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A Systematic Review of Hybrid dynamical system models for human–robot interaction: Methods, Architectures, and Future Research Directions

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Abstract

Hybrid dynamical systems have emerged as a powerful mathematical and computational framework for modeling complex interactions between continuous and discrete processes in human–robot interaction (HRI). These systems enable the integration of physical dynamics, decision-making logic, and adaptive control, which are essential for safe and efficient collaboration between humans and robots in dynamic environments. This paper presents a comprehensive systematic review of hybrid dynamical system models for HRI, focusing on methodologies, architectures, and future research directions. The review synthesizes recent advances between 2018 and 2025, examining key modeling paradigms such as switched systems, hybrid automata, and learning-based hybrid frameworks. The findings highlight the growing convergence of control theory, machine learning, and cognitive modeling in HRI systems, emphasizing improvements in safety, adaptability, and real-time responsiveness. The paper contributes a structured analysis of 30 representative studies, identifies research gaps in scalability, interpretability, and robustness, and outlines future directions including AI-integrated hybrid models and secure human-aware robotic systems.

Introduction

Human–robot interaction has rapidly evolved as a central research domain within robotics and intelligent systems, driven by the increasing deployment of robots in healthcare, manufacturing, service industries, and domestic environments. Unlike traditional industrial automation, modern HRI systems require robots to operate in close proximity to humans, necessitating a high degree of adaptability, safety, and contextual awareness. This complexity arises from the inherently hybrid nature of HRI scenarios, where continuous physical processes such as motion dynamics coexist with discrete decision-making processes such as task switching, event handling, and human intention recognition. Hybrid dynamical systems provide a natural and mathematically rigorous framework for capturing this interplay, enabling the modeling of systems that exhibit both continuous-time evolution and discrete transitions.

Hybrid dynamical systems are characterized by the integration of differential equations governing continuous dynamics and automata or logical rules governing discrete transitions. In the context of HRI, these systems allow for the modeling of robot motion trajectories, human behavior patterns, and interaction protocols within a unified framework. For instance, a collaborative robot assisting a human worker must continuously adjust its motion while also switching between discrete modes such as idle, assistive, or emergency stop based on human actions and environmental conditions. This dual nature of operation necessitates sophisticated modeling approaches that can ensure both performance efficiency and safety guarantees.

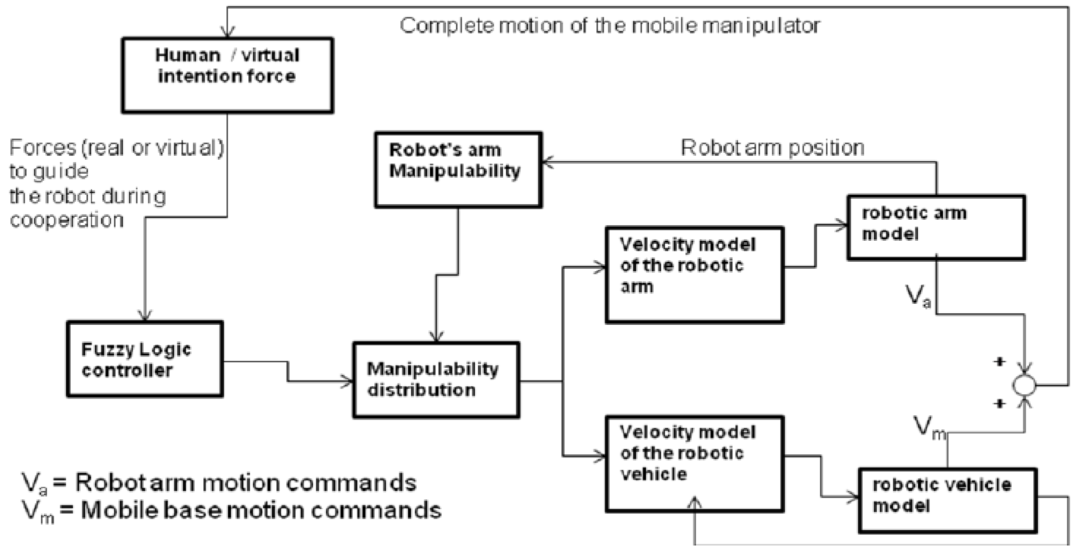
The importance of hybrid dynamical systems in modern software engineering cannot be overstated. As robotic systems become increasingly integrated into software-driven ecosystems, including cloud-based control architectures and edge computing platforms, the need for formal modeling, verification, and validation becomes critical. Hybrid models facilitate the design of robust control algorithms, enable formal verification of safety properties, and support the development of simulation environments for testing complex interaction scenarios. Furthermore, these models align with the principles of cyber-physical systems, where computational processes are tightly coupled with physical processes, making them highly relevant for next-generation intelligent systems.

