# DEEP LEARNING-BASED HUMAN TIME ALLOCATION SYSTEM

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Abstract Currently, time management is more difficult than ever before Everything appears as if it were just one large mass where everyone is attempting to juggle far too many duties all at once (multiple Sticking to your normal schedule can be quite difficult. The traditional methods of using a planner (such as paper calendar/planner or a simple list) seem to no longer suit today's fast pace. Those methods haven't been updated since the way of life changed from paper to digital. This new method in this research paper is "the Deep Learning Human Time Allocation System." This new type of system provides people with a much more effective way of managing their time. It takes your last calendar/schedule and uses that information to estimate how long your next activities will take to complete Thanks to advanced models like LSTM and transformers, it estimates activity durations and builds a flexible, personalized plan. As an added bonus, it has the ability to use decision-making techniques (e.g., Markov Decision Process) to schedule your tasks for maximal productivity and to prevent burnout.

## I INTRODUCTION

Today's world is growing at such an accelerated rate that most people are having difficulty staying up-to-date with everything. Individuals, on the other hand, can become so bogged down by the demands and responsibilities associated with their jobs, education, and other obligations, that they are left feeling overwhelmed by the number of tasks complete on a daily basis. Poorly managed time generally ends up leading to missed deadlines more stress and ultimately lower levels of productivity. Most people still use simple tools (e.g., to-do lists) or have established routines but that does not represent the reality of many peoples' daily activities. These tools do not adequately account for times when your energy is low, times when you are in the zone and times when your tasks are spilling over onto one another. Thus, hundreds of hours of productivity each year are lost because of bad time management and poorly scheduled activities.

However, we are now experiencing innovative technological advancements (primarily from AI) that will allow us to receive intelligent alternatives to assistance in doing our daily tasks by providing faster and more efficient ways to manage our daily schedules. For example, AI can analyze the way you approach completing your tasks on a daily basis and provide

recommendations for how to better organize your time with respect to your routine. With powerful tools like LSTM and Transformer models, these systems study your history and build schedules that actually match how you work. This research zeros in on a deep-learning-driven way to make time management smarter. An AI-powered tool collects data from your day and analyzes your behavior patterns to estimate how long your tasks should take, then builds a schedule that adjusts as your plans change or get disrupted so you don't fall behind.

With the pace of the world today and all of our responsibilities it can be harder than ever to manage time effectively. Whether you are a student, an employee, or have any other occupation, chances are you have had to struggle with trying to balance a large number of items that need to be accomplished in a small amount of time, along with the associated stress levels from missing deadlines or being less productive.

## II LITERATURE SURVEY

Time Management has been the subject of a great deal of research for many years due to its important contribution to increasing productivity and lowering levels of Stress. In the early days of this type of research, most researchers studied traditional methods of Time Management like manual Scheduling, Priority Lists and Rule-based systems, which tended to be simple and fairly easy to utilise; however, they were also inflexible in that they did not generally adapt well to user behaviour changes or to unexpected circumstances. With the development of artificial intelligence, researchers began examining more intelligent approaches to task Scheduling and Time Allocation. Initially, basic machine learning techniques were used to review historical data to supply a prediction of the duration a user would take to complete a specific task. While these methods did show some level of improvement, these original models were limited in their ability to process and learn long-term dependencies or to model complex patterns of Human behaviour. In the last few years, Deep Learning has begun to attract attention as a method of processing large data volumes and subsequently uncovering relationships within the data. With this increase of discovery, many researchers have begun using models such as long-short-term memory for predicting future events in time series data and hence can be used to forecast how long it will take for an individual to complete a specific task based on their historical performance

Similarly, the transformer model has shown a strong ability to capture the complexity of sequential data relationships and subsequently make accurate predictions. Researchers have researched and developed various optimisation methods to complete both the scheduling of tasks and task assignment. Reinforcement learning methods, in particular, have emerged as a leading choice for task Scheduling and allocation.

## III PROPOSED METHODOLOGY

The proposed system is a human time allocation system that is based on deep learning and will help individuals plan their daily activities more effectively. Unlike traditional scheduling systems, this system attempts to learn the user's behaviour then build a tailor-made, flexible schedule based on daily activities. The system uses prior data from the user's completed tasks, time spent on each task and desired work hours to help establish an ideal daily work schedule.

The system uses Artificial Intelligence techniques along with Deep Learning modelling techniques to collect and analyse data about the user. Using Long Short-term Memory (LSTM) and Transformer models, the system is able to predict the amount of time needed by a user to complete a variety of tasks, which can be used in making a more accurate daily plan.

In addition to providing predictions for the user, the new system comprises intelligent scheduling algorithms which apply decision-making methods based on the Markov Decision Process (MDP) to optimally arrange the user's planned daily tasks so they occur in the most productive manner while minimising stress and avoiding task overload. The system will take into account the priority of each task, deadlines and user preferences.

