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WiP: Context-Aware Recommendations for Smart Campus Environments

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***Abstract*—The rapid convergence of IoT technologies and artificial intelligence is reshaping university campuses into dynamic, smart environments. Faced with the challenge of managing increasingly complex and heterogeneous data streams, campus communities often struggle to benefit fully from available digital resources and personalized support. In response, this work presents a modular and scalable system designed to provide context-aware recommendations that enhance both academic and social experiences. By integrating data from physical sensors, mobile devices, and external sources, the proposed framework captures rich contextual insights to deliver adaptive, personalized services that address the diverse needs of students, faculty, and administrative staff. Developed as part of the S3 Campus project at the University of Palermo, this system represents a significant step forward in fostering innovative, intelligent campus solutions that are attuned to the evolving demands of modern educational environments.**

***Index Terms*—Smart Campus, IoT, Hybrid Recommender Systems, Personalized Services, Context Awareness**

I. Introduction

Recent advances in pervasive technologies and the increasing integration of artificial intelligence have ushered in a new era for smart environments, enabling systems to become more responsive, adaptive, and user-centered. University campuses, in particular, serve as ideal microcosms of smart cities, complex ecosystems where digital services, contextual information, and intelligent infrastructures converge to enhance both academic experiences and operational efficiencies [1]. The concept of a Smart Campus extends far beyond mere infrastructural monitoring, aspiring instead to seamlessly integrate physical and digital realms in order to deliver tailored services to students, faculty, and administrative staff alike.

Traditional solutions in the context of smart campus applications, while promising, often exhibit limitations in providing fully personalized experiences. Many of these systems focus primarily on infrastructural oversight or administrative optimization, overlooking the dynamic and heterogeneous needs of campus users. For instance, the absence of user-centric adaptive guidance in environments inundated with diverse streams of information can impede optimal decision-making and result in the under-utilization of available resources. Moreover, the enormous potential of heterogeneous data, drawn from mobile devices [2], IoT sensors [3]–[5], and user interactions across campus, is rarely fully exploited [6]. Addressing these challenges is critical for the evolution of educational environments that aim to be both efficient and deeply responsive to user needs. This work, undertaken at the University of Palermo as part of the S3 Campus project, proposes a novel architectural framework for an augmented university environment. The proposed framework is built upon a hybrid recommendation system that integrates natural language processing techniques with graph-based methodologies. Such integration facilitates the generation of context-aware, personalized recommendations regarding academic resources, campus services, and social engagements. Embracing a cloud paradigm, the system is designed to perform near-source data processing via distributed nodes, while leveraging cloud computing for more resource-intensive analytical tasks. This dual-layer approach not only ensures rapid response times but also maintains scalability and flexibility, allowing for incremental integration of new functionalities. Central to the proposed framework are two advanced recommendation engines. The first employs a Transformer-based architecture to extract semantically rich representations of the learning trajectories of students, thus identifying meaningful sequential patterns within educational activities. The second utilizes graph-based modeling to capture and exploit the intricate social and academic relationships among users, enabling the formation of study groups and the facilitation of collaborative learning environments. Together, these complementary components are envisioned to support a wide range of services, from personalized academic advisories and resource suggestions to the promotion of community engagement among students. The primary objectives of this research are threefold: (i) to design a scalable, modular architecture that effectively integrates cyber-physical and user-centric data streams within a smart campus setting; (ii) to develop robust recommendation strategies that are attuned to both individual preferences and collective group dynamics; and (iii) to validate the efficacy of the proposed framework through realistic application scenarios and pilot implementations. The remainder of this paper is organized as follows. Section II presents a review of related work in smart campus systems and recommendation frameworks. Section III presents an overview of the proposed system and discusses several application scenarios that demonstrate the practical benefits of the approach.

II. Related Work

The concept of the Smart Campus is increasingly gaining attention as educational institutions strive to enhance operational efficiency, environmental sustainability, and student engagement through pervasive digital technologies. A Smart Campus can be viewed as an extension of the smart city paradigm, where Internet of Things (IoT) devices, mobile technologies, and artificial intelligence (AI) are leveraged to monitor and optimize campus services [1], [7], [8]. Within this context, personalized recommendation systems are emerging as a key component for delivering user-centric services that respond to students' academic, social, and environmental needs [9].

Several Smart Campus systems have explored the use of context-aware technologies to deliver real-time insights on energy consumption, space utilization, or environmental conditions [7], [10]. While these systems contribute significantly to the monitoring and optimization of campus infrastructure, they often lack integration with user-level personalization mechanisms. As a result, students frequently interact with complex and data-rich environments without adequate support in decision-making related to learning resources, scheduling, or peer collaboration. The approach presented in [11] combines collaborative filtering with semantic similarity modules to enable recommendation in a Cyber-Physical System (CPS) context. By leveraging a deep neural network (DNN), the model captures nonlinear interactions between Mashups and Web services, while embedding techniques are employed to extract meaningful representations from textual service descriptions. This hybrid architecture [12] addresses several limitations of traditional approaches, which often struggle to model complex relationships. In [13], the authors review the use of ontologies in e-learning recommender systems, highlighting their potential to improve personalization by formally modeling relationships between users and learning content. While ontologies can enhance recommendation relevance, their effectiveness depends heavily on the availability of high-quality structured data [14] and often involves complex implementation, which may hinder scalability. In [15], the authors propose a university recommendation system based on student profiles, utilizing weighted features and K-Nearest Neighbors (KNN) to match applicants with suitable academic programs. While effective in offering personalized suggestions, the system is limited by its reliance on historical data and its lack of integration of contextual variables, which are often crucial in influencing student decisions. Overall, while prior works have laid a strong foundation for personalized educational recommender systems, they often lack the integration of real-time contextual and environmental data, social dynamics, and hybrid modeling strategies. These limitations highlight the need for more comprehensive and adaptive solutions that can fully exploit the multifaceted nature of smart campus environments.

