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HUMAN-CENTERED PERSPECTIVES IN INTERACTIVE MACHINE LEARNING FOR ADVANCING AMBIENT INTELLIGENCE

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***Abstract*-As the vision of Ambient Intelligence (AmI) becomes more feasible, the challenge of designing effective and usable human-machine interaction in this context becomes increasingly important. Interactive Machine Learning (IML) offers a set of techniques and tools to involve end-users in the machine learning process, making it possible to build more trustworthy and adaptable ambient systems. In this paper, our focus is on exploring ap proaches to effectively integrate and assist human users within ML-based AmI systems. Through a survey of key IML-related contributions, we identify principles for designing effective human-AI interaction in AmI applications. We apply them to the case of Op portunistic Composition, which is an approach to achieve AmI, to enhance collaboration between humans and Artificial Intelligence. Our study highlights the need for user-centered and context-aware design, and provides insights into the challenges and opportunities of integrating IML techniques into AmI systems**

Keywords:Human-Computer Interaction, User Interfaces, Machine Learning, Reinforcement Learning.

I. INTRODUCTION

Ambient Intelligence (AmI) aims to provide a personalized physical and software environ-ment that adapts to users' needs and situations (Sadri, 2011; Dunne et al., 2021). Its potential impact is significant, as it can enhance human-environment interaction through the integration of intelligent systems into everyday life. There are various applications ofAmI, particularly in the fields of healthcare (Acampora et al., 2013), transportation (Ve-lastin et al., 2004), energy management (Robinson et al., 2015), and smart homes (Makoninet al., 2012).However, the dynamics, openness, and unpredictability of ambient environments pose significant challenges to the development of effective AmI systems, particularly due to the mobility of devices and users, and the diversity of components in the environment. To overcome these challenges, solutions must take into account the operational context, including user preferences and needs that may vary with time. Opportunistic Composition isan approach to achieve AmI. It revolves around the idea of dynamically and opportunistically constructing complex applications by leveraging existing software components in the environment. The goal of Opportunistic Composition is to enable the seamless integrationand collaboration of these components to create adaptive and context-aware systems. Itis achieved by the Opportunistic Composition Engine (OCE) (Delcourt et al., 2021), that relies on Machine Learning in interaction with the human user.

Interactive Machine Learning (IML) (Fails & Olsen Jr, 2003) investigates ways to enable humans to teach machine learning algorithms, with a focus on providing tools that are usable by end-users without machine learning backgrounds. As such, IML can provide a valuable set of tools and techniques for addressing the challenges of AmI and enabling more effective human-machine interaction. The aim of this paper is to survey design solutions and recommendations that enhance the collaboration between a human and a learning machine. Then, we analyze their appli cation to Opportunistic Composition. To achieve this goal, we undertake a critical review (Grant & Booth, 2009) of the existing IML-related literature. By critically analyzing and synthesizing insights from this body of work, we aim to advance Opportunistic Compo sition while uncovering potential applications beyond the specific context of our project. Indeed, the solutions and recommendations we provide mark the initial steps in addressing the question of designing socially responsible AI solutions (Cheng et al., 2021) that provide a fair, transparent and secure interaction. The article is structured as follows: • Section 2 offers a comprehensive overview of the fields of Machine Learning, Interactive Machine Learning, and sets the research questions that this survey aims to address. • Section 3 provides a thorough analysis of several key IML-related contributions that are relevant to the challenges of AmI. These contributions are analyzed based on the research questions outlined in Section 2, and provide insights into how IML can be used to address the specific challenges of AmI systems. • Section 4 provides a comprehensive synthesis of the key findings from the previous section. • Section 5 presents the principles of Opportunistic Composition and the Opportunistic Composition Engine (OCE). Then, it discusses how the findings from Sections 3 and 4 can be applied to Opportunistic Composition to enhance human-AI collaboration within this project. • Section 6 provides concluding remarks and suggests potential avenues for future re search in the areas of Opportunistic Composition, IML, and AmI.

