Human-Centered E-Business Systems based on Situation Awareness: a contextual framework driven by Artificial Intelligence*

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Abstract

In recent years, e-business ecosystems have evolved into complex and data-driven information systems, where adaptability to the context has become a critical success factor. Traditional decision-making models, however, often prove inadequate to manage the dynamism and uncertainty of today's digital environments, creating a gap between the richness of available data and the ability of systems to exploit it proactively. This article proposes an innovative framework integrating Artificial Intelligence and Situation Awareness to develop human-centered and adaptive E-Business Information Systems (EBIS). Our approach combines the Situation Awareness (SA) paradigm, which is the ability to perceive, understand, and project future states of the context, with a multilevel software architecture. By leveraging the integration of data from the Internet of Things (IoT), the formalization of knowledge through semantic ontologies, and the predictive power of Bayesian probabilistic models, the framework enables systems to react and anticipate user needs. The validation of the framework, conducted through a use case in the domain of smart cultural tourism at the Archaeological Park of Pompeii, demonstrated the effectiveness of our approach by defining a solid methodological basis for the creation of next-generation e-business systems, capable of learning and reacting dynamically, improving the resilience of processes and placing the user at the center of an intelligent and personalized digital experience.

1 Introduction

The digital age has triggered a profound metamorphosis in the commerce landscape, evolving e-business from simple transactional platforms to complex socio-technical ecosystems in which the interaction between physical and digital components requires a high capacity for adaptation. This

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convergence, orchestrated by a dense network of sensors, IoT devices, online platforms, and perpetually connected users, has generated a deluge of heterogeneous contextual data, biometric data from wearables, eye-tracking signals, application metadata, and social interactions, which contain immense information potential for personalization[1]. Despite this wealth of information, traditional decision-making models, often anchored to predefined logics and the static analysis of historical data, reveal a profound inadequacy. Their structural rigidity and lack of semantic understanding of context make them unable to handle the uncertainty, volatility, and fluidity that characterize modern digital scenarios, where user needs and operating conditions evolve in real time[2]. This creates a critical gap between the availability of situational data and the limited ability of current systems to interpret it to orchestrate authentically adaptive and proactive behavior. Research has progressively embraced the Situation Awareness (SA) paradigm to overcome these limitations, a construct that goes beyond simple "context-awareness". SA is defined as a cognitive process articulated in three hierarchical phases: perception of elements in context, understanding their meaning, and projection of their future state, which are essential for effective decision-making in complex environments[3], [4]. The application of SA in Service-Based Systems (SBS) demonstrated the need to decompose and automate analysis processes through autonomous software agents (SAW agents) to manage distributed complexity [5]. In this scenario, the present work proposes an innovative framework based on artificial intelligence and situation awareness designed to design adaptive and human-centered E-Business Information Systems (EBIS). Unlike single-aspect approaches, our framework synergistically integrates a multi-layered architecture for data acquisition and analysis, knowledge formalization through semantic ontologies to ensure interoperability, and the predictive power of Bayesian probabilistic models. The goal is to equip e-business systems with the ability not only to react, but to anticipate and respond dynamically to changes, optimizing the digital customer journey [6], improving the resilience of processes, and placing the individual at the center of a proactive and truly personalized digital experience.

2 Related Words

The evolution of e-business systems towards intelligent and adaptive environments has made traditional models obsolete, mainly focused on the a posteriori analysis of historical data. The scientific literature has responded to this challenge by exploring advanced computational paradigms, progressively shifting the focus from simple Context-Awareness, the ability of a system to use contextual information to deliver relevant services, to the more complex and proactive Situation Awareness (SA) [7]. While the former is limited to a reaction based on environmental parameters, SA introduces a three-phase cognitive model - perception, understanding, and projection - which allows systems to interpret the current state and anticipate their future evolutions. This predictive capability supports automated decision-making processes in dynamic and uncertain environments, improving human-machine interaction and overall system resilience. The analysis of the recent literature reveals several converging lines of research that address the problem from architectural, semantic and applicative perspectives[8].

