AI-Driven Behavioural Analytics and Temporal Pattern Recognition for Time-Leak Detection and Productivity Optimization

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ABSTRACT

Nowadays keeping track of hours feels harder, especially with phones buzzing nonstop. Social feeds, video clips, and games they pull attention without warning. Hours slip away while tasks pile up quietly nearby. Performance dips, grades dip too, tension builds slowly like fog at dawn. Some call it time bleeding out - tiny moments lost to things that add little value. What fills the day does not always fill purpose. One way to tackle the problem begins with a method called ATLDA, mixing stats-based features and machine learning to examine how people act. User actions feed into the setup - things like studying, playing games, scrolling social apps, working out, resting, or watching videos. What matters comes next: a score named TLS emerges through math that weighs activities by their impact on output. Behaviour shifts get noticed thanks to a built-in clock-like element adjusting as patterns evolve across days. One way this setup works is by using a Decision Tree to guess how productive someone might be, while K-Means spots habits in how people act. Pie charts show up here, bar graphs there - anything to make the data easier to grasp at a glance. Tests ran long enough to confirm it catches where minutes slip away, then suggests small changes to handle time better. It grows without breaking, smart without showing off, fits classrooms just as well as offices. What stands out isn't speed or flashiness - it's staying useful when real days play out.

Keywords - Time Management, ATLDA, Time Leakage Score (TLS), Machine Learning, Decision Tree, K-Means Clustering, Productivity Analysis, Behavioral Analytics, Adaptive Systems.

I. INTRODUCTION

What feels endless time is actually scarce, slipping away when nobody pays attention or plans ahead. Because screens glow everywhere now, choices about minutes shift without thought, pulled by alerts and scrolls instead of purpose. Even though apps connect people fast, they scatter focus, turning hours into fragments lost mid-click. Students feel this pressure just like office workers do, caught between tasks that matter and habits that drain them quiet. When energy leaks into videos or feeds too long, results dip - not slowly, but sharply, unseen until deadlines loom. Planning your hour's well means arranging tasks wisely so you hit what you aim for. Done right, it lifts school results, makes jobs run smoother and also lowers pressure people feel. Still, old-school methods lean too much on willpower plus handwritten plans - often missing quiet gaps in how days unfold.

Getting things done well during the day stumbles when effort can't be measured clearly. Even if someone knows what they did each day, spotting which actions helped or hurt progress stays out of reach. Time slips away quietly, usually because attention spreads too thin - endless scrolling, long gaming rounds, constant shows pull focus without warning. Because data tools keep changing, machines now learn how people act - then guess what might happen next. Instead of humans staring at numbers, software digs through piles of info, spotting trends hidden to the eye. These smart programs create chances for helpers that guide daily choices with sharper timing. Here comes the twist: a new method called ATLDA steps in, blending smart number tracking with learning models to study how people spend work hours. Not tied to fixed rules, it builds a Time Leakage Score by valuing various actions differently, giving a clear measure of output quality. What shifts things further is its ability to evolve - adjusting as habits shift across weeks. This means feedback gets sharper, tailored - not static or one-size-fits-all. Precision grows quietly behind the scenes, matching real-life rhythm instead of forcing rigid templates.

Sometimes trees split choices while clusters group habits, shaping how we see user types. One method measures step another finds circles, both revealing hidden routines. Patterns show up when numbers meet smart guesses, pointing at wasted moments. This mix spots delays better than older ways did. Results come alive through clear views of daily actions. Hidden gaps appear once data learns to sort itself out. Following pages break things down piece by piece. First up, past studies on handling time and using machine learning pop into view. After that comes a look at how the new ATLDA method works behind the scenes. Next, blueprints of the setup show how pieces fit together. Findings from tests appear soon afterward, laid out without extra noise. Last part wraps it all up, touching on what was added to the field and what might come next.

