Personalised Training: Integrating Recommender Systems in XR Training Platforms

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ABSTRACT

The fast-paced growth of Extended Reality (XR) technologies in complex environments, such as training scenarios, has highlighted the need to implement Artificial Intelligence (AI) modules in the simulations to support trainers and trainees in these unfamiliar contexts. Among the possible AI solutions, recommender systems (RS) could be used to improve the users' interactions and experience in immersive training environments. This work describes the integration of a RS in the framework of an XR training platform and how the design of interfaces to present recommendations can maximize acceptance of the suggestions in hybrid human-intelligent systems. By allowing trainers to adapt training scenarios during the execution of the exercise, successful and personalized training goals can be achieved.

KEYWORDS

Extended Reality, Virtual Reality, Augmented Reality, XR Training, Artificial Intelligence, Recommender System

1 INTRODUCTION

Extended Reality (XR) training systems are becoming increasingly popular across several disciplines such as law enforcement, medical first responders, and CBRNe specialists [7, 11, 13, 15]. These systems make it possible to recreate detailed scenarios of complex environments that can be fully customised to meet the needs of trainers and trainees. In addition, many of the available XR training systems use physiological signals such as heartbeat and galvanic skin response to measure participants' stress during exercise. Although effective and successful, XR training systems have little room for adaptation: for example, the trainer cannot make changes to the virtual environment during a training session. For example, if a scenario is too stressful for the trainees, it is not possible to make changes to reduce the stress factor, or vice versa if the trainees are not stressed enough, an additional stress factor must be introduced. To address this problem, automatic suggestions, adapted to the users' conditions, could be introduced in an XR training system using a recommendation system (RS).

The scope of this work is to present an integration of a recommender system (RS) in an XR training platform for real-time scenario adaptation.

2 RELATED WORKS

Recommender systems are extensively used in websites and applications to increase users' experience by providing personalised lists of items tailored to their past interactions with the system. Recommender systems aim primarily to advertise products or services that users might be interested in. The focus of researchers in recommender systems is mainly directed toward the computational aspect of this issue, with deep and geometric learning [9, 20] and Bayesian and collaborative filtering methods [4, 17] as main approaches to enhance the efficacy and pertinence of the recommendations. While many AI techniques have been devised over the years [19] to improve the relevance of recommender systems, very little has been done to improve the way users interact with them.

In the last years, research has directed its attention towards the presentation level of recommender systems [8] focusing on the effects it has on persuasion and satisfaction [12]. In fact, as the quality of the recommendations increases, users need to be supported with additional visualisations that keep RS transparent and interpretable [16]. Following the example of Gironacci [5], this work describes how a RS can be included in the framework of an XR training system to support trainers in scenario generation and real-time adaptation based on trainees' stress measurement.

3 PROPOSED USE CASE

In the context of the Med1stMR project, [7] (funded by European Union's Horizon 2020 Research and Innovation Program under grant agreement No 101021775) the use of XR is fundamental to combining real-world medical simulators with virtual environments to train medical first responders specifically for mass casualty incidents (MCIs). Among the aims of the project is to create a new training platform for instantaneous modification of the virtual environment tailored to the trainee's response.

To tackle these issues, the proposed solution has trainers decide which stressors to include in the scene before the training session with the possibility to modify them during the exercise. A machine learning approach is implemented to provide trainers with meaningful suggestions of elements such as stressors, weather conditions and NPCs that could benefit the scenario. Moreover, the data collected during previous training are used to tailor each scenario to the participants' needs. Figure 1 shows a diagram of the suggested RS and its role in the XR training system. This novel approach exploits data from both the trainer, which interacts with the RS

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through an interface and the trainees acting within the training platform.

To implement this solution, a user interface is designed to allow direct communication between the trainer and the RS. During the preparation of the training, the trainer selects which scenario wants to run, how many trainees will be there, the level of difficulty and other options such as weather conditions and duration. Based on the data stored in the previous training sessions, the system provides recommendations to improve the current setup. Using the provided interface, the trainer is guided to a step-by-step scenario generation supported by the system's recommendations based on existing training data (such as physiological feedback, behaviour during training, etc.). For example, the system recommends training in the medium to the high-stress range in an urban area with a collapsed school with an unknown number of casualties. However, the trainer changes the scenario from a school to a residential building, due to an actual incident that occurred a few days before.

