A Framework based on Recommender Systems as Enabler of Cultural Heritage E-Business*

Casillo Mario[1], Castiglione Arcangelo[1], Molinara Mario[2], Strollo Pietro Giuseppe[3], and Valentino Carmine[1†]

[1] University of Salerno, Fisciano, Italy
{mcasillo,arcastiglione,cvalentino}@unisa.it
[2] University of Cassino, Cassino (FR), Italy
m.molinara@unicas.it
[3] University of Basilicata, Italy
pietrogiuseppe.strollo@studenti.unibas.it

Abstract

The convergence of e-business models and digital cultural heritage has redefined how institutions create, distribute, and sustain cultural value in the digital economy. This paper presents a recommender system-based framework to enhance user engagement and personalization in cultural heritage e-business contexts. The proposed framework integrates semantic knowledge management, graph-based recommender, and digital storytelling across four functional layers. The system dynamically generates personalized cultural experiences, promoting participation and emotional connection with heritage assets. An experimental phase involving 34 participants demonstrated the framework effectiveness in improving relevance, engagement, and cultural enrichment during site visits.

1 Introduction

In the last two decades, the convergence between e-business models and digital cultural heritage (CH) has opened new opportunities for personalized user experiences and sustainable value creation [4]. The growing digitization of cultural content and the emergence of on-line cultural marketplaces have led institutions to reconsider how cultural assets are offered, accessed, and monetized within the digital economy. In this scenario, Recommender Systems (RSs) have become one of the most effective technologies for improving personalization, engagement, and decision support in e-business applications [2, 16, 11, 5, 18].

Developed initially to alleviate information overload in e-commerce, RSs are now considered a key component of e-service personalization, supporting adaptive content delivery in tourism, education, and e-government sectors. Within e-business, they act as intelligent intermediaries between users and digital platforms, enhancing customer relationship management and increasing the perceived value of products and services [16]. Their ability to predict user preferences based on preferences and contextual data enables a high degree of customization and emotional connection, particularly relevant to cultural heritage.

From an e-business perspective, the tourism sector provides a mature framework to understand the impact of the Internet on cultural consumption. The Internet has profoundly reshaped the travel and tourism industry, enabling new business models based on direct-to-consumer services, on-line intermediaries, and interactive platforms for destination marketing [20]. This

*Proceedings of The 2025 IFIP WG 8.4 International Symposium on E-Business Information Systems Evolution (EBISION 2025), Article No. 21, December 16-18, 2025, Sapporo, Japan.

†Corresponding author

digital transformation has not only increased access to information and services. However, it has also empowered users to participate actively in the cultural value chain. This evolution parallels the current transition of museums, archives, and heritage sites toward user-centered digital ecosystems.

From a technological perspective, recommender systems have undergone a remarkable transformation. The earliest approaches were based on content-based filtering, which analyzed item attributes and user profiles, and collaborative filtering, which inferred preferences from the behaviour of similar users. To overcome the limitations of each approach, such as overspecialization and cold-start problems, hybrid models were introduced, combining multiple recommendation strategies to improve diversity and accuracy [15]. With the rise of deep learning, RSs have entered a new phase: neural architectures such as CNNs, RNNs, and autoencoders are now capable of learning high-level latent representations of user-item interactions, enabling more robust and context-aware recommendations [15]. More recently, graph-based recommender systems have emerged as a significant innovation, allowing for modeling complex and multi-relational data structures. These models represent users, items, and their relations as nodes and edges in a graph, leveraging graph embeddings and graph neural networks (GNNs) to learn topological dependencies and propagate semantic information across the network [8]. Deep knowledge graph-based RSs integrate both explicit and implicit relations, improving accuracy and explainability [9]. These systems are particularly suitable for cultural heritage applications, where recommendations may depend on rich semantic links.