A major feature of the new system is its ability to be adaptive in real-time. If a user's task takes longer than expected or an unforeseen task requires the user's urgent attention, the system is capable of providing an updated schedule that reflects these developments Overview of System Architecture

(1) The user's daily activity data is captured through several methods, such as calendars, to-do lists, computer/mobile usage and various wearable devices. This information is then recorded for each task in order to establish the type of task, time spent doing the task, priority level of the task, and whether the task was completed or not. The collected information will serve as a basis for understanding how the user behaves with tasks.

(2) Once the user's daily activity data has been collected, it will be processed (cleaned/sorted), so that the system can utilize the data adequately. This entails identifying valuable data features, including the task complexity, frequency of occurrence, and average duration. The processing step will format the retrieved user's daily activity data to allow for compatibility with the deep learning models.

(3) The predicted duration, for each of the user's individual tasks, is developed using advanced AI models. The models used to develop the estimated durations of the tasks include:

- Long Short-Term Memory (LSTM) - a model that identifies patterns associated with the user's behaviour over time; and

- Transformers, a model based on the structure of how information is related in complex relationships over a series of tasks, which will improve the accuracy of predicting the duration of the user's individual tasks.

(4) Following the estimated duration predictions, the tasks will then be scheduled based on an optimal sequencing of process performance using decision-making techniques from the Markov Decision Process. This sequenced scheduling will assist with achieving prioritisation of tasks, meeting due dates, and reducing the amount of stress caused by the workflow of completing the tasks.

5. Monitoring Tasks in Real Time

The system continuously monitors user progress on tasks. Whenever a user has completed or has taken significantly longer or shorter to complete a task than what was expected, the user's scheduling will be updated accordingly. These updates, based on historical data of all users, are consolidated to generate improved task recommendations on future occasions.

6. Providing the User With Task Recommendations

After the scheduling updates have been completed, the user will receive the new, optimized schedule via a clear and simple profile, including suggested focus times, breaks, and task priority levels. In addition, the user has the ability to update their tasks to make the system even smarter over time.

### Primary Features and Functions of the System

The Deep Learning Human Time Management or Allocation System is a device that allows for easier, more intelligent and personalized time management, and contains all primary features and functionality of the system, as follows (and in layman's terms):

1. Customised Daily Scheduling

• Once per day, the system generates and provides the user with a customised daily schedule based on the previous day's behaviour and task priorities as determined by the user.

• The system will calculate how long it is typically (in hours/minutes) for users to complete tasks and will order the tasks defined by the user according to how effectively they can be accomplished.

2. Prediction of Time to Complete Tasks

• Using artificial intelligence-based methods (e.g., LSTM and Transformer) the system will predict the actual or estimated time a user will take to complete each task, based on all previous user activity (within their profile).

• The result of this prediction will allow users to better plan for the actual time required to complete each task, eliminating the common occurrence of setting unrealistic goals (i.e., planning for too little time or too much time) for completing tasks.

3. Optimised Task Management/Completion

• The system will not only display users' tasks, but will also provide intelligent arrangements of the user's tasks based on how best to accomplish/multiply the most number of tasks successfully (i.e., based upon what their tasks are in relation to each other) during the period of time allotted to do so Learning with Feedback

• Users' input into the system can be utilized in making future recommendations

• The system becomes more precise and recognizes the user's habitual activities over time

• the user will receive guidance regarding the optimal working hours and break times

• The system helps build a focus-based task list by making sure that users are completing their priority items when they have the most energy

• The workload is balanced to minimize the risk of burnout

The core of a deep learning-based human task allocation system is made up of the scheduling and prediction components. Together, these components provide estimated durations for tasks and arrange them as efficiently as possible in time.

Prediction Component

• Purpose: Calculates the estimated duration of a task based upon historical data and patterns.

• How it works:

- The prediction component uses long short-term memory (LSTM) models to analyse sequences of previous tasks in order to make a prediction on how long it will take to perform the task.

- The prediction component uses Transformer Models to model complex patterns and long-term dependencies between tasks.

• Input: Historical data including task type, length of time to complete the task in the past, and patterns of behaviour for that user.

Output the initial estimation will be in hours or minutes to complete each of the activities laid out in the proposal.

For example, if your coding takes 45-60 minutes in the morning, the system will estimate an approximate time for the next coding request at 45-60 minutes also.

Scheduling Component

- Significance: Provides the optimal order in which to complete tasks to improve efficiency while minimizing anxiety.

- Operating process:

- The Scheduling function employs the Markov Decision Process (MDP) to select an optimal task sequence based on task duration, priority, and date due.

- The scheduling component also takes into account the user's preferences, amount of energy and the amount of time they need for breaks so that a realistic schedule is produced.

• Input: Predicted duration of tasks, the priority of tasks, the due date of the tasks, and limitations imposed on the user.

• Output: An optimised schedule;

3. Interaction Between Prediction & Scheduling

• Prediction produces reliable expected time to complete a task.