A prominent approach to SA implementation is based on developing pattern-based and modular software architectures designed to enable real-time adaptation of interactive systems[9], [10]. A case in point is the SitAdapt system, an integrated architecture for web and mobile applications that aims to improve the user's task accomplishment and the overall user experience [11]. SitAdapt's architecture is typically composed of specialized components: an Observer Component that synchronizes and records signals from a multitude of heterogeneous sources, including eye-trackers, facial emotion recognition software (such as Noldus FaceReader), wearable biometric sensors, and application metadata; a Situation Analytics Component that interprets this data to infer the state of the user and the context; and a Decision Component that, based on this analysis, determines the need for dynamic adaptation, controlling the generation of changes to the interface or workflow[12], [13]. This approach is based on "situation patterns", i.e., recurring patterns that, once recognized, trigger specific adaptation actions, such as changing the visual presentation or dynamically restructuring an interface to offer contextual help.

The research emphasized the importance of ontology-based semantic foundations to ensure that situational knowledge can be shared, reused, and interpreted unambiguously by different entities in a distributed system. In this context, the SAW-OWL-S approach significantly contributes to extending the Web Ontology Language for Services (OWL-S) to formally incorporate SA into the service specification [14]. This model identifies and formalizes four key relationships between contexts/situations and services:

- Service's contextual data: Binds contextual data directly to a service, making it available for evaluating situations.
- Situation precondition: Specifies that the execution of a service can be contingent on the occurrence of a specific external situation.
- Situation post-condition: Defines the effects that the execution of a service has on the external context
- Situation-service-triggering: Models the ability of a situation to automatically trigger a service.

Using hierarchical ontology, which models contexts and situations at different levels of abstraction, allows for automated logical reasoning on service specifications, enabling more intelligent and dynamic service discovery and composition.

In large-scale e-business systems, centralized management of SA becomes inefficient and vulnerable. To address this challenge, a line of research focused on the decomposition of SA requirements and the automated synthesis of autonomous and reusable software agents, called SAW agents [15]. These agents are responsible for specific tasks such as capturing contexts, distributing analysis of situations, and triggering appropriate actions in response to changes [15]. The approach is based on formal-logical models, such as computation and AS^3 logic (Adaptable Situation-Aware Secure Service-Based systems), which allow SA requirements to be specified declaratively and automatically translated into executable agents . A partitioning algorithm optimizes the distribution of analysis tasks among the various agents, considering factors such as network topology, bandwidth, and dependencies between situations, to minimize communication costs and maximize efficiency [16]. This approach dramatically reduces development effort and supports system adaptation at runtime, allowing for dynamic re-synthesis of agents in response to changes in system requirements or conditions[17].

The practical application of these concepts finds fertile ground in optimizing the digital customer journey in marketing and e-commerce. In this domain, the goal is to create a user experience (UX), or more specifically a customer experience (CX), that is highly personalized and seamless across the various "touch points" (touchpoints) between the customer and the company [18]. Research has shown the effectiveness of combining a person-based approach with situational adaptation. "Personas" are archetypes of customer groups, defined based on demographic, behavioral and psychographic data, which allow for initial personalization of content, offers and visual design [19], [20]. On top of this first level of personalization is real-time adaptation, led by SA. Using technologies such as emotion recognition and eye-tracking, systems can infer the user's mental and emotional state (e.g., surprise or happiness in response to a promotional image) and use this information to trigger dynamic adaptations, such as presenting a special offer at the right time, thus improving the awareness, consideration, and conversion phases of the customer journey [18].

The proposed framework is positioned at the intersection of these research strands, suggesting a synthesis that integrates a multilevel architecture for adaptation, a semantic foundation based on ontologies, and, in a distinctive way, the incorporation of probabilistic predictive models to fully realize the “projection” phase of SA, with a specific focus on the creation of authentically human-centered e-business systems.

3 The proposed approach

To overcome the limitations identified in the state of the art, such as the rigidity of traditional models and the predominantly reactive nature of context-aware systems, we propose a structured methodology for the design of authentically adaptive and proactive E-Business Information Systems (EBIS). The proposed approach is not limited to integrating contextual data. Still, it aims to establish a complete cycle of perception, understanding, and situational projection, placing the user at the center of the process. The need for such a framework stems from the observation that the effectiveness of a modern e-business system does not depend only on the amount of data collected, but on its ability to transform this data into actionable and, above all, predictive knowledge. The goal is therefore to provide a conceptual and operational architecture that guides the development of systems capable of learning, anticipating, and reacting dynamically to changes in the context, improving the resilience, reliability, and quality of digital interaction. The framework is articulated in a multilevel architecture that logically decouples the different phases of the SA process, ensuring modularity, scalability, and extensibility [21], [22], [23].