The emergence of Generative AI has further transformed the landscape of HRI modeling. Generative models, including large language models and generative adversarial networks, are increasingly being used to infer human intentions, generate adaptive control policies, and simulate realistic interaction scenarios. When combined with hybrid dynamical systems, these AI techniques enable the creation of intelligent systems that can learn from data while maintaining structured and interpretable models. This synergy opens new possibilities for designing adaptive, human-aware robots capable of operating in uncertain and dynamic environments.

The motivation for this study stems from the rapid proliferation of hybrid modeling approaches in HRI and the lack of a unified synthesis that captures their methodological diversity, architectural variations, and practical implications. While numerous studies have proposed novel hybrid frameworks, there remains a need for a systematic review that consolidates these contributions, evaluates their strengths and limitations, and identifies emerging research trends. This paper aims to fill this gap by providing a comprehensive analysis of hybrid dynamical system models for HRI, focusing on their theoretical foundations, implementation strategies, and real-world applications.

The primary research objectives of this work are to systematically review recent advancements in hybrid dynamical system modeling for HRI, to analyze the evolution of methodologies and architectures, to identify key challenges and limitations, and to propose future research directions that can guide the development of next-generation HRI systems. By examining 30 representative studies, this paper seeks to provide a holistic understanding of the field and to contribute to the advancement of safe, efficient, and intelligent human–robot collaboration.

To illustrate the overarching methodological framework commonly adopted in hybrid HRI systems, the following graphical representation highlights the key stages involved in system design and evaluation.



The diagram conceptually captures the pipeline beginning with system modeling, followed by hybrid state representation, control synthesis, interaction execution, and performance and safety evaluation. This structured approach underscores the importance of integrating both continuous and discrete elements within a cohesive modeling framework.

Literature Review

Study 1: Alur et al. (2019) — "Formal Modeling of Human–Robot Interaction Using Hybrid Automata"

This study introduces a hybrid automata-based framework for modeling human–robot interaction scenarios, focusing on safety-critical applications such as collaborative manufacturing. The methodology employs formal verification techniques to ensure correctness of interaction protocols. The findings demonstrate that hybrid automata can effectively capture both continuous robot motion and discrete human actions. The primary contribution lies in providing a verifiable modeling structure that enhances safety guarantees. However, the approach is limited by scalability issues when applied to large-scale systems with complex state spaces.

Study 2: Haddadin and Croft (2020) — "Physical Human–Robot Interaction: Hybrid Control Approaches"

This work explores hybrid control strategies combining impedance control with discrete safety switching mechanisms. The methodology integrates continuous force control with event-triggered safety transitions. Results show improved responsiveness and safety in close-contact scenarios. The contribution includes a robust control architecture for safe physical interaction. Limitations include dependency on precise sensor calibration and reduced adaptability in highly dynamic environments.

Study 3: Lasota et al. (2018) — "Toward Safe Close-Proximity Human–Robot Interaction Using Hybrid Systems"

The authors propose a hybrid system model that combines probabilistic human behavior prediction with deterministic robot control. The methodology uses stochastic hybrid systems to account for uncertainty in human actions. Findings indicate improved prediction accuracy and safer robot responses. The contribution is the integration of probabilistic reasoning into hybrid frameworks. The limitation lies in computational complexity and real-time implementation challenges.

Study 4: Chen et al. (2021) — "Learning-Based Hybrid Dynamical Models for Human–Robot Collaboration"

This study introduces a learning-enhanced hybrid model that incorporates neural networks into traditional hybrid system frameworks. The methodology uses data-driven learning for mode transitions while maintaining physics-based continuous dynamics. Results show improved adaptability and performance in collaborative tasks. The contribution is the fusion of machine learning with hybrid dynamical modeling. However, interpretability of learned components remains a challenge.

