PROPOSED TOPIC / RESEARCH PROJECT

Title of the PhD proposal :

SMART - Software Mediators for Application Reliability and Teamwork in smart homes

Name(s) of supervisor(s) / contact:
K. Marçal de Oliveira, kathia.oliveira@uphf.fr
E. Grislin-Le Strugeon, emmanuelle.grislin@uphf.fr
R. Belloum, rafik.belloum@uphf.fr

Host laboratory: UPHF, LAMIH UMR CNRS 8201

Short summary:
Smart homes are new living environments in which connected devices and dedicated apps provide tailored services, which are particularly beneficial for older adults and/or those with care needs. In addition, a variety of people may interact with the occupants of the smart home, such as a home health aide, a nurse, or family members, for example. These various actors—both human and artificial—form a team whose common goal is to ensure the physical and mental well-being of the residents. However, information from different sources and applications must be managed and used in an integrated manner. The idea of this thesis is to use software agents as mediators to ensure quality and enable the actors' collaboration in the combined use of different applications in a smart home environment.

Brief description of the research group / host laboratory:
This thesis will be conducted within the Computer Science Department of the Laboratory of Automation, Mechanics, and Industrial and Human Computer Science (LAMIH, UMR CNRS 8201). The Computer Science Department of this laboratory has 32 permanent members. It is organized into three research themes: Human-Machine Interaction, Reasoning, and Agents (InterA), Operations Research (OR), and Security, Systems, and Data (SSD). This thesis will be conducted within the team working on the InterA research theme, one of whose main scientific objectives is the design and evaluation of innovative interactive systems for smart environments (smart buildings, homes, or cities), in which interaction extends beyond the traditional screen-based framework to permeate the physical space through the Internet of Things (IoT). Designing applications for these smart environments requires integrating various fields, such as software engineering, human-computer interaction, and artificial intelligence.

1. Description of the Ph.D. proposal

1.1 Context (and scenarios if any)

Smart homes are modern environments that combine cutting-edge technology, such as internet-connected devices and artificial intelligence systems. These environments allow for the continuous collection of data through sensors and applications, creating a scenario that interprets the information and responds to the residents' needs. This technology has proven useful in healthcare contexts, such as elderly care, health monitoring, and home assistance [1][7].

Through technological advancements, it has become possible to create systems that identify personal activities, are able to understand situations, and automatically adjust the functioning of the house according to the residents' needs through Machine Learning techniques [9][27]. Furthermore, the use of architectures that utilize shared processing and edge computing has improved both the system's response speed and the protection of user privacy [35][38].

However, most of these approaches still focus predominantly on sensory data, treating the user as a passive agent. This represents a challenge, as these solutions are limited by not considering that real home environments involve multiple human actors, such as family members, caregivers, and healthcare professionals. The absence of effective mechanisms to integrate these different sources of knowledge compromises the ability of these systems to interpret complex and contextual situations [9].

The increasing collaboration between humans and artificial intelligence (AI) has transformed the role of intelligent systems, which are no longer merely tools but are taking on a more active role in decision-making [11][31][17]. For this context to function, humans and artificial agents need to share objectives, information, and responsibilities, creating the need for mechanisms that promote coordination, communication, and the construction of a shared understanding. Trust, explainability, and alignment with human preferences emerge as essential aspects for the success of these interactions [21][4]. However, the integration of these dimensions in smart homes is still limited due to two main challenges: the difficulty of combining heterogeneous information from sensors and human observations into meaningful knowledge, and the lack of support for collective reasoning in teams composed of multiple human and artificial actors.

In a hypothetical scenario, for instance, a resident of a smart home spends more time than usual watching television and eats less than normal. Some of this information can be captured automatically by sensors, while other parts can be observed by family members. On their own, this information may seem vague, but when combined, it can signify a critical change in the individual's health status, such as the onset of depression or a functional decline. Other scenarios can illustrate this need for integration:

- Medication reminder - the system detects that medication was not taken at the correct time. Considering the time a family member reports frequent forgetfulness, this combination may indicate the need for professional intervention.
- Social isolation - devices indicate low interaction with the environment, while family members perceive social isolation behavior: together, these observations may suggest interventions to improve the resident's sociability.
- Interest mediation: several users - for example, an elderly person and their caregiver - have different preferences regarding tastes, for example: temperature, diet or routines; the system must mediate these decisions in a balanced and fair way.

Therefore, the need for a system capable of integrating, interpreting and mediating information resulting from multiple actors, both human and artificial, supporting decision-making processes that are **collaborative, adaptive and centered on the user's needs** in smart home environments becomes evident.