Building upon these paradigms, this work explores how RS-based e-business framework can enhance user experience and participation in the cultural heritage domain. By leveraging user data, semantic metadata, and contextual information, such systems can deliver personalized recommendations of artworks, exhibitions, and heritage experiences, facilitating engagement while supporting new sustainable business models for cultural institutions. Through the integration of graph-based neural recommenders, this study investigates the potential of RSs to bridge technological innovation and cultural value, aligning personalization with the broader goals of accessibility, education, and heritage preservation.

This work is organized as follows: Section 2 introduces the background of Recommender Systems and GNN and their employment in the literature; Section describes the proposed framework focused on the cultural heritage; Section 4 is focused on the experimental phase; finally, Section 5 introduces conclusions and future works.

2 Background and Related Works

2.1 Background on Recommender Systems

Recommender Systems (RSs) are computational tools designed to mitigate information overload by predicting a user's potential interest in unseen items [18]. Traditionally, RSs have been categorized into three main paradigms: content-based filtering, which recommends items similar to those previously liked by a user based on item attributes; collaborative filtering, which infers user preferences by exploiting similarities between users or items in the interaction matrix; moreover, hybrid systems, which combine both strategies to leverage their respective advantages and reduce limitations such as sparsity and cold start [18].

Conventional RSs typically operate on user-item matrices or graph-like structures representing explicit (ratings) or implicit (clicks, views) interactions. However, data's growing complexity and heterogeneity have motivated the integration of side information (e.g., user profiles, social links, or contextual data) and external knowledge sources to enhance recommendation accuracy and personalization.

Recent advances in machine learning have introduced graph embedding-based recommender systems, which represent users, items, and their relations within graph structures and learn low-dimensional node embeddings that preserve topological properties [8]. Compared to traditional models relying on handcrafted similarity measures, these approaches enable scalable representation learning over heterogeneous data while capturing higher-order and indirect relationships. Within this context, Graph Neural Networks (GNNs) have emerged as a prominent framework, allowing embeddings to be propagated and updated through the graph topology, which facilitates reasoning over complex dependencies among users and items.

Despite their effectiveness, graph-based RSs still face challenges related to interpretability, data sparsity, and computational scalability [8]. Nevertheless, their capacity to integrate multiple information sources and support downstream machine learning tasks makes them a promising foundation for modern recommender systems, including applications in e-business and digital cultural heritage.

2.2 Background on Graph Neural Networks

Graph Neural Networks (GNNs) represent a class of neural models specifically designed to operate on graph-structured data $G = (V, E)$, where V is the set of nodes and $E \subseteq V \times V$ is the set of edges [1, 19]. Unlike traditional deep learning architectures, GNNs can model relational dependencies among entities connected through arbitrary structures [7, 19].

At their core, GNNs rely on the message passing paradigm, where each node aggregates information from its neighbours and updates its own representation. This process can be expressed as

$$\mathbf{h}_u^{(k)} = \phi\Big(\mathbf{h}_u^{(k-1)}, \bigoplus_{v \in \mathcal{N}(u)} \psi\big(\mathbf{h}_u^{(k-1)}, \mathbf{h}_v^{(k-1)}, \mathbf{e}_{uv}\big)\Big) \tag{1}$$

where $\mathbf{h}_u^{(k)}$ denotes the embedding of node u at layer k, ψ is the message function, $\bigoplus$ is a permutation-invariant aggregation operator (e.g., sum, mean, or max), and ϕ is the update function [19]. Equation (1) describes the fundamental operation of a Graph Neural Network layer, where each node updates its representation by aggregating information from its neighbours. In neural network terms, this corresponds to a message-passing process in which local features are propagated and combined through learnable transformations. This is analogous to how convolutional layers aggregate information from spatially adjacent pixels in traditional CNNs, but extended to arbitrary graph structures.

Traditional convolutions work only on regular data structures such as images or grids, where neighborhood relationships are fixed. Graph data, however, are irregular and have variable connectivity between nodes. The spectral approach introduced by Kipf and Welling [14] solves this problem by redefining convolution as a process of information diffusion along graph connections, allowing each node to aggregate and transform the features of its neighbours through the graph structure.

