Explainable Artificial Intelligence Techniques for Extended Reality Systems: a Systematic Literature Review

Clara Maathuis
Open University
The Netherlands
clara.maathuis@ou.nl

Marina Anca Cidota
University of Bucharest
Romania
cidota@fmi.unibuc.ro

Dragoș Datcu
Independent Research
The Netherlands
email@dragosdatcu.eu

Letiția Marin
University of Bucharest
Romania
letitia@fmi.unibuc.ro

ABSTRACT

The integration of Artificial Intelligence (AI) in the Extended Reality (XR) enables the development of more immersive, interactive, and personalized environments and significantly enhances user experiences. Further, ensuring transparency of data, reasoning, and decision-making processes underlying the AI technologies used, represent critical aspects that require the development and deployment of relevant Explainable AI (XAI) techniques. Implementing such mechanisms not only ensures compliance with existing social and ethical norms and values, but also fosters user trust and supports the further adoption of such solutions. While both research and practitioner efforts are seen in this direction, there is a gap in the existing body of knowledge regarding a review of existing XAI methods and techniques tailored to XR systems. To address this point, this paper presents a systematic literature review of XAI approaches applied in the XR domain to synthesize current research, identify existing trends, and highlight potential future research areas.

Keywords

explainable AI; responsible AI; trustworthy AI; Extended Reality; Mixed Reality; Augmented Reality; Virtual Reality.

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INTRODUCTION

The significant advancements in Artificial Intelligence (AI) and Extended Reality (XR) domains have opened up new possibilities for their widespread application across various sectors. These two technologies have matured to the point where they can seamlessly intersect, enabling innovative solutions to complex challenges in areas such as healthcare, environmental sustainability, cybersecurity, education, industry, and social media. XR, which encompasses virtual, augmented, and mixed reality experiences, has the power to merge the physical and virtual worlds, allowing for real-time interactions with computer-generated elements. The integration of AI and XR is transforming fields such as education, healthcare, entertainment, safety, and industry, by offering personalized and engaging user experiences, enhancing human skills, and fostering fresh perspectives for innovation.

In the context of human-AI interaction, building trust and understanding plays a pivotal role. As AI technologies become more pervasive, transparency becomes essential. Regulations, such as the European Union's General Data Protection Regulation (GDPR), AI Act, and Cyber Resilience Act, emphasize the right to meaningful and secure information about automated decision-making processes and their results. To address potential issues arising from opaque AI behavior, techniques for explaining AI decisions are crucial. By enabling AI algorithms to provide clear explanations on their decision-making processes, we can enhance human understanding and trust.

Thus, the field of Explainable AI (XAI) has arisen with the goal of ensuring that AI systems are transparent, accountable, and trustworthy. XAI aims to provide explanations that can be easily comprehended by users, bridging the gap between AI technology and human understanding.

Numerous surveys that review explainable methods have been done so far, in a larger context or focusing only on certain domains or topics [20], showing the relevance of the XAI domain to the research community.

In this work, we review studies where XAI methods were applied in various tasks in XR environments. The identified tasks were: classification [4,8,9,10,11,13,15,17,12,16,26]; regression/forecasting [1,6,8,9,10]; recommendation [3,24,27,28]; policy learning [22] and survival analysis [7]. The papers surveyed were published in four scientific databases between the years 2013-2023.

After presenting the research methodology involved in this study, we discussed the application domains and the opportunities that XAI in XR environments offer, the types of XR systems that integrate XAI, the XAI techniques used and the evaluation methods. In this paper, we aimed at offering the reader a quick and clear understanding of different aspects of the intersection between XAI and XR, without going much into details.

RESEARCH METHODOLOGY

This research aims to provide an overview of existing studies that tackle the transparency dimension of XR technologies by implementing various XAI methods and techniques

To this end, the following research questions are formulated:

- RQ1: What are application domains and opportunities of integrating XAI in XR systems?
- RQ2: Which XR systems integrate XAI methods and techniques?
- RQ3: What are the XAI methods and techniques used for XR systems?
- RQ4: How are the identified XAI techniques and applications evaluated for XR systems?