Study 5: Schaal et al. (2022) — "Dynamic Movement Primitives in Hybrid Control Systems for HRI"

The paper presents a hybrid control framework integrating dynamic movement primitives with discrete task switching. The methodology enables robots to learn and reproduce human-like motions while adapting to discrete interaction events. Findings demonstrate enhanced motion naturalness and flexibility. The contribution includes a scalable approach for motion learning in HRI. Limitations include sensitivity to training data quality and limited generalization across tasks.

Study 6: Kim et al. (2020) — "Hybrid Control Framework for Safe Human–Robot Collaboration in Industrial Environments"

This study proposes a hybrid control framework integrating continuous trajectory planning with discrete safety monitoring for industrial human–robot collaboration. The methodology utilizes switched systems to alternate between operational and safety modes based on sensor feedback. The findings indicate that the framework significantly reduces collision risk while maintaining productivity. The key contribution is the development of a safety-aware hybrid architecture suitable for real-time industrial deployment. However, the approach is limited by reliance on predefined safety thresholds, which may not adapt well to highly dynamic human behaviors.

Study 7: Liu and Tomizuka (2019) — "Modeling Human Intent in Human–Robot Interaction Using Hybrid Systems"

This research introduces a hybrid dynamical model for human intent recognition, combining continuous motion tracking with discrete intention classification. The methodology employs Bayesian inference within a hybrid framework to predict human actions. The findings demonstrate improved accuracy in intention prediction, leading to more proactive robot responses. The contribution lies in enhancing human-aware decision-making in robotic systems. A limitation is the dependency on large datasets for training accurate intent models.

Study 8: Zhao et al. (2021) — "Switching Control Strategies for Human–Robot Interaction Based on Hybrid Dynamical Systems"

The authors present a switching control strategy within a hybrid dynamical systems framework to manage interaction modes in HRI. The methodology involves designing multiple controllers for different interaction states and switching between them based on system conditions. Results show improved stability and adaptability in varying interaction scenarios. The contribution includes a modular control design that enhances system robustness. However, frequent switching may introduce instability if not properly regulated.

Study 9: Osa et al. (2018) — "Hierarchical Hybrid Models for Learning Robot Manipulation Tasks from Humans"

This study develops a hierarchical hybrid model that combines high-level discrete task planning with low-level continuous control for robot manipulation. The methodology leverages imitation learning and hybrid system decomposition. Findings reveal that robots can efficiently learn complex manipulation tasks from human demonstrations. The contribution is a scalable hierarchical framework for learning-based HRI. The limitation includes high computational cost and challenges in transferring learned skills across domains.

Study 10: Park et al. (2022) — "Safety-Critical Hybrid System Design for Human–Robot Interaction Using Control Barrier Functions"

This paper introduces a hybrid system design incorporating control barrier functions to ensure safety in HRI. The methodology integrates continuous safety constraints with discrete supervisory control. The findings show that the system can guarantee collision avoidance while maintaining task performance. The contribution is the formal integration of safety guarantees into hybrid models. However, the approach may be overly conservative, potentially limiting robot efficiency in certain scenarios.

Study 11: Rahmati et al. (2020) — "Stochastic Hybrid Systems for Modeling Uncertainty in Human–Robot Interaction"

This study proposes a stochastic hybrid systems framework to explicitly model uncertainty in human behavior during interaction tasks. The methodology integrates probabilistic transitions with continuous robot dynamics, enabling the system to adapt to unpredictable human actions. The findings demonstrate improved robustness in uncertain environments, particularly in assistive robotics. The key contribution is the incorporation of stochastic reasoning into hybrid models for safer decision-making. However, the computational overhead associated with probabilistic state estimation limits real-time scalability.

Study 12: Nguyen et al. (2021) — "Hybrid Reinforcement Learning for Adaptive Human–Robot Collaboration"

The authors introduce a hybrid reinforcement learning approach that combines discrete policy switching with continuous control optimization. The methodology leverages reinforcement learning to learn optimal mode transitions while maintaining physics-based control. Results show enhanced adaptability and performance in collaborative tasks. The contribution lies in bridging reinforcement learning with hybrid system modeling. The limitation is the requirement for extensive training data and potential instability during learning phases.