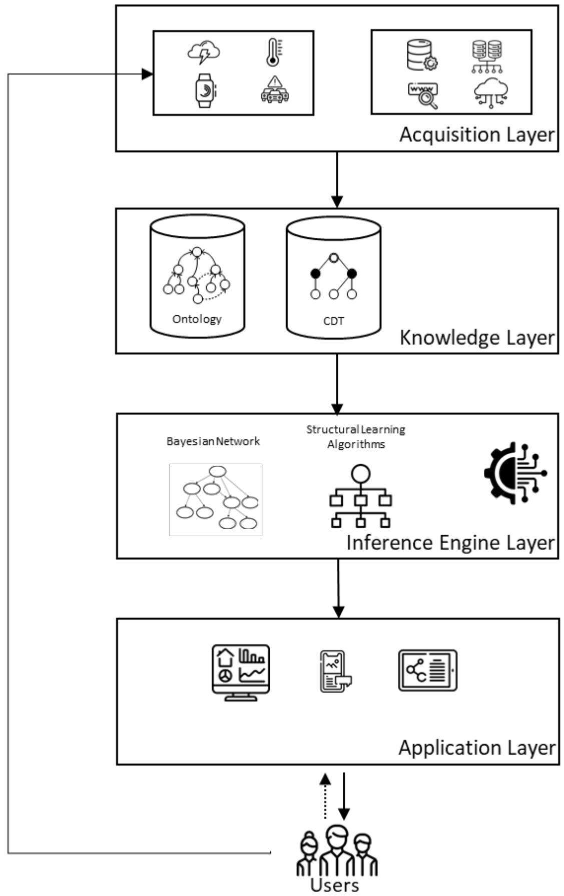

Figure 1. The proposed Architecture

3.1 Level 1: Acquisition Layer

This fundamental layer constitutes the perceptual basis of the system, realizing the first phase of the Situation Awareness model. Its primary function is to collect raw, heterogeneous, and multimodal data from various information sources. Unlike traditional systems that rely on explicit inputs, the Acquisition Layer operates as a pervasive "observer component," drawing on:

- Physical sensors and IoT devices: Environmental data (temperature, brightness), location, and status of smart objects.
- Digital platforms and external APIs: Information from social media, calendars, e-commerce systems, and other web services that enrich the contextual profile.
- User interaction data: Browsing logs, clickstreams, search queries, and application metadata that describe user behavior within the system.
- Biometric and physiological inputs: In specific contexts and with respect for privacy, data from wearables (heart rate, stress levels) or eye-tracking systems can be included to infer the cognitive and emotional state of the user.

This layer acts as an interface between the real/digital world and the framework, normalizing and pre-processing data to make it available at the next level.

3.2 Level 2: Knowledge Layer

While voluminous, the raw data collected by the acquisition layer lacks intrinsic meaning. The Knowledge Layer has the crucial task of transforming this data into structured, formalized, machine-understandable knowledge. This process is essential to enable automatic reasoning and semantic interoperability between the different components of the system. To achieve this, the layer uses two main tools:

- Domain Ontologies: Inspired by models such as SAW-OWL-S, we use ontologies to explicitly define the concepts, properties and relationships that characterize the application domain (e.g. tourism, retail). This allows you to create a shared vocabulary to describe entities such as users, objects, places and events, and to formalize the relationships between them.
- Context Dimension Tree (CDT): Contextual data is organized in a hierarchical tree structure, where each "dimension" represents a category of context (e.g., spatial, temporal, social, computational). This structuring facilitates the aggregation and querying of knowledge, allowing the system to navigate and correlate information efficiently.

In this layer, the datum is transformed into knowledge, enriched by all the semantic properties associated with that place in ontology.

Level 3: Inference Engine Layer

This is the cognitive heart of the framework, where the second ("understanding") and third ("projection") phases of Situation Awareness are carried out. Its purpose is to analyze contextual knowledge to infer the current situation and, above all, to predict its future evolutions. Unlike a purely reactive "Decision Component", our Inference Engine is proactive. Implement AI models, specifically:

- Probabilistic Models: These models are ideal for managing the inherent uncertainty of real-world data. Given the contextual evidence available, they allow you to calculate the probability of a specific situation occurring (e.g., "user interested in buying").
- Structural Learning Algorithms: The system is not based on predefined rules, but autonomously learns the causal dependencies between the different contextual variables directly from the data. This allows the framework to adapt and improve its predictive capabilities over time.