The systematic literature review approach followed the PRISMA methodology [2,21]. In this process, the objectives and corresponding research questions are formulated, the relevant studies are identified and gathered, an in-depth analysis is conducted, and the results obtained are presented in this paper. Furthermore, the activities carried out in each phase of this process are discussed:

Phase 1 - Identification: In this phase, the studies were searched based on combinations of keywords like Extended Reality or XR, Mixed Reality or MR, Augmented Reality or AR, Virtual Reality or VR, XAI, Explainable/Explainability, Interpretable/Interpretability, AI, and Artificial Intelligence. The search was conducted across the ACM, IEEE Digital Library, Web of Science, and Wiley scientific databases between 01.01.2013 and 31.12.2023 taking into consideration the search format that each database has. As a result, a total of 6814 articles were found and further processed.

Phase 2 - Screening: In this phase, the articles were screened based on their abstract, title, and keywords used. In this process, the exclusion criteria adopted are as follows: relevance to the field and the research questions considered, XAI and XR / MR / AR / VR are missing, language is other than English, and short studies less than 3 pages. After applying these criteria, the final set of studies to be considered contains 25 articles.

Phase 3 - Inclusion: In this phase, the articles selected were in-depth analyzed by four researchers, multiple research meetings are organized on this behalf, and in various moments, cross-checking mechanisms are applied. To this end, the articles considered for review are depicted in Table 1 below
:

Ref	**Research Aim**
[1]	To develop an interpretable machine learning approach for forecasting personal learning performance in VR based safety training using real-time biometric responses.
[3]	To assess the role of explanations for trust enhancement in VR assistance systems.
[4]	To develop a machine learning approach for predicting teacher's expertise based on off-the-shelf VR device data.
[5]	To propose ten open challenges, primarily focusing on challenges related to the visualization of medical imaging data, such as explainability and dealing with uncertainty.
[6]	To build a multimodal deep fusion system for cybersickness (i.e., motion sickness due to exposure to XR systems) forecasting based on user's physiological, head-tracking, and eye-tracking data.
[7]	To investigate pedestrian crossing behavior in the presence of automated vehicles and exploring the factors influencing pedestrians' waiting time.
[8]	To develop an XAI-based framework for developing explainable cybersickness detection machine learning (ML) models for VR systems.
[9]	To develop an XAI-based framework named LiveVR for cybersickness detection.
[10]	To improve cybersickness detection models' trustworthiness and provide informed decisions into why and how the applied ML/ Deep Learning (DL) models have arrived at specific decisions.
[11]	To differentiate attention levels that are captured during a perceptual discrimination task presented on two different viewing platforms.
[12]	To investigate users' uni- and bi-manual finger behavior from their interaction with eight different universal interface elements.
[13]	To build a biometric identification system that considers the user's gaze behavior and head orientation while following a moving stimulus.
[14]	To develop a novel AR interface that enables effective diagnosis of a robot's error behavior, enhances its skills, and allows it to upgrade its knowledge structure.
[15]	To predict pedestrian behavior and potential collision situations when crossing the street using ML classification techniques for supporting the design of Autonomous Emergency Braking (AEB) systems in commercial vehicles.
[16]	To understand the classification accuracy of different motor tasks based on brain activity and artifacts in Electroencephalography (EEG) signals for VR neuro-rehabilitation paradigms.
[17]	To build an XAI framework for simulation-based training in surgery.

[18]	To reveal the potential of VR to overcome most of the desktop eye-tracking limitations and become a disruptive technology for clinical practice in assessing X-ray images.
[19]	To provide an XAI, blockchain (BC), and immersive technology-based framework for Metaverse healthcare.
[22]	To investigate the use of AR interfaces for live communication between human and robotic teammates in collaborative tasks focusing on prescriptive and descriptive guidance.
[23]	To discuss research agenda for guiding the development of the next generation of Discrete Event Simulation (DES) systems for real-time interactive animations used in XR systems while taking a human-centric stance and including XAI methods.
[24]	To explore the design space of mobile AR explanations for movie recommendation scores and provide recommendations for designing AR explanations.
[25]	To build a lung cancer patient assistant service named MetaLung on the metaverse together with an AI-based Decision Support System for treatment selection.
[26]	To build an intelligent AR training framework that provides a complete visualization of the Education Training Inspectorate (ETI) procedure for real-time guidance and assessment of trainees.
[27]	To explore the design space of mobile AR explanations for movie recommendation scores.
[28]	To investigate the impact of a smartphone-based AR shopping assistant application that uses personalized recommendations and XAI features related to customer shopping experiences.

