I. INTRODUCTION

The digital era has transformed how we enjoy movies. Viewers no longer need to store movies physically or down- load them as they can easily stream movies online from an almost limitless selection. This shift has driven the growth of streaming platforms like Netflix, which offer content tailored to user preferences. However, the abundance of content often makes it challenging for users to find movies that match their tastes. To address this, platforms employ recommender systems to personalize user experiences while boosting rev- enue. For instance, Netflix reported nearly USD 9.4 billion in revenue during the first quarter of 2024, largely attributed to its ability to retain and attract users through accurate recommendations [1].

Recommender systems have evolved by integrating tem- poral elements to capture changes in user preferences. These temporal factors play a crucial role in identifying user behavior patterns, such as viewing habits at specific times, like evenings or weekends. Collaborative Filtering (CF) based on Matrix Factorization (MF) is a common approach in recommender systems, initially applied through Singular Value De- composition (SVD) to model user-item interactions. SVD++ was later developed to include implicit feedback, such as clicks and viewing duration, alongside explicit user ratings. To capture changes in user preferences over time, Koren [5] introduced TimeSVD++. This model extends SVD++ by adding temporal biases for users and items, allowing the system to dynamically adapt to evolving user preferences.

Building upon these advancements, Azri et al. [2] intro- duced IUAutoTimeSVD++, a hybrid recommender system that combines user and item features using a contractive autoencoder approach. This model not only captures non- linear relationships between features but also dynamically adjusts recommender based on users temporal patterns. Their research demonstrated that IUAutoTimeSVD++ significantly improved recommendation accuracy, particularly in scenarios involving large-scale datasets.

Implicit feedback plays an equally important role as tem- poral factors in improving the relevance of recommendations. According to the study by Xin et al. [3], Multi-Behavior Alignment (MBA) was introduced, integrating various types of implicit feedback to enhance model accuracy in large-scale systems. Similarly, Hu et al. [4] developed a recommendation method based on multiplex implicit feedbacks (RMIF), which utilizes multiplex implicit feedbacks to capture user preferences more accurately. Both studies demonstrate that this approach significantly improves recommendation relevance.

Although many studies have integrated temporal factors, approaches that specifically combine time dimensions with implicit feedback in the movie domain remain limited. Im- plicit feedback, such as viewing duration and completion per- centage, holds significant potential for gaining deeper insights into user preferences. The integration of time dimensions and implicit feedback not only enhances the relevance and accuracy of recommender systems but also addresses the challenge where recommendations often fail to reflect users dynamic behavior patterns over time. To address this gap, TimeSVD++ was selected for its ability to capture temporal dynamics through matrix factorization. Compared to other methods, TimeSVD++ offers greater flexibility in modeling changes in user preferences by incorporating user and item temporal biases directly into the model training process. This capability enables TimeSVD++ to produce more relevant and context-aware predictions, making it a superior choice over similar methods.

The proposed approach integrates dynamic time weights and user interaction weights to better understand temporal variations in user preferences. Time weights are derived from the distribution of user interactions throughout the week, while interaction weights are calculated based on the normalization of implicit feedback, encompassing both positive and negative interactions. The combination of these weights generates a total weight that updates the model parameters and computes prediction scores. By capturing complex temporal patterns and leveraging the relevance of various types of implicit feedback, this approach allows TimeSVD++ to effectively address previous research gaps and deliver more accurate and relevant recommendations.

The structure of this paper is divided into five main sections. Section 1 provides an overview of the problem's background and the study's objectives, emphasizing the rationale for creating a time-based recommender system. Section 2 reviews related literature, discussing methods and approaches from previous studies relevant to the development of temporal-based recommender systems. In Section 3, we describe the design and implementation of our proposed time- based TimeSVD++ model, detailing the steps and method- ologies we used in this research. Section 4 presents the experimental results, including the evaluation of system performance and comparisons with the SVD++ model that does not incorporate temporal effects. Finally, Section 5 concludes our study, summarizing key findings and offering suggestions for future research directions.