II. LITERATURE SURVEY

Topic	Focus Area	Key Contributions	References
Human-Computer Interaction (HCI)	Design for Human Interaction	Discusses designing user interfaces to minimize cognitive load and allow intuitive model control.	Dudley and Kristensson (2018); Wexelblat (1999)
Ambient Intelligence (AmI)	Definition and Applications	Introduces AmI as integrated, responsive environments, with examples in smart homes, healthcare, etc.	Aarts and Marzano (2003); Cook and Das (2004)
Personalization in AmI with IML	User Adaptation and Preferences	IML allows personalized, adaptive user interactions through continuous feedback from users.	Terveen and Hill (2001); Kapoor and Horvitz (2008)
Trust and Interpretability	Transparent Model Design	Highlights the importance of interpretable models to increase user trust and understanding of system behavior.	Doshi-Velez and Kim (2017); Ribeiro et al. (2016)
Future Directions & Ethical Issues	Ethics of Pervasive IML in AmI	Examines ethical issues like privacy, autonomy, and control in IML applications within personal spaces.	Zuboff (2019)

III. PREVIOUS RELATED WORK DONE

In situations where solving complex problems through programming is not feasible, due to a lack of understanding, Machine Learning (ML) is often the go-to method for building a solution. Developing an ML-based solution typically involves engaging an ML expert. This expert is responsible for designing the learning aspect of the solution, such as selecting the appropriate algorithm and tuning the parameters, while working in collaboration with both the end-users and the ML system under development. The users or their representatives provide data to the expert, who then tunes the learning system until it produces satisfactory results. These results are subsequently reviewed by the users, who provide further feedback. This iterative process continues until the ML system, precisely the ML model, is deemed ready for production.

However, as noted by Amershi et al. (Amershi et al., 2014), there is a large demand for machine learning applications but a shortage of experts in this field, which can slow down the development process. To address this challenge, Interactive Machine Learning (IML) approaches have been proposed to allow human users, who are the target users of these applications, to contribute to the learning process without requiring an ML expert. These approaches are designed for humans without prior knowledge of machine learning and are categorized under IML. In certain cases, a user representative with knowledge of the user base and their needs may also be considered a human user.

IV. PURPOSE OF THE WORK

1) To identify and analyse how incorporating user feedback, preferences, and behaviors into interactive machine learning algorithms can improve user experience and satisfaction in ambient intelligent environments.

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 1, 2025

2) To investigate collaborative models where users actively participate in the learning process, contributing their knowledge and insights to enhance system performance while fostering a sense of agency and control over the technology.

V. THE PROPOSED WORK

According to (Fails & Olsen Jr, 2003), IML is the field of machine learning that involves human users interacting with a learning algorithm to provide some or all of the data used for learning. The goal of IML is to produce a solution that meets the needs of the end users of the ML-based solution, with the involvement of humans who typically lack machine learning skills. This human involvement in the learning process enables personalization of the resulting ML system. The iterative operation of an IML system, as depicted in Figure 2, involves the human providing various parameters, preferences, or any data required by the ML system for its operation. The ML system then presents the results of its learning, such as recommendations or predictions, to the human who evaluates if the presented results are satisfactory with respect to their objectives. The human provides additional inputs and feedback, which are then incorporated by the ML system to update its model. The system can be retested with the updated model, and the process repeats until the human is satisfied with the results. In certain cases, the process may continue indefinitely, while the system is operated, to adapt to new data and changes in user preferences or needs.Compared to the process described in Figure 1, IML feedback loops are faster in the absence of the intermediate expert. IML applications have been successfully used to build various machine learning solutions such as image classifiers (Carney et al., 2020), text classifiers (Ramos et al., 2020), trainingrobots to perform handling tasks (Celemin& Ruiz-del Solar, 2019), and recommendations based on user actions (Aamir &Bhusry, 2015). Several research areas share similarities with IML and are closely related. AutoML focuses on automating the entire machine learning pipeline, from data pre-processing to model deployment (Karmaker et al., 2021).

The primary goal of AutoML is to make machine learning more accessible to non-experts and to improve the efficiency of experts. AutoML is primarily an automated, data-driven approach (Hutter et al., 2019), while IML is a more interactive human-driven approach. While AutoML has the potential to improve the efficiency and effectiveness of machine learning systems, it may not be suitable in cases where data is scarce or not available. Human-autonomy teaming, also known as human-autonomy collaboration, refers to the collaboration between humans and autonomous agents to achieve a common goal, such as data processing or decision making (O'Neill et al., 2022). This research field tends to focus on the interactions between humans and AI, for instance, how to coordinate the two in a seamless way (Liang et al., 2019). To highlight the use of AI in autonomous agents, Human-autonomy teams are often referred to as Human-AI teams (Zhang et al., 2021a). Hybrid Intelligence systems are similar to IML, where a human and an AI agent col laborate to solve complex tasks (Dellermann et al., 2019). While the majority of current ML systems do not take into account human feedback after initial training, making them unsuitable for real-world dynamic settings, Hybrid Intelligence theorizes that continuous adaptation of the ML model and continuous human intervention are necessary to achieve results in highly dynamic environments. Our work focuses on the field of Ambient Intelligence (Sadri, 2011), where dynamics are high, and humans constantly interact with their environment. Adaptation is a fundamental property, and IML is a promising approach for building intelligent systems that can adapt to human needs and preferences in real-time.