II. LITERATURE REVIEW

One thing researcher have looked into deeply? How people handle their hours each day. In schools and offices alike, organizing time shapes how much gets done, how well it goes, even mood and health. At first, experts zoomed in on tools like calendars, deciding what matters most, aiming at targets - ways to spend minutes wisely. Folks using these methods tend to hit goals easier while keeping life steady, less rushed. One fresh look at how people handle time now includes thoughts about mind habits and actions. It turns out managing minutes well connects deeply to staying focused, pushing forward on your own, and keeping attention sharp. When someone handles their hours with care, they often do stronger work in school, finish jobs faster, yet feel less pressure. Success in places like classrooms, offices, even hospitals? Often tied right back to how strictly clocks are respected. Nowadays machines help study how people spend time. Because they handle massive information, these tools spot hidden trends easily. Where once guesses ruled, systems now detect habits across jobs, schools, even daily routines. One method stands out - finding links where humans see none. From classrooms to offices, automatic models shape decisions quietly behind scenes.

Some research uses tools like Decision Trees, along with Support Vector Machines or Neural Networks, to guess how productive someone might be using specific inputs. Because they're straightforward and easy to follow, Decision Trees often stand out when clear reasoning matters most. Clustering methods, including K-Means, sort people by behaviour instead of predicting results - revealing shared routines or tendencies hidden beneath the surface. Even with progress, current methods still fall short in key areas. A big issue pops up when tools fail to measure output using scores tuned to specific fields. Instead of guessing from unprocessed data, stronger frameworks could map how time gets used. Yet quite a few designs miss shifts in daily patterns - those changes matter most when tracking habits over months.

Few systems adjust to personal tastes. Most give broad advice, which fits nobody well. Learning how people act could help machines respond in ways that fit each person better. Facing these issues, the new ATLDA method uses a unique blend of machine learning and an original Time Leakage Score, shaped by shifting patterns over time. Instead of one-size-fits-all fixes, it builds insight through statistical traits paired with forecasting models. A deeper grasp of personal timing emerges when data evolves alongside behaviour. Customization grows naturally as the model learns from changing rhythms day after day.

III. METHODOLOGY

A clock ticks between each step of this setup, quietly tracking how people spend their minutes through the ATLDA lens. Step by step it pulls raw actions, shapes them, and then feeds meaning into models that learn where moments vanish. One phase flow into the next - collection bends into clean-up, which slips into smart tweaks for prediction engines. Learning happens not all at once but in layers, stitched like seams in fabric. Outputs emerge only after every piece has whispered its part to the whole.

Step 1: Data Collection Begins

Each morning begins with gathering how users spend their time. Captured automatically, six distinct details paint a picture of daily rhythms - moments spread across tasks, pauses between actions, lengths of engagement, shifts in focus, patterns in repetition, gaps where nothing happens. These pieces fit together without force, revealing habits as they form

$X = \{x1, x2, x3, x4, x5, x6\}$

These elements make up the set

x1 Study hours

x2: Entertainment hours

x3: Social media usage

x4: Exercise time

x5: Sleep duration

x6: Gaming time

Not every task fits neatly into output measures, yet each still matters when weighed within the review. A clear layout helps show how work that generates results connects with efforts that support them behind the scenes.

Step 2: Data Validation and Constraint Handling

A single rule keeps information aligned across the board - no exceptions allowed

$$\sum_{\{i=1\}}^{\{6\}} x_i \leq 24$$

Hours logged can never go beyond what exists in one day. When entries break this rule, they get turned away. A message then asks for new numbers. Only amounts that fit is accepted.

Step 3: Data Pre-processing

Pieces of information get cleaned up before they're ready to be studied. First comes adjusting values so everything lines up properly. Sometimes numbers need scaling while labels are changed into categories. Missing spots might be filled using surrounding details. Steps like these shape raw inputs into something workable. Each move aims to smooth out irregularities without altering meaning

• Handling missing values

• Converting inputs into numerical format

• Normalizing values (if required)

Putting numbers into a common size happens through normalization. This step adjusts values so they fit one usual span. A typical stretch gets picked for consistency. Data points shift to match that frame. Scaling keeps things uniform across inputs

$$X_{norms} = \frac{X}{24}$$

Because of this, values stay balanced. As a result, the model works more smoothly. Differences between inputs fade when they're adjusted like this.