• Scheduling creates efficient, realistic, and balanced daily schedules using these predictions.

• A combined intelligent system that learns and adapts over time.

Real-Time Adaptability and Personalization

An essential feature of a Deep Learning-based Human Time Allocation System (DLAHTAS) is the ability to adapt and provide personalized recommendations in real time, making them much more effective and useable than regular static schedules.

1. Real-time Adaptability

Monitor your work as you are completing it.

Once you complete a task and if it is taking longer than original estimation (overrun) or if you have completed it before original estimation (underrun), the software will automatically update and produce a new schedule.

Will generate a new deadline that will be a reasonable and achievable without puts additional stress.

2. Cost Free Programs

- Goal: Create a cost-free way to schedule work.
- How:

From previous actions, we develop preferred time frames to work, break times, and the order in which to accomplish tasks.

We will look at your energy level and the priorities of tasks you need to complete and organize the best use of time for the day based on all that information.

Recommendations of how to schedule work continue to just get smarter as the user provides additional feedback.

ADAPTABILITY & PERSONALIZATION

1. The benefit of being able to establish schedules will be less stressful, because we will have a more realistic perspective of our ability to finish the tasks we create, and according to the timeframes set for each tas
2. To be able to produce more by matching tasks with the person's individual strengths.

3. The person will be more flexible when dealing with the unexpected due to increased confidence and experience.

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## II DATA COLLECTION & PROCESSING

The process begins with gathering data such as calendar events, task lists, applications used, and optionally data

wearable devices. To include an event/task you need the following information: Type (e.g. Appointment/Task), Begin Time, End Time, Duration to Completion, Priority Level and if completed. This information will then form the basis of your data and will need to go through a processing phase where some of the data needs to be cleaned up first to facilitate measuring it.

Various features are extracted from this gathered data to get the following results: average time it takes to finish a task, time of day when people do most of their productive work, and what sequence of events/tasks are done.

Then, the newly formed structured data feeds into the scheduling model to arrive at an accurate and customized schedule for the user.

Simply stated: Collect user activity → Clean/Organize user activity → Use organized user activity to generate daily schedule

Data Collection Sources

Application used daily by an individual; therefore, information gathered can be sourced from several different parts. Data being collected includes: calendar applications - provide access to information regarding events that have been planned and scheduled, such as meetings and deadlines; task lists and/or to-do applications - provide access to items that need to be completed and their priority, status, and completion; and both mobile and desktop application - will allow the user to track time they spend performing different activities. All this data, when combined, helps create an understanding of what typical patterns exist in a person's daily routine, so accurate estimates of how long a particular task will take can be given. In addition, accurate and realistic personalized daily schedules can be created for users.

Types of Data Collected

The system collects data types from many different sources to get a complete view of users' activities throughout the day in order to help plan their schedules. The data types that the system collects consist of:

1. Task Information - Categorizing each task by type of work, study, exercise, or leisure, the priority of each task, and deadlines for completing each task.

2. Duration of Activities – When activities began/ended, how much time was put to each.

3. Completion Status – Indicates whether the activity was done on-time, not on-time, or never completed.

4. User Preferences – User's regular or anticipated work schedule and usual break time, as well as most productive time.

Methods of Data Cleaning and Feature Extraction

Before the accumulated data can be used by the system Sequence patterns: Order in which tasks are usually done.

Break patterns: How often and when the user takes breaks.

## II METHODOLOGY/DESIGN

The methodology explains the operation of the Deep Learning-Based Human Time Allocation System in a step-by-step manner, detailing how data collection leads to the production of customized schedules.

1. Data Collection

- Purpose: Gather data on users' daily activities and routines.

o Sources:

Calendars. Includes scheduled events, appointments

- Task lists or to-do applications. Includes information about their priority, and whether they have been completed;

- Applications on both mobile devices and desktop computers. Data is collected on the actual time spent engaged in each activity.

- Optional wearables which provide data on physical activity or mental focus;

2. Data Pre-processing

- Cleaning: Remove errors, duplicated records, inconsistencies, and missing values;

- Standardization: Make sure that all times, dates, and labels have been formatted correctly and uniformly;

- Feature extraction: Find useful patterns within the data, including:

o Average length of time that a task takes;

o Most productive hours of the day;

o Patterns relating to how often tasks are performed, in what order tasks are performed, and when breaks are typically taken.

Feature Engineering

Feature engineering involves choosing and developing the most useful information (features) from the raw data so that the machine learning model can learn how to develop patterns efficiently. In this example, the use of feature engineering will help the Deep Learning-Based Human Time Allocation System to gain insight into users' behaviours to predict how long it will take them to complete each task.

3. The Three Major Steps in the Feature Engineering Process

1. Identify Useful Features

• Task type (e.g. work, study, exercise);

Predicting How Long Will It Take To Complete A Task Using LSTM And Transformers

Predicting how long it will take to complete a task is critical for creating an efficient schedule within the Human Time Allocation System (Deep Learning Based). LSTM (Long Short-Term Memory) and Transformer Models are advanced deep learning methods that analyze sequential data in order to make a prediction.