Table 1. Overview of included research studies.

APPLICATION DOMAINS AND OPPORTUNITIES

The explainability of AI methods enhances their usability and trust across various domains where AI tools are applied. This systematic review identified several application domains, the most prominent areas being healthcare, recommendation systems, and safety abilities.

Healthcare is the most frequently mentioned domain of application, appearing in nearly 30% of the reviewed articles. This category includes articles related to AR or VR-based training for health practitioners, such as training for neonatal endotracheal intubation [26]. Other healthcare-related applications include: X-ray readings and diagnoses [18], surgical teaching [17], classification of motor tasks from EEG signals [16], Metaverse clinics and hospitals [19], medical data visualization [19], Metaverse integration for lung cancer detection [25].

Recommendation systems (found in 16% of the reviewed articles) are applied in various contexts, including: movie recommendations [24], shopping [27], action recommendations [22], shopping assistance [28].

Safety Abilities (16% of the papers) include attention assessment [11] and expertise evaluation [4]. Driving safety focuses on collision detection [15] and pedestrian crossing behavior for automated driving [7].

Cybersickness is discussed in 12% of the articles, the focus being on detection methods [6, 8, 10].

Experience Personalization is addressed in 12% of the articles, including biometrics [13], AR shopping assistance [28], and hand tracking data for user identification in AR and VR [12].

Other domains include: prescriptive and descriptive guidance [22], human and robot teams [22], robot improvement through AR interface [4].

From a study and research agenda perspective, the identified literature also covers topics such as: trust in assistance systems [3], Discrete Event Simulation (DES) systems [23], challenges in visualization research [5] and a brief state-of-the-art review of Metaverse healthcare [19].

A significant part of the articles reviewed presents promising opportunities and future perspectives in the field of XAI. These opportunities range from the development of tailored frameworks to address specific domain needs, such as those in healthcare [26], to the exploration of novel methodologies, like cybersickness detection using xML [10], or forecasting cybersickness severity 90 seconds before happening by using deep temporal convolutional forecasting models [6].

Future perspectives often revolve around expanding research findings to larger populations [11], leveraging AR to enhance user experiences, particularly in movie recommendations [24], and exploring the potential of AR in designing explanation artifacts and visualizations for recommendation systems [27]. Other opportunities include the exploration of diverse usage scenarios, such as user authentication and access control through behavioral biometrics [13], as well as investigating human-robot team dynamics in tasks like rescue missions, where visual guidance algorithms play a crucial role [22].

Additionally, while some findings may not yet demonstrate promising outcomes, they still shed light on potential research directions, such as the relationship between trust and reliance in AI systems [3]. A user's shopping experience improvement providing explainable recommendations [28] might allow for better decision making in general. The results in [7] and [15] have a significant potential in sensitive issues like braking assistance and critical issues like pedestrian safety. Improving teaching in medicine is another critical aspect which represents an opportunity [17]. AR and VR also have a big potential in user identification and authorization, and this is a transversal opportunity across almost any information system [12]. Moreover, medical visualization remains one of the most valuable ways to advance the medical field [5]. Interpretability within the context of diagnosing robot behaviors enhances human trust through generated explanations [4]. Other opportunities include identifying the most relevant feature class in cybersickness, proven to be related to eye-tracking [9]; Metaverse medical applications that can incorporate XAI predictive models [25]; predicting teacher expertise [4]; and offering personalized safety training for construction workers [1].

XR SYSTEMS INTEGRATING XAI

Various XR systems integrate methods and techniques related to XAI. They differ given several aspects i.e., the type of visualization device targeted, on whether or not they take extra body measurements or on the application domain.

From the publications studied, 6 publications highlight AR approaches, 14 publications present VR-based approaches, while 5 publications discuss mixed AR/VR systems. Considering the subset of publications describing AR systems, 4 of the systems detailed make use of optical see-through devices while 3 of the systems relate to video see-through equipment. The remaining 4 AR-related publications do not provide specifications with regard to the type of the AR viewer.

With regard to the type of equipment, 13 of the research publications target HMD-oriented systems (Head Mounted Display). From the collection of publications focusing on HMDs, 11 publications target VR HMDs, and 3 publications tackle AR HMDs, while one publication covers both AR and VR HMDs (Figure 1).