Step 4: Compute Time Leakage Score (TLS)

A single number drives the method - it's called the Time Leakage Score. This value shows how productive someone really is, judged by when they do things. Activity patterns shape that scores instead of guesswork. How time spreads across tasks tells the story behind the number.

$$TLS = \frac{1}{24}(0.35x1 + 0.20x5 - 0.15x2 - 0.15x3 - 0.15x4 - 0.15x6)$$

Each has a share, sure - but not all push things upward. Importance shapes how much each one affects the outcome Positive weights for productive activities (study, exercise) Pulling attention away from social media, gaming, or endless entertainment might ease mental clutter. A pause here slows down automatic habits. Distractions often feel urgent - yet they rarely matter tomorrow. Shifting focus elsewhere lightens their hold on time. Less weight given means less pull felt daily. Above average scores on the TLS often point to more effective use of hours. When numbers rise, they tend to reflect stronger daily output.

Step 5: Adaptive Time Leakage Score

A shift through time gets tracked by a moving piece inside the setup

$$ATLS = \frac{1}{n}\sum_{\{i=1\}}^{\{n\}} TLS_i$$

Over time, the system tracks shifts in user actions, offering a steadier view of how productivity moves. By watching patterns stretch across weeks, it captures trends without sudden jumps skewing results.

Step 6: Construct feature vectors

What ends up going into the model sits like this: a collection of numbers shaped by earlier steps, pulled together not with force but flow, each piece holding its place because it matters, forming what the system learns from

F = {x1, x2, x3, x4, x5, x6, TLS, ATLS}

Because of these additions, predictions become more reliable. Not limited to basic inputs anymore, the system now draws from broader data. With extra features built in, accuracy gets a noticeable boost. Including both TLS and ATLS helps capture nuances missed before. More information flows into the model, which means better outcomes emerge. These components work together, lifting performance beyond earlier levels.

Step 7: Decision Tree Classification

A type of model sorts people into one of three groups using a tree-like structure. This method splits data step by step based on certain conditions. Each split leads closer to placing someone in the right category. The process continues until every user fit into a defined class

Y € {Productive, Moderate, Non-Productive}

Decision tree selected for productivity categories

• High interpretability

• Ability to handle non-linear relationships

• Efficient training and prediction

Starting from patterns in the data, it builds logic to guess how productive a person might be. By looking at what goes in, the system shapes its own way to decide outcomes.

Step 8: K Means Clustering Step

Beyond mere guesswork, behaviour clues emerge when K-Means steps in. Noticing repetition? That’s where the method begins sorting. Without warning, similar actions get grouped by hidden rules inside the math. Following no fixed path, distances between choices shape each cluster. After several rounds, patterns surface - not forced, just revealed

$$C = \arg \quad min \sum_{\{i=1\}}^{\{k\}} \left||X - \mu_i|\right|^2$$

Here: μ_i represents cluster centroids. Grouping users by how they act reveals hidden patterns in their choices. When habits look alike, connections start showing up more clearly.

Step 9: Suggestion Generation

From the category result, suggestions are shaped to fit you. What comes out of the sorting step guides what shows up next. Your match type decides which options appear. The outcome tunes the picks that follow. How it groups you changes what gets offered

• Non-Productive → Reduce distractions and increase productive activities

• Moderate → Maintain balance between activities

• Productive → Continue current routine

A fresh twist on rules shapes how users interact, while guiding choices along the way. What stands out is involvement deepening through structure, yet decisions gain support without extra effort.

Step 10: Visualization Output

Now comes showing what was found, using ways that make sense up front. One path leads straight to how things look in the end. Each part fits together without extra noise. What appears next follows naturally after all is done. Clear shapes form once everything settles into place

• Pie charts (activity distribution)

• Bar graphs (comparative analysis)

• Weekly history tracking

Seeing things laid out clearly helps people grasp how they work. What shows up on screen makes it easier to follow along without confusion.