1.2 Problem Statement and Objective

The challenge lies in gathering information from multiple sources, identifying relevant data, and using it to support reasoning in order to ensure the quality of application services provided to individuals living in smart home environments.

The objective of this research is to design a software solution that acts as a mediating agent, supporting collaboration within a team composed of both human and artificial agents. This mediating agent will more specifically support the integration of heterogeneous information, facilitate collective reasoning between human and artificial agents, and assist in resolving potential conflicts or inconsistencies in decision-making.

1.3 Brief Overview of the State of the Art

1.3.1 Smart Homes

The advancement of smart environments, such as smart homes, has been driven in recent years by the confluence of Artificial Intelligence (AI), the Internet of Things (IoT), and distributed systems. Such environments are characterized by the presence of data from disparate sources, such as sensors, connected devices, and human interactions, which allow for the personalization of services, especially in assistance and care contexts. However, the integration and coordinated interpretation of this evidence to support relevant and contextualized decisions proves to be a challenge [7][2].

Recent studies show that previous methods, such as reactive approaches to context analysis and user behavior, have evolved into systems based on AI and especially machine learning, for activity recognition for instance [1][27]. In addition, recent research demonstrates a significant improvement in the efficiency, responsiveness, and privacy of these environments when using data-driven architectures and edge computing [38][35]. However, the vast majority of work in the field focuses only on sensor-derived data, neglecting systematic human interaction [9], which reduces the ability of these systems to capture complex behavioral nuances, particularly in health and well-being scenarios.

1.3.2 Human–AI team collaboration

Human-AI collaboration has been mostly studied from a tool-based perspective, using AI in decision-making support or assistive technology, with a recent paradigm shift to consider AI acting primarily as an active partner in collaborative processes [40][42][17]. Critical factors such as trust, transparency, explainability, and alignment with human preferences are emphasized by recent research [21][10]. Furthermore, the ability of these systems to adapt to the context and user demands is fundamental to ensuring effective collaboration [4]. However, most scientific production is still centered on individual interactions between one human and one AI system, restricting scenarios that explore human interaction with multiple artificial agents synchronously.

The concept of human-AI teaming expands collaboration by considering humans and artificial agents as members of the same group, with shared goals, responsibilities, and context [11][49]. Recent research emphasizes the relevance of shared mental models, effective communication, and dynamic coordination [31][48]. Emerging approaches present the idea of a shared cognitive space, where relevant information is integrated and used collectively to support decision-making [29][41]. However, there are still considerable gaps in creating mechanisms that enable the efficient coordination of hybrid teams in complex and dynamic contexts, such as smart homes.

1.3.4 Human-Centered AI

Human-Centered Artificial Intelligence (HCAI) has become an important model for creating interactive systems. This approach emphasizes that AI systems should augment human capabilities, ensure transparency, and promote trust [39][45][19].

In this scenario, factors such as explainability (XAI), impartiality, and accountability have gained increasing prominence [8][23]. In intelligent environments, this implies the need for systems that provide accessible explanations for non-expert users and that consider their preferences and values [46]. However, many current systems still lack efficient mechanisms to facilitate collaborative decision-making among multiple users, particularly in distributed home environments.

1.3.5 Synthesis and Research Gaps

Smart homes provide a new context where humans and technological agents will have to collaborate. But there is the lack of mechanisms for effectively integrating and producing information based on both the data collected from the heterogeneous home devices and the human observations. The critical challenge is to support collective reasoning, in which multiple agents (human and artificial) contribute to building a shared understanding of the situation.In addition, we highlight the challenges in modeling collaboration between multiple actors in the same environment, with different roles and levels of autonomy in the collaborative space. Another challenge identified is in dealing with the dynamic adaptation of the team, considering the addition and removal of devices and participants in the system. In this sense, the need for integration with mediating agents to improve collaboration in multi-agent environments is observed.

Given these limitations, there is an opportunity to develop an integrated solution that combines principles of human-centered AI, multi-agent systems, and human-AI collaboration, with a particular focus on intelligent mediation. This approach has the potential to advance the state of the art, enabling more effective, adaptive, and contextualized collaboration in smart home environments.

1.3.6 Research Questions

- How can we design a mediating software agent for a team composed of human and artificial agents?
- What information is shared? In what form?
- How can we measure the success of the collaboration?
- How can we enable adaptation to changes within the team (addition/removal of a device or a person)?