Table I:Summary of the answers to the research questions

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 1, 2025

Contribution	RQ11	RQ12	RQ21	RQ22
Carney et al., 2020	Selection of concept, samples, parameters	Heavy	Labeled images, parameters	Guiding HMI
Fails and Olsen Jr, 2003	Coloring of portions of an image	Medium	Base image, labeled pixels	Request for a natural task
Berg et al., 2019	Choice of workflow, parameters, samples	Heavy	Algorithm, labeled data, parameters	No assistance
Flutura et al., 2018	Reporting of false positive/negatives	Medium	Body movements, explicit feedback	Targeted sound notifications
Zheng et al., 2018	Browsing of news recommendations	Light	Usage data	No assistance
Ramos et al., 2020	Selection of examples and labels	Medium	Labeled textual data	Results' visualization, expert patterns
Kessler Faulkner and Thomaz, 2021	Monitoring and rewarding	Light	Positive rewards	No assistance
Akrour et al., 2014	Comparison of every action sequences	Heavy	Reinforcement feedback	No assistance
Christiano et al., 2017	Comparison of some action sequences	Medium	Reinforcement feedback	Shortcuts
Honeycutt et al., 2020	Assessment of face recognition	Light	Performance feedback	No assistance
Holzinger et al., 2019	Interaction with a snake-like game	Light	Guidance of a MAS	No assistance
Schnabel et al., 2020	Selection of news to read	Light	Usage data	Pre-visualization of the recommendation update
Amershi et al., 2019	Providing granular feedback	Light	Additional feedback, guidance from the human	Building trust, explainability

4.3 RQ21-Information

The information provided by the human is crucial for the learner to function, and the wayit is used varies between contributions. In Table 3, column RQ21 summarizes what kindof human data fuels the ML system, while in column RQ21 of Table 4, the richness of thedata is indicated. Low-dimensional, simpler data is rated - while higher dimensional datais rated + or ++.Contributions rated ++ offer richer interactions, allowing humans to steer the ML processmore effectively towards their preferences. For example, Teachable Machine (Carneyet al., 2020) offers deeper access to the learner’ s settings, but requires more learning skillsfrom the human. Some implicit sources of interaction, such as mouse hovering (Schnabelet al., 2020) or attention detection (Kessler Faulkner & Thomaz, 2021), allow the humanto indirectly influence the learner. These methods provide non-intrusive ways to supportthe learning process and are accessible to non-specialist end-users.

4.4 RQ22-Assistance

The assistance provided to the human is summarized in column RQ22 of Table 3 and itslevel is rated on a scale to - to ++ in column RQ22 of Table 4.In the majority of applications, we found no significant level of assistance provided tothe humans, hence rated -. Some applications, like the face recognition system (Honeycuttet al., 2020) and the snake-like game (Holzinger et al., 2019), were designed without anyassistance to the humans, likely due to their research nature.However, contributions rated + and ++ offer various techniques to alleviate the workloadfor humans. Interactive Machine Teaching (Wall et al., 2019), for example, providesnotifications and advice based on expert knowledge in machine learning. In the recommendationapplication (Schnabel et al., 2020), previsualization techniques allow humans to seethe consequences of their actions on the machine learning process, thereby improving theirexperience. Additionally, guidelines from (Amershi et al., 2019) can be a useful tool forproviding assistance in any application because they offer a comprehensive framework fordesigning human-AI collaborative systems. They address the assistance needs we identifiedin the literature by advocating for various measures, such as providing comprehensible explanationsof the ML system’ s purpose or performance, among other things.

Table II: Summary of the levels of response to the different research questions (the scale ” -” to ” ++” indicates the level of response to a question)

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 1, 2025

Contribution	RQ11	RQ12	RQ21	RQ22
Carney et al., 2020	+	-	++	+
Fails and Olsen Jr, 2003	+	+	-	+
Berg et al., 2019	-	-	++	-
Flutura et al., 2018	+	+	+	+
Zheng et al., 2018	+	++	+	-
Ramos et al., 2020	+	+	+	++
Kessler Faulkner and Thomaz, 2021	++	++	+	-
Akrour et al., 2014	+	-	-	-
Christiano et al., 2017	+	+	-	+
Honeycutt et al., 2020	++	++	-	-
Holzinger et al., 2019	++	++	-	-
Schnabel et al., 2020	+	++	+	++
Amershi et al., 2019	+	++	+	++

VI. IMPLEMENTATION

Given the importance of effective human integration for successful IML solutions (Amershiet al., 2014), we aim to draw insights and guidelines from the IML literature that can beapplied to ambient systems. To achieve this goal, we have formulated the following researchquestions that will guide our analysis of key contributions to the field of IML. The answersto these questions will enable us to identify recommendations in the context of an AmIsystem, which will be presented in Section 5 based on our discussion.