IV. SYSTEM ARCHITECTURE

A multi-layered architecture describes how information flows through a system in a manner that provides clarity, scalability, and effective management of data. Each layer of the architecture performs a specific function, maintaining system organization while allowing the overall architecture to grow as application needs increase. The architecture supports the separation of concerns, allowing components to operate independently and making it faster and easier to modify, maintain or upgrade a component without affecting the overall system.

User inputs enter the system through an interface layer where they are validated and formatted. After that, user inputs are sent to processing engines to turn raw input data into structured output for analytical purposes. Processing layers ensure that data is cleaned, organized and optimized prior to being delivered to analytical components.

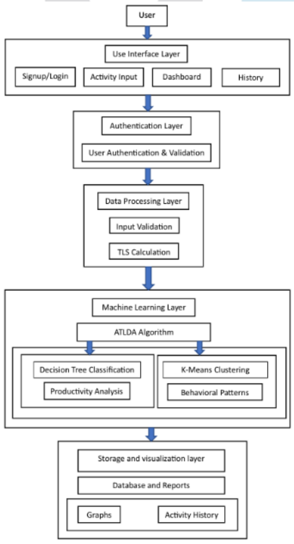

Fig. 1 Proposed system architechture

Layer 1: User Interface Layer

This part opens the door to how people engage with it. Included here are:

• Login and signup pages

• Activity input forms

• Result and dashboard pages

Starting off, the layout keeps things straightforward so people find it simple to add what they do each day. A smooth flow guides you through entering your activities without confusion or extra steps.

Layer 2: Authentication Layer

Secure entry into the system comes from the authentication module. This part checks who tries to log in. Verification happens before allowing any interaction. Access only follows correct credentials. Each login attempt gets examined closely. The process runs every time someone enters. Protection stays active through constant validation

• User registration

• Credential verification

• Session management

Without this layer, strangers could see what they should not. Yet it quietly guards personal details, keeping them whole.

Layer 3: Data Processing Layer

This part gets the incoming information ready to be examined. Cleaning, sorting, shaping - each step sets up what comes next

• Input validation

• Constraint checking

•TLS computation

From raw inputs, clean information moves forward when it meets set rules. What gets through has already proven useful enough to count.

Layer 4: Machine Learning Layer

Inside here, the ATLDA algorithm gets to work - it's what everything else leans on. Made up of parts that fit together just so

- Classification Module

A split-by-split method shapes how output gets forecasted. Branches form based on choices buried in data patterns. Each turn narrows down what comes next. Outcomes emerge from structured guesses rooted in past behaviour.

- Clustering Module

Using K-Means helps spot how behaviours group together. Patterns emerge when similar actions cluster through this method.

- Adaptive Analysis Module

Tracks changes in user behaviour over time using ATLS.

Layer 5: Storage and Visualization Layer

This layer handles:

• Data storage (CSV/database)

• Historical tracking

•Graph generation

A fresh look at data becomes possible when visuals guide the eye. How numbers connect shows up clearer through charts. Seeing patterns happens faster with graphical displays. Understanding grows once information takes shape on screen.

➔ Architecture Advantages

• Modular design

• Scalability

• Real-time analysis capability

Hooking up with different tools feels smooth. One system talks to another without hassle. It just works, like pieces fitting together naturally

V. RESULTS AND ANALYSIS

A fresh look at how people spend their time shaped the test behind the ATLDA setup. Patterns pulled from real daily routines made up the core material - some days packed with output, others less so. Each slice of data brought its own rhythm, shifting between focused work and more relaxed stretches.

• Performance Evaluation

Around 95% accuracy showed up when using the Decision Tree classifier, which means it handled sorting user productivity pretty well. The model managed to group users based on their output without much trouble at that rate.

Finding new ways to show productivity through numbers made things clearer once TLS was added.