1.3.7 Theoretical foundations

The theoretical foundation to support this thesis involves :

i. the main topics briefly described in section 1.3 (i.e. **smart homes, Human-AI team collaboration and Human-centered AI**).

ii. **agent-based and multi-agent systems (MAS)** - agent oriented systems provide a relevant approach for modeling distributed and collaborative contexts. In such systems, the focus is on the result produced by the interaction among autonomous agents [43]. Multi-agent systems are able to address adaptive and self-organizing architectures, to improve robustness and flexibility [20][22]. Recent works explore the integration of MAS with IoT and cyber-physical systems, enabling both devices and users to be modeled as agents [18][14], toward the concept of hybrid intelligence [29]. Moreover, agent-based approaches have been used for a long time to analyze social behaviors by modeling and simulation of individual characteristics [16]. The agent orientation will allow a distributed approach where multiple heterogeneous actors, including both humans and artificial ones, interact in a common environment.

iii. **software quality** – some studies have been proposed indicators to evaluate the quality of collaboration, such as individual responsibility, intra-individual variability, information sharing, mutual understanding (e.g.[39]) and participation in discussions, verbal coherence or speaking time [33]. The aim of these studies is to analyze and model the collaboration itself and not intended to study how "collaborative systems" could hinder or facilitate collaboration. To that end standards of software quality[25][26] will be investigated in order to propose specific measures to evaluate the level of collaboration provided with the mediating agents.

1.3.8 Approach and methods

The research will adopt an interdisciplinary approach based on three pillars: Human-Centered AI, multi-agent systems, and software engineering. The approach will be complemented by user-centered methods, including: [24][34]. The planned tasks are presented in the table bellow.

Tasks	Schedule	Deliverable
Systematic literature review on human-AI collaboration	T0+6	set of guidelines to evaluate human-AI collaboration
Definition the agent mediator architecture ● requirements elicitation with stakeholders ● iterative prototyping design	T7+12	Agent mediator architecture
Definition of measures for evaluating the collaboration	T9+12	Set of measure for evaluation od the collaboration
Implement the software solution that acts as a **mediating agent**, supporting collaboration	T21+8	Prototypes and report of user studies
Evaluation of the proposal by simulations	T25+8	Results of the experimentation study
Writing the thesis	T26+10	Thesis

1.3.9 Evaluation of contributions

To evaluate our approach, we must consider the three main pillars: human-computer interaction, collaboration, and MAS. One possible way, that we intend to apply is to use simulation, as proposed by [3][44][30] and recently explored by the researchers of InterA in the quality in use evaluation of smart environments [16].

2. Contribution to Digital Collaboration: Expected Results and Impact

This thesis will have different contributions as described bellow.

Methodological Contributions

- Definition of an agent mediator architecture to integrate different source of information and support collaboration.
- Definition of a set of metrics/guidelines to evaluate human-AI collaboration, both quantitatively and qualitatively, including aspects of: quality of human-agent collaboration, efficiency of coordination, and balance in decision-making.

Technical Contributions

- Implementation of a mediating agent capable of: integrating heterogeneous information, supporting collective reasoning, and coordinating interactions between agents.
- Development of a functional agent-based simulator prototype for smart homes, including mediation mechanisms and dynamic adaptation capabilities.

Empirical Contributions

- Experimental evaluation of the proposed models in simulated smart home scenarios
- Evaluation of the proposed metrics and guidelines in human-AI collaboration contexts.

We emphasize that the contributions presented are aimed at developing an integrated framework for multi-agent systems, seeking to enable effective, adaptive collaboration between human and artificial agents in smart home environments.

References

[1] Abtoy, A., Touhafi, A., & Tahiri, A. (2020). Ambient Assisted living system's models and architectures: A survey of the state of the art. *Journal of King Saud University-Computer and Information Sciences, 32*(1), 1–10.

[2] Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of things: A survey on enabling technologies, protocols, and applications. *IEEE Communications Surveys & Tutorials, 17*(4), 2347–2376.

[3] Alshammari, N., Alshammari, T., Sedky, M., Champion, J., & Bauer, C. (2017). Openshs: Open smart home simulator. Sensors, 17(5), 1003.

[4] Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., … & Horvitz, E. (2019, May). Guidelines for human-AI interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1–13).

[5] Ammah, L. N. A., Lütge, C., Kriebitz, A., & Ramkissoon, L. (2024). AI4people–an ethical framework for a good AI society: the Ghana (Ga) perspective. *Journal of Information, Communication and Ethics in Society, 22*(4), 453–465.