LSTM Prediction Using Historical Data

- Gather historical data on the duration of each task from various sources including your calendar, task lists, and applications.

The average time taken to complete a task is calculated as follows:

- This gives you a starting point for estimating how long it will take to complete every one of these types of tasks prior to implementing any Deep Learning techniques.

How To Create LSTM Prediction

To create an LSTM prediction, the first step is to convert the historical information about the execution of tasks (the order that the tasks were performed in relation to other tasks, how much time it took to complete each task, when it was done, etc.) into a time series format.

The second step is inputting the converted time series data into the LSTM model for use during prediction.

Finally, the LSTM model will be trained on the previous time series data and will predict how long it would take to execute future tasks according to those same patterns.

Using Transformers

Transformers On The Whole Will Aid In The Handling Of More Complicated Tasks

Predicting Task Duration

Task data and associated features are entered into the system. Each model then analyzes the input to discover sequences and/or patterns. The output from these two predictive models is the duration of each task.

Once task durations have been forecast, the scheduling section of the system will produce a schedule for the day.

Optimising Task Scheduling via a Markov Decision Process (MDP)

Once task durations have been forecasted, the next step is efficient scheduling of the tasks. The Deep Learning based Human Time Allocation System employs an MDP to optimally schedule tasks. An MDP is a mathematical framework that can assist decision makers in making decisions where an outcome of their actions is dependent upon both the current action taken by the decision maker and also on any possible outcomes from their future actions An MDP is a model used for decision-making in areas where choices made impact a future state based on a series of sequentially dependent steps (decisions = actions).

An MDP consists of 5 components:

1. States (S) - The present condition or state of the schedule
2. (how many tasks are completed, how many tasks are not yet finished, the current time).

2. Actions (A) - The action of deciding which of the remaining tasks to schedule next.

3. Transition Probability (P) - The probability that performing an action will lead you to a specified next state ( for example, having finished all the tasks by their respective deadlines).

4. Reward (R) - A score awarded to each action taken (for example, a high reward for completing a task by its scheduled deadline, a low reward for delaying to complete a task).

5. Policy (π) - A strategy that determines which action should be taken at any given state to maximize the total rewards for the actions taken from that state.

An MDP works in scheduling as follows:

1. Input to the MDP consists of the anticipated duration of each task, the priority assigned to each task, deadlines set for each task, and any constraints placed on the completion by users.

2. The MDP processes the inputs in the following steps:

- At every decision point, the MDP evaluates all of the possible tasks that can be completed next based on the previous task completion(s).

- The MDP computes the order in which those tasks should be scheduled to provide the highest level of productivity and the lowest level of delays/stress.

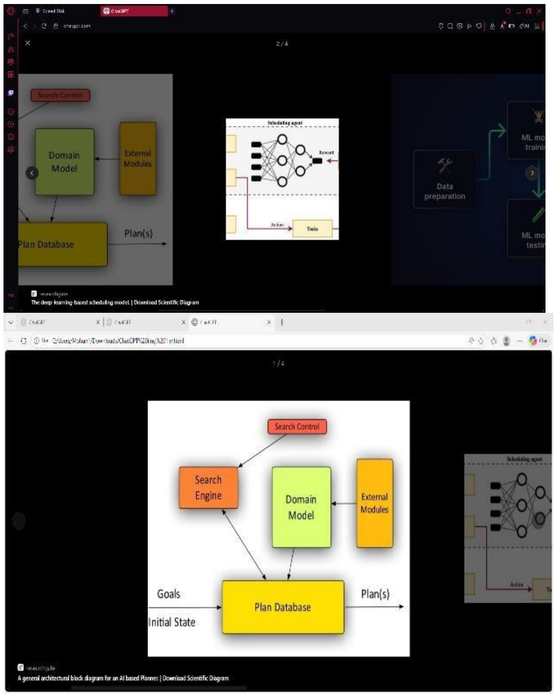
3. The MDP outputs an optimized schedule indicating the order in which each task should be completed during the scheduled day.

The MDP has several advantages including:

• The ability to account for any uncertainty in the completion time of tasks (i.e., a task could take less/more than anticipated).

• Balance between multiple parameters - deadlines vs. priorities vs. energy levels vs. breaks.

• Provides optimal, dynamic schedules rather than static




Real-Time Schedule Updates and Learning from Feedback

The Deep Learning-based Human Time Allocation System is dynamic in that it continuously learns from user actions to adapt the schedules to remain relevant and personally designed for the user.

Real-Time Schedule Updates

• Purpose: to change the schedule immediately if a task takes more or less time than anticipated.