RQ1-Human. What are the human' s role and responsibilities in the loop?

RQ11-Tasks. What tasks should the human perform? To accomplish these tasks,how much machine learning skills are required?This understanding is important to ensure that the human is not overburdened withtasks that are beyond their skills. It can guide the design of IML systems that takeinto account the skills and limitations of the human user.

RQ12-Workload. How much and what workload is imposed on the human user?What level of commitment or involvement is expected?

Understanding the workload and level of commitment required from the human user iscrucial to ensure that the system is designed to provide the right level of support andassistance to optimize performance and user experience. In the following, to enable acomparison of the workload imposed on human users across different applications, wehave defined three distinct levels of workload: light, medium, and heavy. These levelsare determined based on our assessment of the time needed to complete tasks withthe system, the number of steps involved, and the degree of mental effort required.

RQ2-Learner. How is the human taken into account by the ML system?

RQ21-Information. What information is needed from the human and what is itused for?The exchanged information can affect the accuracy and reliability of the system.Understanding what information is needed from the human user and how it can beincorporated into the system can help to improve the performance and effectivenessof the IML system. Offering varied and comprehensive methods of interacting withAI systems has been shown to improve both system performance and user experience(Amershi et al., 2014).

RQ22-Assistance. How does the system guide and assist the human?The provided assistance affects the efficiency, accuracy, and user experience of thesystem. Providing the right level of guidance and assistance to the human user canhelp to optimize their performance and ensure that the system operates effectively.To answer this question, we examine how the system delivers context-specific help andfeedback to the user as they perform their tasks. Additionally, we assess the systemability to offer recommendations and suggestions to the user, enabling them to makeinformed decisions and complete their tasks with greater efficiency.

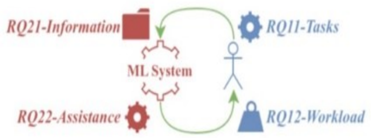
Figure 1:Research questions (RQs)

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 1, 2025

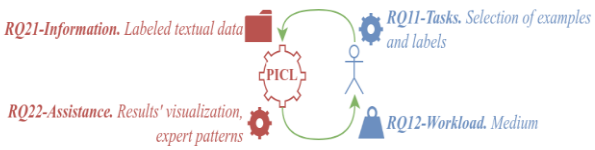


Derived from Figure 2, Figure 3 places the different research questions in relation to theIML process presented in Section 2.1. They cover all aspects of the interaction between thehuman and the ML system. In fact, these questions go beyond ML and address the relationshipbetween humans and AI more broadly, as discussed, for example, by (Saisubramanianet al., 2022).

Defined in (Ramos et al., 2020), Interactive Machine Teaching is an approach to IML inwhich the human plays the role of a teacher, and must teach a task to the machine. Thenotion of teaching includes the choice of information at the source of learning, and theevaluation of the learner' s performance. The underlying assumption that the authors makeis that humans acquire pedagogical skills more easily than machine learning skills, as theseskills are more prevalent in the general public (Wall et al., 2019).The concepts and processes studied in Interactive Machine Teaching are applicable toany learning paradigm. Nevertheless, the authors present a demonstration application,called PICL (Ramos et al., 2020) (formerly MATE (Wall et al., 2019)), that applies InteractiveMachine Teaching principles to supervised learning by allowing users to teachtext classification tasks. As shown in Figure 9, we consider PICL, not Interactive MachineTeaching, as the reference for studying the answers to the RQs.

RQ11-Tasks. The human, playing here the role of a teacher, must plan a curriculum andthen update it according to the learner' s results. A curriculum refers to the data (examples,labels) used by the learner. The skills required are mostly of a pedagogical nature.

Figure 2:Answers to RQs for Microsoft's PICL



RQ12-Workload. Involving the human in selecting relevant examples or teaching conceptsmoderately engages them in the process. In addition, they must judge whether thelearner' s results are satisfactory.