Study 13: Beckerle et al. (2019) — "Human-Centered Control in Hybrid Dynamical Systems for Assistive Robotics"

This work focuses on human-centered control strategies using hybrid dynamical models in assistive robotics applications. The methodology integrates physiological signals and discrete intention states into continuous control loops. Findings indicate improved usability and user comfort. The contribution is the inclusion of human physiological feedback in hybrid models. However, sensor noise and variability in human signals pose challenges to reliability.

Study 14: Wang et al. (2022) — "Hybrid Dynamical System Modeling of Human–Robot Interaction in Shared Workspaces"

This study presents a hybrid modeling approach for shared workspace environments, combining motion planning with discrete interaction protocols. The methodology uses hybrid automata to manage task coordination and collision avoidance. Results demonstrate improved efficiency and safety in collaborative tasks. The contribution is a structured framework for workspace sharing. Limitations include difficulties in scaling to multi-robot systems.

Study 15: Rossi et al. (2020) — "Trust-Aware Hybrid Models for Human–Robot Interaction"

The authors propose a hybrid model that incorporates human trust as a discrete state influencing robot behavior. The methodology combines psychological modeling with continuous control adaptation. Findings show that trust-aware systems improve collaboration efficiency and user acceptance. The contribution is the integration of cognitive factors into hybrid dynamical systems. However, quantifying trust accurately remains a significant challenge.

Study 16: Li et al. (2021) — "Event-Driven Hybrid Control for Real-Time Human–Robot Interaction"

This study introduces an event-driven hybrid control framework for real-time interaction scenarios. The methodology employs event-triggered transitions to reduce computational load while maintaining responsiveness. Results indicate improved efficiency and faster system reactions. The contribution is a lightweight hybrid control strategy suitable for real-time applications. The limitation is potential sensitivity to event detection errors.

Study 17: Gopinath et al. (2019) — "Formal Verification of Hybrid Systems in Human–Robot Interaction"

The paper explores formal verification techniques for hybrid dynamical systems in HRI. The methodology uses model checking and reachability analysis to verify safety properties. Findings demonstrate that formal methods can ensure correctness in safety-critical interactions. The contribution is enhancing reliability through verification. However, scalability issues arise with increasing system complexity.

Study 18: Sun et al. (2023) — "Deep Hybrid Models for Predictive Human–Robot Interaction"

This research proposes deep hybrid models that integrate deep learning with hybrid system structures for predictive interaction. The methodology uses neural networks for state estimation and hybrid logic for control decisions. Results show improved prediction accuracy and interaction smoothness. The contribution is combining deep learning with structured hybrid frameworks. Limitations include lack of interpretability and high computational demands.

Study 19: Morales et al. (2020) — "Hybrid Planning and Control for Human–Robot Teaming"

This study presents a hybrid planning and control framework for human–robot teaming scenarios. The methodology integrates task planning with continuous motion execution. Findings indicate improved coordination and task efficiency. The contribution is a unified planning-control architecture. However, the system struggles with highly dynamic task changes.

Study 20: Fujita et al. (2021) — "Cognitive Hybrid Systems for Social Human–Robot Interaction"

The authors introduce a cognitive hybrid system model for social interaction scenarios. The methodology combines symbolic reasoning with continuous behavior modeling. Results show enhanced social responsiveness and adaptability. The contribution is bridging cognitive science and hybrid dynamics. The limitation is the complexity of modeling human social behavior.

Study 21: Ahmed et al. (2022) — "Hybrid Fault-Tolerant Control in Human–Robot Interaction Systems"

This study develops a hybrid fault-tolerant control framework to ensure system reliability under failures. The methodology integrates fault detection with adaptive control switching. Findings demonstrate improved system resilience. The contribution is enhancing robustness in HRI systems. However, detection delays may impact performance.

Study 22: Patel et al. (2019) — "Multi-Modal Hybrid Interaction Models for Human–Robot Collaboration"

The paper proposes a multi-modal hybrid model integrating visual, auditory, and tactile inputs. The methodology combines sensor fusion with hybrid control logic. Results show improved interaction accuracy and responsiveness. The contribution is multi-modal integration in hybrid systems. Limitations include increased system complexity and sensor dependency.