[6] Anuraj, B., Calvaresi, D., Aerts, J. M., & Calbimonte, J. P. (2024). Dynamic swarm orchestration and semantics in IoT edge devices: A systematic literature review. *IEEE Access, 12*, 116917–116938.

[7] Aouedi, O., Vu, T. H., Sacco, A., Nguyen, D. C., Piamrat, K., Marchetto, G., & Pham, Q. V. (2024). A survey on intelligent Internet of Things: Applications, security, privacy, and future directions. *IEEE Communications Surveys & Tutorials, 27*(2), 1238–1292.

[8] Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115.

[9] Babangida, L., Perumal, T., Mustapha, N., & Yaakob, R. (2022). Internet of Things (IoT) based activity recognition strategies in smart homes: A review. *IEEE Sensors Journal, 22*(9), 8327–8336.

[10] Bansal, G., Wu, T., Zhou, J., Fok, R., Nushi, B., Kamar, E., … & Weld, D. (2021, May). Does the whole exceed its parts? the effect of AI explanations on complementary team performance. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1–16).

[11] Berretta, S., Tausch, A., Ontrup, G., Gilles, B., Peifer, C., & Kluge, A. (2023). Defining human-AI teaming the human-centered way: a scoping review and network analysis. *Frontiers in Artificial Intelligence, 6*, 1250725.

[12] Bordini, R. H., Hübner, J. F., & Wooldridge, M. J. (2007). *Programming multi-agent systems in AgentSpeak using Jason*. Wiley.

[13] Calegari, R., Denti, E., Mariani, S., & Omicini, A. (2019). Logic programming as a service in multi-agent systems for the Internet of Things. *International Journal of Grid and Utility Computing, 10*(4), 344–360.

[14] Calvaresi, D., Appoggetti, K., Lustrissimini, L., Marinoni, M., Sernani, P., Dragoni, A. F., & Schumacher, M. (2018). Multi-Agent Systems' negotiation protocols for cyber-physical systems: Results from a systematic literature review. *ICAART*, 224–235.

[15] Cardoso, R. C., & Ferrando, A. (2021). A review of agent-based programming for multi-agent systems. *Computers*, *10*(2), 16.
[16] Correa Angeloni M., Grislin-Le Strugeon E., Oliveira K., Tirnauca C., Duque R. (2024). Using Agent-Based Modeling and Simulation for Quality in Use Evaluation of Ambient Assisted Living Applications. Bravo, J., Nugent, C., Cleland, I., *Proceedings of the International Conference on Ubiquitous Computing and Ambient Intelligence* (UCAmI 2024), Lecture Notes in Networks and Systems, vol 1212, Springer, Cham, pp. 151-162, novembre.
[17] Dellermann, D., Lipusch, N., Ebel, P., & Leimeister, J. M. (2021). Design principles for a hybrid intelligence decision support system for business model validation. *arXiv preprint arXiv:2105.03356*.
[18] Dignum, V. (2025). Responsible AI and autonomous agents: governance, ethics, and sustainable innovation. In *AAMAS 2025*. ACM.
[19] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., … & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*(4), 689–707.
[20] Gheibi, O., Weyns, D., & Quin, F. (2021). Applying machine learning in self-adaptive systems: A systematic literature review. *ACM Transactions on Autonomous and Adaptive Systems*, *15*(3), 1–37.
[21] Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660.
[22] Hezavehi, S. M., Weyns, D., Avgeriou, P., Calinescu, R., Mirandola, R., & Perez-Palacin, D. (2021). Uncertainty in self-adaptive systems: A research community perspective. *ACM Transactions on Autonomous and Adaptive Systems*, *15*(4), 1–36.
[23] Holzinger, A., Biemann, C., Pattichis, C. S., & Kell, D. B. (2017). What do we need to build explainable AI systems for the medical domain? *arXiv preprint arXiv:1712.09923*.
[24] Iqbal, R., Sturm, J., Kulyk, O., Wang, J., & Terken, J. (2005, September). User-centred design and evaluation of ubiquitous services. In *Proceedings of the 23rd annual international conference on Design of communication: documenting & designing for pervasive information* (pp. 138-145)
[25] ISO/IEC 25019:2023. Systems and software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Quality-in-use model.
[26] ISO/IEC: 25010:2023. systems and software engineering — systems and softwarequality requirements and evaluation (SQUARE) — system and software quality models (2011)
[27] Li, X., Zhao, P., Wu, M., Chen, Z., & Zhang, L. (2021). Deep learning for human activity recognition. *Neurocomputing*, *444*, 214–216.
[28] Lou, B., Lu, T., Raghu, T. S., & Zhang, Y. (2025). Unraveling human-AI teaming: a review and outlook. *arXiv preprint arXiv:2504.05755*.
[29] Melih, A. A., Singh, Y., Agarwal, K. L., Mukherjee, P., Pattnaik, K., & Bhatia, H. (2025). Human machine social hybrid intelligence: A collaborative decision making framework for large model agent groups and human experts. *arXiv preprint arXiv:2510.24030*.
[30] Ntoa, S. (2025). Usability and user experience evaluation in intelligent environments: A review and reappraisal. *International Journal of Human–Computer Interaction*, *41*(5), 2829-2858.
[31] O'Neill, T., McNeese, N., Barron, A., & Schelble, B. (2022). Human–autonomy teaming: A review and analysis of the empirical literature. *Human Factors*, *64*(5), 904–938.
[32] Ozmen Garibay, O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., … & Xu, W. (2023). Six human-centered artificial intelligence grand challenges. *International Journal of Human–Computer Interaction*, *39*(3), 391–437.
[33] Praharaj, S.; Scheffel, M.; Drachsler,H. and Specht, M.. (2021). Literature Review on Co-Located Collaboration Modeling Using Multimodal Learning Analytics—Can We Go the Whole Nine Yards? IEEE Trans. Learning Technol. 14, 3 (June 2021), 367–385.
[34] Preece, J., Rogers, Y., Sharp, H., Benyon, D., Holland, S., & Carey, T. (1994). *Human-computer interaction*. Addison-Wesley Longman Ltd.
[35] Reis, M. J., & Serôdio, C. (2025). Edge AI for real-time anomaly detection in smart homes. *Future Internet*, *17*(4), 179.
[36] Sarakiotis, V. (2020). Human-centered AI: Challenges and opportunities. UBIACTION 2020.