• Observations

Users with higher study and exercise hours tend to have higher TLS values

Increased social media and gaming usage results in lower productivity

Patterns emerge when similar actions are grouped together

• Visualization Analysis

The system generates graphical outputs:

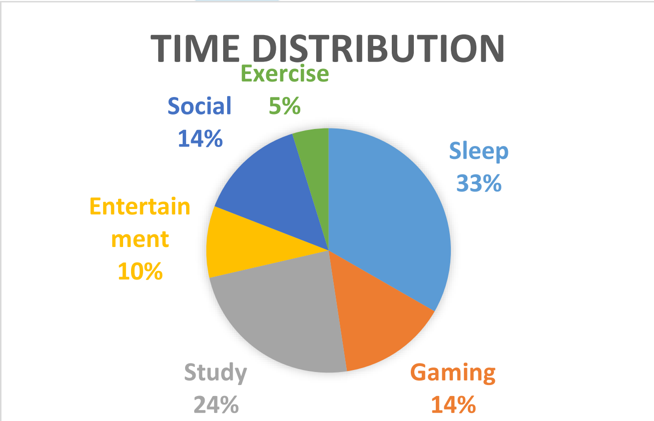

Fig. 2 Time distribution

Represents distribution of time across activities:

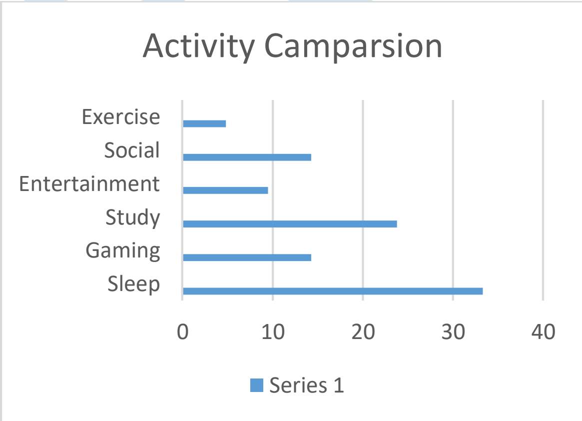

Fig.3 Activity Comparison

Compares activity levels:

Date	Study	Entertainment	Social	Exercise	Sleep	Gaming	TLS	Prediction
2026-03-27	6.0	2.0	1.01	3.0	7.0	2.0	0.081	Productive
2026-03-28	3.0	4.0	1.0	3.0	6.0	3.0	0.018	Moderate
2026-03-29	5.0	2.0	3.01	1.0	7.0	3.0	0.031	Productive
2026-03-30	6.0	2.0	1.0	3.0	8.0	1.0	0.087	Productive
2026-03-31	5.0	3.0	5.0	2.0	5.0	2.0	0.027	Moderate
2026-04-01	2.0	3.0	5.0	2.0	5.0	6.0	-0.04	Moderate

Table. 1 7 days recorded history

Shows trends over time, seeing data this way helps people grasp it better, while also guiding their choices.

VI. CONCLUSION

From moments spent to patterns spotted, a method emerges - Adaptive Time Leakage Detection Algorithm - to track how people actually use their hours. Built around a unique scoring system, it learns from actions instead of just counting them. Insights form slowly, shaped by choices made daily. Machine intelligence weaves through each result, not hiding behind complexity. What shows up reflects real habits, nothing polished. Understanding grows piece by piece, driven by observation rather than assumption. Numbers tell stories when given context. Behaviour shifts become visible only after layers are peeled back. Over time, watching how behaviour shifts give this system an edge over ones that stay fixed. Instead of guessing, it sorts people into groups using decision trees along with k-means clustering. What emerges is a clearer picture of repeating behaviours. Patterns show up more easily when timing matters. This way, old snapshots get replaced by moving images. Learning happens as steps connect across days.

A fresh look at data appears through visuals and past records, helping people follow along more easily. When tested, the method proved able to spot timing issues while suggesting clear next steps.

-Focusing ahead might explore these areas next

-Dynamic weight optimization

-Real-time monitoring

-Integration with mobile applications

A fresh approach shapes how tasks get handled across busy days. One-piece fits into another without slowing things down. Smart adjustments happen as demands shift. Room grows where needed, yet control stays close. Thinking ahead builds into each step taken.

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