Recent advancements have applied these principles to graph-based recommender systems, where user-item interactions are modeled as bipartite graphs. In this setting, GNNs propagate user and item embeddings across the graph, capturing higher-order relationships and improving personalization and robustness. LightGCN [13] represents an example of the application of GNNs as recommender systems. It simplifies traditional GCN architectures by removing non-linear activations and learnable transformations, focusing solely on linear neighbourhood aggregation. The embedding propagation for user u at layer k is defined as:

$$\mathbf{h}_u^{(k)} = \sum_{i \in \mathcal{N}(u)} \frac{1}{\sqrt{|\mathcal{N}(u)|\,|\mathcal{N}(i)|}}\,\mathbf{h}_i^{(k-1)}. \tag{2}$$

Equation (2) can thus be interpreted as a special case of the general message-passing formulation in (1), where the message function ψ simply scales neighbouring embeddings by degree-normalized weights, and the update function *phi* is an identity mapping, as reported below

$$\psi(\mathbf{h}_i^{(k-1)}, \mathbf{h}_u^{(k-1)}) = \frac{1}{\sqrt{|\mathcal{N}(u)|\,|\mathcal{N}(i)|}}\,\mathbf{h}_i^{(k-1)}, \quad \phi(\cdot) = \mathrm{id}(\cdot) \tag{3}$$

This simplification makes LightGCN a purely linear model that focuses on efficient information propagation across the user-item graph.

The final representation is obtained as a weighted sum across layers:

$$\mathbf{h}_u = \sum_{k=0}^{K} \alpha_k\,\mathbf{h}_u^{(k)} \tag{4}$$

Therefore, applying GNNs to recommender systems allows for integrating user-item interactions into a graph structure. The propagation of embeddings across connected nodes allows the model to incorporate relational information into the recommendation process.

2.3 Related Works

The development of graph-based recommender systems has been driven by the increasing need to capture the complex and multi-relational nature of user-item interactions. Graph Neural Networks (GNNs) have emerged as a framework for learning embeddings that incorporate first-order and higher-order connectivity patterns, enabling more expressive representations of preferences and behaviours.

Ying et al. [24] propose PinSage, which introduced an efficient graph convolutional approach for large-scale recommendation tasks. PinSage utilizes random walks to sample local neighbourhoods and an importance-based pooling strategy to aggregate features, making it scalable to billions of nodes and edges in industrial applications. Its success demonstrated that GNNs could be effectively adapted to web-scale e-business environments while maintaining high recommendation accuracy and computational feasibility.

Wang et al. [22] introduce, Neural Graph Collaborative Filtering (NGCF), represented a conceptual breakthrough by integrating the user–item bipartite structure directly into the message-passing framework. NGCF recursively propagates embeddings along the graph, encoding not only direct interactions but also higher-order collaborative signals derived from multi-hop connections. This approach replaced explicit similarity computation with learned relational representations, marking the transition toward deep graph-based collaborative filtering.

To address the complexity and non-linearity of deep GCN layers, Chen et al. [6] proposed LR-GCCF (Linear Residual Graph Convolutional Collaborative Filtering), a simplified yet efficient variant that removes non-linear activations and introduces residual connections to stabilize learning. This linear formulation preserves essential graph aggregation properties while reducing over-smoothing and computational overhead, paving the way for later architectures such as LightGCN.

The integration of additional contextual and social dimensions has further enhanced the expressiveness of graph-based RSs. GraphRec [10] introduced a framework that jointly models user-item and user-user social graphs, capturing the influence of social relationships on user preferences. Through attention mechanisms, GraphRec learns the relative importance of social neighbours, allowing the system to weigh friendship and trust differently when predicting interactions. This model highlighted the potential of GNNs to combine collaborative and social signals in a unified architecture, a property that is particularly valuable in on-line communities and cultural networks.