In the next step, based on the participants' expected stress score, the RS now suggests a selection of stressors to use as a starting point. The system suggests changing the weather to increase the stress or introducing a different stressor as the one chosen was not very effective in previous sessions. During this process, the RS records which suggestions the trainer accepted and will use this information to update future training designs.

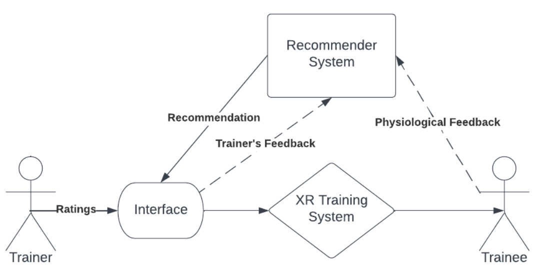

Figure 1: Diagram of the proposed integration

Once the training begins, the system monitors in real-time the physiological signals of the trainees and if the stress level is below the required threshold an adjustment to the scenario is suggested to the trainer. For example, the RS proposes to increase the number of casualties to elicit more stress. If the suggestion is approved, new casualties are placed on the scene. Similarly, if the stress level is above the established parameter, the RS will provide a recommendation to reduce the stress. For instance, removing a stressor or improving the weather conditions. The expected stress level proposed in this work should be calculated by integrating trainees' subjective ratings of stressful situations faced in the past and quantitative parameters such as trainee's years of experience, age and physiological data (e.g. mean heart rate variability, mean respiratory rate). By correcting the scenario during the execution to achieve the expected stress level, training goals can be achieved and a formative experience is ensured.

3.1 Methods and performance metrics

The evaluation phase focuses on two aspects: evaluation of the RS and evaluation of the recommendations' presentation. To evaluate the efficacy of the RS, researchers have determined several approaches [3, 6, 18]. To achieve the goal of this enquiry the ResQue evaluation framework [14] will be used as it provides an efficient method to identify areas of improvement. For the scope of this study, at least two interfaces will be designed which will display recommendations using different modalities (e.g. text-only, text + image, etc.) on a 2D interface on a tablet device. Future versions of this framework will implement the interface on XR devices such as Augmented Reality headsets.

To evaluate the presentation features of the RS different interfaces will be designed and compared. Three constructs will be used to assess the efficacy of the interfaces: 1) Satisfaction with the system. 2) Satisfaction with the recommendation process. 3) The likelihood of selecting a recommendation [12]. Additionally, a System Usability Scale [10] will be gathered to evaluate the system's ease of use. Possible interface designs will be prototyped after collecting trainers' requirements during focus group sessions.

3.2 Explainability

To foster a trustworthy relationship between the trainer and the proposed RS, several strategies can be implemented. Following the example of [1, 2] the system should inform the user on which data are currently being used to make a recommendation while providing a justification that motivates the proposed suggestions (e.g. the suggested stressor is an angry dog because 5 trainees found this item very stressful).

4 CONCLUSION

This work describes the integration of a RS in the framework of an XR training platform and how the design of interfaces to present recommendations can maximize acceptance of the suggestions in hybrid human-intelligent systems. While recommender systems are widely adopted in the context of e-commerce and media services their application in the XR domain has only been partially addressed in recent times [5]. The use case proposed in this work leverages the assumption that data gathered from the trainees guarantee the objectivity of the system and allow the algorithm to formulate meaningful suggestions, reducing the potential subjectivity that may emerge if the RS was trained only on ratings provided by expert trainers. In fact, the novelty of the framework discussed here consists in using input from two sources, the data gathered from the trainer interacting with the system interface and the data from the trainees interacting with the training platform.

To conclude, future work on this subject will investigate the richness and persuasive strength of recommender systems by proposing novel interfaces for XR technologies augmented with persuasion techniques.

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