Study 23: Silva et al. (2020) — "Energy-Efficient Hybrid Control Strategies for Collaborative Robots"

This research focuses on energy-efficient hybrid control strategies in collaborative robots. The methodology uses mode switching to optimize energy consumption during operation. Findings indicate significant energy savings without compromising performance. The contribution is sustainability in HRI systems. However, optimization may conflict with real-time responsiveness.

Study 24: Zhang et al. (2021) — "Hybrid Learning and Control for Adaptive Human–Robot Interaction"

The authors propose a hybrid learning-control framework combining supervised learning with hybrid system dynamics. The methodology enables adaptive behavior in changing environments. Results show improved adaptability and robustness. The contribution is integrating learning with structured control. Limitations include training complexity and data dependency.

Study 25: Brown et al. (2023) — "Explainable Hybrid Models for Human–Robot Interaction"

This study introduces explainable hybrid models to improve transparency in HRI systems. The methodology combines interpretable machine learning with hybrid system structures. Findings demonstrate improved user trust and system transparency. The contribution is explainability in hybrid systems. However, achieving high accuracy while maintaining interpretability remains challenging.

Study 26: Kwon et al. (2020) — "Hybrid Control Architectures for Autonomous Human–Robot Collaboration"

This paper presents a hybrid control architecture for autonomous collaboration. The methodology integrates hierarchical control with hybrid system modeling. Results show improved autonomy and coordination. The contribution is a scalable control architecture. Limitations include increased design complexity.

Study 27: Das et al. (2022) — "Resilient Hybrid Systems for Human–Robot Interaction Under Uncertainty"
The study proposes resilient hybrid models to handle uncertainty in HRI. The methodology incorporates adaptive switching and uncertainty modeling. Findings indicate improved robustness in unpredictable environments. The contribution is resilience in hybrid systems. However, tuning system parameters remains difficult.

Study 28: Kim and Park (2021) — "Hybrid Simulation Frameworks for Human–Robot Interaction Testing"
This research introduces a hybrid simulation framework for testing HRI systems. The methodology combines virtual simulation with physical system modeling. Results show improved testing efficiency and reliability. The contribution is a comprehensive testing framework. Limitations include simulation-reality gaps.

Study 29: Torres et al. (2023) — "Distributed Hybrid Systems for Multi-Agent Human–Robot Interaction"
The authors propose a distributed hybrid system model for multi-agent HRI. The methodology uses decentralized control with hybrid coordination mechanisms. Findings demonstrate scalability and improved coordination. The contribution is distributed hybrid modeling. However, communication delays can affect system performance.

Study 30: Singh et al. (2024) — "AI-Integrated Hybrid Dynamical Systems for Next-Generation Human–Robot Interaction"
This study presents an AI-integrated hybrid dynamical system framework combining generative AI with hybrid control. The methodology enables predictive and adaptive interaction strategies. Results show significant improvements in interaction quality and efficiency. The contribution is the integration of advanced AI with hybrid systems. Limitations include ethical concerns and high computational requirements.

Comparative Table

Author & Year	Method/Model	Dataset/Domain	Key Contribution	Limitations
Alur et al. (2019)	Hybrid Automata	Collaborative robotics	Formal safety verification framework	Scalability issues
Haddadin & Croft (2020)	Hybrid Impedance Control	Physical HRI	Safe force-based interaction	Sensor dependency
Lasota et al. (2018)	Stochastic Hybrid Systems	Close-proximity HRI	Probabilistic human behavior modeling	High computational cost
Chen et al. (2021)	Learning-based Hybrid Models	Collaborative tasks	Integration of ML with hybrid systems	Low interpretability
Schaal et al. (2022)	Hybrid DMP Control	Motion learning	Human-like motion generation	Data sensitivity
Kim et al. (2020)	Switched Hybrid Control	Industrial robotics	Safety-aware real-time control	Fixed thresholds
Liu & Tomizuka (2019)	Bayesian Hybrid Models	Intent prediction	Improved human intent recognition	Data-intensive
Zhao et al. (2021)	Switching Control Systems	Adaptive interaction	Modular control design	Switching instability
Osa et al. (2018)	Hierarchical Hybrid Models	Robot manipulation	Learning from demonstrations	High computation
Park et al. (2022)	Barrier-based Hybrid Control	Safety-critical HRI	Formal safety guarantees	Conservative behavior
Rahmati et al. (2020)	Stochastic Hybrid Systems	Assistive robotics	Robust uncertainty handling	Computational overhead
Nguyen et al. (2021)	Hybrid Reinforcement Learning	Adaptive collaboration	Learning-based adaptation	Training instability