III. System Architecture

The architecture presented in this preliminary work is designed to serve as an end-to-end solution for delivering personalized, context-aware recommendations within a Smart Campus environment. At its core, the system integrates heterogeneous data from cyber-physical sensors, personal devices,

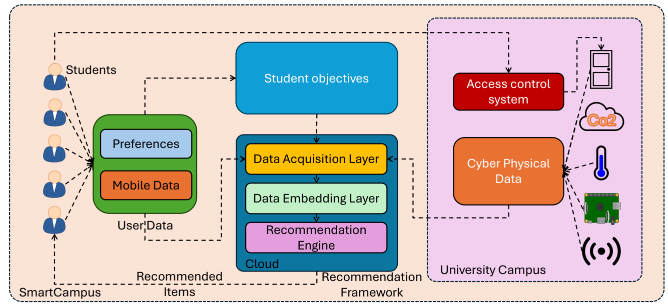

Fig. 1. System architecture for personalized and context-aware services in a Smart Campus.

and academic records into a unified framework, which then feeds into advanced recommendation engines to support both individual academic guidance and group-based initiatives. An overview of the system is provided in Figure 1, where the architectural flow is organized into three principal layers: the Data Acquisition Layer, the Data Embedding Layer, and the Recommendation Engine. The **Data Acquisition Layer** represents the initial stage of the framework, where raw data is continuously acquired from multiple sources. Physical sensors distributed across the campus capture environmental parameters such as occupancy levels, lighting conditions, and air quality metrics, while access control systems and other IoT devices provide information on the utilization of campus spaces [16]. In parallel, personal devices including smartphones and wearables contribute user-centric data such as location, movement trajectories, and explicit preference inputs. Furthermore, academic records, encompassing questionnaire responses, course performance, and participation logs, are collected to model individual student profiles. Together, these diverse data streams form a comprehensive and multifactor representation of the campus environment and user behavior, which is transmitted securely via robust communication protocols to ensure data integrity and privacy [17]. Once acquired, the heterogeneous data undergoes a series of transformations in the **Data Embedding Layer**, where normalization, fusion, and feature extraction processes are applied. This entire process is carried out within the cloud infrastructure, which provides the necessary computational resources for handling large volumes of multi-modal data. At this stage, raw user information, environmental data, and item descriptions are mapped into dense vector representations within a shared latent space. For instance, user-related information derived from questionnaires and historical academic interactions is embedded into continuous representations that capture personalized interests and learning trajectories. Concurrently, textual descriptions of study subjects, thesis proposals, and study group information are processed using pre-trained language models to generate semantic embeddings that encapsulate content and contextual signals. Environmental data, aggregated over relevant time intervals, is compressed into a low-dimensional form via autoencoder-based techniques that preserve the key statistical properties necessary to reflect space utilization dynamics. These embeddings are then aligned to enable a comprehensive integration of contextual, content-based, and collaborative information, establishing a data foundation for the recommendation process.

The **Recommendation Engine**, forming the core of the architecture, leverages the aggregated and transformed representations to generate tailored suggestions across different application domains. This engine comprises two major modules that operate in tandem. One module is dedicated to adaptive study group recommendations. This component exploits a graph-based model to capture and analyze the complex interrelations among students by representing users and groups as nodes within a bipartite graph. The model dynamically integrates multiple signals, including content similarity, historical collaborative interactions, and real-time contextual data such as temporal availability and spatial information, to compute compatibility scores that indicate the likelihood of successful group participation. By taking into account both individual preferences and collective dynamics, this module is able to suggest optimal study group formations as well as the creation of new groups when the aggregated demand among a set of students exceeds a certain threshold. In parallel, the second module extends sequence modeling techniques to the academic domain, aiming to predict the next course or suggest a thesis topic that aligns with a student's academic path. This module employs a bidirectional Transformer architecture inspired by state-of-the-art sequential recommendation models. By processing the sequence of courses a student has already undertaken, augmented with positional and contextual embeddings, the model derives a nuanced representation of the student's learning journey. This sequential representation is then used to compare the student's profile against a set of candidate items, selecting the one that maximizes alignment with the observed learning trajectory and academic interests. The integration of these hybrid approaches, graph-based and sequential modeling, not only enhances the accuracy of individual recommendations but also provides complementary insights that foster both personal academic advancement and effective study group formation. The outputs of the recommendation engine are managed by a centralized cloud infrastructure that orchestrates advanced analytics, historical data storage, and dynamic service reconfiguration [18]. This centralized component harmonizes real-time processing carried out at distributed edge nodes with more computationally intensive tasks executed in the cloud. The synergy between these processing layers ensures low latency in handling real-time data streams while preserving the flexibility and scalability to incorporate new functionalities as the campus environment and student needs evolve. In summary, the architecture embodies a comprehensive framework that unifies cyber-physical sensor data, advanced embedding techniques, and dual-mode recommendation models to deliver personalized and contextually aware services in a Smart Campus. Deployed as part of the S3 Campus project at the University of Palermo, this system not only meets current operational demands but also provides a scalable, adaptable platform for future enhancements and extensions in intelligent campus environments.

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