This engine is able to transform descriptive knowledge into situational understanding and projection.

3.3 Level 4: Application Layer

The last layer is where the engine's inferences and predictions translate into concrete actions visible to the end user. Its function is to orchestrate the dynamic adaptation of the interface and functionality of the system to make it human-centered. Decisions made at this level are aimed at improving the user experience, facilitating the achievement of objectives, and optimizing the effectiveness of the process. Adaptations can manifest in various forms, including:

- Content Personalization: Dynamically display recommendations of products, articles, or tourist routes based on the inferred situation.
- User Interface (UI) Reconfiguration: Change the layout, highlight certain features, or simplify the navigation flow to support the user's current task.
- Proactive Notifications and Suggestions: Send contextual alerts (e.g. "the work you are interested in is less crowded now") or suggestions to improve the process (e.g. "activate the quick payment mode").

This layer closes the loop, ensuring that the system's intelligence translates into tangible value for the user, creating a fluid, personalized, and truly supportive interaction.

4 Validation and Use Case

This section aims to validate the applicability and effectiveness of the proposed framework through the implementation and testing of a prototype in a realistic and complex scenario. The objective is twofold: on the one hand, to quantitatively measure the performance increase of our approach compared to traditional non-adaptive solutions; on the other hand, to qualitatively demonstrate how the framework achieves a proactive and human-centered user experience, transforming interaction from reactive to predictive and personalized.

To test the proposed framework, the domain of cultural tourism was chosen as a case study as it represents an ideal test bed for a situation-aware system, thanks to its intrinsic wealth of dynamically changing contextual variables. An archaeological site like Pompeii is a complex, vast, and often crowded environment, where visitors can be significantly enhanced by intelligent and personalized support. The context in this domain is multidimensional and includes:

- Spatial Context: The granular position of the user within the park, obtained via GPS.
- Time Context: The time of day, the overall duration of the visit, and the time spent in specific areas.
- Environmental Context: The level of crowding in certain areas or buildings.
- User Context: A dynamic profile that includes preferences (inferred from behavior), language, age, and prior knowledge of the domain of interest (stated or inferred).

To put the validation into context, we defined the following scenario: A visitor, with a generic interest in Roman history but a limited time of three hours, uses a prototype mobile application (based on our framework) to explore the Archaeological Park of Pompeii. The application must guide him on a personalized tour route, helping him to discover the domus and points of interest (POIs) most in line with his emerging interests, optimizing the route to avoid the most congested areas, and maximizing the cultural value of his visit in the time available.

The prototype of the museum guide application was developed by implementing the four framework levels, but based only on some acquisition data and specific points of interest. Only a structural learning algorithm model and a Bayesian network were used in this preliminary phase.

Results

For the evaluation, a field test was conducted with 30 volunteers, divided equally into two groups of 15. The first (experimental) group was provided with the application based on the proposed framework. At the same time, the second (control) used a static version of the same app, which offered only predefined thematic paths without any dynamic customization. Each participant was assigned the same task: to explore the Archaeological Park of Pompeii for a period of three hours, following the suggestions of the application.

Quantitative Metrics

During the test, performance metrics were collected for each user to evaluate the inference engine's effectiveness in personalizing the experience.

The preliminary results are shown in Figure 2, where the performance of the proposed system compared to a traditional approach is reported in percentage.