Beyond collaborative filtering, the use of knowledge graphs has expanded recommender systems into semantically rich domains. The Deep Knowledge-aware Network (DKN) [21] fused textual and knowledge-level features by aligning word embeddings with entity embeddings derived from external knowledge graphs. This fusion enables news recommender systems to reason about semantic relations among entities, improving interpretability and generalization to unseen content. Similarly, Wang et al. (2019) [23] proposed an explainable reasoning framework over knowledge graphs, which learns relational paths connecting users and items, thus offering interpretable explanations for recommendations. This direction underscores the growing interest in combining reasoning and explainability with graph representation learning.

More recently, hybrid GNN-based architectures have evolved to incorporate multi-relational, temporal, and multimodal information in order to improve personalization in dynamic environments. These approaches extend the standard message-passing paradigm by integrating contextual dimensions such as time, location, and behavioural sequences into the graph embedding process, allowing models to better capture user dynamics and long-term dependencies [8]. Modern recommender systems increasingly rely on heterogeneous and contextual data sources, enabling richer user modeling and adaptive responses to shifting preferences [18].

In e-business, such capabilities are particularly relevant for adapting to rapidly evolving user behaviours and market dynamics, where graph-based models can track and represent shifting interaction patterns over time. In the cultural heritage sector, similar principles may be applied to model relationships among visitors, artefacts, exhibitions, and contextual data. This opens opportunities for personalized digital experiences, enhanced knowledge discovery, and adaptive content delivery across digital archives, museums, and heritage platforms [8, 18].

3 The proposed framework

The proposed framework (Figure 1) is structured into four functional layers to support data-driven personalization and adaptive services in the cultural heritage domain: Acquisition, Knowledge, Inference Engine, and Application Layers. Grounded in the e-business paradigm, the architecture reinterprets value creation beyond commercial transactions, emphasizing the design of personalized, user-centered experiences. Prioritizing engagement, accessibility, and satisfaction positions digital interaction as a driver for cultural participation and sustainable audience development.

The Acquisition Layer is the primary entry point for information and comprises Context, Entities, and Open Data & API modules. It integrates heterogeneous data sources and contextual signals through three dedicated modules. The Context Module captures environmental, temporal, and spatial parameters, such as user location, device metadata, and visit context, allowing the system to adapt its responses dynamically [3, 12, 17]. The Entities Module collects structured data on users (profiles, preferences, behaviors) and cultural items (artworks, monuments, exhibitions), bridging individual interests and available resources. The Open Data & API Module enriches this information space by connecting to external repositories, such as open cultural datasets, institutional databases, and third-party APIs. These modules ensure a continuous, multimodal data flow that feeds the system with relevant, real-world information,