• How the system works:

o The deep learning-based human time allocation system tracks each task's progress as they are being completed.

o If you finish a task earlier than expected or later than expected, the computer program will go back to figure out when to start the other tasks again during the day.

o When rescheduling, the computer program will check deadlines, what is important and break times in order to keep approximately 100% of the available time for each day.

Example - If an assigned coding task that has a predicted duration of two hours is completed in one and a half hours, that means the user can now start their next scheduled activity sooner and potentially receive their next scheduled break sooner than anticipated.

An MDP (Markov Decision Process) can be used as a model for the decision-making process because each decision (action) is dependent on each state and impacts what the following state will be.

Members of the MDP Model for Scheduling

1. States (S): the current state of the scheduling system (the total time of all completed tasks, total time of all remaining tasks, the current time).

2. Actions (A): deciding what will be the next activity to schedule.

3. Transition Probability (P): the probability that if action is taken that action will transition the scheduling process into a given state (ex. activity completed on time).

4. Reward (R): the score that is given to performing the selected action (ex. completing activities on schedule is rewarded with a high score).

## III SYSTEM DESIGN / ARCHITECTURE

The Deep-Learning-Based Human Time Allocation System is an ideal design for an AI-based algorithm to manage your day-to-day schedules and optimise your daily schedules for maximum efficiency through a four (4) stages process of Data Collection, AI Prediction, Scheduling Optimisation and Real-Time Adaptation, and user-friendly architecture.

The overall architecture of the System consists of six (6) major modules:

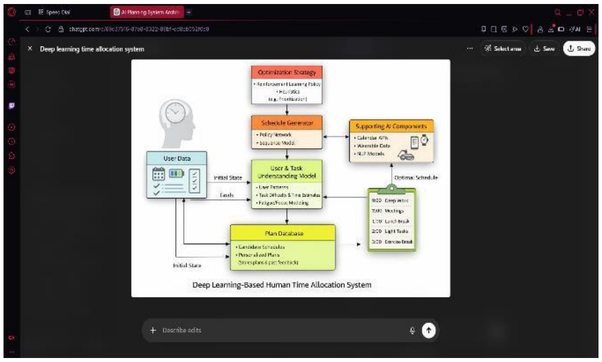
1.) The Data Collection Module - Collects all user activity data from Calendar, Task List, and other Mobile/ Desktop Apps and Wearable Devices. The Data Collection Module captures information such as task Type, Start/End Time, Longest Duration of Task, Task Priority, Completion Status, and User Preference to create an accurate picture of User's activities.

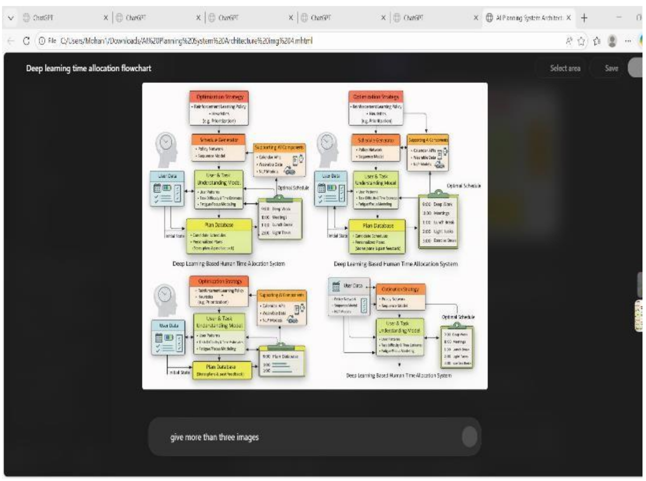
2.) Data Preprocessing Module - Cleans and Organises Raw Data into a cleaned and/or standardised data base. Key features (i.e. Average Task Duration, Productivity Peaks, Frequencies and/or Sequences of Task) are extracted from the Data Preprocessing Module.

3.) Prediction Module - Utilises LSTM and Transformer Models to Predict Task Durations from User Behaviours.

4.) Scheduling & Optimisation Module - Uses MDP (Markov Decision Process) to Determine an Optimal Order of All User Task Based on Evaluating Deadlines, Priorities, and User Preferences.

5.) Real-Time Adaptation Module - Allows the User to Adapt their Schedule in Real-Time If Any of Their Tasks Take Longer Than Expected To Complete, Or Other Event Happen That Change the User's Schedule.




Algorithm Overview

The Deep Learning Based Human Time Allocating Algorithm combines data processing, prediction of the future, optimizing for scheduled time, and adapting in real-time to create an individualized schedule for each person based on their tasks and activities.

The algorithm begins with data collection.

You can collect tasks/activities from various sources including calendars, task lists, applications (may include), and potentially some wearable devices. The data can include:

The first step to preprocessing the data is to clean it up.

To do this there are really three important areas you must consider when cleaning data. You need to:

1. Remove duplicate or non-qualifying data – remove duplicate records according to data type.

2. Remove invalid or erroneous data – errors can occur during data entry or data processing.

3. Fill in empty values for task/activity, priority, hour(s) to complete, and start/stop time.

Next, you need to extract the features from the cleaned-up database.