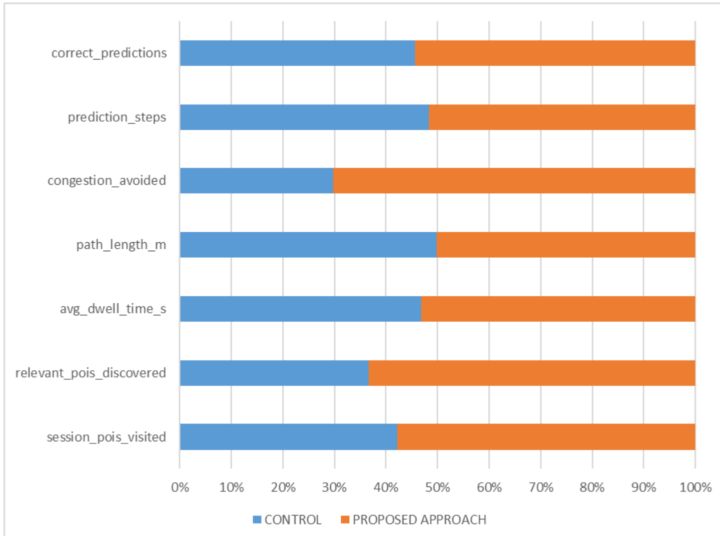

Figure. 2 System performance

The aggregate analysis of this data revealed a clear improvement of the adaptive system compared to the control version:

- Accuracy (+9%): Measures the system's ability to correctly predict the next area of interest a user would visit. A 9% increase indicates a significantly better understanding of user intent.
- Recall (+12%): The system can suggest all POIs relevant to the user's inferred interest profile. A +12% means that users in the experimental group discovered more places of interest to them.
- F1-Score (+10%): Represents the harmonic average of precision and recall, confirming a solid balance between the relevance and completeness of the recommendations generated by the system.

Qualitative Metrics: Usability and Satisfaction Questionnaire

At the end of the test, a questionnaire was administered to all 30 participants to assess the subjective perception of the experience. The questions were formulated to investigate usability, relevance, and overall satisfaction, with responses based on a 5-point Likert scale (1 = "Strongly disagree" to 5 = "Strongly agree").

Questionnaire Questions:

- Q1: The app helped me discover points of interest that I wouldn't have found on my own.
- Q2: The suggestions provided by the app were relevant to my interests.
- Q3: I found the app easy and intuitive to use.
- Q4: The app has adapted intelligently and usefully to my visit route.
- Q5: Overall, I am satisfied with my experience using this application.

The results of the answers are shown in the following graphs (Fig. 3).

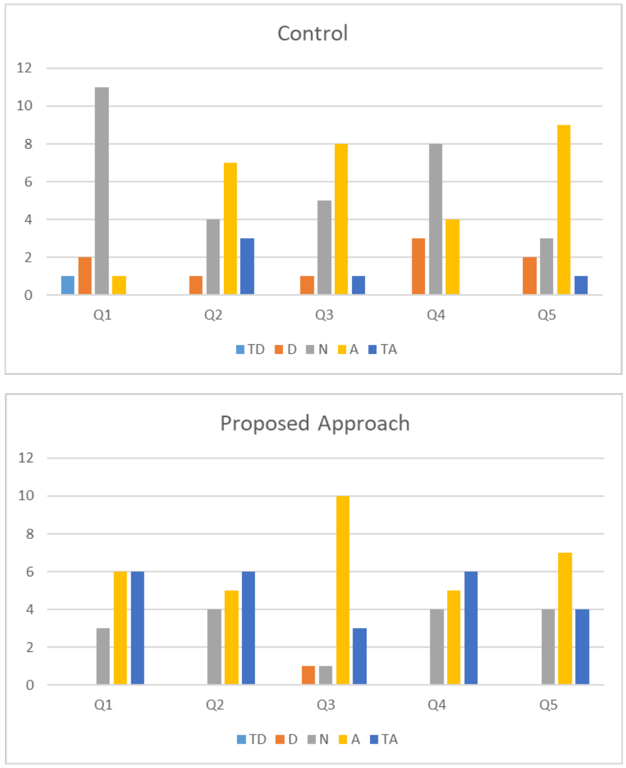

Figure.3 Questionnaire Results

4.1 Discussion of Results

Although preliminary, the results confirmed the validity of the proposed framework. The increase in quantitative metrics is not a mere statistic, but translates into a tangibly superior visit experience. For example, a 12% increase in Eecall means turning a potentially dispersive visit into a focused and enriching exploration, allowing the user to discover hidden gems that they would otherwise have ignored. Qualitative data strongly corroborate this conclusion. The responses to the questionnaire show that users in the experimental group assigned significantly higher average scores on all dimensions investigated, in particular on the perception of relevance (Q2) and adaptivity (Q4). This indicates that users perceived the proactive system not as intrusive, but as an intelligent "travel companion" that facilitates exploration and increases its value. Together, these results demonstrate that the framework's proactive, situational approach overcomes the limitations of static applications and creates a truly human-centered system.