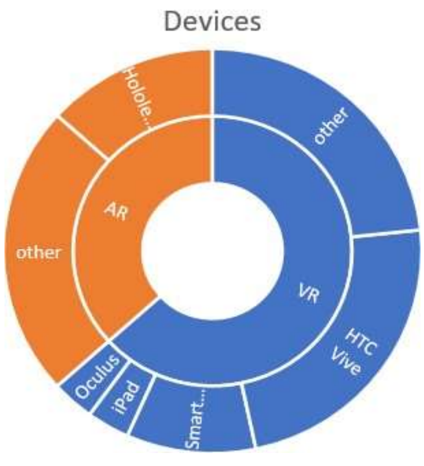

Figure 1. Considering equipment type, 13 publications target HMD-oriented systems, 11 publications target VR HMDs and 3 publications target AR HMDs.

Moreover, 3 publications focus on the use of smartphone devices, one focuses on the use of tablets and one focuses on the use of monitors.

The most used AR device is Hololens (including versions), in 4 of the AR-related publications. At the same time, HTC Vive (including multiple versions) is the most employed VR device to support the research approaches in 7 of the VR-publications. Oculus headset shows up in one publication.

From the publications which advance VR systems running on smartphones, in the first place is Android OS smartphones (showing up in 2 publications). On the other hand, the iPad is the most used tablet to support explainable AI techniques in VR-related research.

Some of the publications on explainable AI-enhanced techniques for XR in our review study make use of extra sensors (13 publications). The integration of the extra sensors allows for analyzing and tracking the user behavior at specific time moments as well as dynamically. Additional sensors are employed in 3 of the AR-oriented publications and by 10 of the VR-oriented publications (Figure 2).

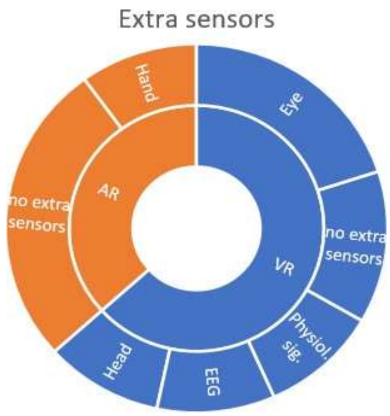

Figure 2. Additional sensors are employed in 3 of the AR-oriented publications and in 10 of the VR-oriented publications.

The most integrated type of extra sensors is the eye-tracker, in 6 VR publications. Other sensors like head-trackers, brain-related sensors (i.e., EEG), or physiological trackers (i.e., related to heart rate, galvanic skin-response, breath-rate) each showing up in 3 VR-related publications on explainable AI techniques for XR systems. In the area of AR systems, 3 of the publications employ hand-oriented sensors.

Some publications highlight the contribution of explainable AI to XR systems by framing the research to specific application domains. In our review study, about 16 of all XR scientific publications do focus on explicit application domains. More exactly, 8 of the AR-based systems and 12 of the VR systems proposed to study the contribution of explainable AI, are applied to a specific application domain. The most studied application domain in our study over the selected XR systems does relate to the medical domain. Other application domains relate to educational, industrial or construction domains.

The research findings on explainable AI for XR systems are facilitated through analysis of data collected during own experiments (in 19 XR publications) or by using open-source datasets. Data from own experiments is employed in 7 publications regarding AR-based systems and in 13 publications on VR systems.

Some of the research publications from our review validate their findings through particular investigation methods. Questionnaires are typically used in user studies to collect feedback from the user during or after experiments.

In our selection of scientific publications, the questionnaire is used as a tool to validate the findings regarding explainable AI techniques for XR systems, in 4 AR-related publications and in 7 VR-related publications. The rest of the publications do not report questionnaire-oriented validation for their systems.

From our review study, it turns out research on XR systems integrating XAI focuses more on VR technology and HMD setups. HTC Vive is the most used HMD for VR, while Hololens is the HMD which empowers most of the AR-oriented platforms. The subset of publications which employ additional sensors tracking user behavior and the subset which doesn't employ additional sensors, are balanced. However, more than double (in relative percentage) number of VR systems use extra body sensors as compared to AR systems.