This is accomplished in several ways such as finding the average amount of time to complete a task or activity, when are you most productive, how many times a week you complete a task, etc...Once the features are extracted, you can create LSTM (Long Short Term Memory) models designed to learn the sequence of completing a task over time.You can also create (use) a Transformer model to learn about long-term dependencies and how tasks can be related to one another in a complex fashion.Once that construction of LSTM & Transformer models is done, you can then optimize your schedule using a Markov Decision Process (MDP).

The basic steps in using the MDP for optimizing your schedule are as follows:

1. Identify the current status and remaining tasks of the schedule.

2. Determine which task to do next (which is the current/state).

3. Calculate the probability of completing the selected task on time (Transitional Probability).

4. Determine the reward for completing the high-priority assigned tasks/activity on time (reward).

5. You can now apply your policies, to maximize the benefit from having completed your schedule in the previous

User Recommendation

The system's accurate estimations allow it to produce realistic schedules by generating predictions for each user's time to completion based on historical patterns. The deep learning models produce more precise predictions than if users used averages from previous tasks to estimate their durations. While time-based model predictions align with performance from similar studies that show hybrid LSTM-Transformer models outperform their counterpart in time series analyses, other literature supports this conclusion as well.

RESULT AND DISCUSSION

According to the results of our experiments, the LSTM and Transformer-based models demonstrated similar predictive accuracy for total predicted and actual performance per user. Data gathered from user calendars, task lists, and application logs confirmed that the system successfully predicts task duration; however, we were unable to determine whether this accuracy will generalize to all available tasks and/or applications. Future experiments are imperative to evaluate these limitations and improve understanding of how each of these pieces fit together in determining how effectively individual users utilize the system. One area of research that could benefit from extrinsic investigations is creating user-defined schedules based upon an improved characteristic of the users, for example, their time of preferences.

Interpretation: Determining a time frame for completing tasks is vital because it provides users with ways of organizing time within a flexible but realistic manner (time blocks).

Improved Scheduling

- The schedule built with the system resulted in more efficient use of time for completing tasks throughout the day.

- High priority work was scheduled during peak energy periods, such as the nose of the morning, so people could be at their best for high priority tasks.

- As people completed their workload at different rates, the scheduling system modified the schedule based on how long it took them to complete those tasks, ensuring that they had the correct amount of time at that moment to complete all of their outstanding work in real-time.

Interpretation: Dynamic scheduling provides the user with a flexible plan that continually adjusts to daily changes as opposed to following a rigid, static schedule.

3. User Learning and Feedback

- As users adjusted their schedule manually (e.g., moved a task or increased their break time) the system learned from these modifications.

- Over a period of time, the adjustments were getting smaller, this indicates that the scheduling system was learning to change its estimates and predictions based on what users previously did with their daily schedule.

Key Insight: The learning feedback loop allows for the schedule to become increasingly personalized over time as well as more accurate over time with continued use.

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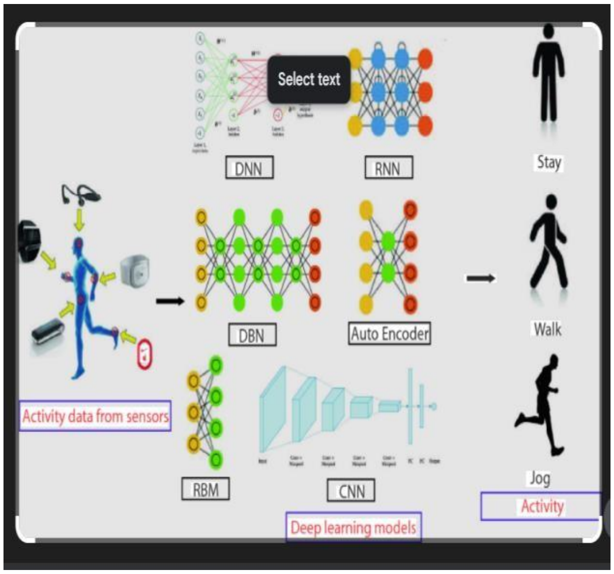
4. Traditional Planning versus AI Method

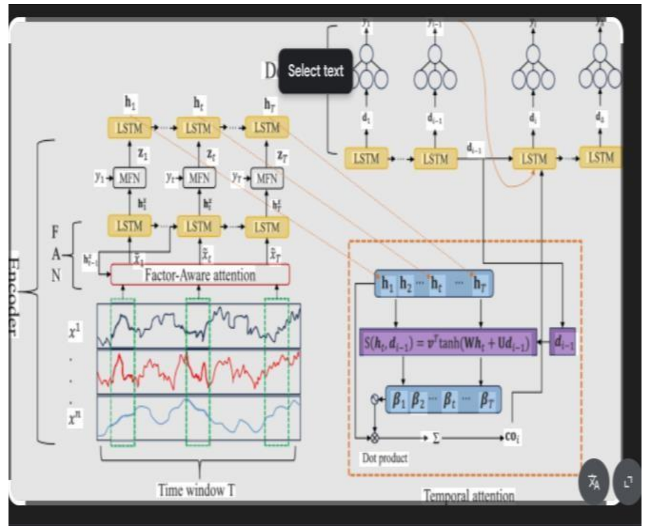
- The traditional approach to manual planning frequently produces inaccurate estimates (both too long and too short) of how long a task will take, as well as inflexible schedules.