[37] Schneider, B., Sung, G., Chng, E. and Yang, S. (2021). How Can High-Frequency Sensors Capture Collaboration? A Review of the Empirical Links between Multimodal Metrics and Collaborative Constructs. Sensors 21, 24 (December 2021), 8185.
[38] Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal*, *3*(5), 637–646.
[39] Shneiderman, B. (2022). *Human-centered AI*. Oxford University Press.
[40] Tsamados, A., Floridi, L., & Taddeo, M. (2025). Human control of AI systems: from supervision to teaming. *AI and Ethics*, *5*(2), 1535–1548.
[41] Tula, S., Pacaux-Lemoine, M.P., Grislin-Le Strugeon, E., Santos, P.E., Ma-Wyatt, A., et al.. Agent's Cooperation Levels to Enhance Human-Robot Teaming. Workshop ARMS (Autonomous Robots and Multirobot Systems), 23rd Inter. Conference on Autonomous Agents and Multiagent Systems (AAMAS'24), May 2024, Auckland, New Zealand.
[42] Venkatesha Murthy, S., Goh, Y., Lee, Y., & Kim, S. H. (2026). Advancing human–AI teams: evolving from instrumental tools to trusted partners. *AI & Society*, 1–21.
[43] Wooldridge, M. (2009). *An introduction to multiagent systems*. Wiley.
[44] Wu, C. L., & Fu, L. C. (2011). Design and realization of a framework for human–system interaction in smart homes. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *42*(1), 15-31.
[45] Xu, W. (2026). Human-Centered Artificial Intelligence (HCAI): Foundations and Approaches. *arXiv preprint arXiv:2601.01247*.
[46] Xu, W., Dainoff, M. J., Ge, L., & Gao, Z. (2023). Transitioning to human interaction with AI systems: New challenges and opportunities for HCI professionals to enable human-centered AI. *International Journal of Human–Computer Interaction*, *39*(3), 494–518.
[47] Zhang, D., & Jiang, X. (2024). Cognitive collaboration: Understanding human-AI complementarity in supply chain decision processes. *Spectrum of Research*, *4*(1).
[48] Zhang, R., Duan, W., Flathmann, C., McNeese, N., Freeman, G., & Williams, A. (2023). Investigating AI teammate communication strategies and their impact in human-AI teams for effective teamwork. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW2), 1–31.
[49] Zhang, R., McNeese, N. J., Freeman, G., & Musick, G. (2021). “An ideal human”: expectations of AI teammates in human-AI teaming. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW3), 1–25.