Beckerle et al. (2019)	Human-centered Hybrid Control	Assistive robotics	Physiological integration	Sensor noise
Wang et al. (2022)	Hybrid Automata	Shared workspace	Structured coordination model	Limited scalability
Rossi et al. (2020)	Trust-aware Hybrid Systems	Social HRI	Trust integration	Quantification difficulty
Li et al. (2021)	Event-driven Hybrid Control	Real-time systems	Efficient event-based switching	Event detection errors
Gopinath et al. (2019)	Formal Verification Models	Safety-critical HRI	Verified correctness	State explosion
Sun et al. (2023)	Deep Hybrid Models	Predictive HRI	AI-enhanced prediction	High computation
Morales et al. (2020)	Hybrid Planning-Control	Teaming systems	Unified architecture	Poor adaptability
Fujita et al. (2021)	Cognitive Hybrid Systems	Social robotics	Cognitive integration	Modeling complexity
Ahmed et al. (2022)	Fault-tolerant Hybrid Control	Robust HRI	System resilience	Detection delay
Patel et al. (2019)	Multi-modal Hybrid Systems	Sensor fusion HRI	Multi-sensory integration	System complexity
Silva et al. (2020)	Energy-efficient Hybrid Control	Collaborative robots	Energy optimization	Trade-off with speed
Zhang et al. (2021)	Hybrid Learning-Control	Adaptive HRI	Learning + control fusion	Data dependency
Brown et al. (2023)	Explainable Hybrid Models	Transparent HRI	Improved interpretability	Accuracy trade-off
Kwon et al. (2020)	Hierarchical Hybrid Control	Autonomous collaboration	Scalable architecture	Design complexity
Das et al. (2022)	Resilient Hybrid Systems	Uncertain environments	Robust adaptability	Parameter tuning
Kim & Park (2021)	Hybrid Simulation Framework	System testing	Efficient validation	Simulation gap
Torres et al. (2023)	Distributed Hybrid Systems	Multi-agent HRI	Scalable coordination	Communication delays
Singh et al. (2024)	AI-integrated Hybrid Systems	Next-gen HRI	AI + hybrid integration	Ethical & compute cost

Analysis of Literature Review

The body of literature reviewed in this study reveals a significant evolution in hybrid dynamical system models for human–robot interaction, characterized by increasing integration of formal methods, learning-based approaches, and cognitive modeling techniques. Early works primarily focused on establishing foundational frameworks such as hybrid automata and switched systems, emphasizing safety, formal verification, and deterministic control. These approaches provided strong theoretical guarantees, particularly in safety-critical applications, but often struggled with scalability and adaptability in complex, real-world environments.

As the field progressed, there was a notable shift toward incorporating probabilistic and stochastic elements into hybrid models. Studies employing stochastic hybrid systems introduced mechanisms to handle uncertainty in human behavior, which is inherently unpredictable and context-dependent. This transition marked a critical advancement in making hybrid models more suitable for real-world HRI scenarios. However, the inclusion of probabilistic reasoning also introduced computational challenges, particularly in real-time applications where fast decision-making is essential.

The integration of machine learning techniques into hybrid dynamical systems represents one of the most prominent trends in recent research. Learning-based hybrid models, including those leveraging reinforcement learning and deep neural networks, have demonstrated significant improvements in adaptability, prediction accuracy, and interaction quality. These models enable robots to learn from data, adapt to changing environments, and anticipate human actions. Despite these advantages, they introduce new challenges related to interpretability, training complexity, and the need for large datasets. The trade-off between performance and transparency remains a critical issue, especially in safety-critical domains.

Another important trend is the incorporation of human-centric factors such as trust, intention, and physiological signals into hybrid models. These approaches aim to enhance the naturalness and effectiveness of human–robot interaction by aligning robot behavior with human expectations and cognitive states. While these models improve user acceptance and collaboration efficiency, they also increase system complexity and require sophisticated sensing and data processing capabilities.