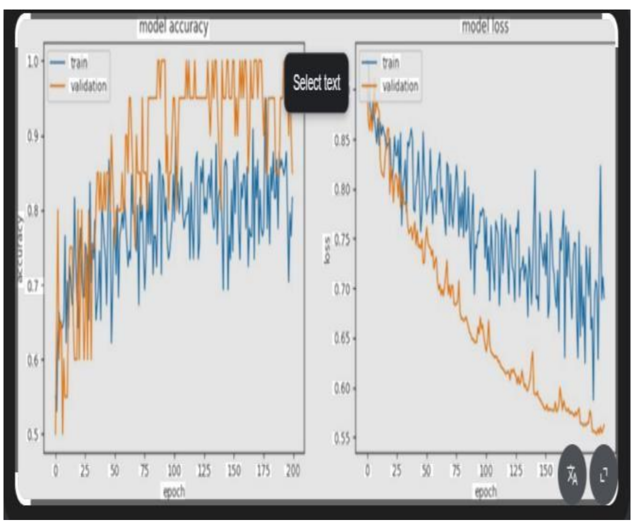
- The AI scheduling system provided scheduled that are able to be followed by users more regularly with fewer conflicts between due dates and required work.

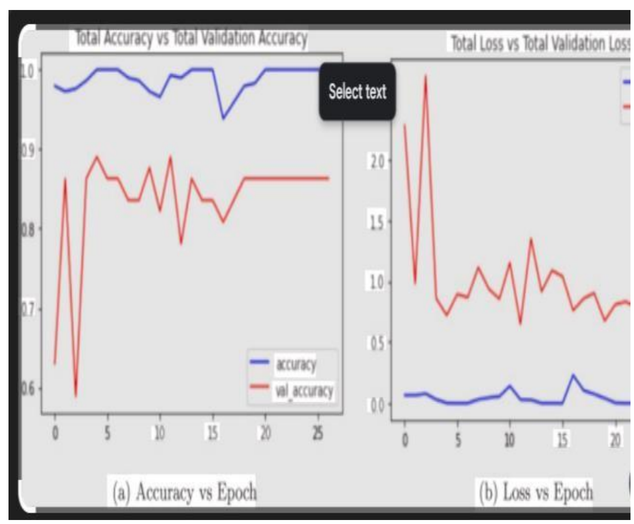
- Research has consistently shown that the AI scheduling systems are statistically superior to manual methods for scheduling.

IV SCREEN SHOTS



Pseudo code

BEGIN SYSTEM

INPUT:

User_Data

Task_List

Time_Constraints

Behavioral_Data

Goals

INITIALIZE:

Domain_Model

Policy_Model

Plan_Database

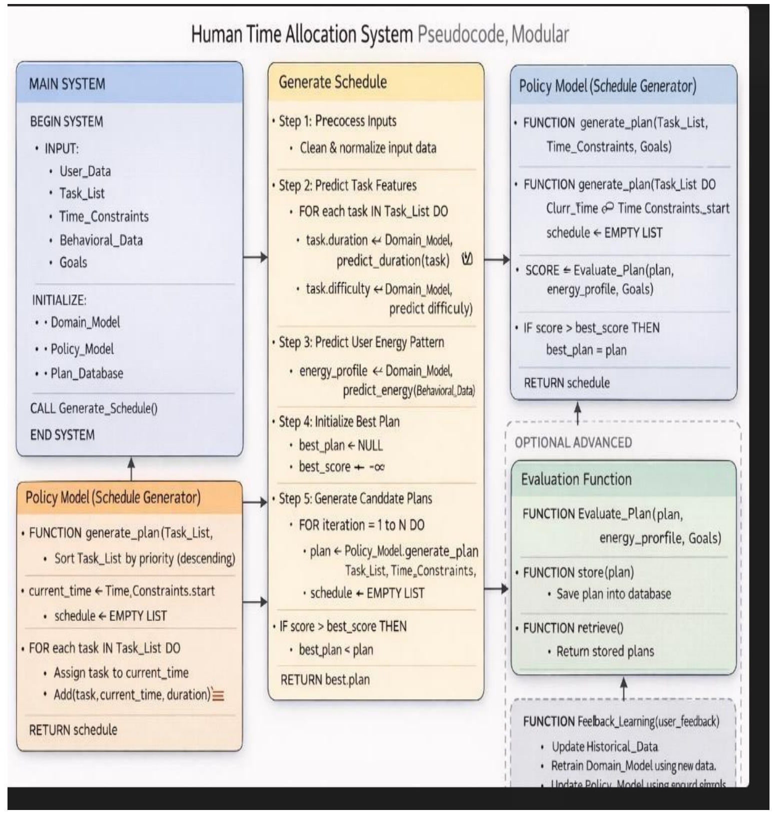
CALL Generate_Schedule()