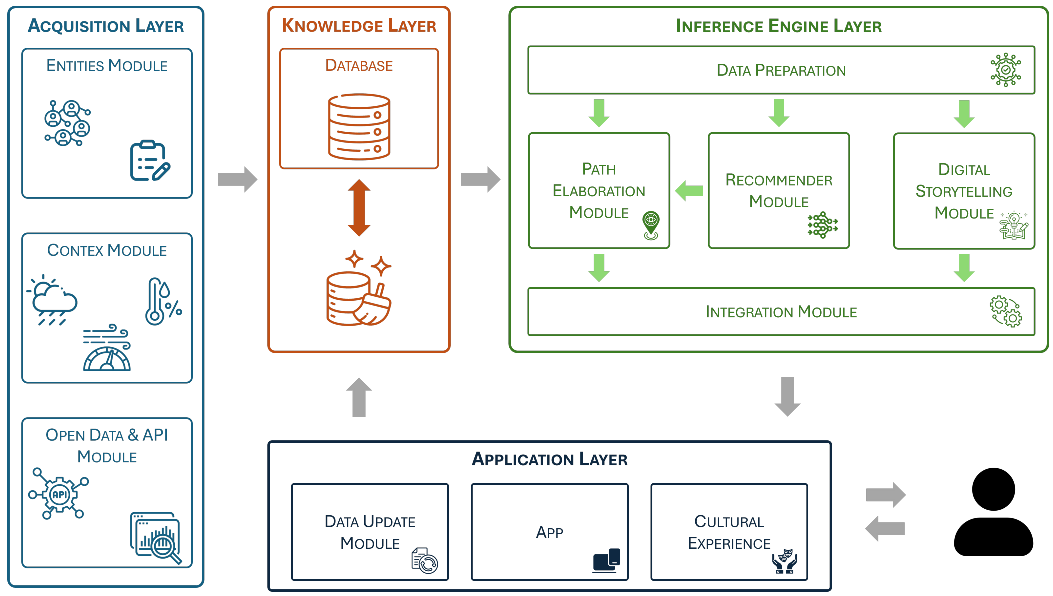

Figure 1: The architecture related to the proposed framework.

forming the basis for personalized recommendations and analytics.

The Knowledge Layer manages, stores, and validates the collected data. The main component of the layer consists of the database that ensures structured and persistent storage of user-item interactions and contextual data. Complementing it, the Data Cleaning Module operates at both ingestion and loading stages, ensuring the coherence and reliability of the dataset, minimizing redundancy and inconsistency across sources.

The Inference Engine Layer represents the elaboration core of the proposed framework. It orchestrates several interconnected modules that transform data to personalize the cultural experience of users:

- The Data Preparation Module handles feature extraction, encoding, and normalization, preparing data for the recommendation process and contextual embeddings.
- The Recommender Module implements graph-based recommendation models that can capture higher-order relations between users and items. This module provides the best-ranked cultural points of interest to be organized in a path.
- The Path Elaboration Module dynamically structures recommended items into coherent cultural routes, optimizing sequence and thematic consistency according to user profiles and contextual constraints.
- The Digital Storytelling Module transforms these routes into narrative experiences, enriching recommendations.
- The Integration Module integrates the path with the Digital Storytelling Module preparing the cultural experience of the user.

The Application Layer delivers the results of the inference process to end users through interactive and responsive interfaces. It includes the Data Update Module, which maintains

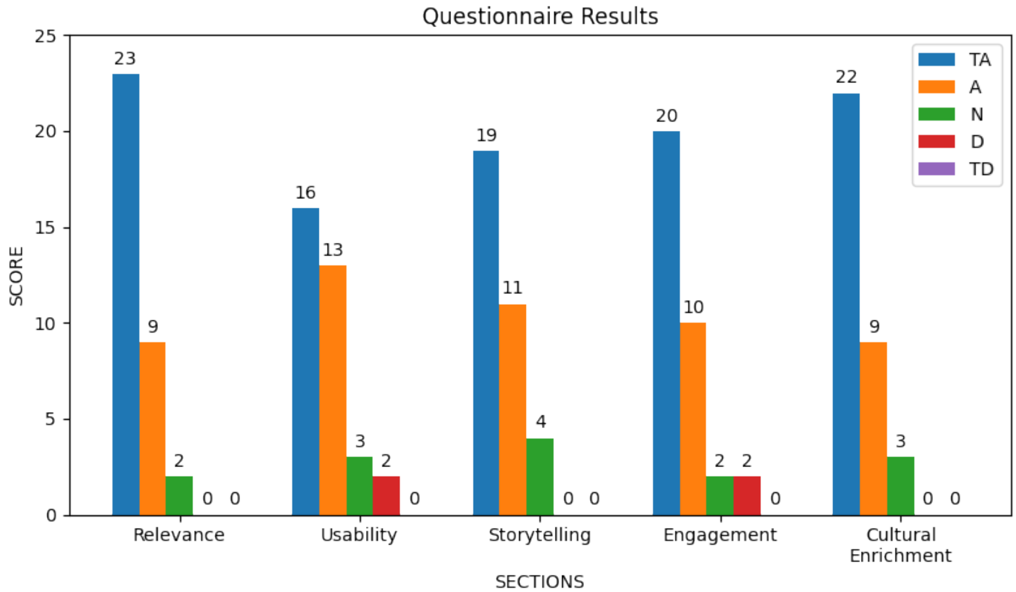

Figure 2: Results obtained from the participants concerning the submitted questionnaire.

synchronization between system components and ensures continuous adaptation of models to evolving user behaviours. Then, the Application Layer serves as the main access point to the platform through web or mobile interfaces, guaranteeing a cultural experience to the users by personalizing content delivery and supporting immersive and narrative experiences prepared by the Inference Engine Layer.