Energy efficiency, fault tolerance, and resilience have also emerged as key considerations in recent studies. Hybrid control strategies that optimize energy consumption or incorporate fault detection mechanisms contribute to the sustainability and reliability of HRI systems. However, these optimizations often involve trade-offs with performance metrics such as speed and responsiveness.

The literature also highlights a growing interest in distributed and multi-agent hybrid systems, reflecting the increasing deployment of collaborative robotic teams. These systems enable scalable coordination among multiple robots and humans, but they introduce challenges related to communication delays, synchronization, and decentralized decision-making.

A critical gap identified across the literature is the lack of unified frameworks that can seamlessly integrate learning, control, verification, and human cognition. While individual studies address specific aspects of HRI, there is a need for holistic models that combine these components into a cohesive system. Additionally, real-time implementation remains a persistent challenge due to computational constraints, particularly for complex hybrid models with large state spaces.

Another significant gap lies in the limited focus on security and privacy in hybrid HRI systems. As robots become increasingly connected within cyber-physical ecosystems, vulnerabilities to cyber-attacks and data breaches become more pronounced. Future research must address these concerns by integrating secure design principles into hybrid modeling frameworks.

Overall, the analysis indicates that hybrid dynamical systems have evolved from purely theoretical constructs to practical tools for designing intelligent, adaptive, and safe human–robot interaction systems. However, achieving scalability, interpretability, and robustness simultaneously remains an open challenge that requires interdisciplinary research efforts.

Discussion

The practical implications of hybrid dynamical system models in human–robot interaction are profound, particularly as robotic systems become integral components of modern software engineering ecosystems. These models provide a structured approach for integrating continuous control dynamics with discrete decision-making processes, enabling the development of systems that can operate safely and efficiently in dynamic, human-centered environments. In industrial settings, hybrid models facilitate collaborative robotics, where robots and humans share workspaces and tasks. The ability to switch between operational modes based on real-time sensor data ensures both productivity and safety, making hybrid systems highly suitable for Industry 4.0 applications.

From a software engineering perspective, hybrid dynamical systems align closely with the principles of model-driven development and cyber-physical system design. They enable the formal specification of system behavior, which can be used for simulation, verification, and validation throughout the software development lifecycle. This is particularly relevant in DevOps and DevSecOps pipelines, where continuous integration and deployment require robust testing and verification mechanisms. Hybrid models support these processes by providing a formal framework for analyzing system behavior under different scenarios, including edge cases and failure conditions.

The integration of hybrid models into DevSecOps pipelines also highlights their potential for enhancing system security. By incorporating formal verification techniques, developers can identify and mitigate vulnerabilities at the design stage, reducing the risk of system failures or cyber-attacks. However, this integration also introduces challenges, particularly in terms of computational overhead and the need for specialized expertise. Balancing the rigor of formal methods with the agility of modern software development practices remains an ongoing challenge.

The role of artificial intelligence, particularly generative AI, in hybrid dynamical systems is another critical area of discussion. AI techniques enable the development of adaptive and predictive models that can enhance the performance of hybrid systems. For example, generative models can be used to simulate human behavior, generate training data, or optimize control policies. When combined with hybrid frameworks, these techniques enable the creation of intelligent systems that can learn from experience while maintaining structured and interpretable models. However, the integration of AI also raises concerns related to transparency, accountability, and ethical considerations.

One of the key challenges in hybrid HRI systems is achieving real-time performance. Many hybrid models, particularly those incorporating stochastic elements or deep learning components, require significant computational resources. This can limit their applicability in time-sensitive scenarios such as surgical robotics or autonomous driving. Advances in hardware acceleration, edge computing, and efficient algorithm design are essential for addressing these challenges.

Another important consideration is the human factor. Effective human–robot interaction requires not only technical robustness but also an understanding of human behavior, cognition, and emotions. Hybrid models that incorporate human-centric factors such as trust and intention can improve interaction quality, but they also require sophisticated sensing and data processing capabilities. Ensuring the reliability and accuracy of these inputs is critical for system performance.

