiv preprint arXiv:2403.12910*, 2024.

[246] Y. Cui, S. Karamcheti, R. Palleti, N. Shivakumar, P. Liang, and D. Sadigh, "No, to the right: Online language corrections for robotic manipulation via shared autonomy," in *Proceedings of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*, 2023, pp. 93–101.

[247] T. Yoneda, L. Sun, B. Stadie, M. Walter *et al.*, "To the noise and back: Diffusion for shared autonomy," *arXiv preprint arXiv:2302.12244*, 2023.

[248] Y. Fan and M. Kennedy III, "Diffusion-safe: Shared autonomy framework with diffusion for safe human-to-robot driving handover," *arXiv preprint arXiv:2505.09889*, 2025.

[249] B. McMahan, Z. M. Peng, B. Zhou, and J. Kao, "Shared autonomy with ida: interventional diffusion assistance," *Advances in Neural Information Processing Systems*, vol. 37, pp. 128 330–128 354, 2024.

[250] E. Ng, Z. Liu, and M. Kennedy, "Diffusion co-policy for synergistic human-robot collaborative tasks," *IEEE Robotics and Automation Letters*, vol. 9, no. 1, pp. 215–222, 2023.

[251] L. Sun, J. Ji, X. Tan, and M. Walter, "Flashback: Consistency model-accelerated shared autonomy," in *Conference on Robot Learning*. PMLR, 2025, pp. 924–940.

[252] H. J. Jeon, S. Milli, and A. Dragan, "Reward-rational (implicit) choice: A unifying formalism for reward learning," *Advances in Neural Information Processing Systems*, vol. 33, pp. 4415–4426, 2020.

[253] K. Blanchet, A. Bouzeghoub, S. Kchir, and O. Lebec, "How to guide humans towards skills improvement in physical human-robot collaboration using reinforcement learning?" in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2020, pp. 4281–4287.

[254] S. A. Mehta and D. P. Losey, "Unified learning from demonstrations, corrections, and preferences during physical human-robot interaction," *arXiv preprint arXiv:2207.03395*, 2022.

[255] E. Bıyık, D. P. Losey, M. Palan, N. C. Landolfi, G. Shevchuk, and D. Sadigh, "Learning reward functions from diverse sources of human feedback: Optimally integrating demonstrations and preferences," *The International Journal of Robotics Research*, vol. 41, no. 1, pp. 45–67, 2022.

[256] M. Palan, N. C. Landolfi, G. Shevchuk, and D. Sadigh, "Learning reward functions by integrating human demonstrations and preferences," *arXiv preprint arXiv:1906.08928*, 2019.

[257] B. Ibarz, J. Leike, T. Pohlen, G. Irving, S. Legg, and D. Amodei, "Reward learning from human preferences and demonstrations in atari," *Advances in neural information processing systems*, vol. 31, 2018.

[258] D. Brown, W. Goo, P. Nagarajan, and S. Niekum, "Extrapolating beyond suboptimal demonstrations via inverse reinforcement learning from observations," in *International conference on machine learning*. PMLR, 2019, pp. 783–792.

[259] T. Fitzgerald, P. Koppol, P. Callaghan, R. Q. J. H. Wong, R. Simmons, O. Kroemer, and H. Admoni, "Inquire: Interactive querying for user-aware informative reasoning," in *6th Annual Conference on Robot Learning*, 2022.

[260] M. Hagenow and J. A. Shah, "Realm: Real-time estimates of assistance for learned models in human-robot interaction," *IEEE Robotics and Automation Letters*, 2025.

[261] H. Qi, H. Yin, A. Zhu, Y. Du, and H. Yang, "Strengthening generative robot policies through predictive world modeling," *arXiv preprint arXiv:2502.00622*, 2025.

[262] Y. Du, S. Yang, P. Florence, F. Xia, A. Wahid, B. Ichter, P. Sermanet, T. Yu, P. Abbeel, J. B. Tenenbaum, L. P. Kaelbling, A. Zeng, and J. Tompson, "Video language planning," in *The Twelfth International Conference on Learning Representations*, vol. 3, 2024.

[263] L. Brunke, M. Greeff, A. W. Hall, Z. Yuan, S. Zhou, J. Panerati, and A. P. Schoellig, "Safe learning in robotics: From learning-based control to safe reinforcement learning," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 5, no. 1, pp. 411–444, 2022.

[264] P. A. Lasota, T. Fong, J. A. Shah *et al.*, "A survey of methods for safe human-robot interaction," *Foundations and Trends® in Robotics*, vol. 5, no. 4, pp. 261–349, 2017.

[265] A. Jonnavittula, S. A. Mehta, and D. P. Losey, "Sari: Shared autonomy across repeated interaction," *ACM Transactions on Human-Robot Interaction*, vol. 13, no. 2, pp. 1–36, 2024.