5 Conclusions and Future Perspectives

In this work, we addressed the growing need for adaptability and proactivity in E-Business Information Systems (EBIS), highlighting the limitations of traditional decision-making models in dynamic and data-driven contexts. To overcome these challenges, we proposed an integrated framework, methodology, and architecture that places Situation Awareness (SA) at the center of human-centered system design. Our approach stands out for its ability to realize the entire SA cycle, perception, understanding, and, above all, projection, through a synergy between a multilevel architecture, semantic ontologies for the formalization of knowledge, and Bayesian probabilistic models for inference and prediction.

The experimental validation, conducted through a case study in the complex domain of cultural tourism at the Archaeological Park of Pompeii, provided empirical evidence of the framework's effectiveness. The results not only demonstrated a significant increase in quantitative performance (with improvements in accuracy, recall, and F1-score) compared to a static control system, but also confirmed, through qualitative metrics, a user experience perceived as more useful, intuitive, and satisfying. Therefore, the main contribution of this work lies in the proposal of a holistic methodology that equips EBISs with the ability to anticipate user needs and adapt proactively, transforming digital interaction into a more innovative and more resilient experience.

The future prospects of this research are manifold and focus on extending the framework to address emerging challenges. Among the most promising directions are the integration with Digital Twin technologies to create virtual models that are even richer and more dynamic of the operational context, the exploration of blockchain to ensure the transparency and reliability of interactions in decentralized ecosystems, and the development of Explainable AI (XAI) models. The latter direction is particularly crucial to increase user trust, making the system's decision-making processes transparent and understandable and consolidating the transition to e-business systems that are not only intelligent but also reliable and responsible.

References

[1] P. Barra, M. Giammetti, A. Tortora, and A. Della Greca, "Redefining Interaction in a Digital Twin Laboratory with Mixed Reality," 2024, pp. 295–307. doi: 10.1007/978-3-031-60611-3_21.

[2] R. Dobrescu, D. Merezeanu, and S. Mocanu, "Context-aware control and monitoring system with IoT and cloud support," *Comput Electron Agric*, vol. 160, pp. 91–99, May 2019, doi: 10.1016/j.compag.2019.03.005.

[3] K. S. Tekinbaş, K. Jagannath, U. Lyngs, and P. Slovák, "Designing for Youth-Centered Moderation and Community Governance in Minecraft," *ACM Transactions on Computer-Human Interaction*, vol. 28, no. 4, pp. 1–41, Aug. 2021, doi: 10.1145/3450290.

[4] A. A. Cantone, G. Cossentino, M. Sebillo, and G. Vitiello, "People and Technology: An Investigation of the Adoption of Artificial Intelligence in the Kinesiology Context," 2024, pp. 307–318. doi: 10.1007/978-3-031-60615-1_21.

[5] M. R. Endsley, "Toward a Theory of Situation Awareness in Dynamic Systems," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 37, no. 1, pp. 32–64, Mar. 1995, doi: 10.1518/001872095779049543.

[6] E. Fernando, M. Meyliana, H. L. Hendric Spits Warnars, and E. Abdurachman, "Key strategic issues pharmaceutical industry of SCM: A systematic literature review," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 2, pp. 808–817, Apr. 2020, doi: 10.11591/eei.v9i2.1264.

[7] M. R. Endsley, *Designing for Situation Awareness*. 2016. doi: 10.1201/b11371.

[8] L. Gualtieri, A. Revolti, and P. Dallasega, "A human-centered conceptual model for integrating Augmented Reality and Dynamic Digital Models to reduce occupational risks in industrial contexts," *Procedia Comput Sci*, vol. 217, pp. 765–773, 2023, doi: 10.1016/j.procs.2022.12.273.