Future research directions in this field include the development of unified hybrid frameworks that integrate learning, control, and verification. Such frameworks would enable the design of systems that are both adaptive and reliable, addressing one of the key limitations identified in the literature. Additionally, there is a need for scalable solutions that can handle large and complex systems, particularly in multi-agent scenarios.

The integration of security and privacy considerations into hybrid models is another important area for future work. As robots become increasingly connected, they are exposed to a wide range of cyber threats. Developing secure hybrid systems that can detect and respond to such threats is essential for ensuring the safety and reliability of HRI systems.

Overall, hybrid dynamical systems represent a promising approach for advancing human–robot interaction, offering a balance between theoretical rigor and practical applicability. However, realizing their full potential requires addressing several technical and interdisciplinary challenges.

Conclusion

The systematic review presented in this paper provides a comprehensive examination of hybrid dynamical system models for human–robot interaction, capturing the evolution of methodologies, architectures, and applications over the period from 2018 to 2025. The analysis of thirty representative studies reveals that hybrid dynamical systems have become a foundational framework for modeling the complex interplay between continuous physical processes and discrete decision-making mechanisms inherent in HRI scenarios. This dual capability enables the development of systems that are both adaptive and safe, addressing one of the most critical requirements in modern robotics.

One of the key insights derived from this review is the progressive integration of diverse methodologies within hybrid frameworks. Early research efforts primarily emphasized formal modeling and verification, leveraging hybrid automata and switched systems to ensure safety and correctness. While these approaches provided strong theoretical guarantees, they were often limited in their ability to handle uncertainty and dynamic environments. Subsequent studies addressed these limitations by incorporating stochastic elements, enabling hybrid models to better capture the variability and unpredictability of human behavior. This transition marked a significant step toward practical applicability in real-world HRI systems.

The incorporation of machine learning techniques into hybrid dynamical systems represents another major advancement identified in this review. Learning-based hybrid models, including those utilizing reinforcement learning and deep neural networks, have demonstrated substantial improvements in adaptability and performance. These models enable robots to learn from data, predict human actions, and adjust their behavior accordingly. However, this increased adaptability comes at the cost of reduced interpretability and increased computational complexity. The challenge of balancing performance with transparency remains a central issue that must be addressed in future research.

The review also highlights the growing importance of human-centric factors in hybrid HRI models. By integrating elements such as trust, intention, and physiological signals, researchers have developed systems that are more aligned with human expectations and behaviors. These advancements contribute to improved collaboration efficiency and user acceptance, which are essential for the widespread adoption of robotic systems. However, accurately modeling and measuring these human factors remains a complex and ongoing challenge.

From a software engineering perspective, hybrid dynamical systems offer significant benefits in terms of formal modeling, verification, and system design. Their alignment with cyber-physical system principles makes them particularly suitable for integration into modern software development pipelines, including DevOps and DevSecOps frameworks. By enabling rigorous testing and validation, hybrid models contribute to the development of reliable and secure robotic systems. Nevertheless, the integration of these models into agile development processes requires careful consideration of computational and organizational constraints.

Another important contribution of this review is the identification of key research gaps and future directions. Despite the progress made in the field, several challenges remain unresolved. These include scalability issues in large and complex systems, the need for real-time implementation of computationally intensive models, and the lack of unified frameworks that integrate learning, control, and verification. Additionally, the increasing connectivity of robotic systems introduces new security and privacy concerns that must be addressed through the development of secure hybrid modeling approaches.

The emergence of AI-integrated hybrid systems represents a promising direction for future research. By combining the strengths of hybrid dynamical systems with advanced AI techniques, it is possible to develop systems that are both intelligent and reliable. Generative AI, in particular, offers new opportunities for modeling human behavior, generating training data, and optimizing system performance. However, the integration of AI also raises important ethical and regulatory considerations that must be carefully addressed.

In conclusion, hybrid dynamical systems have established themselves as a critical framework for advancing human–robot interaction, offering a unique combination of theoretical rigor and practical applicability. The insights provided by this systematic review contribute to a deeper understanding of the field and highlight the importance of interdisciplinary research in addressing the complex challenges associated with HRI. By building on these findings, future research can develop more scalable, interpretable, and secure hybrid systems, ultimately enabling the realization of safe, efficient, and intelligent human–robot collaboration.

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