[266] M. Zolotas and Y. Demiris, "Towards explainable shared control," in *Proceedings of the IEEE/RSJ International Conference on Robots and Systems*, 2019, pp. 3020–3026.

[267] S.-W. Lee, X. Kang, and Y.-L. Kuo, "Diff-dagger: Uncertainty estimation with diffusion policy for robotic manipulation," in *2025 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2025, pp. 4845–4852.

[268] Z. He, Y. Cao, and M. Ciocarlie, "Uncertainty comes for free: Human-in-the-loop policies with diffusion models," *arXiv preprint arXiv:2503.01876*, 2025.

[269] U. B. Karli, Z. Shangguan, and T. FItzgerald, "Insight: Inference-time sequence introspection for generating help triggers in vision-language-action models," *arXiv preprint arXiv:2510.01389*, 2025.

[270] P. Valle, C. Lu, S. Ali, and A. Arrieta, "Evaluating uncertainty and quality of visual language action-enabled robots," *arXiv preprint arXiv:2507.17049*, 2025.

[271] W. Huang, F. Xia, T. Xiao, H. Chan, J. Liang, P. Florence, A. Zeng, J. Tompson, I. Mordatch, Y. Chebotar *et al.*, "Inner monologue: Embodied reasoning through planning with language models," *arXiv preprint arXiv:2207.05608*, 2022.

[272] R. Bommasani, "On the opportunities and risks of foundation models," *arXiv preprint arXiv:2108.07258*, 2021.

[273] B. Calli, A. Walsman, A. Singh, S. Srinivasa, P. Abbeel, and A. M. Dollar, "Benchmarking in manipulation research: Using the yale-cmu-berkeley object and model set," *IEEE Robotics & Automation Magazine*, vol. 22, no. 3, pp. 36–52, 2015.

[274] Y. Duan, X. Chen, R. Houthooft, J. Schulman, and P. Abbeel, "Benchmarking deep reinforcement learning for continuous control," in *International conference on machine learning*. PMLR, 2016, pp. 1329–1338.

[275] M. Moll, I. A. Sucan, and L. E. Kavraki, "Benchmarking motion planning algorithms: An extensible infrastructure for analysis and visualization," *IEEE Robotics & Automation Magazine*, vol. 22, no. 3, pp. 96–102, 2015.

[276] J. Pan, J. Eden, D. Oetomo, and W. Johal, "Using fitts' law to benchmark assisted human-robot performance," in *2025 20th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2025, pp. 203–212.

[277] M. F. Stoelen, V. F. Tejada, A. J. Huete, F. Bonsignorio, and C. Balaguer, "Benchmarking shared control for assistive manipulators: From controllability to the speed-accuracy trade-off," in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2012, pp. 4386–4391.

[278] Z. Erickson, V. Gangaram, A. Kapusta, C. K. Liu, and C. C. Kemp, "Assistive gym: A physics simulation framework for assistive robotics," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 10 169–10 176.

[279] D. R. Olsen Jr and S. B. Wood, "Fan-out: Measuring human control of multiple robots," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2004, pp. 231–238.

Appendix A
Review and Categorization Methodology

Our literature search was conducted using Google Scholar. Google Scholar was selected due to its broad coverage of robotics. As described in Section III, we surveyed three general robotics venues: IEEE Robotics and Automation Letters (RA-L), the IEEE International Conference on Robotics and Automation (ICRA), and Science Robotics. We conducted our survey on March 18, 2025. All retrieved records were exported and archived at the time of search. The search was conducted with the following search criteria (with a custom time range of 2020 to 2024):

```
robot AND
("shared autonomy" OR "shared control") AND
(source:"robotics and automation letters"
OR source:"icra" OR
source:"science robotics")
```

The results were cached at the time to a table to be used for subsequent analysis. Section IV reports both descriptive and high-level trends for design decisions related to shared control and shared autonomy systems. As part of the initial review, we also flagged papers for exclusion. The predefined exclusion criteria included workshop papers, position/opinion papers, and papers that did not implement shared control/autonomy (i.e., the only mention of shared autonomy was in in related or future work). There was one duplicate entry which was consolidated to the published venue version. Out of the 405 initial papers, this led to 210 exclusions, and a final set of 195 papers for review.

For any paper that was included, we coded the input method, modeling approach, and application for each paper and transcribed other pertinent paper information, such as the study population and recorded evaluation metrics. The review and coding was conducted by five of the authors. Code consolidation was conducted by one author and independently verified by a second author, leading to the final categories in Section IV. For the input method, modeling approach, and application, papers could be selected for multiple values (e.g., if they used two modeling approaches), whereas the primary human benefit focused on the best-fit category. In addition to coding, as part of the paper review process, we also noted any trends or discussion points that were common across papers. The initial review generated 17 thematic trends, which were then grouped and distilled into the principal-human benefit taxonomy in Section IV and the five recommendation areas presented in Section VI.