Ideally, more research publications on AR systems integrating tracking sensors to support XAI will be available in the future. Equally relevant, more publications will appropriately be made available on XAI-enhanced XR systems targeting even more applications domains. At the moment, the medical domain is the most explored among the few domains tackled in the existing literature. Surprisingly, the questionnaire-driven method has relatively low incidence for assessing the approaches presented in the selected publications.

XAI METHODS AND TECHNIQUES USED

To understand how XAI is applied in the XR domain, one needs to explore various directions being taken using specific XAI techniques given particular taxonomic categories of XAI methods. This taxonomy includes distinctions between model-based and model-agnostic methods, as well as global versus local explanations. Model-based techniques are intrinsically tied to specific AI models, leveraging their internal structures to provide explanations. In contrast, model-agnostic techniques operate independently of the underlying AI model by making use of mechanisms like input perturbation and surrogate models to provide insights applicable across various AI systems. Specifically, 44% of the studies adopt a model-based approach, 20% a model-agnostic approach, and 36% of the studies either do not mention or represent a position perspective (Figure 3). Accordingly, the core model-based and model-agnostic XAI techniques used are classified as follows:

- Model-based: attention-based CNN and GRAD- CAM++ [26]; EFGNet that uses DeepLift [11]; decision tree, logistic regression, and explainable boosting machine [10]; NBEATs [6]; k-NN explainable classifier [13]; Markov Decision Process [22]; Chi-Square test [15]; SVM [17]; random forests [12]; AOG (And-Or-Graph) [14].
- Model-agnostic: decision tree [10]: SHAP, MSA, LIME, PDP can also be seen as model-agnostic [8]; RRELIEF and SHAP [7]; LIME and SHAP [19]; SHAP [4,9,25].

In particular, two among the most well-known model-agnostic XAI techniques are LIME (Local Interpretable Model-agnostic Explanations) and SHAP (Shapley Additive exPlanations).

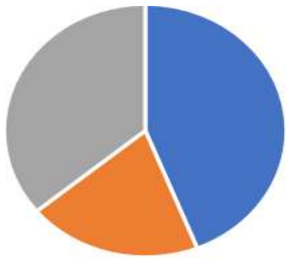

Figure 3. XAI techniques given particular taxonomic distinction on model-based versus model-agnostic methods.

LIME approximates the AI model locally around a specific prediction by generating a simpler model that mimics the behavior of the AI model in the vicinity of the input being explained. This technique facilitates understanding which features influence the prediction for that particular instance. SHAP is based on game theory and uses Shapley values to provide explanations by assigning an importance value to each feature by considering all possible combinations of features together with their contributions to the prediction.

Furthermore, while global explanations provide an overview of an AI model's behavior through insights into how the model makes decisions across all possible inputs, local explanations focus on specific instances in order to clarify why the AI model makes a particular decision for a given specific input. Specifically, 32% of the studies consider local explanations, 12% global explanations, 24% a combination of both local and global explanations, and 32% do not adopt such an approach (Figure 4). For instance, in the area of machine learning, [10] uses Explainable Boosting Machine (EBM), decision trees, and logistic regression to detect and predict cybersickness.

In this study, the authors provide explanations in both psychological and gameplay datasets while reflecting on the feature importance rankings for cybersickness classification and assuring the model's interpretability through a combination of both global and local explanations. At the same time, adopting a deep learning approach, [26] implements Gradient-weighted Class Activation Class

Activation Mapping (Grad-CAM) for generating a heatmap that shows which part of the input were the most important or have the highest influence when making the clinical prediction in training settings. Moreover, this technique improved the discriminative power of the model while providing user-friendly interpretations and real-time evaluations for clinical training.

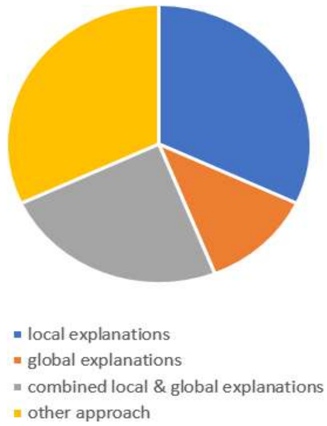

Figure 4. XAI techniques given particular taxonomic distinction on global versus local explanations.