[9] M. Casillo, F. Colace, A. Lorusso, D. Santaniello, and C. Valentino, “Integrating Physical and Virtual Experiences in Cultural Tourism: An Adaptive Multimodal Recommender System,” *IEEE Access*, vol. 13, pp. 28353–28368, 2025, doi: 10.1109/ACCESS.2025.3539205.
[10] A. Gaeta, V. Loia, A. Lorusso, F. Orciuoli, and A. Pascuzzo, “Towards a LLM-based intelligent system for detecting propaganda within textual content,” *Computers and Electrical Engineering*, vol. 128, p. 110765, Dec. 2025, doi: 10.1016/j.compeleceng.2025.110765.
[11] C. Herdin, C. Märtin, and P. Forbrig, “SitAdapt: An Architecture for Situation-Aware Runtime Adaptation of Interactive Systems,” 2017, pp. 447–455. doi: 10.1007/978-3-319-58071-5_33.
[12] M. Casillo *et al.*, “A Situation Awareness Approach for Smart Home Management,” in *2021 International Seminar on Machine Learning, Optimization, and Data Science (ISMODE)*, IEEE, Jan. 2022, pp. 260–265. doi: 10.1109/ISMODE53584.2022.9742901.
[13] M. Casillo, F. Colace, A. Lorusso, D. Santaniello, and C. Valentino, “A multilevel graph approach for IoT-based complex scenario management through situation awareness and semantic approaches,” *J Reliab Intell Environ*, vol. 10, no. 4, pp. 395–411, Dec. 2024, doi: 10.1007/s40860-024-00224-0.
[14] S. S. Yau and Junwei Liu, “Incorporating Situation Awareness in Service Specifications,” in *Ninth IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC’06)*, IEEE, pp. 287–294. doi: 10.1109/ISORC.2006.39.
[15] S. S. Yau, H. Gong, D. Huang, W. Gao, and L. Zhu, “Specification, decomposition and agent synthesis for situation-aware service-based systems,” *Journal of Systems and Software*, vol. 81, no. 10, pp. 1663–1680, Oct. 2008, doi: 10.1016/j.jss.2008.02.035.
[16] A. C. Pogmore, R. J. Davies, and N. J. Cooke, “Virtual Versus Reality: A Systematic Review of Real-World Built Environment Tasks Performed in CAVEs and a Framework for Performance and Experience Evaluation,” *Virtual Worlds*, vol. 3, no. 4, pp. 536–571, Nov. 2024, doi: 10.3390/virtualworlds3040028.
[17] R. Addesso, S. Pingaro, B. Bisceglia, and D. Baldantoni, “Sustainable Tourism and Conservation of Underground Ecosystems through Airflow and Particle Distribution Modeling,” *Sustainability*, vol. 14, no. 13, p. 7979, Jun. 2022, doi: 10.3390/su14137979.
[18] C. Märtin, P. Asta, and B. Bissinger, “Optimizing the Digital Customer Journey – Improving User Experience by Persona-Based and Situation-Aware Adaptations,” 2020, pp. 141–148. doi: 10.1007/978-3-030-47595-6_18.
[19] J. Thorne, A. Vlachos, C. Christodoulopoulos, and A. Mittal, “FEVER: a Large-scale Dataset for Fact Extraction and VERification,” in *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, Stroudsburg, PA, USA: Association for Computational Linguistics, 2018, pp. 809–819. doi: 10.18653/v1/N18-1074.
[20] A. Hogan *et al.*, “Knowledge Graphs,” *ACM Comput Surv*, vol. 54, no. 4, pp. 1–37, May 2022, doi: 10.1145/3447772.
[21] F. Colace, M. Lombardi, F. Pascale, D. Santaniello, A. Tucker, and P. Villani, “MuG: A Multilevel Graph Representation for Big Data Interpretation,” in *Proceedings - 20th International Conference on High Performance Computing and Communications, 16th International Conference on Smart City and 4th International Conference on Data Science and Systems, HPCC/SmartCity/DSS 2018*, 2019, pp. 1408–1413. doi: 10.1109/HPCC/SmartCity/DSS.2018.00233.
[22] M. D. Santo, L. Fabbri, R. Mosca, M. Lombardi, A. Romano, and D. Santaniello, “A Multilevel approach to recommend working paths in industry 4.0,” in *Proceedings of 2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering, TALE 2020*, 2020, pp. 754–757. doi: 10.1109/TALE48869.2020.9368327.

[23] M. Casillo, F. Colace, A. Lorusso, D. Santaniello, and C. Valentino, “A multilevel graph approach for IoT-based complex scenario management through situation awareness and semantic approaches,” *J Reliab Intell Environ*, 2024, doi: 10.1007/s40860-024-00224-0.