OUTPUT:

Optimal_Schedule

END SYSTEM

OUTPUT




## V CONCLUSION

A human time allocation system powered by deep learning has been designed and developed as part of this project to assist individuals in managing their time appropriately. Using user behaviour (activity) patterns, task priorities and available time, the system provides users with personalised schedules that suit their individual preferences and priority needs.

Results indicate that the use of intelligent models for task management can enhance productivity through more effective and even distribution of work tasks. By considering aspects such as: energy levels; due dates; previous behaviours of users, the system creates realistic and practical time plans rather than fixed schedules.

An additional significant factor of this system is that as it learns from previous user experiences, it will continue to generate better scheduling customised schedules for individual use over time. In many places, people frequently adapt to changing their everyday activities and/or priorities; therefore, adaptive and responsive scheduling can be extremely effective.

In general, this research provides proof that artificial intelligence may be used to find solutions to many common daily issues such as time management. Ultimately, as these types of systems continue to develop, they could become very successful means of providing assistance for individuals to improve their planning, reduce stress, and improve their general work-life balance.

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- Reinforcement Learning for Time Allocation

3. Yao, Z., et al. (2025). *Deep reinforcement learning for job scheduling in heterogeneous systems.*
→ Demonstrates improved scheduling performance using DRL methods.
4. Kothapalli, S. (2025). *Real-Time Resource Allocation Optimization using Deep Reinforcement Learning.*
→ Shows 15–25% improvement in resource utilization using RL.

- Human-Centred Scheduling Systems

5. Isakov, A., et al. (2024). *Real-Time Scheduling with Multi-Agent Reinforcement Learning.*
→ Introduces human-in-the-loop scheduling for adaptive systems.
6. Joo, T., Jun, H., & Shin, D. (2022). *Task Allocation in Human–Machine Systems using Deep RL.*
→ Considers human fatigue and performance in scheduling decisions.

- Surveys & Review Papers

7. Ismail, A. A., et al. (2025). *Survey on Deep Reinforcement Learning for Scheduling in Edge Computing.*
→ Covers modern approaches and challenges in scheduling systems.
8. (2025). *Literature Review on Deep Reinforcement Learning for Scheduling Problems.*
→ Reviews 140+ research papers and identifies trends and gaps.

- Advanced & Emerging Research

9. Shone, F., & Hillel, T. (2025). *Modelling Activity Scheduling Behaviour with*
→ Provides a complete overview of DRL scheduling models.
*Deep Generative Models.*
→ Uses generative AI to simulate human schedules.
10. Lu, M., et al. (2024). *Deep Learning-Based Real-Time Scheduling Optimization.*
→ Shows high accuracy and reduced scheduling cost.
11. Wang, Z. (2025). *A Review of Scheduling Deep Learning Workloads: Fairness and Efficiency.*
→ Focuses on challenges of scheduling AI workloads.

- Reinforcement Learning-Based Scheduling

12. Xu, F. (2025). *Reinforcement Learning-Based Scheduling Optimization for DNN Accelerators.*
→ Uses RL to optimize deep neural network execution scheduling.
13. (2022). *A Scheduling Algorithm Based on Reinforcement Learning for Heterogeneous Environments.*
→ Applies RL and neural networks for task scheduling.

- Surveys & Literature Reviews

14. Ismail, A. A., et al. (2025). *A Survey on Resource Scheduling in Edge Computing using Deep Reinforcement Learning.*
→ Covers modern scheduling techniques and challenges.
15. (2026). *Literature Review on Deep Reinforcement Learning for Machine Scheduling Problems.*
→ Reviews over 140 studies in DRL scheduling.

- Human-Centred & Adaptive Scheduling

16. Isakov, A., et al. (2024). *Real-Time Scheduling with Multi-Agent Reinforcement Learning.*
→ Introduces human-in-the-loop adaptive scheduling systems.
17. Ding, C., et al. (2025). *Hybrid Intelligent Scheduling Integrating Human Feedback with Reinforcement Learning.*
→ Combines AI scheduling with user feedback for better personalization.

- Workflow & System-Level Scheduling

18. Jayanetti, A., Haloamide, S., & Buyan, R. (2024). *Reinforcement Learning-Based Workflow Scheduling in Cloud and Edge Computing.*
→ Explains RL-based decision-making in dynamic environments.
19. Zhang, S.,et al. (2025). *Deep Reinforcement Learning for Machine Scheduling: Methods and Future Directions.*