While various XAI methods are used either standalone or in combination with human experts/users, no study considered their use on application based on recent advancements in the AI domain, in particular, Generative AI techniques such as the ones based on Large Language Models (LLMs) which help when dealing with issues such as data scarcity. This represents an important research line to be considered in order to build and enhance transparency in the XR domain through XAI.

EVALUATION METHODS

We identified three directions for evaluation of the XAI systems in XR environments: 1) the performance of the proposed AI models for different tasks; 2) the user experience in the XR environments and 3) the explanations of the AI models.

While for the performance of the models and for the user experience there are widely accepted metrics, there is no standard evaluation strategy for the explanations.

1. **Performance**: depending on the type of the task, various measures were used to assess the performance of the proposed models:

- **classification tasks** [1,4,8,9,10,11,12,13,15,16,17], [26]: accuracy, precision/specificity, recall, F-1 score, ROC (Receiver Operating Characteristic Curve) , AUC (Area Under the ROC Curve), confusion matrices;

- **regression/forecasting** [6,8,9,10]: Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R2 score; Pearson Linear Correlation Coefficient (PLCC); *overfitting index* defined as MAE(test)−MAE(train)>0; symmetric mean absolute percentage error (sMAPE), mean squared logarithmic error (MSLE)

- **policy learning** [22]: Objective metrics: Total Moves (the total number of moves needed to solve the puzzle), Total Time (the total time needed to solve the puzzle, in seconds), Time per Move (the average time per move, in seconds), Compliance Rate (the percentage of moves taken matching the recommendation provided by the system);

- **survival analysis** [7]: To measure the goodness of fit of the models, Concordance Index (C-index) is used as a global index for comparing survival times.

2. **User experience in XR environments** was assessed through users studies [1,3,4,7,10,12,15,22,24,27,28], by asking the participants to answer questions in open/semi-structured interviews and/or to fill in validated questionnaires like SUS, NASA-TLX, Simulator Sickness Questionnaire (SSQ).

3. **The evaluation of the explanations**: we followed the classification proposed in [20], by identifying the main types of XAI evaluations: with and without users.

In the XAI evaluation where users were involved, there are two types of assessments in controlled human experiments with lay persons (i.e., non experts in the field of application): i) subjective evaluation by asking users for perceived quality in the presence of explanations [3,24,27], and ii) objective evaluation by comparing the performance of participants on specific tasks with/without explanations available [22].

The XAI evaluation without users has two approaches: i) the explanations provided by the system are assessed by a human expert in the field of the application [26] or by comparison with known results in the field [11] and ii) assessing the explanations through the system performance (i.e., the explanations are the features of the most accurate model) [1,8,11,12,26].

Due to the subjective nature of the metrics like trust and comprehensibility and the lack of ground truth for interpretability, quantifying how well an explanation aligns with human understanding and intuition remains a challenge.

CONCLUSIONS

This review paper proposed a systematic literature review over the existent XAI methods and techniques applied in the XR domain. The current research on XAI methods and techniques applied on XR were synthesized and further on existing trends were identified while discussing potential future research areas.

Four research questions have been considered and analyzed aiming at studying the impact of implementing various XAI methods and techniques to the transparency dimension of XR technologies. Opportunities have been spotted on the development of tailored frameworks to address specific domain needs, such as those in healthcare, to the exploration of novel methodologies, like cybersickness detection using xML, or forecasting cybersickness severity by using deep temporal convolutional forecasting models.

Research on XR systems integrating XAI focuses more on VR technology and HMD setups. The subsets of publications which employ additional sensors tracking user behavior and the one which does not, are balanced. However, more than double (in relative percentage) number of VR systems use extra body sensors as compared to AR systems. While various XAI methods are used either standalone or in combination with human experts/users, no study considered their use on application based on recent advancements in the AI domain, in particular, Generative AI techniques such as the ones based on LLMs.
Regarding the evaluation of the XAI systems in XR environments, we found three approaches. While for the evaluation of the performance of the AI models and for the user experience there are widely accepted metrics involved, the evaluation of the explanations needs further consideration from the researchers, as quantifying how well an explanation aligns with human understanding and intuition remains a challenge.
As a next step for our review on XAI techniques as support for XR, we are considering extending the study with clusters and classes, lines and ideas of future research perspectives, also by taking into account the relation to the limitations and complexities existing in this domain which were already emphasized in this paper.

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