4 Experimental Results

Once the proposed e-business-oriented architecture was designed to enhance cultural heritage engagement, an experimental phase was conducted to assess its preliminary effectiveness in improving the user experience. The evaluation consisted of developing a prototype that integrates the four-layer architecture and testing its ability to deliver personalized and narrative-driven cultural experiences. The prototype allowed users to interact with a digital platform combining contextual data acquisition, recommendation, and narrative presentation. Thirty-four participants were involved in this study to explore the usability and experiential impact of the system. Involved users were introduced to the system through a short briefing explaining the interaction flow and the type of cultural content available. Each participant experimented in situ, using a mobile device while visiting the cultural site.

During the visit, users interacted with the system to explore recommended items and follow a narrative path generated by the Digital Storytelling module. The recommendations are dynamically adapted to contextual factors such as location and weather. At the end of the experiment, each user completed a questionnaire designed to evaluate their perceptions of the system. The questionnaire consisted of five sections reflecting the main dimensions of the user experience:

- Section A - Relevance and Personalization
  The recommended items and paths were relevant to personal interests and the visit context.

- Section B - Usability and Clarity
  The mobile interface was easy to use during the visit.

- Section C - Storytelling
  The storytelling helped to understand better and connect the cultural items.

- Section D - Engagement
  The system made the visit more engaging and enjoyable.

- Section E - Cultural Enrichment and Experience Quality
  The system enhanced the cultural experience and helped appreciate the heritage content more deeply.

Each question was rated using five possible answers: Totally Agree (TA), Agree (A), Neutral (N), Disagree (D), Totally Disagree (TD).

The results of the in-situ questionnaire (Figure 2) with 34 participants indicates consistently positive perceptions across all evaluated dimensions. Relevance and personalization are rated highly, suggesting that the recommended items and paths were aligned with users' interests and context. Usability and clarity receive scores that suggest the need to improve the interface. The storytelling component is perceived as beneficial for understanding and connecting cultural items, while engagement scores confirm that the experience felt coherent and enjoyable on site. Finally, the item on cultural enrichment points to an added experiential value beyond simple item discovery. These results provide a coherent signal that the proposed framework can effectively support user-centred cultural experiences in e-business scenarios.

5 Conclusions and Future Works

This work presented a conceptual and technological framework to integrate recommender systems, semantic knowledge management, and digital storytelling within an e-business perspective for cultural heritage. The proposed architecture, composed of four functional layers, enables the dynamic creation of user-centered experiences, focusing on generating digital cultural value rather than transactional exchange. By combining personalization techniques and contextual data with narrative-driven presentation, the framework supports new forms of engagement that connect visitors, collections, and institutions in a continuous digital ecosystem.

Although limited in scale, the evaluation provided preliminary evidence of the framework's ability to improve user satisfaction and engagement through coherent and meaningful cultural journeys. The participants' feedback confirmed that integrating recommender models and storytelling modules can enhance usability and emotional resonance, offering a richer and more intuitive interaction with digital heritage content. These findings are consistent with the current evolution of e-business models in the cultural domain, which emphasize audience development, accessibility, and experience co-creation.

Future work will extend the experimental phase to a broader and more heterogeneous group of users to evaluate its adaptability to different cultural contexts.

References

[1] D. Bacciu, F. Errica, A. Micheli, and M. Podda. A gentle introduction to deep learning for graphs. *Neural Netw.*, 129:203 – 221, 2020.

[2] M. Casillo, F. Colace, B. B. Gupta, A. Lorusso, D. Santaniello, and C. Valentino. *The role of AI in improving interaction with cultural heritage: An overview.* " ", 2023.

[3] 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.*, 10(4):395 – 411, 2024.

[4] 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*, 13:28353 – 28368, 2025.