RQ21-Information. The labels and concepts provided by the human are the source ofsupervised learning.

RQ22-Assistance. The interface of the presented tools (Ramos et al., 2020) assists thehuman by allowing them to effectively visualize the learner' s results. A study of the behaviorof supervised learning experts on PICL/MATE (Wall et al., 2019) has also identified goodpractices for automatic teaching, implemented in the form of notifications.

VII. EXPERIMENTAL RESULTS

Honeycutt et al. conducted a study that addresses the issue of user trust in machine learningapplications (Honeycutt et al., 2020). It is based on results in psychology (Van den Boset al., 1996) which show that the confidence of an individual Towards a human decisionalgroup increases if an opinion expressed by the individual is taken into account by thegroup. Conversely, the individual will have less confidence if his opinion is ignored. Theobjective of this study is to recover these results by replacing the human decision groupwith an automatic learner, in this case an interactive supervised learning application forface recognition in images.

The online experiment measured the confidence of human users towards this applicationwith or without interaction on the one hand, and with increasing, constant or decreasinglearner performance on the other hand. In practice, the participants had to check andcorrect the learner' s errors.The results unexpectedly have shown that in general the interacting group has lessconfidence in the system than the non-interacting group. The

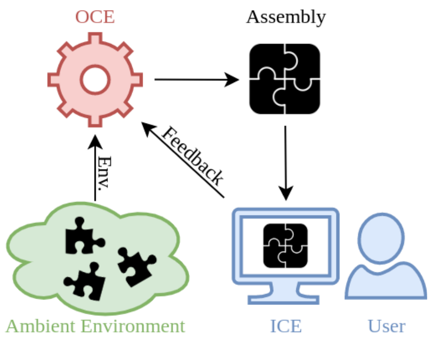
INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 1, 2025

explanation put forward bythe authors is that the interacting group spent more time focused on the system errors tocorrect them.

Figure 3:Answers to RQs for the face classification application

As illustrated in Figure 4, we consider the face recognition application that supportedthe experiment to look at the research questions.

Figure 4:Opportunistic Software Composition



RQ11-Tasks. The expected skills for the users are only related to the task at hand: facerecognition. The human must recognize and correct the mistakes made by the system, e.g.faces that are not detected or falsely detected.

RQ12-Workload. The user is only involved in the tasks of checking and correcting thelearner's output.

RQ21-Information. The simulated application takes into account feedback from userson its errors in order to refine its model.

RQ22-Assistance. Users are voluntarily given little guidance in order to measure theirsubjective appreciation of the application's performance, which is a measure proportionalto the confidence they feel in the system (Yin et al., 2019).

VIII. CONCLUSION

In this paper, we have explored the Interactive Machine Learning (IML) literature to identifypotential solutions for the challenges faced by Ambient Intelligent (AmI) systems. Wehave conducted a critical review of the literature, resulting in a set of design solutions toimprove human-AI interaction. Then we have considered their application in the case ofOpportunistic Composition, and formulateddesign solutions. In this concluding section,we discuss future directions and prospects for Opportunistic Composition, IML, and AmIbased on the findings of this study.The next phase of our work is the development of a new prototype for OCE that implementsthe design solutions relative to the guidelines G10 and G15, which pose significant scientificchallenges, as discussed in Section 5.3. This prototype will be put through a series of testswith human users to evaluate the impact of the design solutions on the user experience. learning process, and performance. The results from these tests should provide importantinsights into the broader field of Interactive Machine Learning and Ambient Intelligence,and inform future research in these areas.One important aspect to consider in the design of OCE is the diversity of human users' skills and knowledge. Some may have extensive technical expertise and be comfortable withprogramming and software development, while others may have limited experience in theseareas. Therefore, it is essential to design OCE in a way that caters to the needs of all humanusers and allows them to participate at their own level of proficiency. Taking into accountthe diversity of users and their needs is an important scientific challenge in the developmentof OCE.imard et al. (Simard et al.,

2017) make a parallel between Interactive Machine Learningand the general programming activity through their study on Interactive Machine Teaching(Section 3.2.1). IML and programming share, for example, the production by a humanof an artifact (a learned model or a program) that meets the needs of one or more humanusers. This comparison leads the authors to believe that, just as programming has benefitedfrom high-level tools and languages, like modern integrated development environments, IMLneeds its own tools and abstractions to facilitate the work of humans. Although the fieldof interactive machine learning and human-ML interaction is not yet mature, there arepatterns and guidelines that can assist in this interaction. Our work may identify andcontribute to these patterns.

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