[5] L. Cecere, F. Colace, A. Lorusso, F. Marongiu, M. Pellegrino, and D. Santaniello. Iot and deep learning for smart energy management. *Lect. Notes Netw. Syst.*, 695 LNNS:1037 – 1046, 2024.

[6] L. Chen, L. Wu, R. Hong, K. Zhang, and M. Wang. Revisiting graph based collaborative filtering: A linear residual graph convolutional network approach. In *AAAI 2020*, page 27 – 34, 2020.

[7] A. Daigavane, B. Ravindran, and G. Aggarwal. Understanding convolutions on graphs. *Distill*, 2021. https://distill.pub/2021/understanding-gnns.

[8] Y. Deng. Recommender systems based on graph embedding techniques: A review. *IEEE Access*, 10:51587 – 51633, 2022.

[9] R. F. Doh, C. Zhou, J. K. Arthur, I. Tawiah, and B. Doh. A systematic review of deep knowledge graph-based recommender systems, with focus on explainable embeddings. *Data*, 7(7), 2022.

[10] W. Fan, Y. Ma, Q. Li, Y. He, E. Zhao, J. Tang, and D. Yin. Graph neural networks for social recommendation. In *WWW 2019*, page 417 – 426, 2019.

[11] A. Gaeta, V. Loia, A. Lorusso, F. Orciuoli, and A. Pascuzzo. Towards a llm-based intelligent system for detecting propaganda within textual content. *Comput. Electr. Eng.*, 128, 2025.

[12] C. G. Guida, B. B. Gupta, A. Lorusso, F. Marongiu, D. Santaniello, and A. Troiano. An integrated bim-iot approach to support energy monitoring. In *" "*, volume 3080, 2021.

[13] X. He, K. Deng, X. Wang, Y. Li, Y. Zhang, and M. Wang. Lightgcn: Simplifying and powering graph convolution network for recommendation. In *SIGIR 2020*, page 639 – 648, 2020.

[14] T. N. Kipf and M. Welling. Semi-supervised classification with graph convolutional networks. In *ICLR 2017 - Conference Track Proceedings*, 2017.

[15] C. Li, I. Ishak, H. Ibrahim, M. Zolkepli, F. Sidi, and C. Li. Deep learning-based recommendation system: Systematic review and classification. *IEEE Access*, 11:113790 – 113835, 2023.

[16] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang. Recommender system application developments: A survey. *Decis. Support Syst.*, 74:12 – 32, 2015.

[17] D. Nawara and R. Kashef. Context-aware recommendation systems in the iot environment (iot-cars)-a comprehensive overview. *IEEE Access*, 9:144270 – 144284, 2021.

[18] F. Ricci, L. Rokach, and B. Shapira. *Recommender Systems: Techniques, Applications, and Challenges.* " ", 2022.

[19] B. Sanchez-Lengeling, E. Reif, A. Pearce, and A. B. Wiltschko. A gentle introduction to graph neural networks. *Distill*, 2021. https://distill.pub/2021/gnn-intro.

[20] C. Standing, J. Tang-Taye, and M. Boyer. The impact of the internet in travel and tourism: A research review 2001-2010. *J. Travel Tour. Mark.*, 31(1):82 – 113, 2014.

[21] H. Wang, F. Zhang, X. Xie, and M. Guo. Dkn: Deep knowledge-aware network for news recommendation. In *WWW 2018*, page 1835 – 1844, 2018.

[22] X. Wang, X. He, M. Wang, F. Feng, and T. Chua. Neural graph collaborative filtering. In *SIGIR 2019 - Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, page 165 – 174, 2019.

[23] X. Wang, D. Wang, C. Xu, X. He, Y. Cao, and T. Chua. Explainable reasoning over knowledge graphs for recommendation. In *AAAI 2019, IAAI 2019 and EAAI 2019*, page 5329 – 5336, 2019.

[24] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, and J. Leskovec. Graph convolutional neural networks for web-scale recommender systems. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, page 974 – 983, 2018.